ASSESSING CHANGES IN TRAVEL MODE CHOICE PREFERENCES DURING SMOG CRISIS: EVIDENCE FROM CHIANG RAI

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IN
INTERNATIONAL LOGISTICS AND
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THIS THESIS IS A PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF MASTER OF BUSINESS ADMINISTRATION IN INTERNATIONAL LOGISTICS AND SUPPLY CHAIN MANAGEMENT

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ABSTRACT

This study explores how smog crisis events influence travel mode choices in Chiang Rai, Thailand. As seasonal air pollution becomes more severe, understanding its impact on urban mobility is essential for public health and transportation planning. Using data from 406 respondents, this research compares travel behavior during non-air quality crisis and air quality crisis. A mixed methods approach was employed, integrating Multinomial Logit Model (MNL) and Exploratory Factor Analysis (EFA) to identify key behavioral and perceptual factors influencing mode selection. Results reveal that during air quality crisis, motorcycle usage declines while the use of private cars and alternatives increases, reflecting a preference for enclosed and flexible transport options. EFA identified five latent constructs Mode Choice, Health and Constraint, Social Recommendation, Perceived Behavioral Control, and Service Improvement that shape individual decisions. Regression analysis confirmed that income, travel cost, health concerns, and trip frequency play more significant roles under poor air quality. These findings provide critical insights for designing adaptive transport policies that prioritize safety, accessibility, and sustainability during environmental crisis in secondary cities like Chiang Rai.

Keywords: Mode Choice, Air Pollution, Urban Mobility, Multinomial Logit Model, Exploratory Factor Analysis

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ABBREVIATIONS AND SYMBOLS

N-AQC	Non-air quality crisis
AQC	Air quality crisis

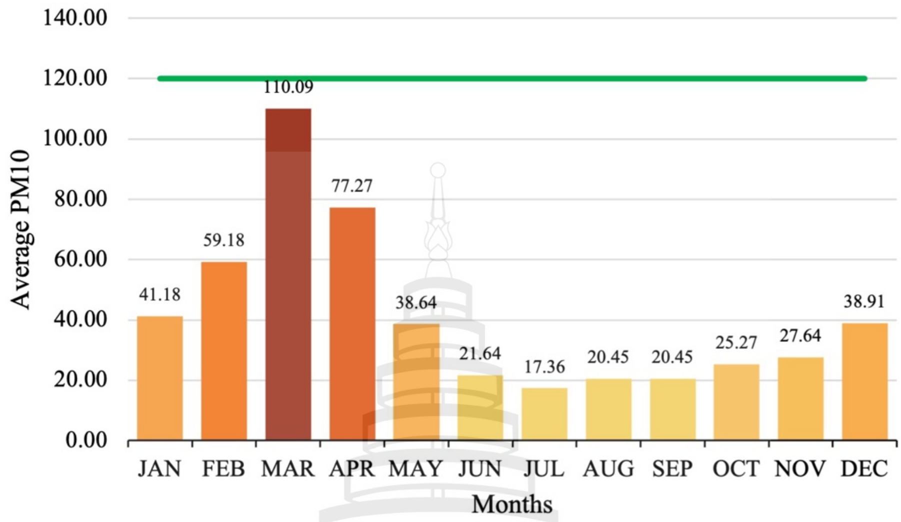
CHAPTER 1

INTRODUCTION

1.1 Background

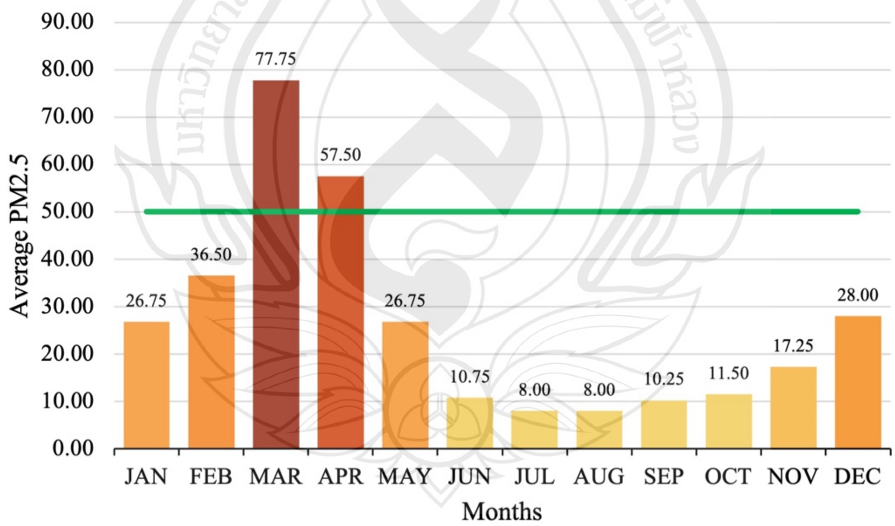
In the global context, air pollution has escalated to become not just an environmental issue but a multidisciplinary crisis impacting urban health systems, climate resilience, economic productivity, and social behavior. With Southeast Asia being one of the regions most affected by seasonal haze and transboundary pollution, it becomes imperative to understand how pollution events alter not only public health dynamics but also daily routines such as commuting. Air pollution is a major environmental challenge with far-reaching impacts on human health, economic productivity, and urban life quality. Smog events marked by elevated levels of particulate matter (PM2.5 and PM10) are especially hazardous in urban centers, where transportation and industrial activity are dense. In recent years, Southeast Asian cities have increasingly faced smog crisis driven by rapid urbanization, seasonal biomass burning, and vehicle emissions. These events pose significant public health risks and disrupt daily activities, including travel behavior (Pramitha & Haryanto, 2019; Li et al., 2022). Such knowledge is crucial for integrating environmental data into transport planning and public policy.

The selection of Chiang Rai for this study is informed by both empirical and strategic considerations. Empirically, it is a city that faces recurrent smog episodes, offering a clear setting for temporal comparison of behavior. Strategically, its mid-sized scale and varied transport infrastructure make it a representative case for other similar urban centers in Southeast Asia. According to data from the Pollution Control Department, air pollution in Chiang Rai spikes during March, when PM2.5 and PM10 levels frequently exceed national safety thresholds of 50 $\mu g/m^3$ and 120 $\mu g/m^3$ respectively (Pollution Control Department, 2022). Figure 1.1 shows the monthly average PM10 concentration over a 10-year period, while Figure 1.2 presents the monthly PM2.5 concentration. These figures highlight March as the most polluted month each year, reinforcing the focus of this study on smog-period travel behavior.



Source Pollution Control Department (2022)

Figure 1.1 Average Monthly PM10 in Chiang Rai, 2012–2022



Source Pollution Control Department (2022)

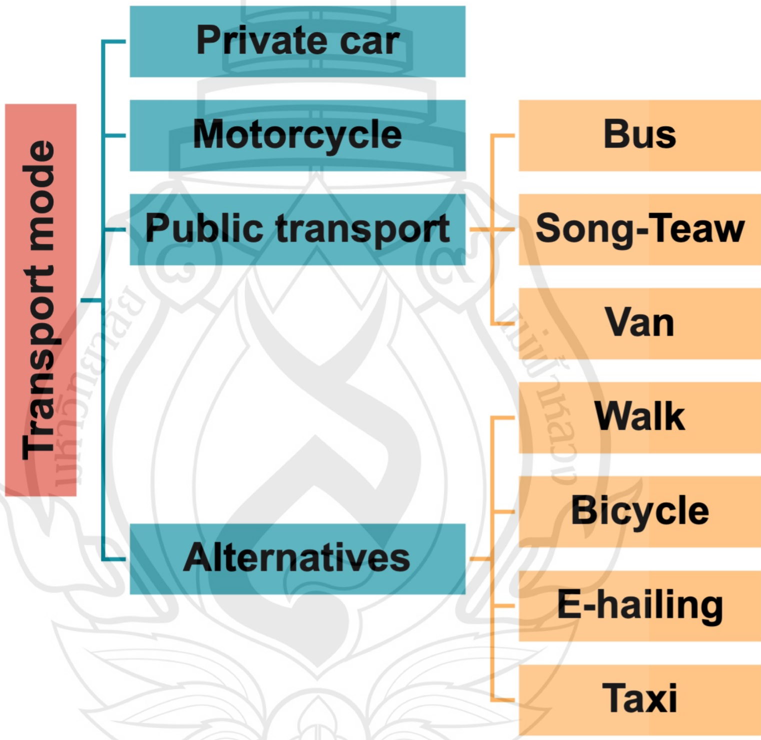
Figure 1.2 Average Monthly PM2.5 in Chiang Rai, 2012–2022

The transportation landscape in Chiang Rai features a range of travel options that reflect both traditional and modern mobility patterns in medium-sized Southeast

Asian cities. As shown in Figure 1.3, four primary categories of travel modes are commonly used:

1. Private Car
2. Motorcycle
3. Public Transport – including buses, mini-buses (Songthaew), and vans with intra-city and inter-city routes
4. Alternatives – such as walking, bicycling, taxi, and e-hailing services

Due to their relatively small modal shares, alternative modes are grouped together to allow for more robust analysis. This classification provides a practical foundation for assessing modal choice behavior under varying air quality conditions.



Source Developed by Author

Figure 1.3 Transport Modes in Chiang Rai

Behavioral adaptation to air quality appears context dependent. Large-scale mobility data from Xi'an, China, showed that air pollution reduces travel distance and discourages travel area especially among younger individuals suggesting demographic variation in smog responses (Xu et al., 2021). Furthermore, systematic observations indicate that pedestrians and cyclists face greater pollution exposure than travellers using enclosed transport, highlighting health implications linked to mode choice (Singh et al., 2021).

While studies have explored the links between air quality and health or economic outcomes, less is known about how air pollution influences transportation choices especially in non-capital, developing cities. Understanding this relationship is essential for urban planning and public health strategies, as individual travel decisions during air quality events can inform future transport and environmental policy. This study addresses this gap by examining how air quality conditions influence travel mode selection and identifying key factors that drive behavioral change in Chiang Rai during air pollution events.

1.2 Research Objectives and Questions

In the context of this research, the objectives are framed to generate both descriptive and inferential knowledge. Descriptively, the aim is to map behavioral shifts in commuting patterns across defined air quality scenarios. Inferentially, the goal is to determine the predictive power of different perceptual, economic, and environmental factors on mode choice. This dual-layered objective strengthens both the academic contribution and policy relevance of the study.

This study aims to investigate changes in travel behavior in Chiang Rai during air quality crisis, and to identify the main factors influencing travel mode choices under varying air quality crisis.

Research Objectives:

1. To examine how travel mode choices differ between non-air quality crisis and air quality crisis.

2. To identify key factors such as health concern, visibility concern, and travel cost consciousness that influence individuals' travel behavior during air quality crisis events.

3. To statistically model the influence of sociodemographic and perceptual factors on travel mode selection.

Research Questions:

RQ1: How do travel mode choices change during air quality crisis compared to non-air quality crisis in Chiang Rai?

RQ2: What are the key factors that influence travel behavior under air quality crisis conditions?

RQ3: How can these factors be used to predict the likelihood of choosing specific travel modes?

1.3 Expected Outcome

In addition to the outcomes listed, this research is anticipated to contribute to theoretical advancements in the intersection of environmental perception and transport behavior. By offering a data-driven insight into how individuals prioritize health, cost, and accessibility under environmental stress, this study may inform urban transport modeling frameworks, environmental justice considerations, and behaviorally sensitive policy tools. The methodological approach also sets a foundation for future longitudinal studies in similar settings.

The study is expected to yield several key outcomes that will advance understanding of pollution-related travel behavior. First, it aims to identify statistically significant factors such as health and visibility concerns that influence travel behavior during air quality crisis, providing empirical evidence of the relationship between environmental conditions and mobility choices. Second, the research will establish a validated factor structure of latent perceptual and behavioral influences using Exploratory Factor Analysis (EFA), offering a comprehensive framework for understanding the underlying dimensions that drive travel decisions during air quality crisis. Third, it will develop a predictive model of travel mode choice using Multinomial Logit Model (MNL), applicable across both non-air quality crisis and air quality crisis, enabling comparative analysis and forecasting capabilities. Finally, the study will generate actionable insights for policymakers and planners to promote adaptive and sustainable travel options in response to air quality deterioration, contributing to more resilient urban transportation systems in pollution-prone regions.

1.4 Scope of Study

The geographical and demographic scope has been defined to ensure both manageability and representativeness. Urban and suburban zones of Chiang Rai provide contrasting transport environments, which enrich the comparative aspect of the study. The target population (aged 21–60) reflects the active commuting segment, who are most likely to adjust travel behavior due to external stimuli such as air pollution. The temporal scope aligns with the historical trends of air quality deterioration, ensuring data relevance and analytical precision.

This research focuses on urban and suburban areas of Chiang Rai, Thailand, which has a population of approximately 1.3 million. The study targets residents aged 21–60, with demographic data collected through online surveys. Key variables include gender, education level, occupation, income, and marital status.

The analysis compares two-time frames:

1. Non-air quality crisis (N-AQC) – when PM2.5 < 50 μg/m³ and PM10 < 120 μg/m³

2. Air quality crisis (AQC) – when PM2.5 ≥ 50 μg/m³ and/or PM10 ≥ 120 μg/m³

Modes of transport studied include private cars, motorcycles, public transportation (bus, van, Songthaew), and alternatives such as walking, cycling, taxis, and e-hailing services.

1.5 Conceptual Framework

This conceptual structure enables a holistic understanding of how internal perceptions (e.g., health and visibility concerns) interact with external conditions (e.g., air pollution levels) and personal characteristics (e.g., income, occupation) to shape transport decisions. The choice of EFA ensures that latent structures are empirically grounded, while the use of MNL allows for probabilistic interpretation of behavioral outcomes. Together, this framework supports evidence-based decision-making and reinforces the policy translation potential of the findings.

This study aims to investigate the factors influencing travel behavior changes during non-air quality crisis and air quality crisis in Chiang Rai, Thailand. The conceptual framework is built upon empirical insights from the literature on environmental psychology, transportation studies, and air pollution impacts. It focuses on identifying key perceptions and concerns that shape individuals' travel decisions in the context of deteriorating air quality.

To structure and validate these constructs, this study adopts a two-stage analytical approach

1. Multinomial Logit Model (MNL) is then employed to estimate the likelihood of selecting specific travel modes based on the identified factors from EFA, along with sociodemographic and environmental variables.

2. Exploratory Factor Analysis (EFA) is used to identify the latent variables underlying survey items related to perceptions, concerns, and decision-making factors.

This integrated approach provides a comprehensive understanding of behavioral responses to air pollution and supports data-driven policy development for sustainable urban transport.

CHAPTER 2

LITERATURE REVIEW

2.1 Disaster Affected Transportation

2.1.1 Natural Disaster

Natural disasters profoundly and immediately impact travel mode preferences, leading to a paradigm shift in transportation dynamics within affected regions (Ishikawa et al., 2015). The destruction of transportation infrastructure by hurricanes, earthquakes, and floods prompts reconfiguring how people navigate their surroundings. This often results in an increased reliance on personal vehicles for autonomy and adaptability. During evacuations, there is a heightened demand for emergency transportation services, emphasizing the importance of organized evacuation plans in safeguarding lives (Kreibich et al., 2017).

The interplay between disaster response and transportation planning becomes crucial as communities grapple with the need to evacuate swiftly and safely. The aftermath of natural disasters provides an opportunity to reassess transportation choices, integrating sustainable options into rebuilding initiatives. Reconstruction often involves restoring public transportation infrastructure and introducing innovations aligned with sustainability goals(Martins et al., 2019).Government initiatives prioritizing resilient infrastructure and incentivizing shared mobility options contribute to broader rebuilding efforts.

The evolving travel mode preferences post-disaster highlight the adaptability of individuals and the resilience and sustainability of transportation systems. The nexus between disaster response, transportation planning, and sustainable rebuilding is pivotal for ensuring transportation networks' long-term viability and adaptability in the aftermath of natural disasters (Li et al., 2023).

2.1.2 Air Pollution

Air pollution significantly impacts transportation preferences, especially during smog crisis. High concentrations of pollutants in the air, as observed during smog events, have direct implications for public health and the environment (Yang et al., 2020). Studies underline the severe health risks associated with exposure to air pollution, including respiratory diseases, cardiovascular issues, and cancer. In the context of transportation, these health concerns during smog crisis prompt individuals to reevaluate their travel mode choices (Kopytenkova et al., 2019). Residents consider the type of transport and the level of air pollution they may encounter during their travel decisions. This heightened awareness of air quality often leads to shifts in travel behavior, with individuals showing a preference for modes perceived as less exposed to pollution. Sustainable transportation alternatives, such as active or public transit, may become more appealing during smog crisis as people seek to minimize their exposure to harmful pollutants. Conversely, there may be a decrease in the use of private vehicles, a significant contributor to air pollution, during such events (Romero-Ania et al., 2022). Understanding these dynamics is crucial for policymakers and urban planners aiming to promote sustainable transportation and mitigate the impact of air pollution on public health during environmental crisis like smog events.

2.1.3 Virus Pandemics Crisis

The COVID-19 pandemic has led to significant changes in commuting patterns and transportation preferences, driven by lockdowns and social distancing measures. Remote work became widespread, causing a substantial reduction in daily commuting. With the traditional need to commute to centralized workplaces diminishing, people reevaluated their reliance on conventional transportation modes, resulting in a nuanced transformation in preferences. During the pandemic, there was a noticeable shift away from crowded public transportation, with individuals opting for private modes like personal vehicles, bicycles, and walking due to fear of virus transmission (Both et al., 2022). These individualized modes' perceived safety and social distancing became increasingly preferred.

The adoption of telecommuting during the pandemic fostered a more flexible approach to work, with lasting implications for commuting patterns. Recognizing these shifts is crucial for urban planners and policymakers, emphasizing the need for adaptable and resilient transportation infrastructure. It suggests the potential for a long-term reconfiguration of urban mobility.

Policymakers should consider the continued prevalence of remote work and corresponding changes in commuting habits when planning future transportation systems, promoting sustainable alternatives, and addressing challenges arising from altered travel patterns in a post-pandemic world (Abdullah et al., 2022).

2.1.4 Extreme Weather Events

Extreme weather events significantly impact transportation preferences, disrupting traditional commuting patterns (Liu et al., 2021).The research underscores the role of these events, from heat waves to storms, in influencing individuals to choose more sustainable transportation options. As extreme weather events become more frequent and unpredictable, there is a growing inclination towards resilient and environmentally friendly modes of transport, such as public transit, cycling, or walking (Cardwell & Elliott, 2013).The vulnerability of conventional transportation infrastructure to climate-related damage has increased awareness of the environmental impact of transportation. This awareness is driving a shift toward modes of transport with a lower carbon footprint. The imperative to reduce greenhouse gas emissions and adapt to climate change is reshaping transportation preferences. Individuals are increasingly seeking eco-friendly mobility solutions (Anwar et al., 2022).

Urban planners and policymakers are urged to prioritize the development of transportation systems that can withstand extreme weather events while promoting sustainable travel options. The evolving transportation landscape reflects a broader societal acknowledgment of the interconnectedness between climate change, extreme weather events, and transportation preferences. As environmental considerations become integral to transportation choices, fostering resilient and sustainable transit alternatives becomes crucial in mitigating the impacts of climate change on urban mobility.

2.2 Travel Mode Preference Studies

Case studies examining travel mode preferences in diverse urban settings have enriched our understanding of transportation decisions' complex dynamics (Rahman et al., 2022).Infrastructure development is a critical determinant of travel mode preferences in densely populated urban areas. Well-connected and convenient transit options influence choices, revealing the intricate relationship between urban planning, accessibility, and mode selection (Feys et al., 2020). In suburban settings, factors like accessibility and land-use patterns prove instrumental in shaping preferences, elucidating the unique challenges of suburban mobility.

Exploring public transit preferences has highlighted vital elements influencing ridership patterns, including reliability, accessibility, and cost-effectiveness (Wang et al., 2015). Addressing these factors is crucial to enhancing public transit systems' appeal and efficiency. Contemporary trends, such as the rising interest in active transportation modes and the influence of shared mobility options, reflect shifts driven by health considerations and ride-sharing services. Insights into safety considerations emphasize the significance of real and perceived safety measures in shaping mode choices.

A demographic perspective reveals the heterogeneity in travel preferences among different population groups, emphasizing the need for targeted interventions and policies to address diverse demographics' needs. These case studies offer a comprehensive picture of the nuanced factors influencing travel mode preferences, from infrastructure intricacies to contemporary trends (Müller et al., 2008). Integrating these insights is crucial for shaping effective urban planning strategies that cater to urban populations' diverse and evolving needs.

2.2.1 Public Transit

Public transit preferences, as explored in research, are vital in shaping travel mode choices within urban environments. The reliability and accessibility of public transit are pivotal determinants influencing individuals' decisions, with commuters favoring systems that adhere to schedules and minimize uncertainties in travel times (Chen et al., 2022). Cost-effectiveness, including considerations like ticket prices and overall affordability, plays a significant role in decision-making. Policies enhancing service punctuality and affordability can contribute to increased public transit ridership.

Additionally, the convenience and ease of using transit systems, influenced by factors such as the proximity of stops and the comprehensiveness of the transit network, shape individuals' perceptions of convenience (Dogan et al., 2021). Environmental considerations are increasingly important, with commuters valuing the sustainability of public transit compared to private vehicles. Lastly, effective integration with other modes of transportation, such as cycling and walking, enhances the attractiveness of public transit, as commuters appreciate a seamless and integrated transportation network.

In Chiang Rai province has public transit four types. Namely, bus, mini-bus, van, and taxi. Bus and taxi service operate both intra-city and inter-city that services connecting different districts and nearby provinces. However, mini-bus and van operate for local transportation within the province. Understanding these nuances in public transit preferences is essential for urban planners and policymakers. It provides valuable insights for developing comprehensive strategies that improve transit systems and encourage sustainable mobility within cities, creating transit-friendly urban environments (Lehner & Blaschke, 2019).

2.2.2 Active Transportation Trends

Contemporary travel mode preferences increasingly favor active transportation, such as walking and cycling, reflecting a societal shift toward sustainable and health-conscious mobility choices (Liu et al., 2021). This trend is driven by a heightened awareness of the health benefits associated with walking and cycling, with individuals valuing the positive impact of physical activity on overall well-being. Active transportation also aligns with environmental sustainability goals, attracting those who prioritize eco-friendly choices and contribute to reduced carbon footprints.

The availability of dedicated infrastructure, including well-designed walking paths and cycling lanes, significantly influences the attractiveness of active transportation. Cities investing in such infrastructure improvements, along with considerations of urban design and accessibility, are more likely to witness increased adoption of walking and cycling as preferred modes of transit (Ge et al., 2015).

Chiang Rai province promote active transportation by Chiang Rai Bike Tour, bike around Chiang Rai, discover its surroundings and enjoy its main monuments and iconic landmarks such as the White Temple. Individual preferences and lifestyle choices shape active transportation trends, with commuters seeking a more relaxed and enjoyable commute or incorporating physical activity into their daily routines leaning towards these modes. Policymakers and urban planners aiming to promote sustainable and healthier urban mobility choices must understand and leverage the factors driving active transportation trends.

2.2.3 E-hailing Mode

E-hailing mode have emerged as transformative elements in shaping contemporary travel mode preferences, introducing new dynamics to urban mobility patterns (Dorynek et al., 2022). Investigative studies delve into how individuals assess the advantages and disadvantages of e-hailing mode compared to traditional transportation options. A key driver of the popularity of shared mobility is its transformative effect on mobility patterns, offering the convenience of summoning a ride through mobile apps and the flexibility of shared services. Cost considerations play a pivotal role, with individuals evaluating the economic feasibility of e-hailing mode compared to private vehicle ownership or traditional transportation modes. The convenience and flexibility of shared mobility services offered, providing door-to-door service without parking, contribute significantly to their appeal. In Chiang Rai has e-hailing service namely Grab car.

Moreover, e-hailing mode can reduce traffic congestion by optimizing vehicle occupancy and encouraging carpooling. Integrating shared mobility with public transit further enhances its attractiveness, addressing the first-mile/last-mile challenge and extending the reach and accessibility of public transit networks (Merlin, 2017). Technological advancements, particularly the prevalence of smartphone apps, play a crucial role in the rise of shared mobility, making these services more accessible and user-friendly.

2.2.4 Travel Time Considerations

Travel time represents one of the most critical factors in mode choice decisions across diverse urban contexts. Research consistently demonstrates that perceived and actual travel time significantly influence transportation preferences, with individuals generally seeking to minimize total journey duration while considering reliability and predictability (De Vos et al., 2013).Asian contexts, studies have shown that travel time sensitivity varies by mode, with private vehicle users typically exhibiting higher time sensitivity compared to public transport users who may accept longer but more predictable journey times (Beck & Hensher, 2020). During environmental stress conditions, travel time considerations become more complex as individuals balance speed with exposure minimization. Research in Beijing found that during high pollution days, commuters were willing to accept up to 15-20% longer travel times to use enclosed transportation modes, indicating that environmental factors can alter traditional time-cost trade-offs (Zhao et al., 2018). The reliability aspect of travel time becomes particularly important during crisis periods, as unpredictable delays may force individuals into longer exposure situations (Wang et al., 2014).

2.2.5 Travel Cost Sensitivity

Travel cost remains a fundamental determinant of mode choice, with extensive literature documenting income-elastic responses to transportation pricing across different demographic groups (Tirachini, 2020). In developing country contexts, cost sensitivity is particularly pronounced among lower-income populations, who may face binding budget constraints that limit their ability to choose preferred modes during crisis periods (Cervero, 2013). Research in Southeast Asian cities has demonstrated that even small changes in relative costs between modes can produce significant shifts in travel behavior, particularly for discretionary trips. During air quality crisis, cost considerations interact with health concerns to create complex decision-making scenarios. Studies in Delhi found that middle-income households were willing to pay premium prices (30-50% higher) for enclosed transportation during severe pollution episodes, while lower-income groups faced constrained choices due to financial limitations (Guttikunda & Mohan, 2014). The willingness-to-pay for health-protective transportation varies significantly by income level, creating potential equity issues during environmental crisis periods (Pongprasert & Kubota, 2017).

2.2.6 Travel Frequency Patterns

Travel frequency represents both a determinant and outcome of mode choice decisions, with research indicating that regular commuters develop different modal preferences compared to occasional travelers (Beige & Axhausen, 2012). High-frequency travelers typically prioritize convenience, reliability, and routine optimization, often leading to single-mode dependency that may become problematic during crisis periods (Klinger et al., 2013). Studies examining travel frequency responses to environmental conditions have found that individuals with flexible schedules reduce overall trip frequency during pollution events, while those with rigid commitments (employment, education) maintain travel frequency but may alter mode choices (Li & Kamargianni, 2017). Research in Taiyuan, China, demonstrated that during air quality crisis, optional trips decreased by 25-30%, while mandatory trips remained constant but shifted toward enclosed modes. The concept of trip frequency flexibility emerges as an important factor, with individuals having greater flexibility showing more adaptive responses to environmental stress (Xu et al., 2021).

2.2.7 Travel Distance Relationships

Travel distance significantly influences mode choice through its interaction with time, cost, and comfort considerations across different trip purposes (Ewing & Cervero, 2010). Short-distance trips typically favor walking, cycling, or motorcycles, while longer distances increasingly favor motorized options, though this relationship varies by urban context and infrastructure availability (Marshall & Garrick, 2010). In air quality crisis contexts, distance considerations become more complex as longer trips involve greater cumulative exposure, potentially motivating shifts toward enclosed modes regardless of traditional distance-mode relationships (Xu et al., 2021). Research in Chinese cities found that during pollution events, the traditional distance-mode relationship was disrupted, with individuals choosing enclosed options even for short trips where walking or cycling would normally be preferred. Distance also interacts with urgency and flexibility factors, as longer trips are often associated with less flexible scheduling, limiting adaptive options during crisis periods (Rahman et al., 2022).

2.3 Air Pollution and PM2.5 Smog Impact on Travel Behavior

Fine particulate matter (PM), which consists of airborne particles with aerodynamic diameters smaller than 2.5 micrometers (PM2.5), has been identified as a major air pollutant affecting human health and travel behavior. PM2.5 is particularly concerning due to its ability to penetrate deep into the respiratory system and enter the bloodstream, causing various health issues (World Health Organization, 2021). Studies consistently show that deteriorating air quality, especially elevated PM2.5 levels, influences travelers to shift between different transportation modes. In Delhi, India, when PM2.5 concentrations exceed 150 μg/m³ (six times higher than the WHO's recommended 24-hour guideline of 25 μg/m³), commuters increasingly prefer closed modes of transportation over open modes. This was demonstrated through machine learning models and logit analysis comparing enclosed vehicles (cars, air-conditioned buses) versus open vehicles (auto rickshaws, non-air-conditioned buses) (Meena, Taneja et al., 2024). The impact of air pollution on mode choice varies across different urban contexts. In Taiyuan, China, high PM2.5 concentrations negatively impacted the selection of non-motorized transport modes (walking, cycling) in favor of motorized vehicles (cars, buses) (Li & Kamargianni, 2017). Similarly, in Zhengzhou, China, a study examining car use, public transit (buses and subway), and active modes (walking and cycling) found that car commuters tend to maintain their preference for private vehicles even after receiving health information about PM2.5 exposure (Luo et al., 2021).

Income levels play a significant role in mode choice during pollution events. In Seoul, South Korea, public transit usage increases among lower-income groups during high pollution periods, particularly for bus and subway services, as revealed through an Integrated Choice and Latent Variable (ICLV) model. This finding was further supported by multilevel logistic regression modeling comparing non-motorized modes (walking or biking), public transit (bus or subway), and cars (Kim et al., 2023). In Karaj, Iran, when PM2.5 concentrations exceed 75 μg/m³, poor air quality increases private car usage compared to walking and public transit options, as shown through Exploratory Factor Analysis and hybrid choice modeling (Dabirinejad et al., 2024). In the United States, a comprehensive study across 929 urban areas examined how emissions affect choices between driving alone, carpooling, public transportation, walking, and other modes, finding that vehicle ownership significantly influences transportation mode choices (Ercan et al., 2022). Recent research in Delhi has employed sophisticated analytical methods to study a wide range of transportation modes, including auto rickshaws, buses, cars, two-wheelers, two-wheeler sharing, walking, bicycles, car sharing, and metro services. These studies consistently show that as PM2.5 levels rise above national and WHO standards, travelers modify their behavior to minimize exposure, with a clear preference for enclosed modes of transportation (Meena, Bairwa, et al., 2024). In Beijing, daily average PM2.5 concentrations significantly impact choices between cycling, cars, taxis, buses, metros, and walking, with notable shifts observed when levels exceed 150 µg/m³ (Zhao et al., 2018). The impact of PM2.5 pollution extends beyond mode choice to affect spatial travel patterns, as revealed by a big data field study in Xi'an, China (Xu et al., 2021), shown in Table 2.1.

While these studies have provided valuable insights into travel behavior during air quality crisis, there remains a gap in understanding how PM2.5 air quality crisis specifically affect travel mode choices in Southeast Asian secondary cities, particularly in areas prone to seasonal smog events. The present study addresses this gap by examining travel mode choice behavior in Chiang Rai, Thailand, where severe seasonal PM2.5 smog episodes frequently occur. Using a combination of Multinomial Logit Model (MNL) and descriptive statistics, this research investigates how commuters adapt their travel mode choices during non-air quality crisis and air quality crisis in an urban area where PM2.5 levels often exceed 150 µg/m³ during the dry season. Unlike previous studies that primarily focused on major metropolitan areas, this research provides insights into travel behavior adaptations in a secondary city context, where transportation options and infrastructure may differ significantly from larger urban centers. The study's findings are particularly relevant for urban areas in the Greater Mekong Subregion that face similar seasonal air quality challenges, contributing to a more comprehensive understanding of how environmental crisis affect transportation choices in developing regions.

Table 2.1 Summary of previous studies on mode choice during air quality crisis

Reference	Pollution type	Location	Method used	Mode of transport	Finding
(Li & Kamargianni, 2017)	Air pollution	Taiyuan, China	Mode choice models	Motorized and Nonmotorized vehicles	Air pollution negatively impacts nonmotorized transport mode choice.
(Zhao et al., 2018)	Air pollution, PM2.5	Beijing, China	Binary logistic model	Cycle, cars, taxis, buses, metros, and walking	Air quality significantly influences travel mode choices.
(Luo et al., 2021)	Air pollution, PM2.5	Zhengzhou, China	Multinomial logit (MNL) models and Difference-in-difference (DID) regression methods	Car, public transit, and active modes	Car commuters rebound towards car travel after health information.

Table 2.1 (continued)

Reference	Pollution type	Location	Method used	Mode of transport	Finding
(Xu et al., 2021)	Ambient air pollution	Xi'an, China	Regression model	N/A	People reduce travel area more than travel distance on polluted days.
(Ercan et al., 2022)	Emissions (CO, CO2, NOX, SOX, PM10, PM2.5, and VOCs)	929 urban areas in the U.S.	Multinomial logit and system dynamics (SD) modeling	Drive alone, carpool, public transportation, walk, and other	Vehicle ownership significantly impacts transportation mode choices.
(Kim et al., 2023)	Air pollution	Seoul, South Korea	Multilevel logistic regression modeling	Non-motorized modes (walking or biking), public transit (bus or subway), and cars	Lower-income groups shift to public transit during poor air quality.

Table 2.1 (continued)

Reference	Pollution type	Location	Method used	Mode of transport	Finding
(Meena, Taneja, et al., 2024)	Air pollution	Delhi, India	Machine learning models and logit model.	Open and closed travel modes	Commuters prefer closed modes as air quality worsens.
(Dabirinejad et al., 2024)	Air pollution	Karaj, Iran	Exploratory Factor Analysis (EFA) and hybrid choice modeling (HCM)	Walking, car, and public transit	Poor air quality increases private car usage.
(Meena, Bairwa, et al., 2024)	Air pollution	Delhi, India	Random Forest, XGBoost, Naive Bayes (NB), K-Nearest Neighbor, Support Vector Machine (SVM), and Multinomial Logistic Regression (MLR)	Auto rickshaw, bus, car, two wheeler, two wheeler sharing, walk, bicycle, car sharing, and metro	Commuters shift to closed modes during poor air quality.

Table 2.1 (continued)

Reference	Pollution type	Location	Method used	Mode of transport	Finding
Present study	Air pollution, PM2.5	Chiang Rai, Thailand	Multinomial Logit Model (MNL), Descriptive statistic	Private car, motorcycle, public transport, and alternatives	Travel mode choice during non-air quality crisis (N-AQC) and air quality crisis (AQC) commuting in urban area

2.4 Commuting Preference Analysis Methods

The analysis of commuting preferences and travel mode choices has employed various methodological approaches in transportation research. These methods aim to understand the factors influencing individuals' travel decisions and predict future travel behaviors. Transportation research has employed various methodological approaches to analyze commuting preferences and travel mode choices. Discrete choice models, particularly Multinomial Logit Model (MNL) and nested logit models, have been widely used to understand travel decisions (Ben-Akiva & Lerman, 1985). The MNL model assumes that travelers choose the option that maximizes their utility, with the probability of choosing a particular mode expressed as a function of its attributes and the individual's characteristics. These models are often supported by data collected through stated preference (SP) and revealed preference (RP) surveys. SP surveys present hypothetical scenarios to understand potential behavioral responses, while RP surveys collect data on actual travel behaviors, emphasizing the value of combining both approaches for robust analysis (Hensher et al., 2005). Advanced econometric techniques have also been applied, such as multiple discrete-continuous extreme value (MDCEV) model for analyzing activity-travel behavior (Bhat, 2000). This model extends traditional discrete choice frameworks by simultaneously considering multiple alternatives and their usage intensities. Machine learning techniques have gained prominence in recent years, with methods such as random forests and support vector machines often achieving higher predictive accuracy than traditional logit models (Hagenauer & Helbich, 2017). These advanced techniques can capture complex non-linear relationships and interactions between variables that might be missed by conventional approaches. Structural equation modeling (SEM) has also been employed to examine the intricate relationships between various factors influencing travel behavior, with SEM being used to analyze how residential location choice, travel attitudes, and actual travel behavior interact (De Vos et al., 2013). Logistic regression models have been used to examine the impact of air pollution on cycling behavior in Beijing (Zhao et al., 2018). Time series analysis has been applied to investigate the relationship between extreme haze events and public transit ridership (Li et al., 2019).

While substantial research has been conducted on the relationship between air pollution and travel behavior, there remains a gap in understanding these dynamics in the specific context of Chiang Rai, Thailand. The unique characteristics of the region, including its seasonal air quality crisis, socio-economic factors, and existing transportation infrastructure, warrant a focused investigation. Additionally, most studies have examined general air pollution levels rather than acute air quality crisis, which may elicit different behavioral responses. This study aims to address these gaps by providing insights into travel mode choice preferences during air quality crisis in Chiang Rai, contributing to the broader understanding of how environmental factors influence urban mobility in Southeast Asian contexts.

2.5 Exploratory Factor Analysis (EFA) for Travel Mode Choice

Exploratory Factor Analysis (EFA) has been employed in this study as a statistical technique to uncover latent constructs influencing travel mode choices during non-air quality crisis and air quality crisis in Chiang Rai. EFA is widely recognized for its ability to reduce a large set of interrelated variables into underlying factors, thereby clarifying the structure of commuter attitudes and perceptions (Costello & Osborne, 2005). In transportation research, this method is especially useful for identifying unobservable psychological traits such as health concern, environmental awareness, cost sensitivity, and convenience orientation that influence behavioral outcomes (Zhao et al., 2018). In this study, responses were collected through structured questionnaires using Likert-scale items related to transport satisfaction, air pollution perception, safety, and travel decision-making. The Principal Axis Factoring (PAF) method was applied due to its robustness in cases where the assumption of multivariate normality may not be met, as is common in survey-based social science data (Fabrigar et al., 1999). Varimax rotation was used to simplify factor loadings, thus enhancing interpretability. The suitability of the dataset was confirmed through the Kaiser-Meyer-Olkin (KMO) measure, which exceeded 0.7, and Bartlett's Test of Sphericity, which was statistically significant ($p < 0.05$), indicating strong inter-variable correlation.

Factors with eigenvalues greater than one were retained, and only items with factor loadings above 0.4 were included for further interpretation (Hair et al., 2013).

The application of EFA revealed key dimensions underlying travel mode choices during different air quality conditions. During air quality crisis, latent factors associated with health concerns and risk avoidance were found to be more prominent, indicating that air pollution has a psychological influence on transportation decisions. These findings align with prior studies that observed an increased preference for enclosed or less-exposed transport options during air quality crisis (Dabirinejad et al., 2024). In contrast, during non-air quality crisis, factors such as convenience, routine, and cost-efficiency emerged as more influential. This shift suggests that environmental risk perception acts as a contextual trigger that temporarily reshapes commuter priorities. Among low-income respondents, economic sensitivity remained a consistent factor across both periods, supporting findings from similar studies in Seoul and Taiyuan, where public transit use increased during high pollution days among cost-sensitive group (Kim et al., 2023). The extracted factors were subsequently incorporated into a Multinomial Logit Model (MNL), enabling the assessment of how these latent constructs translate into actual mode choice probabilities. By combining EFA and MNL, this research adopted a robust mixed-methods framework to analyze both psychological and behavioral dimensions of travel under environmental stress. The insights gained from EFA offer valuable implications for transportation planning and policy design. For example, during air quality crisis, strategies that prioritize health-safe alternatives such as promoting enclosed public transport options or enhancing e-hailing services could be emphasized, whereas during cleaner periods, investments in walkability and cycling infrastructure may be more impactful. Thus, EFA has not only served as a tool for dimensional reduction but has also offered critical empirical support for tailoring transportation interventions to varying environmental conditions in Chiang Rai.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Study Area

This study was conducted in Chiang Rai province, the northernmost province of Thailand. Covering an area of 11,678 km^2, Chiang Rai is characterized by its diverse topography, including mountains, hills, and lowland plains. As of 2024, Chiang Rai had a population of 1,298,977 (National Statistical Office of Thailand, 2024). The climate of Chiang Rai is tropical savanna, characterized by distinct wet and dry seasons. The dry season, from November to April, coincides with the period of severe air quality crisis. The practice of crop residue burning, particularly prevalent during the dry season, significantly contributes to the region's air pollution problems (Pimonsree & Vongruang, 2018). During these air quality crisis, PM2.5 levels often exceed 150 $\mu g/m^3$, significantly higher than the World Health Organization's guideline of 25 $\mu g/m^3$ for 24-hour mean (World Health Organization, 2021). In 2023, Chiang Rai experienced 76 days where PM2.5 levels exceeded the Thai national standard of 50 $\mu g/m^3$ (Pollution Control Department, 2023).

3.2 Data Collection

The survey was primarily administered through an online questionnaire using the Google Forms platform, optimized for mobile devices and available in Thai language with English translation option. Prior to full deployment, the questionnaire underwent comprehensive pilot testing with 20 respondents selected through convenience sampling from Mae Fah Luang University community. The pilot test employed a mixed-methods approach conducted in January 2024, combining quantitative reliability assessment and cognitive interviews with a subset of participants using think-aloud protocols to verbalize their interpretation of survey items and provide feedback on question comprehension. Quantitative results revealed strong internal consistency (Cronbach's $\alpha = 0.876$) indicating excellent reliability of the travel behavior change intention scale, with completion times averaging 15-20 minutes, while cognitive interviews identified critical issues including confusion distinguishing "air quality crisis" from "air pollution crisis", difficulty recalling specific travel costs during different environmental conditions, and confusion about the "alternatives" transportation category. Based on this comprehensive pretesting feedback, significant adjustments were made including enhanced operational definitions with clear air quality crisis explanations, simplified response options using cost ranges rather than exact amounts, improved Likert scale anchoring with balanced response options, clearer category descriptions with examples for transportation modes, and enhanced mobile device compatibility before online deployment via Google Forms from February to March 2024. The final questionnaire maintained an average completion time of 15-20 minutes following these refinements.

A stratified random sampling approach was initially planned, but practical limitations during implementation resulted in a multi-stage stratified random sampling method. The sample size was calculated using Taro Yamane's Formula as Equation 1 (Yamane, 1973), considering Chiang Rai's population of (N), a 95% confidence level (e), the sample size is 399.88 (n) that approximately to a minimum required sample size of 400 respondents.

$$n = \frac{N}{1 + Ne^2} \tag{1}$$

Multiple distribution channels were utilized to reach respondents including social media platforms (Facebook, Line), community networks through district offices, local university student and staff networks, and community leader assistance in rural areas, with QR codes strategically posted in public spaces to facilitate easy access. This non-probability sampling approach has potential for selection bias, particularly toward younger, more educated, and digitally connected individuals, which is acknowledged as a limitation of the study. A total of 428 responses were received, with 406 deemed valid after data cleaning, yielding a response rate of 90%. Invalid responses were removed due to incomplete information, duplicate submissions, out-of-province residents, or inconsistent response patterns.

3.2.1 Variable Measurement

The study employed both categorical and continuous variables, each coded systematically for statistical analysis.

Categorical Variables:

1. Gender: Nominal categorical variable with three categories inclusive gender identification while maintaining statistical validity for analysis.

2. Age: Ordinal categorical variable with five life stage categories relevant to transportation behavior.

3. Monthly Income: Ordinal categorical variable with seven income brackets relevant to transportation affordability in Thailand.

4. Marital Status: Nominal categorical variable capturing primary relationship status categories.

5. Vehicle Ownership: Binary categorical variable indicating household vehicle access.

6. Driving License Status: Binary categorical variables for motorcycle and private car licenses.

7. Travel Mode Choice: Nominal categorical variable representing the dependent variable for mode choice analysis.

Continuous Variables:

1. Travel Time: Measured in minutes, representing actual travel duration

2. Travel Cost: Measured in Thai Baht (THB), representing monetary expenditure per trip

3. Travel Frequency: Measured as trips per week, representing travel pattern intensity

Effect Variables (Crisis Impact):

1. Effect on Healthcare: Binary categorical variable measuring health impact perception

2. Effect on Finance: Binary categorical variable measuring economic impact perception

3.3 Survey Instruments

The questionnaire was comprehensively designed with five main sections to capture both quantitative and behavioral data related to travel mode choices during varying air quality crisis. The survey instrument was structured as follows.

3.3.1 Demographic Information

This section collected fundamental socioeconomic and demographic characteristics including gender, age, occupation, monthly income, marital status, vehicle ownership status, and driving license possession. These variables serve as key predictors in the Multinomial Logit Model for both non-air quality crisis and air quality crisis.

3.3.2 Impact of Air Quality Crisis

This section examined respondents' direct experiences with air quality crisis, including perceived health impacts, financial effects, and their understanding of pollution sources. Questions addressed whether respondents experienced effects on healthcare, travel patterns, living conditions, and accidents during smog episodes.

3.3.3 Travel Behavior Under Non-Air Quality Crisis (N-AQC)

This section captured baseline travel patterns during non-air quality crisis, including primary mode choice (private car, motorcycle, public transport, or alternatives), travel time, cost, frequency, and distance. These variables establish the reference point for comparing behavioral changes during air quality crisis.

3.3.4 Travel Behavior During Air Quality Crisis (AQC)

Parallel to Section 3, this section measured the same travel characteristics but specifically during periods when PM2.5 $\geq$ 50 μg/m³ and/or PM10 $\geq$ 120 μg/m³. This design enables direct comparison of individual behavioral adaptations between the two environmental conditions.

3.3.5 Factors Influencing Travel Mode Change Behavior (Exploratory Factor Analysis Variables)

This section represents the most methodologically complex component of the questionnaire, designed specifically to capture latent psychological and behavioral constructs that influence travel behavior change during air quality crisis. The section consists of 25 carefully designed items that underwent rigorous development and validation processes. All 25 items in Section 5 utilize a 5-point Likert scale format, which provides optimal balance between response precision and respondent comprehension on a 5-point Likert scale (1 = strongly disagree, 2 = disagree, 3 = neutral/unsure, 4 = agree, 5 = strongly agree).

The questions in Section 5 were systematically developed through a multi-stage process grounded in established theoretical frameworks and empirical research in transportation psychology and environmental behavior. The theoretical foundation for question development was derived from the Theory of Planned Behaviorn (Ajzen, 1991), which identifies three primary constructs influencing behavioral intention: attitude toward behavior, subjective norms, and perceived behavioral control. Additional constructs were incorporated from environmental psychology literature, specifically focusing on risk perception, health concerns, and crisis response behavior to capture the unique aspects of travel behavior during environmental stress conditions.

Each question was designed based on established scales and measurements from previous studies in transportation behavior, air pollution response, and environmental crisis adaptation. This literature review integration ensured that the questions built upon validated measurement approaches while adapting them to the specific context of air quality crisis in Thailand. Key references that informed the question development included works on mode choice behavior (Ben-Akiva & Lerman, 1985), environmental risk perception (Zhang & Batterman, 2013), and crisis-driven behavioral change (Xu et al., 2021), providing a solid empirical foundation for the measurement instrument.

While grounded in established theory and empirical research, questions were specifically adapted to the Chiang Rai air quality crisis context to ensure relevance and cultural appropriateness. This contextual adaptation incorporated local transportation modes such as Songthaew and motorcycle taxis, cultural considerations relevant to Thai society, and specific pollution characteristics including PM2.5 concentrations and visibility concerns that are particularly relevant during smog episodes in northern Thailand. This adaptation process ensured that the questions would resonate with local respondents while maintaining theoretical validity and cross-cultural research standards.

3.4 Analysis Method

3.4.1 The Multinomial Logit Model (MNL)

The Multinomial Logit Model (MNL) approach has been successfully applied in various Southeast Asian contexts to identify statistically significant parameters that determine choice probabilities among discrete alternatives (Chansuk et al., 2022; Rahman & Baker, 2018). A comprehensive analytical approach was employed to examine travel mode choices during non-air quality crisis (N-AQC) and air quality crisis (AQC) in Chiang Rai, based on random utility theory. The dependent variable was travel mode choice, with data collected from identical respondents across both periods, creating paired samples for direct comparison of individual behavioral changes. Prior to analysis, the dataset underwent preparation including categorical variable coding using effect coding, continuous variable standardization, and missing data handling using multiple imputation with chained equations (van Buuren & Groothuis-Oudshoorn, 2011). The utility function for individual mode choice was specified as Equation 2 (Arreeras et al., 2020).

$$U_i = V_i + \varepsilon_i \tag{2}$$

Where U_i represents the utility of mode i, V_i is the deterministic component of utility for mode i often modeled as Equation 3, and ε_i is the random error term assumed to be independently, capturing unobservable factors influencing the choice.

$$V_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \cdots + \beta_k x_{ki} \tag{3}$$

Multinomial Logit Model was employed to model travel mode choices, a method widely used in transportation research for analyzing discrete choice scenarios (Ben-Akiva & Lerman, 1985). This technique allows for estimating the probability of selecting a specific travel mode from multiple alternatives, considering various predictor variables. Information on travel costs, time, and other characteristics was collected for the respondent's actual chosen mode rather than for all potential alternatives. This approach provides revealed preference data about the selected mode but does not include attributes of non-chosen alternatives. Consequently, the

Multinomial Logit Model estimated in this study capture the influence of socio-demographic factors and trip characteristics on mode choice.

The MNL model, as expressed in Equation 4, where $P(Y = i)$ represents the probability of choosing travel mode i and V_i is the systematic utility of that mode. The numerator, exp (V_i), converts the utility into a positive number, making it comparable across options. The denominator, $\sum_{j=1}^{J} \exp(V_j)$, sums the exponentiated utilities of all available travel modes to ensure that the total probability across all choices adds up to 1. This model specification allows for the examination of how factors such as travel time, cost, frequency, and distance, as well as demographic characteristics, influence mode choice during non-air quality crisis and air quality crisis. Similar approaches have been used in studies examining the impact of environmental factors on travel behavior (Liu et al., 2015).

$$P(Y = i) = \frac{\exp(V_i)}{\sum_{j=1}^{J} \exp(V_j)} \tag{4}$$

The model's performance was assessed using Akaike's Information Criteria (AIC) and Bayesian Information Criteria (BIC). These information criteria are valuable tools for comparing different model specifications and selecting the most appropriate model. The AIC can be computed as Equation 5.

$$AIC = \left(\frac{-2}{N} * LL\right) + \left(2 * \frac{k}{N}\right) \tag{5}$$

Where N represents the number of examples in the training dataset, LL is the log-likelihood of the model, and k represents the number of parameters in the model. Similarly, the BIC is calculated as Equation 6.

$$BIC = (-2 * LL) + [\log(N) * k] \tag{6}$$

Where log( ) represents the natural logarithm (base-e), LL is the log-likelihood of the model, N is the number of examples in the training dataset, and k represents the number of parameters in the model. Lower values of both AIC and BIC indicate better model fit, with BIC generally imposing a stronger penalty for additional parameters compared to AIC (Co et al., 2023)

3.4.2 Exploratory Factor Analysis (EFA)

Exploratory Factor Analysis (EFA) was employed in this study to identify latent constructs underlying travel behavior variables during non-air quality crisis and air quality crisis. EFA is a statistical technique widely used in social science and transportation research to explore the underlying structure of a relatively large set of observed variables and reduce them into fewer meaningful factors (Costello & Osborne, 2005). In the context of this research, EFA was utilized to examine the interrelationships among key indicators related to travel behavior, including travel frequency adaptations, mode use preferences, cost sensitivity factors, environmental concern dimensions, perceived health risks, and trip characteristics. This analysis aimed to uncover latent dimensions that influence travel mode choice during air quality crisis in Chiang Rai province. Prior to conducting EFA, the suitability of the dataset was assessed using the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's Test of Sphericity. The KMO value exceeded the acceptable threshold of 0.60, indicating adequate intercorrelation among variables, while the significance of Bartlett's Test ($p < 0.05$) confirmed that the data were appropriate for factor extraction (Kaiser, 1974). Principal axis factoring was selected as the extraction method due to its robustness in handling non-normal distributions, which is particularly relevant for ordinal data derived from Likert-scale responses. Unlike Principal Components Analysis, PAF focuses on shared variance among variables rather than total variance, making it more appropriate for identifying true latent factors rather than mathematical composites (Fabrigar et al., 1999). To enhance factor interpretability, Varimax rotation was applied, which maximizes the variance of loadings on each factor and produces orthogonal (uncorrelated) factors (Tabachnick et al., 2018).

The number of factors retained was determined based on multiple criteria: eigenvalues greater than 1, examination of the scree plot, and theoretical interpretability. Items with factor loadings below 0.40 or cross-loading on multiple factors were removed to ensure construct clarity (Fabrigar et al., 1999). The final factor structure revealed distinct dimensions of travel behavior adaptation, and these latent constructs were subsequently used as predictor variables in the Multinomial Logit Model (MNL) to examine their influence on travel mode choices during non-air quality crisis and air quality crisis. EFA allowed the transformation of a complex set of observed travel behavior indicators into fewer, theoretically coherent constructs, which was crucial for improving model parsimony and avoiding multicollinearity in subsequent regression analyses. The identification of behavioral factors that significantly shifted during air quality crisis provided valuable insights into how residents of Chiang Rai adjust their mobility preferences in response to deteriorating air quality crisis. This approach aligns with prior transportation behavior studies employing factor analysis to capture hidden attitudinal or perceptual dimensions influencing mode choice (Ringle et al., 2020).

3.5 Analysis Framework

The overall research methodology is illustrated in Figure 3.1, which presents the systematic process adopted in this study, starting from the identification of the research question and culminating in the discussion and conclusion of findings. The methodology follows a structured and sequential approach, integrating both qualitative reasoning and quantitative analysis to investigate travel mode choice behavior during air quality crisis.

The process begins with the formulation of the research question, which was developed based on observed behavioral changes during smog events in Chiang Rai. From this, a research gap was identified through a systematic literature review, highlighting the limited empirical evidence on how air pollution influences transportation behavior in medium-sized Southeast Asian cities. Based on the literature and theoretical framework, a questionnaire was designed to collect primary data. The questionnaire included items related to socio-demographics, travel behavior, and perceptions during both non-air quality crisis and air quality crisis. Following the questionnaire design, data collection was conducted through an online survey using a multi-stage stratified sampling approach. The collected data were then prepared for descriptive statistical analysis, which provided an overview of respondent characteristics and general travel patterns. These descriptive insights informed the next stages of analysis.

Subsequently, two main analytical techniques were applied. First, Multinomial Logit Model (MNL) was employed to model the probability of travel mode choice under varying air quality crisis, incorporating variables such as travel time, cost, and socio-demographic factors. Second, Exploratory Factor Analysis (EFA) was performed to identify latent constructs related to travel behavior and perceptions, such as health concerns, environmental awareness, and convenience. These factors were used to enhance the interpretation of regression results and support theoretical insights. The results from both quantitative models were synthesized to identify significant behavioral patterns and mode choice determinants. These results formed the basis for the discussion, where findings were compared with prior studies and theoretical expectations. Finally, the study concluded by summarizing the key insights, implications for transport policy during smog events, and suggestions for future research, as presented in the conclusion section.

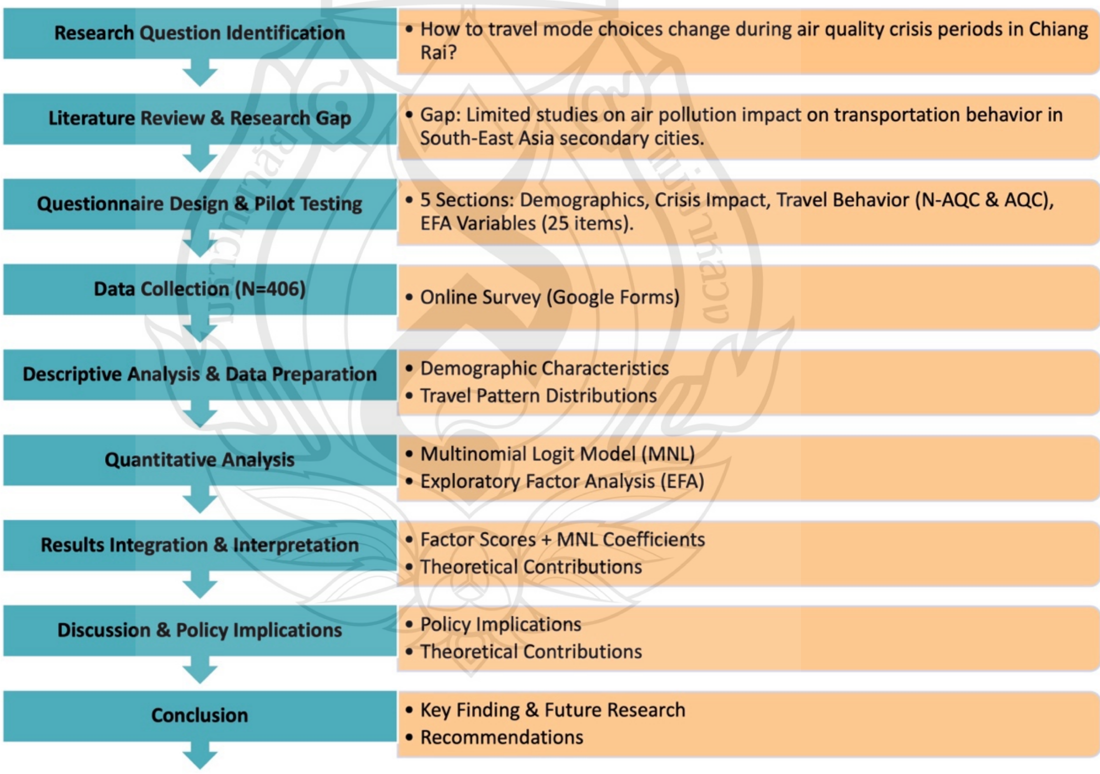


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Figure 3.1 Analysis Framework

CHAPTER 4

RESULTS

4.1 Demographic Characteristics of Respondents

The respondent profile reveals critical socioeconomic and demographic patterns relevant to travel behavior under environmental stress. Gender distribution showed that the sample was predominantly female (63.8%),with males comprising 31.3% and individuals identifying as other genders making up 4.9%. The gender variable was measured as a nominal categorical variable with three distinct categories to ensure inclusive representation while maintaining statistical validity for multinomial logit analysis. This distribution reflects the higher response rate among female participants often observed in online survey research and transportation behavior studies. Age distribution revealed a significant proportion of respondents were young adults, with 85.9% under the age of 30, indicating a digitally engaged and mobile demographic often reached through online survey platforms. The age variable was operationalized as an ordinal categorical variable with five categories representing distinct life stages: 1 = <21 years (26.8%), 2 = 21-30 years (59.1%), 3 = 31-40 years (5.4%), 4 = 41-50 years (6.2%), and 5 = 51-60 years (2.5%). The largest age group, 21–30 years, accounted for 59.1% of the sample, likely influenced by outreach through universities and social media channels. Income levels were measured as an ordinal categorical variable with seven categories representing income brackets relevant to transportation affordability in the Thai context: 1 = <10,000 THB (53.9%), 2 = 10,001-15,000 THB (9.4%), 3 = 15,001-20,000 THB (20.2%), 4 = 20,001-30,000 THB (9.1%), 5 = 30,001-40,000 THB (2.7%), 6 = 40,001-50,000 THB (2.0%), and 7 = >50,001 THB (2.7%). The distribution was skewed toward the lower end of the spectrum, with over half (53.9%) earning less than 10,000 THB per month and only a small minority (2.7%) earning more than 50,000 THB. This economic distribution highlights potential vulnerabilities to rising transport costs, particularly during air quality crisis.

Marital status was captured as a nominal categorical variable with three categories: 1 = Unmarried (83.5%), 2 = Married (9.1%), and 3 = Not mentioned (7.4%). The high proportion of unmarried respondents (83.5%) again underscores a young, possibly student-heavy population characteristic. Vehicle ownership was measured as a binary categorical variable (0 = No, 1 = Yes), showing relatively high ownership at 82.3%. However, driving license possession revealed important distinctions in mobility capabilities. Motorcycle license possession was measured as a binary categorical variable showing 56.4% held motorcycle licenses, while private car license possession showed 40.6% held car licenses. This suggests a mobility pattern dominated by two-wheeled transport, a common feature in many Southeast Asian secondary cities where affordability and accessibility shape transport choices.

These demographic trends provide essential context for interpreting the model estimates and behavioral responses reported later in the study. The socioeconomic composition of the sample predominantly young, low-income, and motorcycle-reliant directly informs how individuals respond to environmental hazards such as air pollution. All categorical variables were systematically coded to facilitate statistical analysis while preserving meaningful distinctions in demographic characteristics that influence transportation behavior during environmental crisis periods. A detailed breakdown of respondent characteristics is provided in Table 4.1, which presents both frequency counts and percentage distributions for all demographic variables, enabling clear interpretation of the sample composition and its implications for the study's findings.

Table 4.1 Respondent’s characteristics

Item	**Value: Description**	**Count**	**Percent**
Total of respondents		406	100
Gender	1: Male	127	31.3
	2: Female	259	63.8
	3: Others	20	4.9
Age, (years)	1: <21	109	26.8
	2: 21-30	240	59.1
	3: 31-40	22	5.4

Table 4.1 (continued)

Item	Value: Description	Count	Percent
Age, (years)	4: 41-50	25	6.2
	5: 51-60	10	2.5
Monthly income, (THB)	1: <10,000	219	53.9
	2: 10,001-15,000	38	9.4
	3: 15,000-20,000	82	20.2
	4: 20,001-30,000	37	9.1
	5: 30,001-40,000	11	2.7
	6: 40,001-50,000	8	2.0
	7: >50,001	11	2.7
Marital status	1: Unmarried	339	83.5
	2: Married	37	9.1
	3: Not mentioned	30	7.4
Vehicle ownership	0: No	72	17.7
	1: Yes	334	82.3
Holding motorcycle driving license	0: No	177	43.6
	1: Yes	229	56.4
Holding private car driving license	0: No	241	59.4
	1: Yes	165	40.6

4.2 Analysis of Travel Distributions

Travel behavior patterns were analyzed across five key dimensions during non-air quality crisis (N-AQC) and air quality crisis (AQC): travel time, travel cost, travel frequency, travel distance, and travel mode distributions. The analysis revealed significant shifts in travel patterns between these periods, reflecting adaptations in response to air quality crisis. Each distribution was examined to identify changes in modal preferences and travel characteristics that emerged during air quality crisis.

4.2.1 Travel Time Distributions

Based on the travel time distribution data in Figure 4.1, the most significant change occurs in motorcycle usage, with an 8% increase for trips lasting 11-20 minutes during air quality crisis. This suggests a shift towards shorter motorcycle trips when air quality deteriorates. Alternatives also see a marked increase, with a 5% rise in the same 11-20 minutes range, indicating a greater preference using alternatives for short trips during air quality crisis. Private car use shows a modest 2% decrease for trips in the 21-30 minutes range, while public transport experiences a slight 1 percentage point increase for 11-20 minutes journeys. These patterns collectively suggest that during periods of poor air quality, residents of Chiang Rai tend to option for shorter trips, with a particular preference for motorcycles and alternatives for shorter distances.

4.2.2 Travel Cost Distribution

The travel cost distributions reveal several notable shifts in commuter behavior. As demonstrated in Figure 4.2, the most significant change is observed in motorcycle usage, where trips costing less than 50 THB decreased 5%, dropping of all motorcycle trips. This substantial reduction in low-cost motorcycle journeys suggests a shift away from this mode for shorter trips during air quality crisis. Private car use increase of 2-3% in the 101-150 THB range during air quality crisis, indicating a potential shift towards longer or different car trips. Public transport usage decreased marginally (1-2%) across all cost categories, reflecting a general reduction in public transit use. Interestingly, alternatives of transport experienced a small increase of 2-3% in the 101-150 THB range, suggesting some commuters may be opting during air quality crisis. Overall, these changes point to a general trend of slightly higher travel costs across most modes during air quality crisis, with the most pronounced shift being away from motorcycle trips.

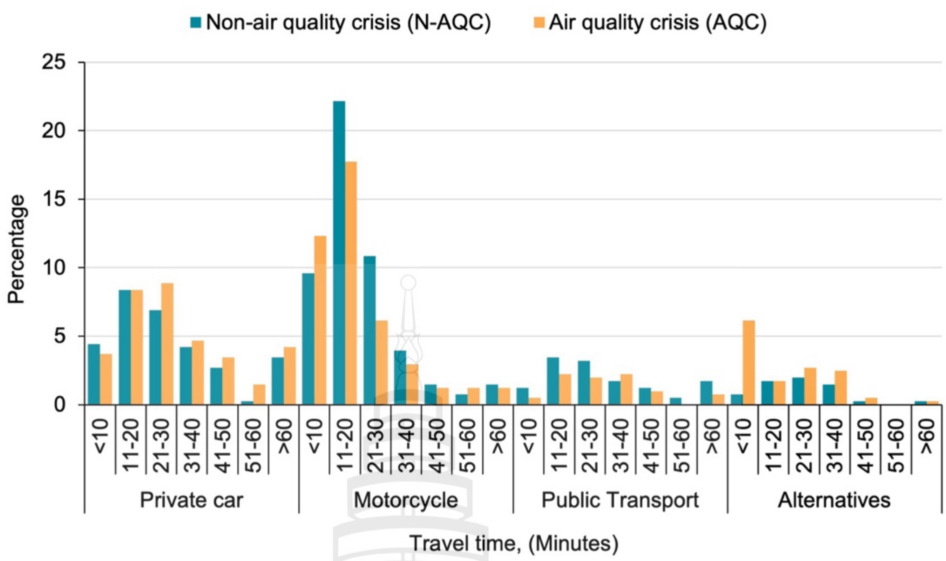

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Figure 4.1 Travel time distributions

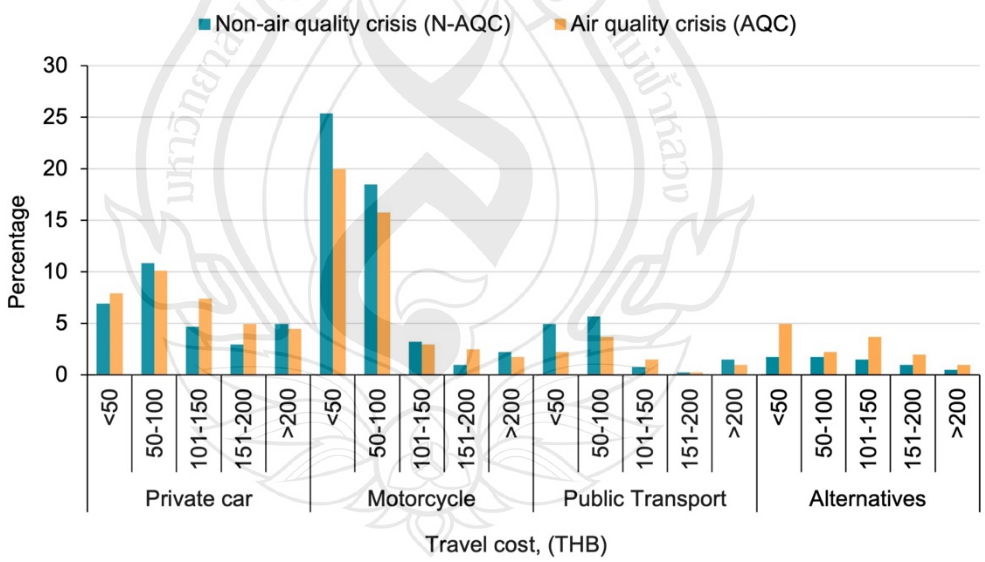

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Figure 4.2 Travel cost distribution

4.2.3 Travel Frequency Changes

The shifts in travel frequency behavior shown in Figure 4.3, particularly in lower-frequency travel categories. Private car use in the 2-3 trips per week category increases 5% while motorcycle use in the same category shows an even more increase 8 percentage. Public transport experiences a modest rise 2% for 2-3 trips per week. However, the most striking change is observed in alternatives of transportation. The percentage of people using alternatives for 1 trip per week jumps from near 0% to 5%, and for 2-3 trips per week it increases from 1% to 4% representing 300% growth. These trends indicate a general reduction in travel frequency during air quality crisis, especially for private vehicles, coupled with a substantial increase in the use of alternatives. This shift suggests that residents are adapting their travel behaviors in response to air quality crisis, likely prioritizing essential trips and perceived safer travel options during periods of high air pollution.

4.2.4 Travel Distance Changes

The statistic of travel distance reveals several notable shifts in behavior. As shown in Figure 4.4, the most significant change is observed in motorcycle usage for longer trips (>5 km), which decreases by approximately 11% during air quality crisis. Conversely, alternatives for shorter trips (<5 km) see a substantial increase of around 6%. Motorcycle use for shorter trips shows a modest increase of about 3% points, while private car use for short distances also rises by roughly 4%. These shifts indicate a clear tendency towards reduced exposure during longer trips and increased use of alternatives for shorter distances when air quality crisis. The data suggests that residents adapt their travel behaviors in response to air quality crisis, prioritizing shorter trips and exploring alternatives option to minimize their exposure to pollutants.

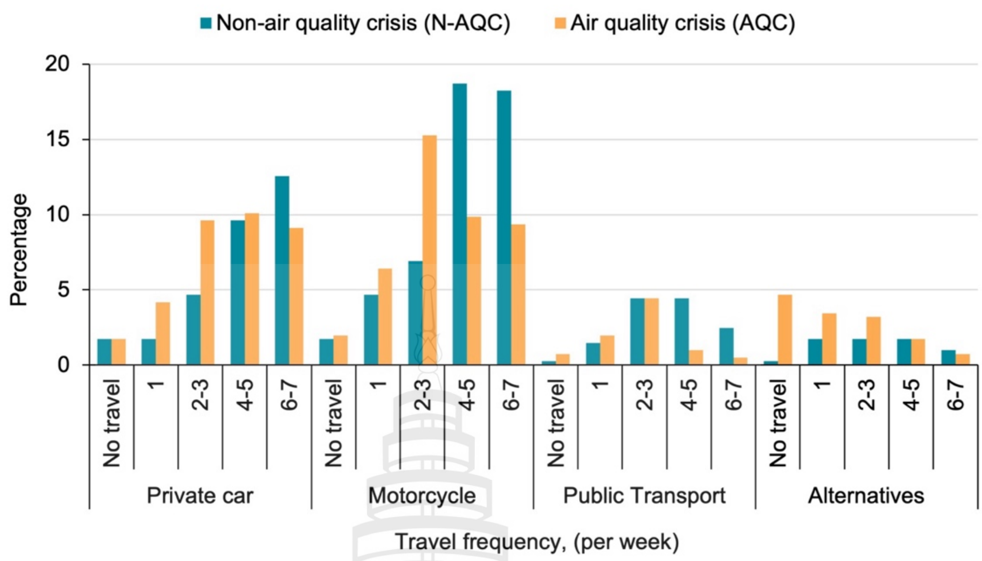

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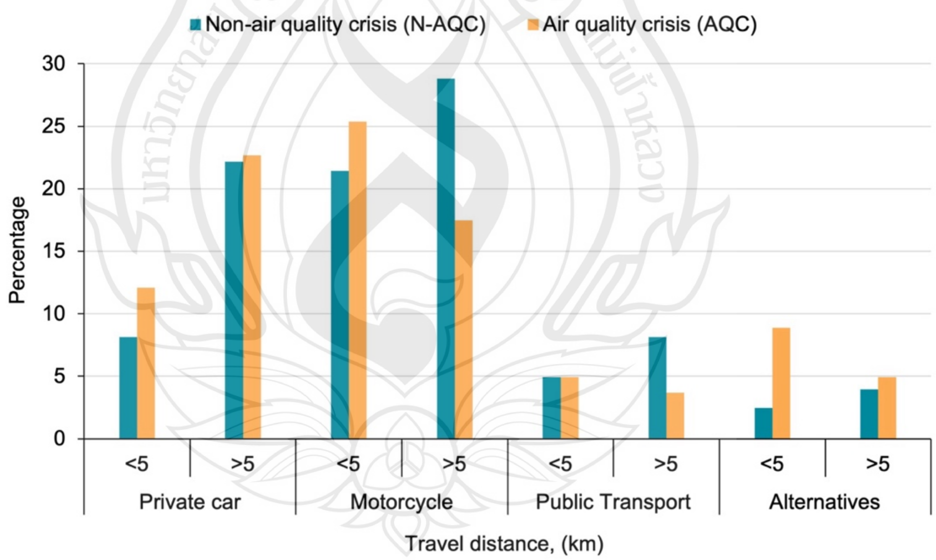
Figure 4.3 Travel frequency changes



Source Developed by Author

Figure 4.4 Travel distance distribution

4.2.5 Travel Mode Distributions

Analysis of travel mode selection in Chiang Rai, Thailand, as shown in Table 4.2, reveals significant shifts during air quality crisis compared to non-air quality crisis. Private car usage increased by 4.40% points to 34.70%, indicating a preference for enclosed transportation during poor air quality. Motorcycle usage saw the largest decrease, dropping 7.30% points to 42.90%, likely due to increased pollution exposure. Public transport usage declined by 4.50% points to 8.60%, possibly reflecting concerns about shared spaces. Notably, alternatives experienced the most substantial increase, rising 7.40% points to 13.80%, suggesting adaptive behavior among residents seeking flexible or less exposed travel options. The "Alternatives" category combines transportation modes with varying air pollution exposure profiles. In Chiang Rai, walking and biking constitute small portions of overall mode share, necessitating their combination with other alternative modes for adequate statistical analysis. Preliminary examination indicated taxi-based services showed proportionally larger increases during air quality crisis compared to active transportation, though sample constraints prevented robust conclusions. This suggests preference for enclosed alternatives that minimize pollutant exposure, demonstrating that air quality significantly influences mode choices toward enclosed transportation during air quality crisis.

Table 4.2 Travel mode distributions

Travel mode	**Percentage**		
	N-AQC	**AQC**	**Change**
Private car	30.30	34.70	+4.40
Motorcycle	50.20	42.90	-7.30
Public transport	13.10	8.60	-4.50
Alternatives	6.40	13.80	+7.40

Note N-AQC is non-air quality crisis, AQC is air quality crisis

4.3 Mode Choice for Non-Air Quality Crisis (N-AQC)

4.3.1 Likelihood Ratio Tests and Collinearity Matrix

The likelihood ratio tests reveal that all examined factors significantly influence travel mode choice under non-air quality crisis in Chiang Rai, Thailand ($p < 0.05$) shown in Table 4.3. The test results demonstrate high statistical significance ($p < 0.001$). The most influential factors include possession of a holding private car driving license, holding motorcycle driving license, vehicle ownership, travel cost, and income. Other significant factors encompass travel time, healthcare effects, gender, age, financial effects, and marital status. The high chi-square values and low p-values (all $p \leq 0.038$) suggest these variables are strong predictors of mode choice in non-air quality crisis. The collinearity matrix presented in Table 4.4 confirms the statistical robustness of the model. Pearson correlation analysis demonstrates that all pairs of independent variables maintain correlation coefficients below 0.80, effectively ruling out significant multicollinearity concerns (Co et al., 2023). Among the observed relationships, three moderate correlations emerge: age and income ($r = 0.562$), travel time and cost ($r = 0.462$), and income and holding of a private car driving license ($r = 0.411$). All other variable pairs exhibit weak correlations ($r < 0.5$), indicating their relative independence. This statistical independence of predictor variables establishes a sound methodological foundation, enabling reliable analysis of travel behavior patterns both under non-air quality crisis and during air quality crisis.

Table 4.3 Likelihood ratio tests of non-air quality crisis (N-AQC)

Effect	Variable	Chi-Square	df	Sig.
Intercept	-	15.011	3	0.002**
Gender	X_G	13.772	3	0.003**
Age	X_A	11.660	3	0.009**
Monthly income	X_{MI}	17.954	3	< 0.001***
Marital status	X_{MS}	8.407	3	0.038*
Vehicle ownership	X_{VO}	24.308	3	< 0.001***
Holding motorcycle driving license	X_{MCDL}	31.509	3	< 0.001***
Holding private car driving license	X_{PCDL}	36.885	3	< 0.001***
Effect on healthcare	X_{EH}	16.341	3	0.001**
Effect on finance	X_{EF}	9.509	3	0.023*
Travel time	X_{TT}	16.703	3	0.001**
Travel cost	X_{TC}	20.630	3	< 0.001***

Note * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4.4 Collinearity matrix of independent variable for non-air quality crisis (N-AQC)

	X_G	X_A	X_{MI}	X_{MS}	X_{VO}	X_{MCDL}	X_{PCDL}	X_{EH}	X_{EF}	X_{TT}	X_{TC}
X_G	-										
X_A	-0.112	-									
X_{MI}	-0.149	0.562	-								
X_{MS}	-0.075	0.177	0.074	-							
X_{VO}	-0.107	0.180	0.119	-0.076	-						
X_{MCDL}	-0.043	0.072	0.048	-0.023	0.294	-					
X_{PCDL}	-0.153	0.360	0.411	0.005	0.187	0.111	-				
X_{EH}	0.109	0.066	0.040	-0.081	-0.046	0.028	0.053	-			
X_{EF}	0.034	0.000	-0.027	-0.004	-0.084	0.031	-0.048	0.185	-		
X_{TT}	-0.068	0.189	0.126	0.023	0.051	0.015	0.196	-0.009	-0.066	-	
X_{TC}	-0.072	0.202	0.214	0.047	0.076	-0.058	0.185	-0.002	-0.073	0.462	-

Note X_G: Gender, X_A: Age, X_{MI}: Monthly income, X_{MS}: Marital status, X_{VO}: Vehicle ownership, X_{MCDL}: Holding motorcycle driving license, X_{PCDL}: Holding private car driving license, X_{EH}: Effect on healthcare, X_{EF}: Effect on finance, X_{TT}: Travel time, X_{TC}: Travel cost

4.3.2 Multinomial Logit Model Parameter Estimates and Utility Function

A Multinomial Logit Model analysis was conducted to examine travel mode choice behavior under non-air quality crisis, with private car designated as the reference category presented in Table 4.5. The model revealed several significant socioeconomic and travel-related factors influencing mode choice across different transportation options. The utility function for mode choice during non-air quality crisis (N-AQC) was specified as Equation 5.

$$U_{N-AQC} = \alpha X_G + \beta X_A + \gamma X_{MI} + \delta X_{MS} + \varepsilon X_{VO} + \zeta X_{MCDL} + \eta X_{PCDL} + \theta X_{EH} + \iota X_{EF} + \kappa X_{TT} + \lambda X_{TC} + c \tag{5}$$

Where the variables represent X_G: Gender, X_A: Age, X_{MI}: Monthly income, X_{MS}: Marital status, X_{VO}: Vehicle ownership, X_{MCDL}: Holding motorcycle driving license, X_{PCDL}: Holding private car driving license, X_{EH}: Effect on healthcare, X_{EF}: Effect on finance, X_{TT}: Travel time, X_{TC}: Travel cost.

The analysis of motorcycle usage revealed that income has a significant negative effect, α = -0.454 : Monthly income (X_{MI}), indicating that higher-income individuals are less likely to choose motorcycles over private cars. License possession showed contrasting effects - holding a motorcycle license significantly increased the likelihood of motorcycle use, β = 1.252 : Holding motorcycle driving license (X_{MCDL}), while possession of a car license decreased it, γ = -1.776 : Holding private car driving license (X_{PCDL}). Travel cost demonstrated a negative relationship with motorcycle choice, δ = -0.477 : Travel cost (X_{TC}), suggesting cost sensitivity among motorcycle users.

For public transport, gender and age emerged as significant positive factors, with females, ε = 1.248 : Gender (X_G), and older individuals, ζ = 0.857 : Age (X_A), showing higher probabilities of choosing this mode. Income exhibited a negative relationship with public transport use, α = -0.475 : Monthly income (X_{MI}), while travel time showed a positive effect, θ = 0.388 : Travel time (X_{TT}), possibly reflecting the reliability of scheduled services for longer journeys. Vehicle ownership was found to significantly decrease public transport use, η = -2.045 : Vehicle ownership (X_{VO}).

Regarding alternative modes, marital status showed a significant negative effect, ι = -1.111 : Marital status (X_{MS}). Both vehicle ownership, η = -1.797 : Vehicle ownership (X_{VO}), and possession of a car license, γ = -2.045 : Holding private car driving license (X_{PCDL}), were found to substantially decrease the likelihood of choosing alternative transportation modes. The findings align with previous studies on mode choice behavior in Southeast Asian contexts. This comprehensive analysis provides valuable insights into the factors influencing travel mode choices under non-air quality crisis, establishing a baseline for comparison with behavior during air quality crisis. The model's results highlight the complex interplay between socioeconomic characteristics, travel attributes, and mode choice decisions.

Table 4.5 MNL parameter estimates of non-air quality crisis model (N-AQC)

Mode	**Variable**	**Coef.**	**Sig.**	**Odds Ratio**
Motorcycle	Intercept	2.832	0.002**	
	Gender (X_G)	0.019	0.944	1.019
	Age (X_A)	0.058	0.780	1.059
	Monthly income (X_{MI})	-0.454	***	0.635
	Marital status (X_{MS})	-0.475	0.046*	0.622
	Vehicle ownership (X_{VO})	-0.331	0.474	0.718
	Holding motorcycle driving license (X_{MCDL})	1.252	***	3.496
	Holding private car driving license (X_{PCDL})	-1.776	***	0.169
	Effect on healthcare (X_{EH})	0.867	0.047*	2.379
	Effect on finance (X_{EF})	0.180	0.588	1.197
	Travel time (X_{TT})	-0.097	0.344	0.907
	Travel cost (X_{TC})	-0.477	***	0.621
Public transport	Intercept	-0.375	0.746	
	Gender (X_G)	1.248	0.001**	3.485
	Age (X_A)	0.857	0.002**	2.356
	Monthly income (X_{MI})	-0.475	0.005**	0.622
	Marital status (X_{MS})	-0.681	0.048*	0.506

Table 4.5 (continued)

Mode	**Variable**	**Coef.**	**Sig.**	**Odds Ratio**
Public transport	Vehicle ownership (X_{VO})	-2.045	***	0.129
	Holding motorcycle driving license (X_{MCDL})	-0.392	0.355	0.676
	Holding private car driving license (X_{PCDL})	-1.346	0.003**	0.260
	Effect on healthcare (X_{EH})	-1.030	0.067	0.357
	Effect on finance (X_{EF})	1.200	0.006**	3.321
	Travel time (X_{TT})	0.388	0.003**	1.474
	Travel cost (X_{TC})	-0.427	0.025*	0.652
Alternatives	Intercept	1.396	0.335	
	Gender (X_G)	0.431	0.381	1.539
	Age (X_A)	0.452	0.206	1.572
	Monthly income (X_{MI})	-0.236	0.210	0.790
	Marital status (X_{MS})	-1.111	0.039*	0.329
	Vehicle ownership (X_{VO})	-1.797	0.003**	0.166
	Holding motorcycle driving license (X_{MCDL})	-0.457	0.395	0.633
	Holding private car driving license (X_{PCDL})	-2.045	0.001**	0.129
	Effect on healthcare (X_{EH})	-1.056	0.093	0.348
	Effect on finance (X_{EF})	0.869	0.108	2.386

Table 4.5 (continued)

Mode	Variable	Coef.	Sig.	Odds Ratio
Alternatives	Travel time (X_{TT})	0.027	0.868	1.027
	Travel cost (X_{TC})	0.141	0.481	1.152

Note * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, Reference mode: private car

4.3.3 Model Fitting and Predictive Accuracy of Non-Air Quality Crisis Model (N-AQC)

The model fitting results for the Multinomial Logit Model (MNL) under non-air quality crisis (N-AQC) are summarized in Table 4.6. The model fitting criteria indicated that the final model (AIC = 746.099; BIC = 890.328) performed substantially better than the intercept model (AIC = 939.296; BIC = 951.316), suggesting an improved fit with the inclusion of explanatory variables. The decrease in -2 Log Likelihood from 933.296 to 674.099 further supported this improvement. The likelihood ratio test revealed a statistically significant chi-square value of 259.197 with 33 degrees of freedom ($p < .001$), confirming that the predictors significantly contributed to explaining mode choice behavior during non-air quality crisis (Hosmer et al., 2013; Long & Freese, 2001).

In terms of goodness-of-fit, the deviance statistic was 674.099 with a p-value of 1.000, indicating an excellent model fit with no significant deviation from the saturated model. However, the Pearson chi-square value of 1306.169 (df = 1182, p = 0.007) suggested a marginal lack of fit, which could be attributed to large sample size or data sparsity in certain categories (Menard, 2014). The model's explanatory power, assessed through pseudo R-square statistics, showed acceptable levels: Cox and Snell $R^2 = 0.472$, Nagelkerke $R^2 = 0.525$, and McFadden $R^2 = 0.278$. These values indicate that the model accounted for approximately 47% to 53% of the variance in mode choice (McFadden, 1972).

The classification results in Table 4.7 evaluated the predictive accuracy of the model. The overall correct classification rate was 67.5%, indicating that the model correctly predicted two-thirds of the respondents' travel mode choices under non-air quality crisis. The highest predictive accuracy was observed for motorcycle users at 83.3%, followed by private car users at 65.9%. In contrast, the model performed less effectively in predicting public transport users (35.8%) and those choosing alternative modes (15.4%). These findings suggest that while the model performs well for dominant travel modes, further refinement may be necessary to improve predictive performance for less frequently used or more heterogeneous modes (Train, 2009; Washington et al., 2020).

Table 4.6 Model summary of Multinomial Logit Model for non-air quality crisis (N-AQC)

Model Info	Model Fitting Criteria	Likelihood Ratio Tests	Goodness-of-Fit	Pseudo R-Square
Model (N-AQC)	AIC: 939.296 (Intercept) 746.099 (Final) BIC: 951.316 (Intercept) 890.328 (Final) -2 Log Likelihood: 933.296 (Intercept) 674.099 (Final)	Chi-Square: 259.197 df: 33 Sig.: 0.001***	Pearson Chi-Square: 1306.169 df: 1182 $p = 0.007$ Deviance: 674.099 df: 1182 $p = 1.000$	Cox and Snell: 0.472 Nagelkerke: 0.525 McFadden: 0.278

Note *** $p < 0.001$

Table 4.7 Percentage correct for non-air quality crisis (N-AQC)

	Classification				
Observed	**Private Car**	**Motorcycle**	**Public Transport**	**Alternatives**	**Percent Correct**
Private car	81	38	2	2	65.90%
Motorcycle	24	170	10	0	83.30%
Public transport	7	26	19	1	35.80%
Alternatives	6	12	4	4	15.40%
Overall Percentage	29.10%	60.60%	8.60%	1.70%	67.50%

4.4 Mode Choice for Air Quality Crisis (AQC)

4.4.1 Likelihood Ratio Tests and Collinearity Matrix

The Likelihood ratio tests, as presented in Table 4.8, indicate that holding a private car driving license, travel frequency, travel time, and vehicle ownership are the most influential predictors. The test results demonstrate high statistical significance ($p < 0.001$). Monthly income, travel cost, and financial impacts of the air quality crisis also significantly affect mode choice. Notably, possession of a motorcycle license was not statistically significant. The collinearity matrix presented in Table 4.9 confirms the statistical soundness of the model through Pearson correlation analysis. The analysis reveals that no pairs of independent variables exceed the correlation coefficient threshold of 0.80, effectively addressing multicollinearity concerns (Co et al., 2023). The strongest observed correlation exists between travel time and cost ($r = 0.559$), while moderate correlations are identified between monthly income and private car license ownership ($r = 0.411$), and between vehicle ownership and motorcycle license possession ($r = 0.294$). All other variable pairs demonstrate weak correlations ($r < 0.5$), indicating their relative independence. These statistical relationships, particularly those involving vehicle access and travel characteristics, illuminate the significant role of socioeconomic factors in shaping travel behavior during air quality crisis. The robust model structure, characterized by significant predictors and minimal variable interdependence, provides a reliable framework for understanding mode choice dynamics during air quality crisis in this urban context.

Table 4.8 Likelihood ratio tests of air quality crisis (AQC)

Effect	**Variable**	**Chi-Square**	**df**	**Sig.**
Intercept	-	22.067	3	$< 0.001^{***}$
Monthly income	X_{MI}	16.396	3	$< 0.001^{***}$
Vehicle ownership	X_{VO}	19.720	3	$< 0.001^{***}$
Holding motorcycle driving license	X_{MCDL}	18.502	3	$< 0.001^{***}$
Holding private car driving license	X_{PCDL}	42.441	3	$< 0.001^{***}$
Effect on finance	X_{EF}	11.451	3	0.010^{*}
Travel time	X_{TT}	28.396	3	$< 0.001^{***}$
Travel cost	X_{TC}	17.775	3	$< 0.001^{***}$
Travel frequency	X_{TF}	41.544	3	$< 0.001^{***}$

Note * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4.9 Collinearity matrix of independent variable for air quality crisis (AQC)

	X_{MI}	X_{VO}	X_{MCDL}	X_{PCDL}	X_{EF}	X_{TT}	X_{TC}	X_{TF}
X_{MI}	-							
X_{VO}	0.119	-						
X_{MCDL}	0.048	0.294	-					
X_{PCDL}	0.411	0.187	0.111	-				
X_{EF}	-0.027	-0.084	0.031	-0.048	-			
X_{TT}	0.161	0.114	0.074	0.215	-0.102	-		
X_{TC}	0.215	0.079	-0.041	0.177	-0.068	0.559	-	
X_{TF}	0.161	0.224	0.112	0.154	-0.018	0.264	0.140	-

Note X_{MI}: Monthly income, X_{VO}: Vehicle ownership, X_{MCDL}: Holding motorcycle driving license, X_{PCDL}: Holding private car driving license, X_{EF}: Effect on finance, X_{TT}: Travel time, X_{TC}: Travel cost, X_{TF}: Travel freqeuncy

4.4.2 Multinomial Logit Model Parameter Estimates and Utility Function

A MNL model analysis was conducted to examine travel mode choice behavior during air quality crisis, with private car serving as the reference category presented in Table 4.10. The model identified several significant factors that influence mode choice during air quality crisis. The utility function for mode choice during air quality crisis (AQC) was specified as Equation 6.

$$U_{AQC} = \alpha X_{MI} + \beta X_{VO} + \gamma X_{MCDL} + \delta X_{PCDL} + \varepsilon X_{EF} + \zeta X_{TT} + \eta X_{TC} + \theta X_{TF} + c \tag{6}$$

Where the variables represent X_{MI}: Monthly income, X_{VO}: Vehicle ownership, X_{MCDL}: Holding motorcycle driving license, X_{PCDL}: Holding private car driving license, X_{EF}: Effect on finance, X_{TT}: Travel time, X_{TC}: Travel cost, X_{TF}: Travel freqeuncy.

The analysis of motorcycle usage during air quality crisis revealed that income maintains a significant negative effect, α = -0.386 : Monthly income (X_{MI}), indicating higher-income individuals are less likely to choose motorcycles over private cars. License possession continued to show contrasting effects holding a motorcycle license remained positively significant, γ = 1.087 : Holding motorcycle driving license (X_{MCDL}), while possession of a car license decreased motorcycle utility, δ = -1.886 : Holding private car driving license (X_{PCDL}). Both travel time, ζ = -0.326 : Travel time (X_{TT}), and costs, η = -0.282 : Travel cost (X_{TC}), emerged as significant deterrents during air quality crisis, suggesting increased sensitivity to these factors during air quality crisis.

For public transport, income demonstrated a persistent negative influence, α = -0.400 : Monthly income (X_{MI}), while vehicle ownership substantially reduced its utility, β = -1.318 : Vehicle ownership (X_{VO}). Notably, financial considerations showed heightened importance during the air quality crisis, ε = 1.304 : Effect on finance (X_{EF}), suggesting that economic factors become more crucial in mode choice decisions during these periods. Travel frequency exhibited a negative association, θ = -0.413 : Travel frequency (X_{TF}), indicating that frequent travelers were less likely to opt for public transport during air quality crisis.

Alternative modes revealed distinct patterns during the air quality crisis, with financial effects showing a significant positive influence, ε = 1.109 : Effect on finance

(X_{EF}), while travel frequency demonstrated a strong negative relationship, θ = -0.849 : Travel frequency (X_{TF}). Vehicle ownership maintained its negative influence, β = -1.159 : Vehicle ownership (X_{VO}), on the choice of alternatives. Interestingly, travel time, ζ = -0.384 : Travel time (X_{TT}), and travel costs, η = 0.418 : Travel cost (X_{TC}), showed opposing effects during air quality crisis, suggesting a complex trade-off between these factors in mode choice decisions.

These findings highlight the significant shifts in travel mode choice behavior during air quality crisis, particularly in how individuals weigh various factors such as financial impacts, travel characteristics, and personal resources in their transportation decisions. The differential coefficient patterns between N-AQC and AQC periods suggest the presence of implicit interaction effects between environmental conditions and behavioral determinants. For instance, the emergence of travel frequency as significant only during AQC periods (coefficients ranging from -0.849 to 0.147 across modes) as shown in Table 4.10 while demographic variables lose significance indicates that environmental stressors fundamentally alter decision-making processes. The results provide valuable insights for transportation planning and policy development during air quality crisis.

Table 4.10 MNL parameter estimates of air quality crisis model (AQC)

Mode	Variable	Coef.	Sig.	Odds Ratio
Motorcycle	Intercept	1.814	0.002**	
	Monthly income (X_{MI})	-0.386	***	0.680
	Vehicle ownership (X_{VO})	0.352	0.422	1.423
	Holding motorcycle driving license (X_{MCDL})	1.087	***	2.967
	Holding private car driving license (X_{PCDL})	-1.886	***	0.152
	Effect on finance (X_{EF})	0.540	0.097	1.715
	Travel time (X_{TT})	-0.326	0.002**	0.722
	Travel cost (X_{TC})	-0.282	0.041*	0.755
	Travel frequency (X_{TF})	0.147	0.252	1.158
Public transport	Intercept	1.539	0.039*	
	Monthly income (X_{MI})	-0.400	0.040*	0.670
	Vehicle ownership (X_{VO})	-1.318	0.010*	0.268
	Holding motorcycle driving license (X_{MCDL})	-0.315	0.511	0.730
	Holding private car driving license (X_{PCDL})	-1.398	0.006**	0.247
	Effect on finance (X_{EF})	1.304	0.005**	3.685
	Travel time (X_{TT})	0.337	0.025*	1.400
	Travel cost (X_{TC})	-0.226	0.283	0.797

Table 4.10 (continued)

Mode	Variable	Coef.	Sig.	Odds Ratio
Public transport	Travel frequency (X_{TF})	-0.413	0.036^{*}	0.662
	Intercept	2.798	***	
	Monthly income (X_{MI})	-0.058	0.652	0.944
	Vehicle ownership (X_{VO})	-1.159	0.011^{*}	0.314
	Holding motorcycle driving license (X_{MCDL})	0.086	0.828	1.090
Alternatives	Holding private car driving license (X_{PCDL})	-1.101	0.009^{**}	0.332
	Effect on finance (X_{EF})	1.109	0.006^{**}	3.030
	Travel time (X_{TT})	-0.384	0.012^{*}	0.681
	Travel cost (X_{TC})	0.418	0.015^{*}	1.520
	Travel frequency (X_{TF})	-0.849	***	0.428

Note * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, Reference mode: private car

Source Authors own

4.4.3 Model Fitting and Predictive Accuracy of Air Quality Crisis Model (AQC)

The model fitting results for the Multinomial Logit Model (MNL) under air quality crisis (AQC) are presented in Table 4.11. The reduction in AIC from 967.119 (intercept) to 745.348 (final model), and in BIC from 979.138 to 853.520, indicates that the model with predictors performs substantially better. Similarly, the drop in -2 Log Likelihood from 961.119 to 691.348 supports an improved model fit. The likelihood ratio test reported a significant chi-square value of 269.771 with 24 degrees of freedom ($p < .001$), suggesting that the final model provides a significantly better fit than the null model (Ben-Akiva & Lerman, 1985; Greene, 2003). Regarding model adequacy, the deviance statistic was 669.272 with a non-significant p-value ($p = 1.000$), indicating no significant deviation from the saturated model. Additionally, the Pearson chi-square (1054.790, df = 1047, $p = 0.427$) further supports a good overall fit (Louviere, Hensher, & Swait, 2000). The pseudo R-square values Cox and Snell $R^2 = 0.485$, Nagelkerke $R^2 = 0.532$, and McFadden $R^2 = 0.273$ indicate moderate explanatory power of the model, with Nagelkerke R^2 exceeding the commonly accepted threshold of 0.5 for behavioral models (de Dios Ortúzar & Willumsen, 2011; Gaudry et al., 1977).

Table 4.12 presents the model's classification accuracy. An overall correct prediction rate of 63.8% was achieved, indicating that nearly two-thirds of actual mode choices were correctly classified. The highest prediction accuracy occurred for motorcycle users (81.0%), followed by private car users (64.5%). In contrast, the model showed weaker predictive accuracy for public transport (17.1%) and alternative modes (37.5%). This distribution of accuracy suggests that while the model is effective in capturing dominant travel behaviors, it may require further refinement or additional variables to improve prediction for less frequently chosen modes (Buehler & Pucher, 2012; Gärling & Fujii, 2009).

The analysis revealed significant differences in mode choice factors between non-air quality crisis (N-AQC) and air quality crisis (AQC) in Chiang Rai, Thailand as shown in Table 4.13. Core economic and operational variables including monthly income, vehicle ownership, driving licenses, travel time, and travel cost remained significant across both conditions, indicating their fundamental role in transportation decisions regardless of environmental conditions.

However, notable shifts occurred in other variable categories. Demographic factors (gender, age, marital status) were only significant during normal conditions, suggesting that routine social and household characteristics lose their predictive power when environmental health threats emerge. The loss of marital status significance during crisis periods reflects how environmental stress overrides typical household coordination patterns, creating behavioral convergence where both married and unmarried individuals prioritize health protection over routine family-based travel decisions.

Conversely, travel frequency emerged as significant exclusively during air quality crisis, indicating that individuals reduce travel to essential trips only when air quality crisis. This behavioral adaptation represents a crisis-specific response not observed during normal conditions.

Particularly noteworthy is the counterintuitive finding that healthcare effects were significant only during non-air quality crisis. This suggests that health-conscious individuals proactively modify their travel behavior as preventive measures during normal times, while during actual crisis periods, health concerns become universally elevated across all respondents, creating a ceiling effect where baseline health awareness differences disappear.

This shift in significant variables suggests that environmental conditions substantially alter commuters' mode choice decision-making processes, with economic considerations maintaining importance regardless of air quality crisis, while demographic influences give way to crisis-driven behavioral patterns. These findings provide valuable insights for developing targeted transportation policies that can adapt to varying air quality crisis, recognizing that crisis periods require different intervention strategies than normal conditions.

Table 4.11 Model summary of Multinomial Logit Model for air quality crisis (AQC)

Model Info	Model Fitting Criteria	Likelihood Ratio Tests	Goodness-of-Fit	Pseudo R-Square
Model (AQC)	AIC: 967.119 (Intercept) 745.348 (Final) BIC: 979.138 (Intercept) 853.520 (Final) -2 Log Likelihood: 961.119 (Intercept) 691.348 (Final)	Chi-Square: 269.771 df: 24 Sig.: 0.001***	Pearson Chi-Square: 1054.790 df: 1047 p = 0.427 Deviance: 669.272 df: 1047 p = 1.000	Cox and Snell: 0.485 Nagelkerke: 0.532 McFadden: 0.273

Note *** $p < 0.001$

Table 4.12 Percentage correct for air quality crisis (AQC)

	Classification				
Observed	**Private Car**	**Motorcycle**	**Public Transport**	**Alternatives**	**Percent Correct**
Private car	91	37	4	9	64.50%
Motorcycle	24	141	2	7	81.00%
Public transport	8	13	6	8	17.10%
Alternatives	10	23	2	21	37.50%
Overall Percentage	32.80%	52.70%	3.40%	11.10%	63.80%

Table 4.13 Significant variables in non-air quality crisis (N-AQC) and air quality crisis (AQC) models

Effect	Variable	Sig. in N-AQC Model	Sig. in AQC Model	Interpretation
Gender	X_G	o		Significant only during normal air quality conditions
Age	X_A	o		Relevant for mode choice only in non-air quality crisis
Monthly income	X_{MI}	o	o	Key factor influencing mode choice in both periods
Marital status	X_{MS}	o		Only significant under normal conditions
Vehicle ownership	X_{VO}	o	o	Significant; access to a vehicle strongly affects mode selection
Holding motorcycle driving license	X_{MCDL}	o	o	Strong predictor for motorcycle uses in both periods
Holding private car driving license	X_{PCDL}	o	o	Influences private car and alternative mode decisions in both periods
Effect on healthcare	X_{EH}	o		Perceived health impact mattered only during non-air quality crisis
Effect on finance	X_{EF}	o	o	Financial concern significantly affects decisions in both scenarios
Travel time	X_{TT}	o	o	Travel duration influences choice across both periods

Table 4.13 (continued)

Effect	**Variable**	**Sig. in N-AQC Model**	**Sig. in AQC Model**	**Interpretation**
Travel cost	X_{TC}	○	○	Cost remains a significant determinant under all air quality conditions
Travel frequency	(X_{TF})		○	Becomes significant only during air quality crisis, indicating crisis-driven behavior change

Note N-AQC is non-air quality crisis, AQC is air quality crisis, ○ is statistically significant ($p < 0.05$), Blank is not statistically significant

4.5 The Predicted Probabilities of Transportation Mode

Table 4.14 and 4.15 present the predicted probabilities of transportation mode choices during non-air quality crisis and air quality crisis in Chiang Rai, Thailand. Transport mode preferences are strongly influenced by socioeconomic and demographic factors. Motorcycles emerge as the dominant mode of transport, particularly favored by younger individuals and lower-income groups. Private car usage increases significantly with income levels, while public transport becomes more prevalent among older age groups. Travel characteristics also play a key role, with longer journeys associated with higher public transport use and higher travel costs linked to increased private car usage. Vehicle ownership and possession of driving licenses strongly correlate with respective mode choices, with non-vehicle owners showing greater reliance on public transport. These findings reflect typical transportation patterns observed in Southeast Asian urban contexts, characterized by high motorcycle dependency among certain demographic groups.

For predicted probabilities of transportation mode choices during the air quality crisis in Chiang Rai, socioeconomic factors, particularly monthly income levels, significantly influence transportation preferences, with higher-income groups demonstrating a strong preference for private cars while lower-income groups predominantly rely on motorcycles. Vehicle ownership and licensing status also play crucial roles in mode selection, with license holders typically choosing their respective vehicle types and non-vehicle owners showing higher public transport usage. Travel characteristics emerge as important determinants - longer journey durations correlate with increased public transport use, while shorter journeys associate with higher motorcycle usage, and higher travel costs lead to greater utilization of alternative modes. The frequency of travel impacts mode selection, with regular commuters showing stronger preferences for private cars while occasional travelers demonstrate more varied choices. Additionally, the financial impact of the air quality crisis notably influences transportation decisions, where individuals reporting financial effects show distinct changes in their choices, including reduced private car usage and increased utilization of both public transport and alternative modes, demonstrating how economic constraints during environmental crisis can significantly reshape transportation behavior.

The analysis of travel mode choices in Chiang Rai reveals distinct shifts between non-air quality crisis and air quality crisis. During air quality crisis private car usage decreased among higher-income groups (from 77 to 70%), while motorcycle dependency reduced among lower-income groups (from 64 to 54%). Public transport usage also declined, particularly among non-vehicle owners (from 28 to 17%). These changes indicate four key impacts of air quality crisis: reduced overall mobility, preference for enclosed transport modes, increased health considerations, and stronger economic influences on travel decisions. These findings contribute to understanding environmental crisis impacts on travel behavior in Southeast Asian contexts, particularly in areas with high motorcycle dependency.

Table 4.14 The predicted probabilities of transportation mode during non-air quality crisis (N-AQC) (%)

	Private Car	**Motorcycle**	**Public Transport**	**Alternatives**
Gender				
Male	32	60	4	4
Female	28	54	12	6
Others	21	41	32	7
Age, (years)				
<21	33	59	4	4
21-30	29	56	9	5
31-40	24	50	19	7
41-50	18	40	33	8
51-60	12	28	51	9
Monthly income, (THB)				
<10,000	20	64	11	5
10,001-15,000	28	57	10	5
15,000-20,000	38	49	8	6
20,001-30,000	48	40	6	6

Table 4.14 (continued)

	Private Car	Motorcycle	Public Transport	Alternatives
Monthly income, (THB)				
30,001-40,000	59	31	5	5
40,001-50,000	69	23	3	5
>50,001	77	16	2	4
Marital status				
Unmarried	27	57	10	6
Married	38	51	7	3
Not mentioned	51	43	5	1
Vehicle ownership				
No	17	42	28	13
Yes	32	57	7	4
Holding motorcycle driving license				
No	39	37	15	9
Yes	21	70	6	3
Holding private car driving license				
No	17	67	9	7
Yes	53	36	8	3
Effect on healthcare				
No	32	29	25	15
Yes	28	60	8	4
Effect on finance				
No	31	57	7	4
Yes	23	51	18	8
Travel time (Minutes)				
<10	28	63	4	5
10-20	29	60	7	5
21-30	29	56	10	5
31-40	29	51	15	6

Table 4.14 (continued)

	Private Car	Motorcycle	Public Transport	Alternatives
Travel time (Minutes)				
41-50	29	45	21	6
51-60	27	38	29	5
> 60	25	32	39	5
Travel cost (THB)				
< 50	20	66	10	3
50-100	29	57	9	5
101-150	38	47	8	8
151-200	47	36	7	11
> 200	54	26	5	15

Note The predicted probabilities were calculated using MNL model presented in Table 4.5. When generating predictions for each variable of interest, all other quantitative variables were held constant at their respective mean values, while categorical variables were fixed at their modal values.

Table 4.15 The predicted probabilities of transportation mode during air quality crisis (AQC) (%).

	Private Car	**Motorcycle**	**Public Transport**	**Alternatives**
Monthly income, (THB)				
<10,000	29	54	8	8
10,001-15,000	36	47	7	10
15,000-20,000	44	39	6	12
20,001-30,000	52	31	5	13
30,001-40,000	59	24	4	14
40,001-50,000	65	18	3	14
>50,001	70	13	2	15
Vehicle ownership				
No	32	29	17	22
Yes	37	49	6	8
Holding motorcycle driving license				
No	47	31	10	12
Yes	29	58	5	8
Holding private car driving license				
No	23	60	8	10
Yes	62	25	5	9
Effect on finance				
No	42	44	5	8
Yes	26	46	12	16
Travel time (Minutes)				
<10	26	57	3	14
10-20	32	51	5	12
21-30	38	44	8	10
31-40	44	36	12	8
41-50	47	28	18	6
51-60	49	21	26	4

Table 4.15 (continued)

	Private Car	Motorcycle	Public Transport	Alternatives
Travel time (Minutes)				
> 60	47	15	36	3
Travel cost (THB)				
< 50	32	55	8	5
50-100	36	47	7	9
101-150	40	39	6	15
151-200	41	30	5	23
> 200	40	22	4	34
Travel frequency (per weeks)				
No travel	24	20	11	45
1	32	32	10	26
2-3	37	43	8	13
4-5	38	51	5	6
6-7	51	20	12	16

Note The predicted probabilities were calculated using MNL model presented in Table 4.10. When generating predictions for each variable of interest, all other quantitative variables were held constant at their respective mean values, while categorical variables were fixed at their modal values.

4.6 Exploratory Factor Analysis of Travel Mode Change Behavior During Air Pollution Crisis

The descriptive statistics of the observed variables measuring travel mode change intentions during the air quality crisis period were analyzed in terms of mean, skewness, and kurtosis. The results indicated that most variables had mean scores above 3.50, reflecting a tendency toward agreement among respondents regarding their intention to change travel behavior during air quality crisis. Particularly high agreement was observed in items concerning protective health measures, such as the use of anti-PM2.5 masks (mean = 4.43) and the prioritization of enclosed or dust-resistant transport systems (mean = 4.42), highlighting heightened public concern over exposure to air pollution. To assess data normality, skewness and kurtosis values were examined. All skewness values were found to be less than 3.0 and all kurtosis values were below 10, which are within acceptable thresholds indicating that the data followed a normal distribution and were thus suitable for multivariate analysis (Watthanaklang et al., 2024). Several variables demonstrated slight negative skewness, suggesting that responses were slightly skewed toward agreement, a common pattern in attitudinal surveys. For instance, the statement "I believe that air pollution crisis affects visibility and makes me change mode of transport" had a mean of 4.17 and a skewness of -0.818. These findings confirm that the observed variables are statistically appropriate for further factorial analysis, as summarized in Table 4.16**.**

Table 4.16 Mean, Skewness, and Kurtosis values of variables used in the model

Variable	**Mean**	**Skewness**	**Kurtosis**
Attitude Toward Behavior			
I like to change mode of transport during air quality crisis if travel time reduced.	4.20	-0.798	0.462
I like to change mode of transport during air quality crisis if transport frequency is increased.	3.93	-0.653	-0.241

Table 4.16 (continued)

Variable	Mean	Skewness	Kurtosis
I think change mode of transport during air quality crisis is incompatible with my mobility needs.	3.81	-0.413	-0.641
I think travel by public transport during air quality crisis can sometimes be easier than private transport.	3.31	0.109	-1.382
I feel that using private transport during air quality crisis is safer than by public transport.	4.20	-0.755	-0.035
Subjective Norms			
I prefer to change mode of transport during air quality crisis as it is recommended by friends.	3.76	-0.388	-0.492
I prefer to change mode of transport during air quality crisis as it has become norm of the society.	3.59	-0.164	-0.683
I prefer to change mode of transport during air quality crisis as it is recommended by people who are important to me.	3.83	-0.470	0.015
People who influence me would want me to using public transport during air quality crisis instead of using private car.	3.38	-0.028	-1.150
Perceived Behavioral Control			
I believe the existing transport infrastructure, eg. frequency/Level of service, makes it difficult to change	4.07	-0.516	0.340

Table 4.16 (continued)

Variable	Mean	Skewness	Kurtosis
mode of transport during air quality crisis.			
I believe that it difficult to change mode of transport during air quality crisis if it will increase travel time.	4.08	-0.630	0.510
I think change mode of transport during air quality crisis would be very easy.	3.38	0.022	-1.101
Whether or not I change mode of transport during air quality crisis is completely up to me.	3.97	-0.666	0.026
I am confident that if I want to I could change mode of transport during air quality crisis.	3.91	-0.459	-0.276
Cost Sensitivity			
I believe that travel cost will affect my intention to change mode of transport during air quality crisis.	4.12	-0.752	0.631
I like to change mode of transport during air quality crisis if that mode fare is lowered.	4.09	-0.750	0.190
Health Concerns			
I pay attention to wearing anti-PM2.5 mask while traveling during air quality crisis, whatever mode of transport.	4.43	-1.080	0.918
I prioritize mode of transport that prevents/reduces exposure to dust e.g. enclosed systems, air purifiers use.	4.42	-1.092	0.837

Table 4.16 (continued)

Variable	Mean	Skewness	Kurtosis
Visibility Concerns			
I believe that air quality crisis affects to city and visibility, that make me change mode of transport.	4.17	-0.818	0.458
I prefer to change mode of transport as the weather forecast said air quality crisis affect to travel visibility.	4.13	-0.740	0.154
I believe that I can accept the risk of unclear visibility during air quality crisis if I still use same mode of transport as normal situation.	3.76	-0.325	-0.789
Behavioral Intention			
I will make an effort to change mode of transport during air quality crisis.	3.86	-0.505	-0.345
I believe that travel time during air quality crisis will affect my intension to change mode of transport.	3.93	-0.580	0.240
I believe that my intension to change mode of transport during air quality crisis depend upon the availability (frequency) of the service for other mode of transport.	4.06	-0.416	-0.010
I should change mode of transport during air quality crisis to reduce congestion and road accidents.	3.97	-0.677	0.212

Note The acceptable ratio of skewness value is < 3.0 and kurtosis value is < 10.

To assess the appropriateness of the dataset for factor analysis, the Kaiser-Meyer-Olkin (KMO) measure and Bartlett's test of sphericity were employed. The KMO value was found to be 0.874, which exceeds the recommended threshold of 0.60, indicating meritorious sampling adequacy for the factor analysis procedure (Kaiser, 1974). Additionally, Bartlett's test of sphericity was highly significant ($\chi^2 = 3351.671$, df = 300, $p < 0.001$), suggesting that the correlation matrix was not an identity matrix and that there were sufficient interrelationships among variables to justify the application of Exploratory Factor Analysis (EFA) (Kline, 2023).These results demonstrate the structural validity of the dataset for extracting latent dimensions underlying travel mode choice behavior during air quality crisis, as shown in Table 4.17.

Table 4.17 KMO and Bartlett's Test of Sampling Adequacy

Test	**Value**
Kaiser-Meyer-Olkin Measure of Sampling Adequacy	0.874
Bartlett's Test of Sphericity	
Approx. Chi-Square	3351.671
df	300
Sig.	0.001

The Exploratory Factor Analysis was conducted using Principal Axis Factoring with Varimax rotation. The initial extraction yielded factors with eigenvalues greater than 1.0, following Kaiser's criterion for factor retention. Internal consistency reliability was assessed for each extracted factor using Cronbach's alpha coefficient. Three factors achieved acceptable reliability levels ($\alpha \geq 0.70$): Health and Constraint ($\alpha = 0.754$), Perceived Behavioral Control ($\alpha = 0.711$), and Service Improvement ($\alpha = 0.704$). Two factors showed questionable but acceptable reliability for exploratory research: Mode Choice ($\alpha = 0.673$) and Social Recommendation ($\alpha = 0.679$). These values are within acceptable ranges for exploratory research, particularly considering the exploratory nature of the study, the cultural adaptation of measures to the Thai context, and the relatively new domain of air quality crisis travel behavior research. The alpha values above 0.60 are acceptable for exploratory studies, and all factors in this study exceed this threshold (George, & Mallery, 2003).

Table 4.18 summarizes the results of Exploratory Factor Analysis conducted to identify latent constructs underlying travel mode change behavior during air quality crisis. The analysis extracted five distinct factors that collectively explain 53.5% of the total variance in observed variables, providing a comprehensive framework for understanding the psychological and behavioral dimensions that influence transportation decisions during environmental stress. This level of variance explanation exceeds the minimum threshold of 50% typically required for satisfactory factor solutions in social science research. The first factor, Mode Choice (MC), captures the largest portion of variance at 15.2% and represents rational decision-making processes related to transportation mode selection, encompassing instrumental evaluations such as travel time considerations, cost-benefit analyses, visibility concerns due to air pollution, and service availability assessments. The high variance explanation indicates that rational, utility-based decision-making remains the primary driver of mode choice even during environmental crisis.

The second factor, Health and Constraint (HC), accounts for 10.6% of the variance and reflects the dual influence of health-protective behaviors and practical limitations on mode choice. It includes health-conscious actions such as mask-wearing, preference for enclosed transportation systems, and the perceived safety of private vehicles versus public transport, while simultaneously capturing infrastructural constraints and time-related barriers that limit mode switching options. The third factor, Social Recommendation (SI), also explains 10.6% of the variance and highlights the role of social influence in transportation decisions, encompassing recommendations from friends, family, and important others, as well as perceived societal norms regarding appropriate travel behavior during air quality crisis. This factor demonstrates that even during health emergencies, social conformity and peer influence remain important behavioral drivers. The fourth factor, Perceived Behavioral Control (BC), explains 10.2% of the variance and relates to individuals' confidence in their ability to change transportation modes and their perceptions of autonomy versus constraint in making such changes, reflecting self-efficacy beliefs and the perceived ease or difficulty of behavioral modification during crisis periods, drawing from the Theory of Planned Behavior framework. Lastly, the fifth factor, Service Improvement (SF), contributes 6.8% of the variance and focuses on external system enhancements that could facilitate mode switching, capturing responses to improved service frequency, reduced travel times, and other infrastructure improvements that might incentivize behavioral change during air quality crisis.

The factor structure reveals that travel behavior during air quality crisis is influenced by a complex interplay of rational decision-making, health concerns, social influences, perceived control, and system-level factors. The remaining 46.5% represents unique variance, measurement error, and potentially unmeasured factors, which is typical for exploratory research in behavioral sciences, particularly for complex phenomena involving environmental psychology and transportation behavior. These factor labels were derived through factor loading interpretation and are consistent with prior mobility studies (Anable, 2005; Gatersleben & Uzzell, 2007), providing a comprehensive foundation for understanding and predicting behavioral responses to environmental challenges.

Table 4.18 Summary of Extracted Factors from Exploratory Factor Analysis (EFA)

Factors	**Eigenvalue**	**Explained Variance (%)**	**Cumulative explained variance (%)**	**Cronbach's Alpha**
MC	6.6	15.2	15.2	0.673
HC	2.7	10.6	25.8	0.754
SR	1.7	10.6	36.4	0.679
BC	1.3	10.2	46.6	0.711
SI	1.1	6.8	53.5	0.704

Note MC: Mode choice, HC: Health and constraint, SR: Social Recommendation, BC: Perceived Behavioral Control, SI: Service improvement

To further explore the interrelationships among the extracted factors, a Pearson correlation matrix was constructed. All five factors showed statistically significant and positive correlations with one another at the 0.01 level. The strongest association was observed between Social Recommendation Factors (SR) and Perceived Behavioral Control Factors (BC) ($r = 0.518$, $p < 0.01$), indicating that social influence and personal efficacy beliefs are closely linked in transportation decision-making during environmental crisis. Moderate correlations were also observed between Mode Choice Factors (MC) and each of the other four dimensions, especially with Service Improvement Factors (SI) ($r = 0.460$, $p < 0.01$), indicating that improvements in service quality are linked to increased motivation for modal change. These findings underscore the interconnectedness of psychological, environmental, and infrastructural factors in shaping transportation choices during air quality crisis, as illustrated in Table 4.19.

Table 4.19 Correlation Matrix

Factor	MC	HC	SI	BC	SF
MC	1				
HC	.437**	1			
SI	.468**	.208**	1		
BC	.412**	.191**	.518**	1	
SF	.460**	.296**	.458**	.322**	1

4.6.1 Mode Choice Factors

The first factor identified through Exploratory Factor Analysis was termed mode choice factors, capturing the rational evaluations that influence individuals' intentions to shift travel modes during air quality crisis. This factor consists of eight items with factor loadings ranging from 0.533 to 0.715, indicating strong internal consistency. The findings reveal that respondents perceived travel time (mean = 3.93) and travel cost (mean = 4.12) as major considerations influencing their decision to change transport modes during air quality crisis. Additionally, concerns about visibility due to air quality crisis, highlighted by statements such as the effect of weather forecasts on travel visibility (mean = 4.13) and city-wide visibility degradation (mean = 4.17), contributed meaningfully to travel behavior adaptations. Moreover, attitudes toward reducing traffic congestion and accidents through mode switching (mean = 3.97) and the willingness to make an effort (mean = 3.86) reflect a sense of civic and safety awareness. Respondents also reported being influenced by the availability and frequency of alternative transport modes (mean = 4.06) and expressed preference for switching when fare reductions are offered (mean = 4.09). This supports the idea that rational, cost-benefit-based evaluations consistent with the instrumental perspective of travel behavior serve as significant motivators for change (Degirmenci & Breitner, 2017). These findings are summarized in Table 4.20.

Table 4.20 Mode choice factors

Variable	**Mean**	**Standard Deviation**	**Factor loadings**
I believe that travel time during air quality crisis will affect my intension to change mode of transport.	3.93	0.78	0.715
I believe that travel cost will affect my intention to change mode of transport during air quality crisis.	4.12	0.75	0.684
I prefer to change mode of transport as the weather forecast said air quality crisis affect to travel visibility.	4.13	0.81	0.676
I believe that air quality crisis affect to city and visibility, that make me change mode of transport.	4.17	0.78	0.673
I should change mode of transport during air quality crisis to reduce congestion and road accidents.	3.97	0.82	0.620
I will make an effort to change mode of transport during air quality crisis.	3.86	0.88	0.579
I believe that my intension to change mode of transport during air quality crisis depend upon the availability (frequency) of the service for other mode of transport.	4.06	0.72	0.570

Table 4.20 (continued)

Variable	**Mean**	**Standard Deviation**	**Factor loadings**
I like to change mode of transport during air quality crisis if that mode fare is lowered.	4.09	0.82	0.533

4.6.2 Health and Constraint Factors

The second factor, labeled health and constraint factors, reflects the dual influence of health-conscious behaviors and infrastructural limitations on mode choice. This factor includes five items with factor loadings ranging from 0.478 to 0.698. Respondents demonstrated strong awareness of health protection measures, with high mean scores for preferences toward enclosed or air-purified transport systems (mean = 4.42) and consistent use of anti-PM2.5 masks while traveling (mean = 4.43). These behaviors suggest a proactive response to minimize exposure to air pollution. However, significant practical constraints also emerged, including the perception that mode switching is difficult if it increases travel time (mean = 4.08) or when the existing transport infrastructure is inadequate (mean = 4.07). Additionally, a commonly held belief was that using private vehicles is safer than public options during the air quality crisis (mean = 4.20). These findings reflect the dual burden of health avoidance behavior and structural limitations in mobility systems, which is consistent with previous literature indicating that air pollution avoidance behavior often leads to increased car use, thus worsening environmental outcomes (Zhang & Batterman, 2013). Detailed results for this factor group are presented in Table 4.21.

Table 4.21 Health and constraint factors

Variable	**Mean**	**Standard Deviation**	**Factor loadings**
I prioritize mode of transport that prevents/reduces exposure to dust e.g. enclosed systems, air purifiers use.	4.42	0.71	0.698

Table 4.21 (continued)

Variable	Mean	Standard Deviation	Factor loadings
I pay attention to wearing anti- PM2.5 mask while traveling during air quality crisis, whatever mode of transport.	4.43	0.69	0.658
I believe that it difficult to change mode of transport during air quality crisis if it will increase travel time.	4.08	0.73	0.575
I feel that using private transport during air quality crisis is safer than by public transport.	4.20	0.80	0.536
I believe the existing transport infrastructure, eg. frequency/Level of service, makes it difficult to change mode of transport during air quality crisis.	4.07	0.71	0.478

4.6.3 Social Recommendation Factors

The third factor, referred to as social recommendation factors, highlights the role of normative social influence on travel mode decisions. This factor comprises three items with relatively high factor loadings ranging from 0.659 to 0.756. While the mean scores were slightly lower than those in other factors, the influence of social networks remains evident. Respondents indicated that they were inclined to switch modes of transport when recommendations came from friends (mean = 3.59), important individuals (mean = 3.83), or when such behavior aligned with perceived societal norms (mean = 3.76). These findings illustrate that even in a context where individual utility is paramount, social persuasion and conformity can influence environmental behavior during health-related crisis. This aligns with broader theories of social norms and behavior change, where injunctive and descriptive norms shape environmentally significant behavior (Farrow et al., 2017; Klöckner, 2013). Supporting data are reported in Table 4.22.

Table 4.22 Social Recommendation Factors

Variable	**Mean**	**Standard Deviation**	**Factor loadings**
I prefer to change mode of transport during air quality crisis as it is recommended by friends.	3.59	0.89	0.756
I prefer to change mode of transport during air quality crisis as it has become norm of the society.	3.76	0.88	0.725
I prefer to change mode of transport during air quality crisis as it is recommended by people who are important to me.	3.83	0.78	0.659

4.6.4 Perceived Behavioral Control Factors

The fourth factor group, titled perceived behavioral control factors, pertains to individuals' confidence in their ability to change transport modes and their perceptions of autonomy or constraint in doing so. This factor includes seven items with factor loadings between 0.454 and 0.643. While respondents generally expressed belief in their personal agency, such as agreeing that changing transport mode is ultimately up to them (mean = 3.97) and that they have the confidence to make a change if desired (mean = 3.91), other statements reveal nuanced challenges. For example, switching modes was not universally perceived as easy (mean = 3.38), and many felt that existing transport options were incompatible with their specific mobility needs (mean = 3.81). Furthermore, the belief that using public transport could be easier than private vehicles under certain conditions (mean = 3.31) was only moderately supported. These perceptions resonate with the concept of perceived behavioral control from behavioral models, such as the Theory of Planned Behavior, which suggests that perceived ease or difficulty significantly influences the likelihood of action (Bamberg & Schmidt, 2003). The statistical details of this factor are provided in Table 4.23.

Table 4.23 Perceived Behavioral Control Factors

Variable	Mean	Standard Deviation	Factor loadings
I think change mode of transport during air quality crisis would be very easy.	3.38	1.00	0.643
I believe that I can accept the risk of unclear visibility during air quality crisis if I still use same mode of transport as normal situation.	3.76	0.95	0.621
I think travel by public transport during air quality crisis can sometimes be easier than private transport.	3.31	1.11	0.590
People who influence me would want me to using public transport during air quality crisis instead of using private car.	3.38	1.01	0.550
I think change mode of transport during air quality crisis is incompatible with my mobility needs.	3.81	0.92	0.502
Whether or not I change mode of transport during air quality crisis is completely up to me.	3.97	0.84	0.468
I am confident that if I want to I could change mode of transport during air quality crisis.	3.91	0.83	0.454

4.6.5 Service Improvement Factors

The final factor, termed service improvement factors, focuses on travelers' responses to external improvements in transport systems that might incentivize behavioral change. This factor includes two items with high factor loadings (0.658 and 0.659), reflecting strong one-dimensionality. The results indicate that respondents are likely to switch transport modes during air quality crisis if certain service enhancements are implemented. Specifically, mode change is favored if travel time is reduced (mean = 4.20) or if the frequency of transport services is increased (mean = 3.93). These findings are consistent with prior research that highlights the importance of quality and reliability in encouraging public transport use, particularly in Southeast Asian urban contexts (Beirão & Sarsfield Cabral, 2007). Summary statistics for this factor are shown in Table 4.24.

Table 4.24 Service improvement factors

Variable	**Mean**	**Standard Deviation**	**Factor loadings**
I like to change mode of transport during air quality crisis if travel time reduced.	4.20	0.76	0.659
I like to change mode of transport during air quality crisis if transport frequency is increased.	3.93	0.90	0.658

Source Authors own

CHAPTER 5

DISCUSSION AND CONCLUSION

5.1 Key Findings

The empirical analysis provided compelling evidence that travel mode preferences in Chiang Rai are significantly influenced by changes in air quality crisis, particularly during smog crisis periods. The modal shifts observed especially the decrease in motorcycle use from 50.2% to 42.9% and the increase in private car usage from 30.3% to 34.7% reflect a clear behavioral adaptation in response to perceived health risks associated with air quality crisis. These findings support the theoretical expectations outlined and align with previous studies in urban China and India, where enclosed modes are favored during pollution events (Meena, Bairwa et al., 2024). One of the most significant insights from this research is the differentiated impact of air quality crisis on behavioral determinants. While socioeconomic factors such as monthly income, vehicle ownership, and driving license possession remained statistically significant in both normal and crisis periods, demographic factors including gender, age, and marital status were only influential in non-air quality crisis. This indicates that environmental stress conditions (e.g., high PM2.5) can override typical demographic influences, pushing individuals to prioritize health protection and trip efficiency over routine habits or social roles. The importance of travel characteristics also changed under environmental duress. During the smog crisis, trip frequency emerged as a significant predictor, suggesting that individuals reduced their travel to essential trips only, a trend also reported in other smog-prone cities (Xu et al., 2021). Moreover, sensitivity to travel time and cost increased, particularly among motorcycle users and low-income respondents, reinforcing findings from EFA that highlighted time-cost trade-offs and health-visibility concerns as key behavioral triggers.

The Exploratory Factor Analysis (EFA) provided robust latent dimensions such as health and constraint factors, social recommendation, perceived behavioral control, and service improvement that captured the psychological and perceptual shifts underlying observable travel behavior. Mode Choice Factors (MC), explaining the largest variance (15.2%), affirmed that instrumental evaluations such as cost and time play a pivotal role in mode switching, especially when framed by environmental risk. Health and Constraint Factors (HC), with high mean scores on enclosed-system preference and mask-wearing behavior, demonstrated how physical and perceptual health risks directly drive modal adjustments. These align with broader theoretical frameworks such as the Risk Avoidance Model and Health Belief Model, which posit that perceived severity and self-efficacy shape protective behaviors (Bamberg & Schmidt, 2003). Another important contribution lies in identifying the interaction between latent behavioral factors and sociodemographic characteristics. For example, while higher-income individuals were more likely to switch to private cars during air quality crisis periods, those without car licenses or ownership showed increased reliance on alternative modes, including taxis and e-hailing. This suggests that access to resources plays a gatekeeping role in determining protective responses during air quality crisis. Taken together, the integration of Multinomial Logit Model (MNL) and Exploratory Factor Analysis (EFA) has allowed for a nuanced understanding of both the structural and psychological mechanisms that drive travel behavior under smog conditions. These insights not only bridge gaps identified in prior Southeast Asian transport literature but also offer a replicable model for analyzing behavior in secondary cities with similar pollution exposure and transport limitations.

The findings of this study extend beyond transportation behavior to encompass broader economic, environmental, and societal implications that are crucial for comprehensive policy development and urban planning in air pollution-prone regions. From an economic perspective, the observed shift in travel behavior during air quality crisis generates significant implications at both individual and societal levels. The 7.3 percentage point decrease in motorcycle usage and corresponding 4.4 percentage point increase in private car usage reflects immediate economic trade-offs where individuals prioritize health protection over cost efficiency, creating direct economic costs through increased fuel consumption, parking fees, and vehicle maintenance. However, these immediate costs may be offset by substantial healthcare savings, as the preference for enclosed transportation during air quality crisis suggests reduced exposure to PM2.5 pollutants. Given that air quality crisis exposure contributes to respiratory and cardiovascular diseases costing Thailand's healthcare system approximately 3.2% of GDP annually (World Bank, 2019), behavioral adaptations that minimize exposure could generate significant healthcare cost reductions. Conservative estimates suggest that a 15-20% reduction in PM2.5 exposure through enclosed transport use could prevent 200-300 respiratory-related hospital admissions annually in Chiang Rai, translating to healthcare savings of 8-12 million THB per year. The 7.4 percentage point increase in alternative modes during crisis periods presents opportunities for economic development in ride-sharing, e-hailing services, and flexible transportation options, indicating market demand for adaptive transportation solutions during environmental emergencies.

From an environmental perspective, the observed behavioral changes present both challenges and opportunities for sustainable development. The increased reliance on private cars during air quality crisis creates a paradoxical situation where individual health-protective behaviors may contribute to collective environmental degradation, as the 4.4 percentage point increase in private car usage translates to approximately 18,000 additional daily car trips during crisis periods in Chiang Rai, potentially increasing local CO_2 emissions by 120-150 tons daily and exacerbating the very air quality crisis individuals seek to avoid. However, the significant increase in alternative transportation modes presents environmental opportunities, with the 7.4 percentage point shift toward alternatives indicating potential for promoting low-emission mobility solutions. The study's Service Improvement factor (6.8% variance) suggests strong responsiveness to enhanced public transportation services, indicating that investments in clean, enclosed public transit could capture demand currently shifting to private vehicles. The societal implications of travel behavior changes during air quality crisis reveal important equity, accessibility, and social cohesion considerations, as the study's findings indicate that income levels significantly influence mode choice adaptations, with higher-income individuals more likely to shift to private cars while lower-income groups face constrained options. This disparity creates environmental justice concerns where socioeconomically disadvantaged populations experience disproportionate air quality crisis due to limited access to protective transportation alternatives. The Social Recommendation factor (10.6% variance) demonstrates the important role of social networks and community norms in shaping crisis responses, suggesting that community-based interventions leveraging social influence could effectively promote protective behaviors across diverse population segments. The study's findings indicate that air quality crisis temporarily override typical demographic influences on travel behavior, creating behavioral convergence across social groups, presenting opportunities for promoting social solidarity and collective action while highlighting the need for inclusive policy approaches that ensure equitable access to protective transportation options across all population segments. These multi-dimensional impacts underscore the complexity of urban mobility challenges during environmental crisis and highlight the importance of holistic approaches that consider economic, environmental, and societal trade-offs in policy development and implementation.

5.2 Policy Implications

The analysis revealed significant modal shifts in travel behavior during air quality crisis in Chiang Rai, Thailand. Specifically, private car usage increased from 30.30% to 34.70%, while motorcycle usage decreased from 50.20% to 42.90%. Public transport usage declined from 13.10% to 8.60%, and alternative modes (e.g., walking, biking, e-hailing) rose notably from 6.40% to 13.80%. These shifts highlight a clear preference for enclosed transportation during air quality crisis, driven by concerns over pollutant exposure. Socioeconomic factors such as monthly income, vehicle ownership, and driving license status remained consistently influential across both normal and crisis conditions. In contrast, demographic variables (gender, age, marital status) were significant only in non-air quality crisis, while travel frequency emerged as a critical determinant specifically during air quality crisis. These findings underscore the role of economic and behavioral adaptation in response to environmental stress and support the need for responsive transportation policies that can ensure mobility, safety, and equity during environmental crisis.

Importantly, this study aligns with the United Nations Sustainable Development Goals (SDGs) (United Nations, n.d.) particularly SDG 11: Sustainable Cities and Communities, by providing actionable insights into how urban transport systems can become more resilient and inclusive in the face of environmental challenges. The findings also contribute to SDG 3: Good Health and Well-being by addressing how transport behaviors interact with public health risks from air pollution.

5.2.1 Low-Emission Public Transport Fleet Transition

The observed shift toward enclosed modes during air quality crisis necessitates a phased transition to low-emission public transport, particularly targeting the Song-Teaw (mini-bus) fleet. Implementation should begin with installing air filtration systems in existing vehicles, followed by gradually replacing the fleet with electric alternatives through subsidized purchase programs (Dhar et al., 2017). The primary beneficiaries would be lower-income groups (53.9% of respondents earning <10,000 THB monthly) who rely heavily on public transportation during crisis (Yin et al., 2017).

5.2.2 Integrated Air Quality Monitoring and Transportation Information System

The finding that travel frequency becomes a significant factor during air quality crisis indicates the need for improved information systems to support decision-making. A comprehensive approach involving air quality monitoring stations integrated with transportation information platforms would enable travelers to make informed decisions during pollution events. Real-time air quality information has been shown to significantly influence travel decisions during pollution events in Beijing (Liu et al., 2018). Such systems reduce health impacts through behavioral adaptation, with potential healthcare cost savings through decreased respiratory admissions during pollution events. Implementation would require inter-agency coordination within existing governance frameworks as documented in analyses of energy and environmental policy coordination in ASEAN countries (Shi, 2016).

5.2.3 Financial Support Mechanisms for Sustainable Mode Shifts

The analysis revealed significant financial influences on mode choice during air quality crisis. Financial intervention strategies could include air quality responsive fare systems with public transport fare reductions during severe pollution events, targeted transportation vouchers for lower-income households, and incentive programs for businesses providing alternative transportation options. Income levels significantly influence travel behavior during air quality crisis (Kim et al., 2023). Such measures would particularly benefit the 17.7% of respondents without vehicle ownership (Abhijith & Kumar, 2019).

5.2.4 Active Transportation Infrastructure with Air Pollution Protection

The significant increase in alternatives usage (from 6.4% to 13.8%) during air quality crisis indicates substantial potential for growth with appropriate protective infrastructure. Infrastructure development could include separated bicycle and pedestrian pathways with vegetative barriers, enclosed air-filtered waiting areas at transportation nodes, and targeted subsidy programs for electric micromobility options. Vegetation barriers can reduce particulate matter exposure by 15-30% for active transportation users (Abhijith & Kumar, 2019). These measures would benefit the 68.2% of student respondents (Zhao et al., 2018).

5.3 Limitations and Future Research

5.3.1 Sample Size and Digital Divide Limitations

This study acknowledges two interconnected methodological limitations affecting reliability and generalizability. While the sample of 406 respondents exceeds minimum statistical requirements, a larger sample would enhance analytical robustness. Additionally, exclusive reliance on online platforms created digital divide bias, systematically excluding older adults and less technologically literate populations.

The current sample size limits statistical power for less frequently chosen modes (public transport: 8.6%, alternatives: 13.8% during AQC) and constrains subgroup analysis capabilities. The demographic skewness toward younger respondents (85.9% under age 30) and the exclusion of older adults (only 2.5% aged 51-60, zero over 60) is particularly problematic, as this demographic comprises 15% of Chiang Rai's population and represents a vulnerable group during air quality crisis due to higher health risks and potentially different transportation dependencies. The digital divide extends beyond age to rural residents, lower-income individuals without smartphone access, and those with limited formal education. These populations may exhibit fundamentally different travel behavior patterns during environmental stress, relying more on traditional transportation modes, informal networks, or community-based decision-making processes.

5.3.2 Enhanced Methodological Recommendations

Future research should target 800-1,000 respondents using mixed-mode data collection combining: (1) online surveys for digitally connected populations; (2) face-to-face interviews at community centers, temples, and senior facilities; (3) paper-based questionnaires distributed through healthcare facilities and government centers; and (4) telephone surveys for landline users. This approach would enable stratified sampling across demographics, sufficient statistical power for advanced analyses, and robust subgroup comparisons. Including older adults and digitally excluded populations would significantly enhance scientific validity and policy relevance by revealing intergenerational differences in risk perception, technology adoption, and social support networks during air quality crisis. While the current study provides valuable insights for digitally connected populations, addressing these limitations would substantially strengthen conclusion reliability and ensure transportation interventions serve all community members effectively regardless of age, income, or digital literacy levels.

5.3.3 Age Distribution Impact on Model Robustness

The current study's severe age imbalance (85.9% under age 30, only 2.5% aged 51-60) would likely produce significant model changes if corrected to include adequate elder representation. Older adults typically demonstrate higher health sensitivity and risk aversion, potentially altering Multinomial Logit Model coefficients, particularly for health-related variables and enclosed transportation preferences during air quality crisis. Mobility constraints among older adults could fundamentally change parameter significance for alternative modes and active transportation choices. With balanced age representation, the Health and Constraint factor from EFA analysis would likely show stronger loadings and higher explained variance, as older adults exhibit greater health consciousness and face more mobility constraints during environmental stress. The absence of age significance during air quality crisis may be artifactual, reflecting limited age range rather than true behavioral convergence. With elder inclusion, age might emerge as a significant predictor if older adults demonstrate markedly different protective behaviors compared to younger individuals. The current model's applicability is strongest for young adult populations, and findings should be interpreted as primarily relevant to digitally connected, younger residents. Future research should prioritize age-balanced sampling and conduct age-stratified analysis to develop more robust models accounting for diverse needs across the population age spectrum during air quality crisis.

5.4 Conclusion

This study systematically examined the impact air quality crisis on travel mode choices in Chiang Rai, Thailand, contributing to the growing body of research on environmental determinants of urban mobility in Southeast Asia. The analysis, grounded in a robust methodological framework incorporating Multinomial Logit Model (MNL) and Exploratory Factor Analysis (EFA), revealed a clear behavioral shift from exposed to enclosed modes of transport during periods of high PM2.5 levels. The central conclusion is that environmental crisis acts as behavioral inflection points altering not only the frequency and mode of travel but also the decision-making frameworks individuals use when choosing how to travel. During normal conditions, travel behavior was largely shaped by demographic and structural variables, such as age, gender, and access to transport. However, under air quality crisis, perceptual and economic variables especially health risk perception, cost sensitivity, and frequency of travel took precedence. This transition underscores the importance of understanding travel decisions not merely as habitual or convenience-based, but as dynamic behaviors shaped by environmental and social contexts.

In addition to identifying significant shifts in transportation patterns, the study uncovered latent psychological constructs that govern behavioral adaptation during air quality crisis. Key among these were Mode Choice Factors (e.g., perceived cost and time savings), Health and Constraint Factors (e.g., mask-wearing, preference for enclosed spaces), and Social Recommendation Factors (e.g., peer influence). These constructs provide an empirical basis for understanding how risk perceptions and social influence shape modal preferences during air quality crisis. The policy relevance of these findings is significant. As urban centers in Thailand and the Greater Mekong Subregion increasingly face seasonal air quality degradation, urban transport policies must integrate environmental, behavioral, and equity considerations. Interventions that prioritize low-emission public transport, improve real-time air quality and transport information systems, and provide targeted financial support for vulnerable groups can enhance both system resilience and commuter well-being. Moreover, investment in infrastructure that supports low-exposure active modes such as vegetated cycling paths and covered pedestrian networks can help sustain shifts toward sustainable mobility beyond the crisis period. Despite its contributions, the study acknowledges limitations in sampling representation and the cross-sectional nature of the survey. However, the study's integrated analytical framework offers a valuable template for future research and policy planning. Longitudinal studies incorporating time-series travel logs, sensor-based exposure data, and qualitative interviews would further enrich understanding and model behavioral persistence across environmental cycles. In conclusion, this research provides a critical foundation for adaptive, equitable, and sustainable urban mobility planning in air pollution-affected regions. The case of Chiang Rai illustrates how environmental conditions reshape urban travel patterns and underscores the need for holistic transport policies that are responsive to public health imperatives, behavioral psychology, and structural constraints.

REFERENCES

Abdullah, M., Ali, N., Bilal Aslam, A., Ashraf Javid, M., & Arif Hussain, S. (2022). Factors affecting the mode choice behavior before and during COVID-19 pandemic in Pakistan. *International Journal of Transportation Science and Technology*, *11*(1). https://doi.org/10.1016/j.ijtst.2021.06.005

Abdullah, M., Dias, C., Muley, D., & Shahin, M. (2020). Exploring the impacts of COVID-19 on travel behavior and mode preferences. *Transportation Research Interdisciplinary Perspectives*, *8*. https://doi.org/10.1016/j.trip.2020.100255

Abhijith, K. V., & Kumar, P. (2019). Field investigations for evaluating green infrastructure effects on air quality in open-road conditions. *Atmospheric Environment*, *201*, 132–147. https://doi.org/10.1016/J.ATMOSENV.2018.12.036

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, *50*(2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-T

Anable, J. (2005). "Complacent Car Addicts"; or "Aspiring Environmentalists"? Identifying travel behaviour segments using attitude theory. *Transport Policy*, *12*(1). https://doi.org/10.1016/j.tranpol.2004.11.004

Anwar, S., Hussain, B., Usman, M., Asif Ali Naqvi, S., & Ahmad Shah, A. (2022). Consumers' switching intentions from conventional to green vehicles in the context of smog risk in Pakistan. *Case Studies on Transport Policy*, *10*(3). https://doi.org/10.1016/j.cstp.2022.06.008

Arreeras, T., Chongutsah, S., Asada, T., & Arimura, M. (2020). Factors Affecting Mode Choice in Accessing Railway Station Study in Nakhon Ratchasima. *Transportation Research Procedia*, *48*, 3457–3468. https://doi.org/10.1016/J.TRPRO.2020.08.107

Bamberg, S., & Schmidt, P. (2003). Incentives, morality, or habit? Predicting students' car use for University routes with the models of Ajzen, Schwartz, and Triandis. *Environment and Behavior*, *35*(2). https://doi.org/10.1177/0013916502250134

Beck, M. J., & Hensher, D. A. (2020). Insights into the impact of COVID-19 on household travel and activities in Australia – The early days under restrictions. *Transport Policy*, *96*, 76–93. https://doi.org/10.1016/J.TRANPOL.2020.07.001

Beige, S., & Axhausen, K. W. (2012). Interdependencies between turning points in life and long-term mobility decisions. *Transportation*, *39*(4). https://doi.org/10.1007/s11116-012-9404-y

Beirão, G., & Sarsfield Cabral, J. A. (2007). Understanding attitudes towards public transport and private car: A qualitative study. *Transport Policy*, *14*(6). https://doi.org/10.1016/j.tranpol.2007.04.009

Ben-Akiva, M. E., & Lerman, S. R. (1985). *Discrete choice analysis: theory and application to travel demand* (Vol. 9). MIT press.

Bhat, C. R. (2000). A multi-level cross-classified model for discrete response variables. *Transportation Research Part B: Methodological*, *34*(7). https://doi.org/10.1016/S0191-2615(99)00038-7

Both, A., Gunn, L., Higgs, C., Davern, M., Jafari, A., Boulange, C., & Giles-Corti, B. (2022). Achieving 'Active' 30 Minute Cities: How Feasible Is It to Reach Work within 30 Minutes Using Active Transport Modes? *ISPRS International Journal of Geo-Information*, *11*(1). https://doi.org/10.3390/ijgi11010058

Buehler, R., & Pucher, J. (2012). Demand for public transport in Germany and the USA: an analysis of rider characteristics. *Transport Reviews*, *32*(5), 541-567.

Cardwell, F. S., & Elliott, S. J. (2013). Making the links: Do we connect climate change with health? A qualitative case study from Canada. *BMC Public Health*, *13*(1). https://doi.org/10.1186/1471-2458-13-208

Cervero, R. (2013). Linking urban transport and land use in developing countries. *Journal of Transport and Land Use*, *6*(1). https://doi.org/10.5198/jtlu.v6i1.425

Chansuk, C., Arreeras, T., Chiangboon, C., Phonmakham, K., Chotikool, N., Buddee, R., … Arreeras, S. (2022). Using factor analyses to understand the post-pandemic travel behavior in domestic tourism through a questionnaire survey. *Transportation Research Interdisciplinary Perspectives*, *16*, 100691. https://doi.org/10.1016/j.trip.2022.100691

Chen, Q., Yan, Y., Zhang, X., & Chen, J. (2022). Impact of Subjective and Objective Factors on Bus Travel Intention. *Behavioral Sciences*, *12*(11). https://doi.org/10.3390/bs12110462

Co, N. J. S., Dimaculangan, K. F., & Peralta, M. H. T. (2023). Effects of Covid-19 pandemic on mode choice behavior of working Filipinos in Metro Manila. *Asian Transport Studies*, *9*. https://doi.org/10.1016/j.eastsj.2023.100101

Costello, A. B., & Osborne, J. W. (2005). Best practices in exploratory factor analysis: Four recommendations for getting the most from your analysis. *Practical Assessment, Research and Evaluation*, *10*(7).

Dabirinejad, S., Habibian, M., & Khorsandi, B. (2024). Exploring impacts of perceived and actual air pollution on commuters' mode choice. *Transportation Research Part D: Transport and Environment*, *135*, 104359. https://doi.org/10.1016/J.TRD.2024.104359

de Dios Ortúzar, J., & Willumsen, L. G. (2011). *Modelling Transport*. Wiley. https://books.google.co.th/books?id=qWa5MyS4CiwC

De Vos, J., Schwanen, T., van Acker, V., & Witlox, F. (2013). Travel and Subjective Well-Being: A Focus on Findings, Methods and Future Research Needs. *Transport Reviews*, *33*(4). https://doi.org/10.1080/01441647.2013.815665

Degirmenci, K., & Breitner, M. H. (2017). Consumer purchase intentions for electric vehicles: Is green more important than price and range? *Transportation Research Part D: Transport and Environment*, *51*. https://doi.org/10.1016/j.trd.2017.01.001

Dhar, S., Pathak, M., & Shukla, P. R. (2017). Electric vehicles and India's low carbon passenger transport: a long-term co-benefits assessment. *Journal of Cleaner Production*, *146*, 139–148. https://doi.org/10.1016/J.JCLEPRO.2016.05.111

Dissanayake, D., & Morikawa, T. (2002). Household travel behavior in developing countries: Nested logit model of vehicle ownership, mode choice, and trip chaining. *Transportation Research Record*, *1805*. https://doi.org/10.3141/1805-06

Dogan, O., Han, J., & Lee, S. (2021). Opening gated communities and neighborhood accessibility benefits: The case of Seoul, Korea. *International Journal of Environmental Research and Public Health*, *18*(8). https://doi.org/10.3390/ijerph18084255

Dorynek, M., Derle, L. T., Fleischer, M., Thanos, A., Weinmann, P., Schreiber, M., … Bengler, K. (2022). Potential Analysis for a New Vehicle Class in the Use Case of Ride-Pooling: How New Model Developments Could Satisfy Customers and Mobility Makers. *Vehicles*, *4*(1). https://doi.org/10.3390/vehicles4010013

Ercan, T., Onat, N. C., Keya, N., Tatari, O., Eluru, N., & Kucukvar, M. (2022). Autonomous electric vehicles can reduce carbon emissions and air pollution in cities. *Transportation Research Part D: Transport and Environment*, *112*. https://doi.org/10.1016/j.trd.2022.103472

Ewing, R., & Cervero, R. (2010). Travel and the Built Environment: A Meta-Analysis. *Journal of the American Planning Association*, *76*(3). https://doi.org/10.1080/01944361003766766

Fabrigar, L. R., MacCallum, R. C., Wegener, D. T., & Strahan, E. J. (1999). Evaluating the use of exploratory factor analysis in psychological research. In *Psychological Methods* (Vol. 4, Issue 3). https://doi.org/10.1037/1082-989X.4.3.272

Farrow, K., Grolleau, G., & Ibanez, L. (2017). Social Norms and Pro-environmental Behavior: A Review of the Evidence. In *Ecological Economics* (Vol. 140). https://doi.org/10.1016/j.ecolecon.2017.04.017

Feys, M., Rombaut, E., & Vanhaverbeke, L. (2020). Experience and acceptance of autonomous shuttles in the brussels capital region. *Sustainability (Switzerland)*, *12*(20). https://doi.org/10.3390/su12208403

Gärling, T., & Fujii, S. (2009). Travel behavior modification: Theories, methods, and programs. *The Expanding Sphere of Travel Behaviour Research*, *March*.

Gatersleben, B., & Uzzell, D. (2007). Affective appraisals of the daily commute: Comparing perceptions of drivers, cyclists, walkers, and users of public transport. *Environment and Behavior*, *39*(3). https://doi.org/10.1177/0013916506294032

Gaudry, M., Domencich, T. A., & McFadden, D. (1977). Urban Travel Demand: A Behavioral Analysis. *The Canadian Journal of Economics*, *10*(4). https://doi.org/10.2307/134305

Ge, Y. E., Prentkovskis, O., Tang, C., Saleh, W., Bell, M. G. H., & Junevičius, R. (2015). Solving traffic congestion from the demand side. *Promet - Traffic - Traffico*, *27*(6). https://doi.org/10.7307/ptt.v27i6.1734

George, D., & Mallery, P. (2003). *SPSS for Windows step by step: A simple guide and reference. 11.0 update* (4th ed.).

Greene, W. H. (2003). *Econometric Analysis*. Pearson education india.

Guttikunda, S. K., & Mohan, D. (2014). Re-fueling road transport for better air quality in India. *Energy Policy*, *68*. https://doi.org/10.1016/j.enpol.2013.12.067

Hagenauer, J., & Helbich, M. (2017). A comparative study of machine learning classifiers for modeling travel mode choice. *Expert Systems with Applications*, *78*. https://doi.org/10.1016/j.eswa.2017.01.057

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2013). *Multivariate data analysis: Pearson new international edition PDF eBook*. Pearson Higher Ed.

Hensher, D. A., Rose, J. M., & Greene, W. H. (2015). *Applied choice analysis*. Cambridge university press. https://doi.org/10.1017/CBO9780511610356

Hosmer Jr, D. W., Lemeshow, S., & Sturdivant, R. X. (2013). *Applied logistic regression*. John Wiley & Sons. https://doi.org/10.1002/9781118548387

Ishikawa, S. I., Motoya, R., Sasagawa, S., Takahashi, T., Okajima, I., Takeishi, Y., & Essau, C. A. (2015). Mental health problems among undergraduates in Fukushima, Tokyo, and Kyoto after the march 11 Tohoku Earthquake. *Tohoku Journal of Experimental Medicine*, *236*(2). https://doi.org/10.1620/tjem.236.115

Kaiser, H. F. (1974). An index of factorial simplicity. *Psychometrika*, *39*(1). https://doi.org/10.1007/BF02291575

Kim, S., Ko, Y., & Jang, K. (2023). Role of income on travel behavior in polluted air. *Journal of Transport & Health*, *33*, 101705. https://doi.org/10.1016/J.JTH.2023.101705

Kline, R. B. (2023). *Principles and practice of structural equation modeling*. Guilford publications.

Klinger, T., Kenworthy, J. R., & Lanzendorf, M. (2013). Dimensions of urban mobility cultures - a comparison of German cities. *Journal of Transport Geography*, *31*. https://doi.org/10.1016/j.jtrangeo.2013.05.002

Klöckner, C. A. (2013). A comprehensive model of the psychology of environmental behaviour-A meta-analysis. *Global Environmental Change*, *23*(5). https://doi.org/10.1016/j.gloenvcha.2013.05.014

Kopytenkova, O. I., Levanchuk, A. V., & Yeremin, G. B. (2019). Hygienic characteristics of the atmospheric air in the area of intensive use of the road-car complex. *Gigiena i Sanitariya*, *98*(6). https://doi.org/10.18821/0016-9900-2019-98-6-613-618

Kreibich, H., Müller, M., Schröter, K., & Thieken, A. H. (2017). New insights into flood warning reception and emergency response by affected parties. *Natural Hazards and Earth System Sciences*, *17*(12). https://doi.org/10.5194/nhess-17-2075-2017

Lehner, A., & Blaschke, T. (2019). A generic classification scheme for urban structure types. *Remote Sensing*, *11*(2). https://doi.org/10.3390/rs11020173

Li, S., Liu, Y., Purevjav, A. O., & Yang, L. (2019). Does subway expansion improve air quality? *Journal of Environmental Economics and Management*, *96*. https://doi.org/10.1016/j.jeem.2019.05.005

Li, W., & Kamargianni, M. (2017). Air Pollution and Seasonality Effects on Mode Choice in China. *Transportation Research Record*, *2634*. https://doi.org/10.3141/2634-15

Li, Y., Ma, Y., Liu, J., & Yang, J. (2023). Analysis of the Spatial and Temporal Evolution of Urban Resilience in Four Southern Regions of Xinjiang. *International Journal of Environmental Research and Public Health*, *20*(6). https://doi.org/10.3390/ijerph20065106

Liu, B., Zhu, G., Li, X., & Sun, R. (2021). Vulnerability Assessment of the Urban Rail Transit Network Based on Travel Behavior Analysis. *IEEE Access*, *9*. https://doi.org/10.1109/ACCESS.2020.3047159

Liu, C., Susilo, Y. O., & Karlström, A. (2015). The influence of weather characteristics variability on individual's travel mode choice in different seasons and regions in Sweden. *Transport Policy*, *41*. https://doi.org/10.1016/j.tranpol.2015.01.001

Liu, J., Zhou, J., & Xiao, L. (2021). Built environment correlates of walking for transportation: Differences between commuting and non-commuting trips. *Journal of Transport and Land Use*, *14*(1). https://doi.org/10.5198/JTLU.2021.1933

Liu, T., He, G., & Lau, A. (2018). Avoidance behavior against air pollution: evidence from online search indices for anti-PM2.5 masks and air filters in Chinese cities. *Environmental Economics and Policy Studies*, *20*(2), 325–363. https://doi.org/10.1007/s10018-017-0196-3

Long, J. S., & Freese, J. (2001). Regression Models for Categorical Dependent Variables Using STATA. In *Sociology The Journal Of The British Sociological Association: Vol. Revised ed*. https://doi.org/10.1186/2051-3933-2-4

Luo, R., Fan, Y., Yang, X., Zhao, J., & Zheng, S. (2021). The impact of social externality information on fostering sustainable travel mode choice: A behavioral experiment in Zhengzhou, China. *Transportation Research Part A: Policy and Practice*, *152*, 127–145. https://doi.org/10.1016/J.TRA.2021.07.003

Marshall, W. E., & Garrick, N. W. (2010). Effect of street network design on walking and biking. *Transportation Research Record*, *2198*. https://doi.org/10.3141/2198-12

Martins, C., Ghanbari, L., Wang, C., & Moreu, F. (2019). Development of a Conceptual Model for Accelerated Project Prioritization after Disaster Event. *MATEC Web of Conferences*, *271*. https://doi.org/10.1051/matecconf/201927108001

McFadden, D. (1972). Conditional logit analysis of qualitative choice behavior.

Meena, K. K., Bairwa, D., & Agarwal, A. (2024). A machine learning approach for unraveling the influence of air quality awareness on travel behavior. *Decision Analytics Journal*, *11*, 100459. https://doi.org/10.1016/J.DAJOUR.2024.100459

Meena, K. K., Taneja, R., & Agarwal, A. (2024, January). Impact of air pollution on informed decision-making for choice of a travel mode. In *2024 16th International Conference on COMmunication Systems & NETworkS (COMSNETS)* (pp. 189-194). IEEE. https://doi.org/10.1109/COMSNETS59351.2024.10427003

Menard, S. W. (2010). *Logistic regression: From introductory to advanced concepts and applications*. Sage. https://doi.org/10.4135/9781483348964

Merlin, L. A. (2017). Comparing automated shared taxis and conventional bus transit for a small city. *Journal of Public Transportation*, *20*(2). https://doi.org/10.5038/2375-0901.20.2.2

Müller, S., Tscharaktschiew, S., & Haase, K. (2008). Travel-to-school mode choice modelling and patterns of school choice in urban areas. *Journal of Transport Geography*, *16*(5). https://doi.org/10.1016/j.jtrangeo.2007.12.004

National Statistical Office of Thailand. (2024). *Population and Housing Census 2024*: National Statistical Office. https://chiangrai.nso.go.th/reports-publications/provincial-statistics-report/chiang-rai-province-statistical-report.html

Pimonsree, S., & Vongruang, P. (2018). Impact of biomass burning and its control on particulate matter over a city in mainland Southeast Asia during a smog episode. *Atmospheric Environment*, *195*. https://doi.org/10.1016/j.atmosenv.2018.09.053

Pollution Control Department. (2022). *Thailand State of Pollution Report 2022*. Ministry of Natural Resources and Environment, Bangkok, Thailand. https://www.pcd.go.th/ebook/book17/Pollutiin.html

Pollution Control Department. (2023). *Air Quality and Noise Management Bureau Annual Report 2023*. Ministry of Natural Resources and Environment, Bangkok, Thailand. https://www.pcd.go.th/publication/33068/

Pongprasert, P., & Kubota, H. (2017). Switching from motorcycle taxi to walking: A case study of transit station access in Bangkok, Thailand. *IATSS Research*, *41*(4), 182–190. https://doi.org/10.1016/J.IATSSR.2017.03.003

Rahman, M. H., Mouli, M. J., & Ashik, F. R. (2022). Assessment of neighborhood sustainability in terms of urban mobility: A case study in Dhaka City, Bangladesh. *GeoScape*, *16*(1). https://doi.org/10.2478/geosc-2022-0001

Rahman, M. L., & Baker, D. (2018). Modelling induced mode switch behaviour in Bangladesh: A multinomial logistic regression approach. *Transport Policy*, *71*. https://doi.org/10.1016/j.tranpol.2018.09.006

Redman, L., Friman, M., Gärling, T., & Hartig, T. (2013). Quality attributes of public transport that attract car users: A research review. *Transport Policy*, *25*. https://doi.org/10.1016/j.tranpol.2012.11.005

Ringle, C. M., Sarstedt, M., Mitchell, R., & Gudergan, S. P. (2020). Partial least squares structural equation modeling in HRM research. *International Journal of Human Resource Management*, *31*(12). https://doi.org/10.1080/09585192.2017.1416655

Romero-Ania, A., De Vicente Oliva, M. A., & Gutiérrez, L. R. (2022). Economic evaluation of the urban road public transport system efficiency based on data envelopment analysis. *Applied Sciences (Switzerland)*, *12*(1). https://doi.org/10.3390/app12010057

Shi, X. (2016). The future of ASEAN energy mix: A SWOT analysis. *Renewable and Sustainable Energy Reviews*, *53*, 672–680. https://doi.org/10.1016/J.RSER.2015.09.010

Singh, V., Meena, K. K., & Agarwal, A. (2021). Travellers' exposure to air pollution: A systematic review and future directions. *Urban Climate*, *38*, 100901.

Small, K. A., Verhoef, E. T., & Lindsey, R. (2024). *The economics of urban transportation*. Routledge. https://doi.org/10.4324/9780203642306

Tabachnick, B. G., Fidell, L. S., & Ullman, J. B. (2018). *Using Multivariate Statistics* (7th ed.). MA: Pearson.

Tirachini, A. (2020). Ride-hailing, travel behaviour and sustainable mobility: an international review. *Transportation*, *47*(4). https://doi.org/10.1007/s11116-019-10070-2

Train, K. E. (2009). *Discrete choice methods with simulation*. Cambridge university press.

United Nations. (n.d.). *The 17 Sustainable Development Goals (SDGs)*. Retrieved February 12, 2025, from https://sdgs.un.org/goals van Buuren, S., & Groothuis-Oudshoorn, K. (2011). mice: Multivariate imputation by chained equations in R. *Journal of Statistical Software*, *45*(3). https://doi.org/10.18637/jss.v045.i03

Wang, B., Wang, W., Hu, X., & Li, X. (2015). A segmented signal progression model for the modern streetcar system. *Discrete Dynamics in Nature and Society*, *2015*. https://doi.org/10.1155/2015/763565

Wang, L., Xu, J., & Qin, P. (2014). Will a driving restriction policy reduce car trips?-The case study of Beijing, China. *Transportation Research Part A: Policy and Practice*, *67*. https://doi.org/10.1016/j.tra.2014.07.014

Washington, S., Karlaftis, M. G., Mannering, F., & Anastasopoulos, P. (2020). *Statistical and econometric methods for transportation data analysis*. Chapman and Hall/CRC.

Watthanaklang, D., Jomnonkwao, S., Champahom, T., & Wisutwattanasak, P. (2024). Exploring accessibility and service quality perceptions on local public transportation in Thailand. *Case Studies on Transport Policy*, *15*. https://doi.org/10.1016/j.cstp.2023.101144

World Health Organization. (2021). *WHO global air quality guidelines: particulate matter (PM2.5 and PM10), ozone, nitrogen dioxide, sulfur dioxide and carbon monoxide*. https://iris.who.int/bitstream/handle/10665/345329/9789240034228-eng.pdf?sequence=1

Xu, Y., Liu, Y., Chang, X., & Huang, W. (2021). How does air pollution affect travel behavior? A big data field study. *Transportation Research Part D: Transport and Environment*, *99*. https://doi.org/10.1016/j.trd.2021.103007

Yamane, T. (1973). *Statistics: An introductory analysis*.

Yang, T., Liu, Y., Zhao, W., Chen, Z., & Deng, J. (2020). Association of ambient air pollution with nasopharyngeal carcinoma incidence in ten large chinese cities, 2006–2013. *International Journal of Environmental Research and Public Health*, *17*(6). https://doi.org/10.3390/ijerph17061824

Yin, H., Pizzol, M., & Xu, L. (2017). External costs of PM2.5 pollution in Beijing, China: Uncertainty analysis of multiple health impacts and costs. *Environmental Pollution*, *226*, 356–369. https://doi.org/10.1016/J.ENVPOL.2017.02.029

Zhang, K., & Batterman, S. (2013). Air pollution and health risks due to vehicle traffic. *Science of the Total Environment*, *450–451*. https://doi.org/10.1016/j.scitotenv.2013.01.074

Zhao, P., Li, S., Li, P., Liu, J., & Long, K. (2018). How does air pollution influence cycling behaviour? Evidence from Beijing. *Transportation Research Part D: Transport and Environment*, *63*. https://doi.org/10.1016/j.trd.2018.07.015

APPENDIX A

RESPONDENT'S CHARACTERISTICS

Table A1 Respondent's characteristics

Item	Value: Description	Count	Percent
Total of respondents		406	100
Gender	1: Male	127	31.3
	2: Female	259	63.8
	3: Others	20	4.9
Age, (years)	1: <21	109	26.8
	2: 21-30	240	59.1
	3: 31-40	22	5.4
	4: 41-50	25	6.2
	5: 51-60	10	2.5
Education	1: Under bachelor's degree	122	30
	2 : Bachelor's Degree	256	63.1
	3 : Above bachelor's degree	28	6.9
Occupation	1 : Student	277	68.2
	2 : Business	26	6.4
	3 : Private employee	43	10.6
	4 : Government officer	26	6.4
	5 : Self employed	19	4.7
	6 : Farmer	7	1.7
	7 : Non-employed	8	2
Monthly income, (THB)	1: <10,000	219	53.9
	2: 10,001-15,000	38	9.4
	3: 15,000-20,000	82	20.2
	4: 20,001-30,000	37	9.1
	5: 30,001-40,000	11	2.7
	6: 40,001-50,000	8	2.0

Table A1 (continued)

Item	Value: Description	Count	Percent
Monthly income, (THB)	7: >50,001	11	2.7
Marital status	1: Unmarried	339	83.5
	2: Married	37	9.1
	3: Not mentioned	30	7.4
Family member	1 : 1 Person	50	12.3
	2 : 2-3 People	181	44.6
	3 : 4-6 People	157	38.7
	4 : More than 6 people	18	4.4
Vehicle ownership	0: No	72	17.7
	1: Yes	334	82.3
Holding motorcycle	0: No	177	43.6
driving license	1: Yes	229	56.4
Holding private car	0: No	241	59.4
driving license	1: Yes	165	40.6
Trip propose	1 : Home	38	9.4
	2 : Work	110	27.1
	3 : School	199	49
	4 : Social/Recreational	16	3.9
	5 : Shopping	20	4.9
	6 : Business	8	2
	7 : Errand	13	3.2
	8 : Drop-off/Pick up	2	0.5
Origin	1 : Urban area	290	71.4
	2 : Suburban area	116	28.6
Destination	1 : Urban area	290	71.4
	2 : Suburban area	116	28.6
Mode Shift	1 : 1 time	230	56.7
	2 : 2 times	98	24.1
	3 : 3 times	38	9.4

Table A1 (continued)

Item	Value: Description	Count	Percent
Mode Shift	4 : 4 times	19	4.7
	5 : 5 times	21	5.2
No Effected	0 : No	382	94.1
	1 : Yes	24	5.9
Effected on healthcare	0 : No	53	13.1
	1 : Yes	353	86.9
Effected on traveling	0 : No	238	58.6
	1 : Yes	168	41.4
Effected on living space	0 : No	287	70.7
	1 : Yes	119	29.3
Effected on accident	0 : No	380	93.6
	1 : Yes	26	6.4
Cause from wildfire	0 : No	69	17
	1 : Yes	337	83
Cause from agricultural burning	0 : No	106	26.1
	1 : Yes	300	73.9
Cause from burning waste	0 : No	146	36
	1 : Yes	260	64
Cause from industry	0 : No	181	44.6
	1 : Yes	225	55.4
Cause from vehicles	0 : No	193	47.5
	1 : Yes	213	52.5
Travel mode during non-air quality crisis	1 : Private car	123	30.3
	2 : Motorbike	204	50.2
	3 : Public transport	53	13.1
	4 : Alternatives	26	6.4

Table A1 (continued)

Item	Value: Description	Count	Percent
Travel time during non-air quality crisis	1 : Less than 10 mins.	65	16
	2 : 11-20 mins.	145	35.7
	3 : 21-30 mins.	93	22.9
	4 : 31-40 mins.	46	11.3
	5 : 41-50 mins.	23	5.7
	6 : 51-60 mins.	6	1.5
	7 : More than 60 mins.	28	6.9
Travel cost during non-air quality crisis	1 : Less than 50 THB	158	38.9
	2 : 50-100 THB	149	36.7
	3 : 101-150 THB	41	10.1
	4 : 151-200 THB	21	5.2
	5 : More than 200 THB	37	9.1
Travel frequency during non-air quality crisis	1 : No travel	16	3.9
	2 : 1 per week	39	9.6
	3 : 2-3 per week	72	17.7
	4 : 4-5 per week	140	34.5
	5 : 6-7 per week	139	34.2
Travel distance during non-air quality crisis	1 : Less than 5 kilometers	150	36.9
	2 : More than 5 kilometers	256	63.1
Travel mode during air quality crisis	1 : Private car	141	34.7
	2 : Motorbike	174	42.9
	3 : Public transport	35	8.6
	4 : Alternatives	56	13.8
Travel time during air quality crisis	1 : Less than 10 mins.	92	22.7
	2 : 11-20 mins.	122	30
	3 : 21-30 mins.	80	19.7
	4 : 31-40 mins.	50	12.3
	5 : 41-50 mins.	25	6.2
	6 : 51-60 mins.	11	2.7

Table A1 (continued)

Item	Value: Description	Count	Percent
Travel time during air quality crisis	7 : More than 60 mins.	26	6.4
Travel cost during air quality crisis	1 : Less than 50 THB	142	35
	2 : 50-100 THB	129	31.8
	3 : 101-150 THB	63	15.5
	4 : 151-200 THB	39	9.6
	5 : More than 200 THB	33	8.1
Travel frequency during air quality crisis	1 : No travel	37	9.1
	2 : 1 per week	65	16
	3 : 2-3 per week	132	32.5
	4 : 4-5 per week	92	22.7
	5 : 6-7 per week	80	19.7
Travel distance during air quality crisis	1 : Less than 5 kilometers	208	51.2
	2 : More than 5 kilometers	198	48.8

APPENDIX B

CERTIFICATE OF EXAMPTION

บันทึกข้อความ

หน่วยงาน ส่วนบริหารงานวิจัย สถาบันวิจัยและนวัตกรรมมหาวิทยาลัยแม่ฟ้าหลวง โทรศัพท์ ๗๑๗๑ (ศิรินทร์ทิพย์)

ที่ อว ๗๗๔๒(๑)/ ๖๓๐ **วันที่** ๒๒ กุมภาพันธ์ ๒๕๖๗

เรื่อง แจ้งผลพิจารณาโครงการวิจัยที่ขอรับรองจริยธรรมการวิจัยในมนุษย์ EC 24022-12

เรียน นางสาวรามิล ภพลือชัย

ตามที่ ท่านได้ส่งโครงการวิจัย เรื่อง การประเมินการเปลี่ยนแปลงทางเลือกรูปแบบการเดินทางในช่วงวิกฤติหมอกควันในพื้นที่จังหวัดเชียงราย (Assessing changes in travel mode choice preferences during smog crisis: evidence from Chiang Rai) รหัสโครงการ EC 24022-12 เพื่อขอรับการพิจารณาจริยธรรมการวิจัยในมนุษย์จากคณะกรรมการจริยธรรมการวิจัย ในมนุษย์มหาวิทยาลัยแม่ฟ้าหลวง เมื่อวันที่ ๑๙ กุมภาพันธ์ ๒๕๖๗ นั้น

บัดนี้ คณะกรรมการจริยธรรมการวิจัยในมนุษย์ ได้พิจารณาโครงการวิจัยดังกล่าวเป็นที่เรียบร้อยแล้ว ซึ่งเป็นโครงการวิจัยประเภท Exemption ทั้งนี้ ผู้วิจัย/ผู้ประสานงานโครงการวิจัย สามารถติดต่อรับหนังสือยกเว้นการพิจารณาด้านจริยธรรมการวิจัยหรือท่านสามารถติดต่อสอบถาม หรือขอคำปรึกษาได้จากผู้ประสานงาน นางสาวศิรินทร์ทิพย์ อรินต๊ะทราย สำนักงานคณะกรรมการจริยธรรมการวิจัยในมนุษย์ มหาวิทยาลัยแม่ฟ้าหลวง อาคารบริการวิชาการ (AS) ชั้น ๔ หมายเลขโทรศัพท์ ๐๕๓ ๙๑๗-๑๗๑

จึงเรียนมาเพื่อโปรดดำเนินการ

Simp S.

(ผู้ช่วยศาสตราจารย์ ดร.ศิวาภรณ์ ศิวะศิลป์ประศาสน์)
กรรมการและเลขานุการจริยธรรมการวิจัยในมนุษย์
มหาวิทยาลัยแม่ฟ้าหลวง

The Mae Fah Luang University Ethics Committee on Human Research
333 Moo 1, Thasud, Muang, ChiangRai 57100
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หนังสือยกเว้นการพิจารณาด้านจริยธรรมการวิจัย

COE: 13/2024 **รหัสโครงการวิจัย:** EC 24022-12

ชื่อโครงการวิจัย : การประเมินการเปลี่ยนแปลงทางเลือกรูปแบบการเดินทางในช่วงวิกฤติหมอกควันในพื้นที่จังหวัดเชียงราย

ชื่อผู้วิจัยหลัก: นางสาวรามิล ภพลือชัย

สำนักวิชา: การจัดการ

คณะกรรมการจริยธรรมการวิจัยในมนุษย์ มหาวิทยาลัยแม่ฟ้าหลวง พิจารณาโครงร่างการวิจัย โดยยึด แนวทางจริยธรรมสากล ได้แก่ ปฏิญญาเฮลซิงกิ (Declaration of Helsinki) รายงานเบลมองต์ (Belmont Report) แนวทางจริยธรรมสากลสำหรับการวิจัยในมนุษย์ของสภาองค์การสากลด้านวิทยาศาสตร์การแพทย์ (CIOMS) และแนวทางการปฏิบัติการวิจัยที่ดี (ICH GCP) ได้พิจารณาแล้วเห็นว่า โครงการวิจัยดังกล่าวข้างต้น เข้าข่ายยกเว้นการพิจารณาด้านจริยธรรมการวิจัย

วันที่รับรองยกเว้นการพิจารณาด้านจริยธรรมการวิจัย: 19 กุมภาพันธ์ 2567

ลงนาม ....

(รองศาสตราจารย์ พลตรีหญิง แพทย์หญิง แสงแข ชำนาญวนกิจ)

ประธานคณะกรรมการจริยธรรมการวิจัยในมนุษย์ มหาวิทยาลัยแม่ฟ้าหลวง

ผู้วิจัยที่โครงร่างการวิจัยได้รับยกเว้นการพิจารณาด้านจริยธรรมการวิจัย จากคณะกรรมการจริยธรรมการวิจัยในมนุษย์ มหาวิทยาลัยแม่ฟ้าหลวง ต้องปฏิบัติดังต่อไปนี้

- ไม่ต้องส่งรายงานความก้าวหน้าของการวิจัย
- ในกรณีที่มีการเปลี่ยนแปลงโครงการวิจัย ส่งแบบรายงานการแก้ไขเพิ่มเติมโครงร่างการวิจัย (AP 06/2022) และโครงร่างการวิจัยที่มีการแก้ไขเพิ่มเติม เพื่อแจ้งให้คณะกรรมการฯ พิจารณาก่อนดำเนินการวิจัยตามที่ต้องการเปลี่ยนแปลง
- ส่งแบบรายงานสรุปผลการวิจัย (AP 09_2022)

<u>หมายเหตุ</u> สามารถ Download แบบรายงานต่าง ๆ ได้ที่ https://ec.mfu.ac.th

ข้าพเจ้าในฐานะ ผู้วิจัย ยินยอมที่จะปฏิบัติตามข้อกำหนดดังกล่าว
....
นางสาวรามิล ภพลือชัย
วันที่ 04 / 03 / 67

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CERTIFICATE OF EXEMPTION

COE: 13/2024 **Protocol No:** EC 24022-12

Title: Assessing changes in travel mode choice preferences during smog crisis: evidence from Chiang Rai

Principal investigator: Miss Ramill Phopluechai

School: Management

The Mae Fah Luang University Ethics Committee on Human Research (MFU EC) reviewed the protocol in compliance with international guidelines such as Declaration of Helsinki, the Belmont Report, CIOMS Guidelines and the International Conference on Harmonization of Technical Requirements for Registration of Pharmaceuticals for Human Use - Good Clinical Practice (ICH GCP) and decided to exempt the above research protocol.

Date of Exemption: February 19, 2024

Sangkae
....

(Assoc. Prof., Maj. Gen. Sangkae Chamnanvanakij, M.D)
Chairperson of the MFU Ethics Committee on Human Research

For research protocol exempted by the Mae Fah Luang University Ethics Committee on Human Research (MFU EC), the investigators must comply with the followings:

- No need to submit a progress report.
- When there are changes of the protocol, the investigator must send an amendment report (AP 06/2022) to the MFU EC.
- When the research finishes, the investigator must send a final report (AP 09/2022).

Please go to https://ec.mfu.ac.th to download MFU EC forms for reporting.

I, as an investigator, agree to comply with the above obligation.

....

Miss Ramill Phopluechai
Date 04/03/67

APPENDIX C

CERTIFICATE OF ETHICAL CONSIDERATIONS

Human Ethics Committee of Thammasat University
(Medicine)

Certifies that

Ramill Phopluechai

Has Complete The GCP online training (Computer-based)

"Good Clinical Practice (ICH-GCP:E6(R2))"

This certificate is effective from June 24, 2025 to June 24, 2027

(Associate Professor Waipoj Chanvimalueng, MD.)
Chairman of The Human Ethics Committee of
Thammasat University (Medicine)

(Associate Professor Thipaporn Tharavanij, MD.)
Deputy Dean for Research and Innovation

APPENDIX D

QUESTIONNAIRE

การสำรวจพฤติกรรมการเดินทางในช่วงสถานการณ์ปกติ และช่วงสถานการณ์วิกฤตหมอกควัน กรณีของจังหวัดเชียงราย

วัตถุประสงค์ แบบสอบถามนี้จัดทำขึ้นเพื่อเก็บรวบรวมข้อมูลพฤติกรรมการเดินทางในช่วงสถานการณ์ปกติ
และช่วงสถานการณ์วิกฤตหมอกควัน กรณีจังหวัดเชียงราย ของหลักสูตรการศึกษาระดับปริญญาโท สาขาการจัดการโลจิสติกส์และโซ่อุปทานระว่างประเทศ สำนักวิชาการจัดการ มหาวิทยาลัยแม่ฟ้าหลวง

คำชี้แจง

1. กรุณาทำเครื่องหมาย ✔ หน้าคำตอบที่ท่านต้องการลงบนแบบสอบถาม
2. แบบสอบถามนี้ประกอบด้วย 4 ส่วน
   - ส่วนที่ 1 ข้อมูลเชิงประชากรศาสตร์
   - ส่วนที่ 2 ข้อมูลผลกระทบของหมอกควัน
   - ส่วนที่ 3 พฤติกรรมการเดินทางในช่วงสถานการณ์ปกติ
   - ส่วนที่ 4 พฤติกรรมการเดินทางในช่วงสถานการณ์วิกฤตหมอกควัน
   - ส่วนที่ 5 ข้อมูลปัจจัยที่ส่งผลต่อพฤติกรรมการเดินทางในช่วงสถานการณ์วิกฤตหมอกควัน (7 ปัจจัย)
3. ข้อมูลที่ได้รับจากท่านจะถูกเก็บไว้เป็นความลับ

ข้อมูลต่างๆ ในการนี้เป็นการศึกษาเชิงวิชาการ จะไม่มีผลกระทบทางลบแก่ผู้ให้ข้อมูลแต่ประการใด จึงขอความอนุเคราะห์จากท่านได้ให้คำตอบในการตอบแบบสอบถามอย่างตรงไปตรงมาตามข้อเท็จจริงทั้งนี้ หวังว่าคงจะได้รับความร่วมมือจากท่านเป็นอย่างดี

ท่านยินดีและสมัครใจที่จะให้ข้อมูลและตอบแบบสอบถามในการวิจัยครั้งนี้ โดยข้าพเจ้ารับทราบรายละเอียดเกี่ยวกับวัตถุประสงค์ในการทำวิจัย และประโยชน์ที่คาดว่าจะได้รับของการวิจัย โดยจะนำเสนอเป็นข้อมูลโดยรวมจากการวิจัยเท่านั้น ข้าพเจ้าได้เข้าใจข้อความในเอกสารชี้แจงผู้เข้าร่วมตอบแบบสอบถาม

ท่านยินยอมให้ข้อมูลในการตอบแบบสอบถามหรือไม่?

☐ ยินยอม ☐ ไม่ยินยอม

ส่วนที่ 1 ข้อมูลเชิงประชากรศาสตร์

1. เพศ
   - ☐ เพศชาย
   - ☐ เพศหญิง
   - ☐ ไม่ระบุ
2. อายุ
   - ☐ อายุน้อยกว่า 21 ปี
   - ☐ อายุ 21-30 ปี
   - ☐ อายุ 31-40 ปี
   - ☐ อายุ 41-50 ปี
   - ☐ อายุ 51-60 ปี
   - ☐ อายุมากกว่า 60 ปี
3. ระดับการศึกษาสูงสุด
   - ☐ ต่ำกว่าปริญญาตรี
   - ☐ ปริญญาตรี
   - ☐ สูงกว่าปริญญาตรี
4. อาชีพ
   - ☐ นักเรียน / นักศึกษา
   - ☐ ธุรกิจส่วนตัว
   - ☐ พนักงานเอกชน
   - ☐ พนักงานราชการ
   - ☐ รับจ้างทั่วไป
   - ☐ เกษตรกร
   - ☐ ว่างงาน
   - ☐ อื่นๆ ________________________________
5. รายได้ต่อเดือน
   - ☐ น้อยกว่า 10,000 บาท
   - ☐ 10,001-15,000 บาท

☐ 15,001-20,000 บาท

☐ 20,001-30,000 บาท

☐ 30,001-40,000 บาท

☐ 40,001-50,000 บาท

☐ มากกว่า 50,001 บาท

6. สถานภาพการแต่งงาน

☐ โสด

☐ แต่งงาน

☐ ไม่ระบุ

7. สมาชิกภายในบ้านที่อาศัยอยู่ด้วยกัน ณ ปัจจุบัน

**รวมผู้ตอบแบบสอบถาม*

☐ 1 คน

☐ 2 – 3 คน

☐ 4 – 6 คน

☐ มากกว่า 6 คน

8. คุณมียานพาหนะในครอบครองหรือไม่

☐ มี

☐ ไม่มี

9. ใบอนุญาตขับขี่

**สามารถระบุได้มากกว่า 1 ตัวเลือก*

☐ ไม่มี

☐ รถจักรยานยนต์

☐ รถยนต์

10. วัตถุประสงค์หลักในการเดินทางในชีวิตประจำวัน

☐ กลับบ้าน

☐ ทำงาน

☐ การเรียน

☐ ท่องเที่ยว

☐ ซื้อของ

☐ ทำธุรกิจ

☐ รับ – ส่ง

11. จุดเริ่มต้นของการเดินทาง

☐ เขตอำเภอเมืองเชียงราย

☐ เขตนอกเมืองเชียงราย

12. จุดหมายปลายทางของการเดินทาง

☐ เขตอำเภอเมืองเชียงราย

☐ เขตนอกเมืองเชียงราย

13. จำนวนครั้งในการต่อรถ ในการเดินทางจากจุดเริ่มต้น จนถึงจุดหมายปลายทาง ทั้งหมดกี่ครั้ง ?

☐ 1 ครั้ง

☐ 2 ครั้ง

☐ 3 ครั้ง

☐ 4 ครั้ง

☐ 5 ครั้ง

ส่วนที่ 2 ข้อมูลผลกระทบของหมอกควัน

1. คุณได้รับผลกระทบจากสถานการณ์วิกฤตหมอกควันด้านใดบ้าง?

**สามารถระบุได้มากกว่า 1 ตัวเลือก*

☐ ไม่ได้รับผลกระทบ

☐ ด้านสุขภาพ

☐ ด้านการเงิน

☐ ด้านการเดินทาง

☐ ด้านที่อยู่อาศัย

☐ อุบัติเหตุ

☐ อื่นๆ ________________________________

2. คุณคิดว่าสาเหตุของสถานการณ์วิกฤตหมอกควันเกิดจากอะไรบ้าง?

**สามารถระบุได้มากกว่า 1 ตัวเลือก*

☐ ไฟป่า

☐ การเผาเศษพืชและเศษวัสดุการเกษตร

☐ การเผาขยะมูลฝอยจากชุมชน

☐ การก่อสร้างและโรงงานอุตสาหกรรม

☐ การเผาไหม้เชื้อเพลิงจากยานพาหนะ ต่างๆ

☐ อื่นๆ ______________________________

ส่วนที่ 3 พฤติกรรมการเดินทางในช่วงสถานการณ์ปกติ

1. ในสถานการณ์ปกติ คุณเดินทางอย่างไร?

☐ รถยนต์ส่วนตัว

☐ รถจักรยานยนต์

☐ รถขนส่งสาธารณะ

☐ แอพพลิเคชั่นบริการเรียกรถ (เช่น Grab, Bolt, Line man เป็นต้น)

☐ การเดิน, จักรยาน และรถไฟฟ้า

☐ ไม่มีการเดินทาง

2. ในสถานการณ์ปกติ คุณใช้ระยะเวลาในการเดินทางต่อวันเท่าไหร่?

☐ น้อยกว่า 10 นาที

☐ 11-20 นาที

☐ 21-30 นาที

☐ 31-40 นาที

☐ 41-50 นาที

☐ 51-60 นาที

☐ มากกว่า 60 นาที

3. ในสถานการณ์ปกติ คุณใช้ค่าใช้จ่ายเท่าไหร่ ในการเดินทางต่อวัน?

☐ น้อยกว่า 50 บาท

☐ 50-100 บาท

☐ 101-150 บาท

☐ 151-200 บาท

☐ มากกว่า 200 บาท

4. ในสถานการณ์ปกติ คุณเดินทางบ่อยแค่ไหน?

☐ ไม่เดินทางเลย

☐ 1 วันต่อสัปดาห์

☐ 2-3 วันต่อสัปดาห์

- ☐ 4-5 วันต่อสัปดาห์
- ☐ 6-7 วันต่อสัปดาห์

5. ในสถานการณ์ปกติ โดยเฉลี่ยต่อวันคุณเดินทางเป็นระยะทางเท่าไหร่?
   - ☐ น้อยกว่า 5 กิโลเมตร
   - ☐ มากกว่า 5 กิโลเมตร

ส่วนที่ 4 พฤติกรรมการเดินทางในช่วงสถานการณ์วิกฤตหมอกควัน

1. ช่วงสถานการณ์วิกฤตหมอกควัน คุณเดินทางอย่างไร?
   - ☐ รถยนต์ส่วนตัว
   - ☐ รถจักรยานยนต์
   - ☐ รถขนส่งสาธารณะ
   - ☐ แอพพลิเคชั่นบริการเรียกรถ (เช่น Grab, Bolt, Line man เป็นต้น)
   - ☐ การเดิน, จักรยาน และรถไฟฟ้า
   - ☐ ไม่มีการเดินทาง
2. ช่วงสถานการณ์วิกฤตหมอกควัน คุณใช้ระยะเวลาในการเดินทางต่อวันเท่าไหร่?
   - ☐ น้อยกว่า 10 นาที
   - ☐ 11-20 นาที
   - ☐ 21-30 นาที
   - ☐ 31-40 นาที
   - ☐ 41-50 นาที
   - ☐ 51-60 นาที
   - ☐ มากกว่า 60 นาที
3. ช่วงสถานการณ์วิกฤตหมอกควัน คุณใช้ค่าใช้จ่ายเท่าไหร่ ในการเดินทางต่อวัน?
   - ☐ น้อยกว่า 50 บาท
   - ☐ 50-100 บาท
   - ☐ 101-150 บาท
   - ☐ 151-200 บาท
   - ☐ มากกว่า 200 บาท
4. ช่วงสถานการณ์วิกฤตหมอกควัน คุณเดินทางบ่อยแค่ไหน?
   - ☐ ไม่เดินทางเลย

☐ 1 วันต่อสัปดาห์

☐ 2-3 วันต่อสัปดาห์

☐ 4-5 วันต่อสัปดาห์

☐ 6-7 วันต่อสัปดาห์

5. ช่วงสถานการณ์วิกฤตหมอกควัน โดยเฉลี่ยต่อวันคุณเดินทางเป็นระยะทางเท่าไหร่?

☐ น้อยกว่า 5 กิโลเมตร

☐ มากกว่า 5 กิโลเมตร

ส่วนที่ 5 ข้อมูลปัจจัยที่ส่งผลต่อพฤติกรรมการเดินทางในช่วงสถานการณ์วิกฤตหมอกควัน

คุณมีความเห็นอย่างไรต่อข้อความดังต่อไปนี้ เรียงตามลำดับจากเห็นด้วยน้อยที่สุดไปมากที่สุดโดย 1 = ไม่เห็นด้วยอย่างยิ่ง, 2 = ไม่เห็นด้วย, 3 = ไม่แน่ใจ, 4 = เห็นด้วย, 5 = เห็นด้วยอย่างยิ่ง

ปัจจัยที่ส่งผลต่อพฤติกรรมการเดินทางในช่วงสถานการณ์วิกฤตหมอกควัน	1	2	3	4	5
1. ปัจจัยด้านทัศนคติต่อพฤติกรรม					
1.1. ฉันอยากที่จะเปลี่ยนรูปแบบของการเดินทางในช่วงสถานการณ์วิกฤตหมอกควัน ถ้าระยะเวลาในการเดินทางลดลง					
1.2. ฉันอยากที่จะเปลี่ยนรูปแบบของการเดินทางในช่วงสถานการณ์วิกฤตหมอกควัน ถ้าความถี่ในของการเดินทางเพิ่มขึ้น					
1.3. ฉันคิดว่าการเปลี่ยนรูปแบบของการเดินทางในช่วงสถานการณ์วิกฤตหมอกควัน ไม่เหมาะสมกับการเดินทางของฉัน					
1.4. ฉันคิดว่าบางครั้งการเดินทางด้วยขนส่งสาธารณะในช่วงสถานการณ์วิกฤตหมอกควัน ง่ายกว่าใช้รถส่วนตัว					
1.5. ฉันคิดว่าบางครั้งการเดินทางด้วยรถส่วนตัวในช่วงสถานการณ์วิกฤตหมอกควัน ปลอดภัยกว่าการใช้ขนส่งสาธารณะ					
2. ปัจจัยด้านการคล้อยตามกลุ่มอ้างอิง					
2.1. ฉันอยากจะเปลี่ยนรูปแบบของการเดินทางในช่วงสถานการณ์วิกฤตหมอกควัน ถ้านั้นเป็นบรรทัดฐานของสังคม					

ปัจจัยที่ส่งผลต่อพฤติกรรมการเดินทางในช่วงสถานการณ์วิกฤตหมอกควัน	1	2	3	4	5
2.2. ฉันอยากจะเปลี่ยนรูปแบบของการเดินทางในช่วงสถานการณ์วิกฤตหมอกควัน ตามที่เพื่อนแนะนำ					
2.3. ฉันจะเปลี่ยนรูปแบบการเดินทางระหว่างช่วงสถานการณ์วิกฤตหมอกควัน ถ้าบุคคลที่มีความสำคัญกับฉันแนะนำให้เปลี่ยน					
2.4. บุคคลที่มีอิทธิพลต่อฉัน จะแนะนำฉันให้ใช้ขนส่งสาธารณะในช่วงสถานการณ์วิกฤตหมอกควัน แทนการใช้รถยนต์ส่วนตัว					
3. ปัจจัยด้านการรับรู้ความสามารถในการควบคุมพฤติกรรม					
3.1. ฉันเชื่อว่าโครงสร้างพื้นฐานด้านการเดินทางในปัจจุบัน เช่น ความถี่/ระดับการให้บริการของขนส่งสาธารณะ ทำให้ยากต่อการเปลี่ยนรูปแบบของการเดินทาง ในช่วงสถานการณ์วิกฤตหมอกควัน					
3.2. ฉันเชื่อว่ามันเป็นเรื่องยากในการเปลี่ยนรูปแบบการเดินทางในช่วงสถานการณ์วิกฤตหมอกควัน ถ้ามันเพิ่มระยะเวลาในการเดินทาง					
3.3. ฉันคิดว่าการเปลี่ยนแปลงรูปแบบการเดินทางในช่วงสถานการณ์วิกฤตหมอกควัน เป็นเรื่องง่าย					
3.4. ไม่ว่าฉันจะเปลี่ยนหรือไม่เปลี่ยนรูปแบบการเดินทางในช่วงสถานการณ์วิกฤตหมอกควัน ก็ขึ้นอยู่กับตัวของฉันเอง					
3.5. ฉันมีความมั่นใจว่า ถ้าฉันต้องการจะเปลี่ยนรูปแบบการเดินทางในช่วงการสถานการณ์วิกฤตหมอกควัน ฉันก็สามารถทำได้					
4. ปัจจัยด้านการรับรู้ความสามารถในการควบคุมพฤติกรรม					
4.1. ฉันเชื่อว่าค่าใช้จ่ายในการเดินทาง จะส่งผลต่อความตั้งใจในการเปลี่ยนรูปแบบของการเดินทางของฉัน ในช่วงสถานการณ์วิกฤตหมอกควัน					
4.2. ฉันอยากจะเปลี่ยนรูปแบบการเดินทางในช่วงสถานการณ์วิกฤตหมอกควัน ถ้าค่าใช้จ่ายลดลง					
5. ปัจจัยด้านความกังวลในเรื่องของสุขภาพ					

ปัจจัยที่ส่งผลต่อพฤติกรรมการเดินทางในช่วงสถานการณ์วิกฤตหมอกควัน	1	2	3	4	5
5.1. ฉันให้ความสำคัญกับการสวมใส่หน้ากากป้องกันฝุ่น ระหว่างการเดินทางในช่วงสถานการณ์วิกฤตหมอกควัน ไม่ว่าจะเดินทางในรูปแบบใดก็ตาม					
5.2. ฉันให้ความสำคัญกับรูปแบบของการเดินทางที่มีการป้องกัน/ลดการสัมผัสฝุ่น เช่น ระบบปิด, มีเครื่องฟอกอากาศ					
6. ปัจจัยด้านความกังวลในเรื่องของทัศนวิสัยในการเดินทาง					
6.1. ฉันเชื่อว่าช่วงสถานการณ์วิกฤตหมอกควัน ส่งผลต่อเมืองและทัศนวิสัย นั้นทำให้ฉันอยากที่จะเปลี่ยนรูปแบบการเดินทาง					
6.2. ฉันอยากจะเปลี่ยนรูปแบบการเดินทางในช่วงวิกฤตกหมอกควัน ถ้าพยากรณ์อากาศแจ้งว่าสถานการณ์หมอกควันกระทบต่อทัศนวิสัยในการเดินทาง					
6.3. ฉันเชื่อว่าสามารถยอมรับความเสี่ยงด้านทัศนวิสัยที่แย่ลงในช่วงสถานการณ์วิกฤตหมอกควันได้ ถ้าฉันยังใช้รูปแบบการเดินทางเดิมกับสถานการณ์ปัจจุบัน					
7. ปัจจัยด้านความตั้งใจที่จะทำพฤติกรรม					
7.1. ฉันพยายามจะเปลี่ยนแปลงรูปแบบการเดินทางในช่วงสถานการณ์วิกฤตหมอกควัน					
7.2. ฉันเชื่อว่าระยะเวลาในการเดินทางช่วงสถานการณ์วิกฤตหมอกควัน จะส่งผลต่อความตั้งใจของฉันในการเปลี่ยนรูปแบบการเดินทาง					
7.3. ฉันเชื่อว่าความตั้งใจในการเปลี่ยนรูปแบบการเดินทางช่วงสถานการณ์วิกฤตหมอกควัน ขึ้นอยู่กับความพร้อม (ความถี่) ในการบริการของรูปแบบการเดินทางอื่นๆ					
7.4. ฉันควรเปลี่ยนรูปแบบการเดินทางในช่วงสถานการณ์วิกฤตหมอกควัน เพื่อลดการแออัดและการเกิดอุบัติเหตุ					

ขอขอบพระคุณสำหรับการตอบแบบสอบถาม

APPENDIX E

CERTIFICATE OF CONFERENCE IEEE

ASU
جامعة العلوم التطبيقية
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ICETSIS 2024

Presenter Certificate

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Ramill Phopluechai

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Examining factors affected to travel decision during air pollution crisis in Chiang Rai using exploratory factor analysis

at the 2024 International Conference in Emerging Technologies for Sustainability and Intelligent Systems (ICETSIS 2024), that was held on January 28th – 29th 2024 at the Applied Science University in the Kingdom of Bahrain.

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APPENDIX F

PUBLICATION PAPER OF CONFERENCE

2024 ASU International Conference in Emerging Technologies for Sustainability and Intelligent Systems (ICETSIS)

Examining factors affected to travel decision during air pollution crisis in Chiang Rai using exploratory factor analysis

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***Abstract*—This study examines the complex dynamics of travel behavior during air pollution crises in Chiang Rai, Thailand. It utilizes exploratory factor analysis (EFA) to identify the underlying determinants that influence individual reactions. The study employs a cross-sectional research approach, utilizing questionnaire surveys distributed to a representative sample of urban residents in Chiang Rai. The data is subjected to thorough analysis using factor analysis techniques. The findings indicate that there are six important factors, Subjective Norm, Intention, Safety, Alternative, Habit, and Risk, that collectively explain 57.1 percent of the variation in travel behavior during air pollution crises. These elements illuminate the impact of society norms, safety concerns, ingrained behaviors, and perceptions of danger on how individuals react to environmental difficulties. The findings provide useful insights for urban planning, public health, and sustainable development, highlighting the necessity for focused actions based on these aspects. This study provides a basis for making well-informed decisions and developing strategies to build resilient urban systems in response to recurring environmental difficulties, particularly those related to air pollution episodes that are a global concern.**

***Keywords*—travel behavior, transportation, air pollution crisis, exploratory factor analysis, Chiang Rai**

I. INTRODUCTION

In recent years, Chiang Rai, Thailand has experienced recurring air pollution crisis that posing significant challenges to the daily lives of its residents. From 2012 until 2022, Chiang Rai has consistently experienced air pollution every year between February and April, based on a decade of documented data. These crises are often attributed to a combination of urbanization, industrial activities, and agricultural burning. Among the various aspects affected for example, public health, respiratory diseases, environment, and climate change [1]–[3]. Including travel behavior as a one of dimension requiring thorough investigation. Understanding how individuals alter their travel behavior during periods of heightened air pollution. This study employs Exploratory Factors Analysis (EFA) as a tool to unravel the intricate factors influencing travel behavior in the context of air pollution crisis. Air quality deterioration not only impacts the physical health of the population but also intricately shapes their transportation, ranging from mode choices selection, travel frequency, travel time, and destination preferences. This research aims to identify latent factors that underlie observed variations on travel behavior during air pollution crisis. The exploration of these factors shows correlation and deeper structures shaping how individuals navigate their surroundings when faced with environmental challenges.

As air pollution incidents become more recurrent globally, understanding the nuanced interplay between air quality crises and travel behavior is crucial for urban planning, public health, and sustainable development. This study contributes to the existing body of knowledge by offering insights into the multifaceted dynamics of travel behavior during air pollution crisis in Chiang Rai, thereby fostering informed decision-making for resilient urban systems strategies.

II. LITERATURE REVIEW

A. Travel Behavior in pollution crisis

Throughout the air pollution crisis, multiple factors exerted an influence on travel behavior, including individuals' attitudes towards travel in unfavorable weather conditions, physical or psychological distress, personal experiences, cognitive evaluations of their ability to move, and subjective social standards [4]. These causes motivated individuals to shift their travel behaviors, leading to a significant negative link between air pollution and travel behavior. As a result, there was a decrease in both trip distance and area. The presence of haze pollution had an influence on how tourists perceived and behaved, but it did not have a substantial impact on domestic travel as a whole. Nevertheless, the increased public awareness of haze pollution had a beneficial impact on domestic travel [5]. Furthermore, the consumption behavior of purchasing air purifiers during transportation was influenced by factors such as PM2.5 concentration, product pricing, and media-related aspects [6]. The presence of smog and its associated health risks led to a higher willingness to switch to green vehicles and adopt protective behavior [7]. Moreover, exposure to air pollution during travel was found to be higher in open transport modes, and pedestrians and cyclists were most affected due to their proximity to the streets [8]. Risk perception, encompassing apprehension over air pollution, exerted a pivotal influence on travel patterns amidst air pollution emergencies, prompting actions such as monitoring meteorological predictions and actively seeking knowledge about the origins of pollution. Prior encounters with air pollution impacts led to a decrease in outdoor activities and an increase in the adoption of protective measures [9]. Travel behavior during air pollution events was found to be influenced by demographic parameters, including age and gender. Female and younger age groups were associated with a higher likelihood of behavioral shift [1]. Various linked elements influence travel behavior during pollution crises, illustrating the intricate relationship between attitudes, perceptions, experiences, and environmental awareness.

B. Data Analysis

Factor analysis methods is used to examine the components that influence behavior change, commonly employed in transportation research, Exploratory factor analysis (EFA) common use to analyses the links between variables by modelling the interaction between underlying components to evaluate how different factors influence changes in behavior[10].It is especially well-suited for analyzing non-normally distributed data with limited sample sizes and specific residual distribution criteria. These factors analysis methods which utilize graphical interfaces, are highly skilled in analyzing the elements that drive behavioral changes in response to stimuli such as air pollution. In travel behavior analysis, factor analysis is frequently used to uncover the fundamental dimensions that contribute to the variation in observed variables. Factor analysis in travel behavior research utilizes techniques such as binary logistic analysis and maximum likelihood to categorize related variables and ascertain their impact on components such as mode choice and travel intentions [11]. Moreover, EFA is a crucial tool in the field of tourism and hospitality management as it helps to identify the fundamental elements that influence travel behavior. EFA's applications encompass mode selection, destination predilections, and post-pandemic travel intents, providing a tool to comprehend the subtle intricacies of travel behavior [12]. Within the setting of a pollution crisis, EFA as provides a clear understanding of why individuals change their travel behaviors. This understanding is achieved using a structural model based on the Theory of Planned Behavior and a map-matching method that incorporates trajectory data [4]. These techniques collectively offer in-depth understanding of the various facets of travel behavior, encompassing both broad variables and specific reactions in times of environmental crises.

III. Methodology

This study adopts a cross-sectional research design to capture a travel behavior during air pollution crisis in Chiang Rai, Thailand. Data will be collected through questionnaire surveys administered to a representative sample of the local population as depicted in Fig. 1.

A. Questionnaire Survey

The purpose of the questionnaire study was to determine the response behavior related to air pollution crisis haze incident and to investigate changes in personal behavior in dealing with pollution during the incident, which affected Chiang Rai province. The survey consisted of 5 sections of questions, demographic information, the effect of the air pollution crisis, travel behavior in normal situation, travel behavior in air pollution crisis and factors that affected travel behavior change in normal situation and during air pollution crisis using a 5 - point Likert scale (1 strongly disagree, 2 disagree, 3 unsure, 4 agree and 5 strongly agree). The section of descriptive information is presented in Table I.

TABLE I. Descriptive Summary Of The Participants (N=308)

Item	Description	Frequency	Percent
Gender	Male	106	34.4
	Female	183	59.4
	Not mention	19	6.2
Age	Less than 21 years old	92	29.9
	21-30 years old	166	53.9
	31-40 years old	17	5.5
	41-50 years old	23	7.5
	51-60 years old	10	3.2
Education Level	Under Bachelor's Degree	107	34.7
	Bachelor's Degree	183	59.4
	Above Bachelor's Degree	18	5.8
Occupation	Student	205	66.6
	Business	19	6.2
	Private employee	35	11.4
	Government officer	19	6.2
	Self employed	17	5.5
	Farmer	6	1.9
	Non-employed	7	2.3
Monthly income	Less than 10,000 THB	172	55.8
	10,001-15,000 THB	16	5.2
	15,001- 20,000 THB	68	22.1
	20,001- 30,000 THB	29	9.4
	30,001- 40,000 THB	8	2.6
	40,001 - 50,000 THB	6	1.9
	More than 50,001 THB	9	2.9

B. Data Collection

The data was collected during September and October 2023, online surveys by Google Forms with a pilot-test, 30 participants. The participants are people who live in urban area of Chiang Rai, Thailand. A total of 332 responses were collected, and after excluding incomplete and unanswered questionnaires, 308 valid responses were considered for the final analysis.

C. Data Analysis

The data analysis methodology utilizes Exploratory Factor Analysis (EFA) to discover underlying characteristics that impact travel behavior during air pollution crises in Chiang Rai. Based on the variables obtained from survey responds, the initial data analysis comprises the use of descriptive statistics to detect and analyze patterns.

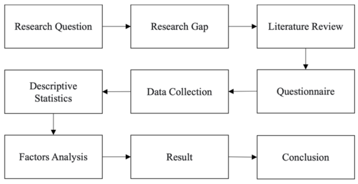

Fig. 1. Reseach methodology

The appropriateness for EFA is evaluated using the Kaiser-Meyer-Olkin (KMO) measure and Bartlett's test. Factor extraction, employing Varimax rotation, reveals latent structures within the dataset, which dictate the interpretation of factor loadings. The determination of the number of maintained factors is based on the eigenvalues. Cronbach's alpha is employed in reliability analysis to assess the internal consistency of variables. Further analysis investigates the connections between factors and trip results. The objective of this systematic approach to EFA is to offer a thorough comprehension of the many elements that influence travel behavior during air pollution crises in Chiang Rai.

IV. Result

The results are shown, Cronbach's alpha coefficient is 0.855, which exceeds the minimum threshold of 0.70 [13]. According to the findings, there are six factors that were responsible for explaining 57.1 percent of the variance in the data. A condensed summary of the findings of the component analysis is provided in Table II. This summary includes the eigenvalue, the explained variance, and the cumulative explained variance. The Kaiser rule involves selecting those elements that have an eigenvalue greater than 1.0 [14]. The analysis produced a Kaiser-Mayer-Olkin score of 0.847, indicating strong correlations among the components that above the acceptable reliability threshold of 0.70.

The correlations between variables are shown in Table III. The correlations offer valuable insights into the interrelationships among these parameters. Positive correlations between SN, IT, SF, AL, HB, and RK indicate that these elements are likely interrelated and have an impact on individuals' perceptions and behaviors. The acceptable number of strong correlations should be ranged between 0.3 and 0.8 to avoid multicollinearity problem.

In addition, Bartlett's test yielded a significance value of less than 0.001. A factor loading of 0.4 was selected as a cautious threshold indicating. The number of variables was established by employing common suggestions of scree cut-off points [15].

TABLE II. FACTOR, EIGENVALUES, AND EXPLAINED VARIANCE

Factor	Description	Eigenvalue	Explained Variance (%)	Cumulative explained variance (%)
SN	Subjective Norm	6.0	13.0	13.0
IT	Intention	3.0	11.7	24.7
SF	Safety	1.7	11.5	36.1
AL	Alternative	1.4	7.8	43.9
HB	Habit	1.1	6.8	50.6
RK	Risk	1.1	6.5	57.1

TABLE III. CORRELATION MATRIX

Factor	SN	IT	SF	AL	HB	RK
SN	1					
IT	0.443**	1				
SF	0.144*	0.491**	1			
AL	0.485**	0.453**	0.233**	1		
HB	0.121*	0.253**	0.301**	0.211**	1	
RK	0.336**	0.381**	0.350**	0.303**	0.332**	1

Note. ** Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed).

The factor loadings of the components in this study range from 0.809 to 0.496, indicating a strong level of consistency with each component.

A. Subjective Norm

This factor explains 13 percent of the overall variance. Factor loadings range from 0.809 to 0.514. The most significant impact is "people who influence me would want me to use public transport during the air pollution crisis instead of using a private car." With 0.809 factor loading, it is evident that influencers have the ability to exert influence on individuals. The evaluated variables have a mean between 3.82 and 3.19, indicating that people would agree to switch modes of transportation during air pollution if their important people suggested it. This variable has the highest mean but has the lowest loading factors, indicating a weak association with subjective norm factors, shown in Table IV.

B. Intention

The intention factor explains for 11.7 percent of the variation. Factor loadings range from 0.722 to 0.496. The highest impact variable is traveling time during air pollution crisis will affect intention to change mode of transport. The evaluated variables have a mean between 4.06 and 3.85, showing that most people agree with if the availability of service for other mode of transport increases, they will have intention to change mode of transport, presented in Table V.

TABLE IV. SUBJECTIVE NORM

Variable	Mean	SD	Factor loadings
People who influence me would want me to using public transport during air pollution crisis instead of using private car.	3.29	1.11	0.809
I think travel by public transport during air pollution can sometimes be easier than private transport.	3.19	1.24	0.753
I think change mode of transport during air pollution crisis would be very easy.	3.32	1.07	0.709
I prefer to change mode of transport during air pollution crisis as it is recommended by friends.	3.56	0.91	0.671
I prefer to change mode of transport during air pollution crisis as it is recommended by people who are important to me.	3.82	0.81	0.514

C. *Safety*

This factor explains 11.5 percent of the variation. Factor loadings range from 0.677 to 0.559. The most significant impact and highest mean is people pay attention to waring PM2.5 protective mask while travel during air pollution crisis. The evaluated variables have a mean between 4.46 and 4.04, showing the participants are most agree with safety risk. For example, prioritize mode of transport to prevents to air pollution and air pollution increasing and affected travel visibility, see in Table VI.

D. *Alternative*

The alternative factor explains 7.8 percent of the variation. Factor loadings are 0.657 and 0.553. The evaluated variables have a mean between 4.18 and 3.74, showing that participants agree to change mode of transport if travel time reduce more than change mode of transport from social norm, shown in Table VII.

TABLE V. INTENTION

Variable	Mean	SD	Factor loadings
I believe that travel time during air pollution crisis will affect my intension to change mode of transport.	3.92	0.76	0.722
I will make an effort to change mode of transport during air pollution crisis.	3.85	0.87	0.685
I should change mode of transport during air pollution crisis to reduce congestion and road accidents.	3.93	0.85	0.675
I believe that my intension to change mode of transport during air pollution crisis depend upon the availability (frequency) of the service for other mode of transport.	4.06	0.69	0.648
I like to change mode of transport during air pollution crisis if transport frequency is increased.	3.90	0.98	0.496

TABLE VI. SAFETY

Variable	Mean	SD	Factor loadings
I pay attention to wearing anti-PM2.5 mask while traveling during air pollution crisis, whatever mode of transport.	4.46	0.67	0.677
I prioritize mode of transport that prevents/reduces exposure to dust e.g. enclosed systems, air purifiers use.	4.37	0.77	0.673
I like to change mode of transport during air pollution crisis if that mode fare is lowered.	4.04	0.89	0.650
I believe that air pollution crisis affect to city and visibility, that make me change mode of transport.	4.17	0.80	0.609
I prefer to change mode of transport as the weather forecast said air pollution crisis affect to travel visibility.	4.12	0.81	0.582
I believe that travel cost will affect my intention to change mode of transport during air pollution crisis.	4.14	0.71	0.559

E. *Habit*

This factor explains 6.8 percent of the variation. Factors loadings range from 0.743 to 0.503. The highest impact variable is participant will change mode of transport by completely up to themselves. The evaluated variables have a mean between 4.19 and 3.90, showing that the most habit of participants prefer to use private vehicle that more safety than public transport, presents in Table VIII.

F. *Risk*

This factor explains 6.5 percent of the variation. Factor loadings are 0.597 and 0.521. The most significant impact variable is participant can accept and agree to use same mode of transport as normal situation during unclear visibility in air pollution crisis, with 3.68 mean value. The evaluated variables have a mean between 4.06 and 3.68. This showing the highest participants agree with existing transport infrastructure in Chiang Rai, makes it difficult to change mode of transport during air pollution crisis, see in Table IX.

TABLE VII. ALTERNATIVE

Variable	Mean	SD	Factor loadings
I like to change mode of transport during air pollution crisis if travel time reduced.	4.18	0.77	0.657
I prefer to change mode of transport during air pollution crisis as it has become norm of the society.	3.74	0.94	0.553

TABLE VIII. HABIT

Variable	Mean	SD	Factor loadings
Whether or not I change mode of transport during air pollution crisis is completely up to me.	3.96	0.88	0.743
I am confident that if I want to I could change mode of transport during air pollution crisis.	3.90	0.89	0.687
I feel that using private transport during air pollution is safer than by public transport.	4.19	0.80	0.503

TABLE IX. RISK

Variable	Mean	SD	Factor loadings
I believe that I can accept the risk of unclear visibility during air pollution crisis if I still use same mode of transport as normal situation.	3.68	1.04	0.597
I believe the existing transport infrastructure, eg. frequency/Level of service, makes it difficult to change mode of transport during air pollution crisis.	4.06	0.72	0.532
I believe that it difficult to change mode of transport during air pollution crisis if it will increase travel time.	4.05	0.76	0.524
I think change mode of transport during air pollution crisis is incompatible with my mobility needs.	3.77	0.96	0.521

V. Conclution

This study examined the complex patterns of travel behavior during periods of air pollution crisis in Chiang Rai, Thailand. It utilized exploratory factor analysis (EFA) to identify the underlying elements that influence how individuals respond to these situations. The results unveiled six different components that collectively account for 57.1 percent of the variability in the data.

The Subjective Norm factor highlighted the impact of influential individuals in the lives of participants, resulting in a strong tendency to alter travel habits during air pollution crisis, including in the more comfortable of travel by public transport than using private vehicle. For the intention emphasized the diverse viewpoints of the transition of transport modes, taking into consideration important elements such as the travel time and availability of alternative transport options. During the air pollution crisis, the participants unanimously agreed on the importance of safety when it comes to using PM2.5 protective mask and expressed a strong preference for transportation methods that minimize dust exposure. For instance, enclosed systems and air purifiers use during travel. The alternative of transportation dimension revealed participants' inclination to change their transportation modes due to reduced travel time and that transportation mode has become norm of the society. The habit factor demonstrated the participants' assurance in altering travel modes under pollution crises, unveiling a contrast between their conviction in the safety of private cars and their recognition of personal preferences. Finally, the risk factor provided distinct viewpoints on the air pollution crisis affect to decreased visibility that influence participants accepted to using same mode of transportation as normal situation.

These findings provide detailed insights into how subjective norms, safety concerns, and habitual behaviors influence travel responses during air pollution crises. With the increasing occurrence of pollution worldwide, it is important to recognize that the effects are not limited to Chiang Rai. This highlights the necessity for specific interventions and awareness campaigns that consider these aspects to promote resilient strategies for urban systems. Further research could improve on this groundwork by investigating the efficacy of certain interventions and evaluating their suitability in various cultural and geographical contexts.

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References

[1] Y. Xu, Y. Liu, X. Chang, and W. Huang, "How does air pollution affect travel behavior? A big data field study," *Transp Res D Transp Environ*, vol. 99, 2021, doi: 10.1016/j.trd.2021.103007.

[2] W. Uddin, "Air quality management using modern remote sensing and spatial technologies and associated societal costs," *Int J Environ Res Public Health*, vol. 3, no. 3, 2006, doi: 10.3390/ijerph2006030028.

[3] Q. Li, S. Soleimaniamiri, and X. Li, "Optimal mass evacuation planning for electric vehicles before natural disasters," *Transp Res D Transp Environ*, vol. 107, p. 103292, Jun. 2022, doi: 10.1016/J.TRD.2022.103292.

[4] C. Li, Y. Huang, G. Li, C. Yi, W. Zhu, and W. Liu, "Analysis of the influence of smog on the travel behavior," *Xi'an Jianzhu Keji Daxue Xuebao/Journal of Xi'an University of Architecture and Technology*, vol. 47, no. 5, 2015, doi: 10.15986/j.1006-7930.2015.05.021.

[5] J. Sun, J. H. Zhang, C. Wang, X. Duan, and Y. Wang, "Escape or stay? Effects of haze pollution on domestic travel: Comparative analysis of different regions in China," *Science of the Total Environment*, vol. 690, 2019, doi: 10.1016/j.scitotenv.2019.06.415.

[6] Y. Yuan and B. Fan, "Protective consumption behavior under smog: using a data-driven dynamic Bayesian network," *Environ Dev Sustain*, 2022, doi: 10.1007/s10668-022-02875-6.

[7] S. Anwar, B. Hussain, M. Usman, S. Asif Ali Naqvi, and A. Ahmad Shah, "Consumers' switching intentions from conventional to green vehicles in the context of smog risk in Pakistan," *Case Stud Transp Policy*, vol. 10, no. 3, 2022, doi: 10.1016/j.cstp.2022.06.008.

[8] V. Singh, K. K. Meena, and A. Agarwal, "Travellers' exposure to air pollution: A systematic review and future directions," *Urban Climate*, vol. 38. 2021. doi: 10.1016/j.uclim.2021.100901.

[9] A. Sajjad, J. Chu, M. A. Anwar, and F. Asmi, "Between green and gray: Smog risk and rationale behind vehicle switching," *J Clean Prod*, vol. 244, 2020, doi: 10.1016/j.jclepro.2019.118674.

[10] W. Yongdong, X. Dongwei, P. Peng, and Z. Guijun, "Analysis of road travel behaviour based on big trajectory data," *IET Intelligent Transport Systems*, vol. 14, no. 12, 2020, doi: 10.1049/iet-its.2019.0785.

[11] T. Arreeras, S. Chongutsah, T. Asada, and M. Arimura, "Factors Affecting Mode Choice in Accessing Railway Station Study in Nakhon Ratchasima," in *Transportation Research Procedia*, 2020. doi: 10.1016/j.trpro.2020.08.107.

[12] C. Chansuk *et al.*, "Using factor analyses to understand the post-pandemic travel behavior in domestic tourism through a questionnaire survey," *Transp Res Interdiscip Perspect*, vol. 16, 2022, doi: 10.1016/j.trip.2022.100691.

[13] L. J. Cronbach, "Coefficient alpha and the internal structure of tests," *Psychometrika*, vol. 16, no. 3, 1951, doi: 10.1007/BF02310555.

[14] H. F. Kaiser, "The Application of Electronic Computers to Factor Analysis," *Educ Psychol Meas*, vol. 20, no. 1, 1960, doi: 10.1177/001316446002000116.

[15] R. B. Cattell, "The scree test for the number of factors," *Multivariate Behav Res*, vol. 1, no. 2, 1966, doi: 10.1207/s15327906mbr0102_10.

APPENDIX G

PUBLICATION PAPER OF JOURNAL

urban science

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Article

Investigating Travel Mode Choices Under Environmental Stress: Evidence from Air Pollution Events in Chiang Rai, Thailand

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Abstract

Air pollution poses growing challenges to public health and urban mobility in Southeast Asia. This study investigates how air quality crises affect travel mode choices in Chiang Rai, Thailand, a secondary city experiencing seasonal PM2.5 smog episodes. A structured online survey was conducted with 406 respondents, collecting paired data on travel behaviors during non-air quality crisis (N-AQC) and air quality crisis (AQC) periods. Using a multinomial logit model (MNL), key socioeconomic and trip-related variables were analyzed to estimate mode choice probabilities. The results reveal significant behavioral shifts during an air quality crisis, with private car usage increasing from 30.30% to 34.70% and motorcycle usage decreasing from 50.20% to 42.90%. Multinomial logit models attained correct classification rates of 67.5% and 63.8%, with pseudo R^2 values exceeding 0.50 for both periods. These findings highlight how environmental stress alters travel behavior, especially among younger and low-income populations. The study contributes new insights from a Southeast Asian urban context, emphasizing the need for adaptive transport policies, protective infrastructure, and equity-focused interventions to promote sustainable mobility during an environmental crisis.

Keywords: mode choice; air quality crisis; air pollution; urban mobility; multinomial logit model; PM2.5

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1. Introduction

Air pollution has emerged as one of the most pressing global environmental challenges of the 21st century, with significant implications for public health and urban mobility patterns. This study examines how air quality crises affect travel mode choices in Chiang Rai, Thailand, with particular focus on the shifts between private vehicles, motorcycles, public transport, and alternative modes, including walking, bicycle, e-hailing service, and taxi. The primary objectives are to (1) quantify changes in travel mode distributions between non-air quality crisis and air quality crisis, (2) identify key socioeconomic and environmental factors influencing mode choice during these periods, and (3) develop evidence-based recommendations for transportation policy adaptation during an air quality crisis. This study makes novel contributions by providing empirical evidence of travel behavior adaptation in medium-sized Southeast Asian cities, introducing a temporal comparative framework for examining mode choice during non-air quality crisis (N-AQC) versus air quality crisis (AQC), and establishing a methodological approach for analyzing environmental impacts on transportation choices in developing urban contexts.

Transportation mode choice behaviors have been significantly influenced by environmental conditions across various Asian contexts [1]. Studies have shown that air quality concerns can substantially alter travel patterns and modal preferences, particularly in developing countries where rapid economic growth often outpaces environmental regulations [2]. Among these pollutants, particulate matter (PM) has garnered significant attention, with PM2.5 and PM10 being of particular concern [3]. According to the World Health Organization, air pollution exposure significantly impacts public health globally, highlighting the critical need to understand how air quality affects transportation choices [4].

In the context of Southeast Asia, rapid urbanization and economic development have led to significant air quality challenges. The region's unique geographical and meteorological conditions, combined with anthropogenic activities such as biomass burning and increasing vehicle emissions, contribute to recurring episodes of severe air pollution, often referred to as "haze" or "smog" crisis [5]. These events not only pose immediate health risks but also disrupt daily activities and potentially influence long-term behavioral patterns, including travel mode choices. Thailand, as one of the more economically developed countries in Southeast Asia, provides an interesting case study for examining the interplay between air pollution and travel behavior. While much attention has been focused on the capital city of Bangkok, smaller cities and provinces in Thailand also face significant air quality issues, often with fewer resources to address them [6].

Chiang Rai province, located in northern Thailand, exemplifies this challenge, experiencing recurring air quality crises primarily caused by a combination of agricultural burning, industrial emissions, and unfavorable weather patterns [7]. According to the Pollution Control Department of Thailand, air pollution in Chiang Rai is characterized by elevated levels of PM10 and PM2.5, with data from 2012 to 2022 indicating that March is typically the month most affected by air pollution [8]. During these periods, both PM10 and PM2.5 levels frequently exceed the recommended standards set by Thai national guidelines. For the purposes of this study, we define two distinct periods: (1) non-air quality crisis, when air quality is within acceptable limits (PM2.5 below 50 $\mu g/m^3$ and PM10 below 120 $\mu g/m^3$), and (2) air quality crisis, when air quality significantly deteriorates (PM2.5 exceeding 50 $\mu g/m^3$ and/or PM10 exceeding 120 $\mu g/m^3$) for prolonged periods. There are a few studies about air pollution impacting travel commuting in Chiang Rai city. For example, studies have investigated factors affecting travel decisions during an air pollution crisis in Chiang Rai [9]. The transportation landscape in Chiang Rai offers a diverse range of options, reflecting both traditional and evolving mobility patterns in medium-sized Southeast Asian cities. Figure 1 shows that available transportation modes in Chiang Rai can be classified into four main categories: (1) private car, (2) motorcycle, (3) public transport (including bus, mini-bus (Song-Teaw), and van with services operating both intra-city and inter-city), and (4) alternatives (including walking, bicycle, e-hailing service, and taxi).

The aggregation of these alternatives into a single category was necessitated by their relatively low individual modal shares in the study area. The quantitative threshold for aggregation was established based on the minimum sample size requirements for multinomial logit modeling, which typically requires at least 30–50 observations per category to ensure parameter stability [10,11]. With only 8–26 individual responses per alternative mode, separate analysis would have resulted in unreliable coefficient estimates and wide confidence intervals, potentially leading to misleading conclusions about environmental crisis impacts. This consolidation approach aligns with established practices in transportation studies of medium-sized cities where emerging mobility options represent smaller modal splits [12,13]. Likewise, previous studies have examined the influence of air pollution on travel behavior in various global contexts [14]; however, there remains a notable gap in understanding these dynamics within Southeast Asian settings, particularly in smaller cities like Chiang Rai.

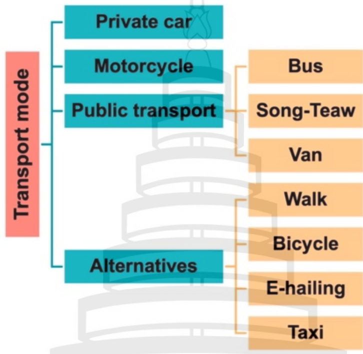

Figure 1. Available transportation modes in Chiang Rai, Thailand.

This study employs a multinomial logit model to analyze mode choice patterns across non-air quality crisis and air quality crisis periods [15]. Through this approach, the probability of specific travel mode selection is estimated based on various predictor variables, including socioeconomic factors, trip characteristics, and air quality conditions. The investigation is structured across two distinct temporal contexts, non-air quality crisis (N-AQC) and air quality crisis (AQC) periods, through which behavioral adaptations in response to air quality deterioration can be analyzed comparatively. The findings from this research are expected to provide valuable insights for developing targeted transportation and environmental policies, particularly for medium-sized cities facing recurring air quality challenges. By bridging the gap between global air quality concerns and local travel behaviors, this study offers important implications for policymakers, urban planners, and researchers working towards more sustainable and health-conscious urban environments in similar contexts across Southeast Asia and beyond.

This paper is organized as follows: Section 2 reviews the literature on the impact of air pollution on travel behavior and the methodological approaches employed in mode choice analysis. Section 3 presents the research methodology, including the study area, data collection, and analytical methods. Section 4 reports the results, focusing on travel behavior patterns and mode choice models during both non-air quality crisis and air quality crisis periods. Section 5 discusses the key findings, policy implications, and limitations of the study. Finally, Section 6 concludes the paper.

2. Literature Review

2.1. Air Pollution and PM2.5 Smog Impact on Travel Behavior

Fine particulate matter (PM), which consists of airborne particles with aerodynamic diameters smaller than 2.5 µm (PM2.5), has been identified as a major air pollutant affecting human health and travel behavior. PM2.5 is particularly concerning due to its ability to penetrate deep into the respiratory system and enter the bloodstream, causing various health issues [4]. Studies consistently show that deteriorating air quality, especially elevated PM2.5 levels, influences travelers to shift between different transportation modes. In Delhi, India, when PM2.5 concentrations exceed 150 $\mu g/m^3$ (six times higher than the WHO's recommended 24 h guideline of 25 $\mu g/m^3$), commuters increasingly prefer closed modes of transportation over open modes. This was demonstrated through machine learning models and logit analysis comparing enclosed vehicles (cars, air-conditioned buses) versus open vehicles (auto rickshaws, non-air-conditioned buses) [16]. The impact of air pollution on mode choice varies across different urban contexts. In Taiyuan, China, high PM2.5 concentrations negatively impacted the selection of non-motorized transport modes (walking, cycling) in favor of motorized vehicles (cars, buses) [17]. Similarly, in Zhengzhou, China, a study examining car use, public transit (buses and subway), and active modes (walking and cycling) found that car commuters tend to maintain their preference for private vehicles even after receiving health information about PM2.5 exposure [18].

Income levels play a significant role in mode choice during pollution events. In Seoul, South Korea, public transit usage increases among lower-income groups during high pollution periods, particularly for bus and subway services, as revealed through an Integrated Choice and Latent Variable (ICLV) model [19]. This finding was further supported by multilevel logistic regression modeling comparing non-motorized modes (walking or biking), public transit (bus or subway), and cars [20]. In Karaj, Iran, when PM2.5 concentrations exceed 75 $\mu g/m^3$, poor air quality increases private car usage compared to walking and public transit options, as shown through exploratory factor analysis and hybrid choice modeling [21]. In the United States, a comprehensive study across 929 urban areas examined how emissions affect choices between driving alone, carpooling, public transportation, walking, and other modes, finding that vehicle ownership significantly influences transportation mode choices [22]. Recent research in Delhi has employed sophisticated analytical methods to study a wide range of transportation modes, including auto rickshaws, buses, cars, two-wheelers, two-wheeler sharing, walking, bicycles, car sharing, and metro services. These studies consistently show that as PM2.5 levels rise above national and WHO standards, travelers modify their behavior to minimize exposure, with a clear preference for enclosed modes of transportation [23]. In Beijing, daily average PM2.5 concentrations significantly impact choices between cycling, cars, taxis, buses, metros, and walking, with notable shifts observed when levels exceed 150 $\mu g/m^3$ [24]. The impact of PM2.5 pollution extends beyond mode choice to affect spatial travel patterns, as revealed by a big data field study in Xi'an, China [25]; these studies are shown in Table 1.

Table 1. Summary of previous studies on mode choice during air pollution events.

Reference	Pollution Type	Location	Method Used	Mode of Transport	Finding
Li and Kamargianni [17]	Air pollution	Taiyuan, China	Mode choice models	Motorized and Non-motorized vehicles	Air pollution negatively impacts non-motorized transport mode choice.
Zhao et al. [24]	Air pollution, PM2.5	Beijing, China	Binary logit model	Cycle, cars, taxis, buses, metros, and walking	Air quality significantly influences travel mode choices.

Table 1. *Cont.*

Reference	Pollution Type	Location	Method Used	Mode of Transport	Finding
Luo et al. [18]	Air pollution, PM2.5	Zhengzhou, China	Multinomial logit model (MNL) and difference-in-difference (DID) regression methods	Car, public transit, and active modes	Car commuters rebound towards car travel after health information.
Xu et al. [25]	Ambient air pollution	Xi'an, China	Regression model	N/A	People reduce travel area more than travel distance on polluted days.
Ercan et al. [22]	Emissions (CO, CO2, NOX, SOX, PM10, PM2.5, and VOCs)	929 urban areas in the U.S.	Multinomial logit model (MNL) and system dynamics (SD) modeling	Drive alone, carpool, public transportation, walk, and other	Vehicle ownership significantly impacts transportation mode choices.
Kim et al. [20]	Air pollution	Seoul, South Korea	Multilevel logistic regression modeling	Non-motorized modes (walking or biking), public transit (bus or subway), and cars	Lower-income groups shift to public transit during poor air quality.
Meena et al. [16]	Air pollution	Delhi, India	Machine learning models and logit model	Open and closed travel modes	Commuters prefer closed modes as air quality worsens.
Dabirinejad et al. [21]	Air pollution	Karaj, Iran	Exploratory factor analysis (EFA) and hybrid choice modeling (HCM)	Walking, car, and public transit	Poor air quality increases private car usage.
Kim et al. [19]	Particulate matter (PM)	Seoul, South Korea	Integrated Choice and Latent Variable (ICLV) model	Public transit	Public transit usage increases among lower-income groups during pollution events.
Meena et al. [23]	Air pollution	Delhi, India	Random Forest, XGBoost, Naive Bayes (NB), K-Nearest Neighbor, Support Vector Machine (SVM), and Multinomial logit model (MNL)	Auto rickshaw, bus, car, two-wheeler, two-wheeler sharing, walk, bicycle, car sharing, and metro	Commuters shift to closed modes during poor air quality.
Present study	Air pollution, PM2.5	Chiang Rai, Thailand	Descriptive statistic and Multinomial logit model (MNL),	Private car, motorcycle, public transport, and alternatives	Travel mode choice during non-air quality crisis and air quality crisis in urban area

While these studies have provided valuable insights into travel behavior during air pollution events, there remains a gap in understanding how the PM2.5 smog crisis specifically affects travel mode choices in Southeast Asian secondary cities, particularly in areas prone to seasonal smog events. The present study addresses this gap by examining travel mode choice behavior in Chiang Rai, Thailand, where severe seasonal air quality crises frequently occur. Using a combination of multinomial logit modeling (MNL) and descriptive statistics, this research investigates how commuters adapt their travel mode choices during non-air quality crisis and air quality crisis in an urban area where PM2.5 levels often exceed 150 $\mu g/m^3$ during the dry season. Unlike previous studies that primarily focused on major metropolitan areas, this research provides insights into travel behavior adaptations in a secondary city context, where transportation options and infrastructure may differ significantly from larger urban centers. The study's findings are particularly relevant for urban areas in the Greater Mekong Subregion that face similar seasonal air quality challenges, contributing to a more comprehensive understanding of how environmental crises affect transportation choices in developing regions.

2.2. Commuting Preference Analysis Methods

The analysis of commuting preferences and travel mode choices has employed various methodological approaches in transportation research. These methods aim to understand the factors influencing individuals' travel decisions and predict future travel behaviors. Transportation research has employed various methodological approaches to analyze commuting preferences and travel mode choices. Discrete choice models, particularly multinomial logit (MNL) and nested logit models, have been widely used to understand travel decisions [26]. The MNL model assumes that travelers choose the option that maximizes their utility, with the probability of choosing a particular mode expressed as a function of its attributes and the individual's characteristics. These models are often supported by data collected through stated preference (SP) and revealed preference (RP) surveys. SP surveys present hypothetical scenarios to understand potential behavioral responses, while RP surveys collect data on actual travel behaviors, emphasizing the value of combining both approaches for robust analysis [27]. Advanced econometric techniques have also been applied, such as the multiple discrete-continuous extreme value (MDCEV) model for analyzing activity–travel behavior [28]. This model extends traditional discrete choice frameworks by simultaneously considering multiple alternatives and their usage intensities. Machine learning techniques have gained prominence in recent years, with methods such as random forests and support vector machines often achieving higher predictive accuracy than traditional logit models [29]. These advanced techniques can capture complex non-linear relationships and interactions between variables that might be missed by conventional approaches. Structural equation modeling (SEM) has also been employed to examine the intricate relationships between various factors influencing travel behavior, with SEM being used to analyze how residential location choice, travel attitudes, and actual travel behavior interact [30]. Logistic regression models have been used to examine the impact of air pollution on cycling behavior in Beijing [24]. Time series analysis has been applied to investigate the relationship between extreme haze events and public transit ridership [31].

While substantial research has been conducted on the relationship between air pollution and travel behavior, there remains a gap in understanding these dynamics in the specific context of Chiang Rai, Thailand. The unique characteristics of the region, including its seasonal air quality crisis, socioeconomic factors, and existing transportation infrastructure, warrant a focused investigation. Additionally, most studies have examined general air pollution levels rather than acute air quality crisis events, which may elicit different behavioral responses. This study aims to address these gaps by providing insights into travel mode choice preferences during an air quality crisis in Chiang Rai, contributing to the broader understanding of how environmental factors influence urban mobility in Southeast Asian contexts.

3. Methodology

3.1. Study Area

This study was conducted in Chiang Rai province, the northernmost province of Thailand. Covering an area of 11,678 km^2, Chiang Rai is characterized by its diverse topography, including mountains, hills, and lowland plains. As of 2024, Chiang Rai had a population of 1,298,977 [32]. The climate of Chiang Rai is tropical savanna, characterized by distinct wet and dry seasons. The dry season, from November to April, coincides with the period of severe air pollution events. The practice of crop residue burning, particularly prevalent during the dry season, significantly contributes to the region's air pollution problems [7]. During these air quality crises, PM2.5 levels often exceed 150 $\mu g/m^3$, significantly higher than the World Health Organization's guideline of 25 $\mu g/m^3$ for 24 h mean [4]. In 2023, Chiang Rai experienced 76 days where PM2.5 levels exceeded the Thai national standard of 50 $\mu g/m^3$ [33].

3.2. Data Collection

This study employed a probability sampling approach to ensure representative data collection from Chiang Rai province's population. The sample size was calculated using Taro Yamane's Formula as Equation (1) [34], considering Chiang Rai's population of 1,298,977, a 95% confidence level, and a 5% margin of error, yielding a minimum required sample size of 400 respondents.

$$n = \frac{N}{1 + Ne^2} \tag{1}$$

Initially, stratified random sampling was planned to ensure proportional demographic representation. However, practical limitations during implementation, including restricted access to comprehensive population lists, necessitated adopting simple random sampling while maintaining the probability framework. The survey was administered through an online questionnaire using Google Forms, optimized for mobile devices and available in Thai with English translation. Average completion time was 15–20 min. Prior to deployment, the questionnaire underwent pilot testing with 20 respondents and cognitive interviews using think-aloud protocols to ensure clarity and effectiveness. Minor adjustments were made based on feedback before online deployment from February to March 2024. Multiple distribution channels maintained random sampling integrity, including social network service (SNS), community networks through district offices, university networks, and community leaders in rural areas. QR codes were strategically posted in public spaces for easy access. To address online survey coverage bias, supplementary data collection methods were employed for respondents lacking internet access, including telephone interviews and paper-based questionnaires administered by trained enumerators. A total of 428 responses were received, with 406 deemed valid after data cleaning (response rate: 95%). Invalid responses were removed due to incomplete information, duplicate submissions, out-of-province residents, or inconsistent response patterns. This implementation enhances sample representativeness while acknowledging demographic limitations inherent in online survey methodology.

3.3. Survey Instruments

The questionnaire was designed with four sections: (1) demographic information, (2) impact of the air quality crisis, (3) travel behavior under non-air quality crisis, and (4) travel behavior during the air quality crisis. Demographic information included gender, age, occupation, income, marital status, vehicle ownership, and driving license status. Questions about experiences during air quality crisis and perceived main causes were included. Travel behavior sections covered mode choice, travel time, cost, frequency, and distance for both non-air quality crisis and air quality crisis conditions. This approach of comparing travel behavior across different environmental conditions aligns with previous studies examining the impact of air pollution on mode choice [24]. The questionnaire utilized a multiple-choice approach to capture both quantitative data. This approach allows for a nuanced understanding of travel behavior changes, similar to methods used in recent studies examining environmental impacts on transportation choices [35].

3.4. Analysis Method

The multinomial logit model (MNL) approach has been successfully applied in various Southeast Asian contexts to identify statistically significant parameters that determine choice probabilities among discrete alternatives [36,37]. A comprehensive analytical approach was employed to examine travel mode choices during non-air quality crisis (N-AQC) and air quality crisis (AQC) periods in Chiang Rai, based on random utility theory. The dependent variable was travel mode choice, with data collected from identical respondents across both periods, creating paired samples for direct comparison of individual behavioral changes. Prior to analysis, the dataset underwent preparation, including categorical variable coding using effect coding, continuous variable standardization, and missing data handling using multiple imputation with chained equations [38]. The utility function for individual mode choice was specified as Equation (2) [39].

$$U_i = V_i + \varepsilon_i \tag{2}$$

Here, U_i represents the utility of mode i, V_i is the deterministic component of utility for mode i often modeled as Equation (3), and ε_i is the random error term assumed to be independently capturing unobservable factors influencing the choice.

$$V_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \cdots + \beta_k x_{ki} \tag{3}$$

This modeling method was employed to model travel mode choices, a method widely used in transportation research for analyzing discrete choice scenarios [26]. This technique allows for estimating the probability of selecting a specific travel mode from multiple alternatives, considering various predictor variables. Information on travel costs, time, and other characteristics was collected for the respondent's actual chosen mode rather than for all potential alternatives. This approach provides revealed preference data about the selected mode but does not include attributes of non-chosen alternatives. Consequently, the multinomial logit model estimated in this study captured the influence of sociodemographic factors and trip characteristics on mode choice.

The probability estimation model, as expressed in Equation (4), where $P(Y = i)$ represents the probability of choosing travel mode i and V_i is the systematic utility of that mode. The numerator, $\exp(V_i)$, converts the utility into a positive number, making it comparable across options. The denominator, $\sum_{j=1}^{J} \exp(V_j)$, sums the exponentiated utilities of all available travel modes to ensure that the total probability across all choices adds up to 1. This model specification allows for the examination of how factors such as travel time, cost, frequency, and distance, as well as demographic characteristics, influence mode choice during non-air quality crisis and air quality crisis. Similar approaches have been used in studies examining the impact of environmental factors on travel behavior [40].

$$P(Y = i) = \frac{\exp(V_i)}{\sum_{j=1}^{J} \exp(V_j)} \tag{4}$$

The model's performance was assessed using Akaike's Information Criteria (AIC) and Bayesian Information Criteria (BIC). These information criteria are valuable tools for comparing different model specifications and selecting the most appropriate model. In addition to AIC and BIC, McFadden, Cox and Snell, and Nagelkerke pseudo R-squared (R^2) were calculated to assess model fit [41].

4. Results

4.1. Demographic Characteristics of Respondents

The respondent profile reveals critical socioeconomic and demographic patterns relevant to travel behavior under environmental stress. The sample was predominantly female (63.8%), with males comprising 31.3% and individuals identifying as other genders making up 4.9%. A significant proportion of respondents were young adults, with 85.9% under the age of 30, indicating a digitally engaged and mobile demographic often reached through online survey platforms. The largest age group, 21–30 years, accounted for 59.1% of the sample, likely influenced by outreach through universities and social media channels. Income levels were skewed toward the lower end of the spectrum, with over half (53.9%) earning less than 10,000 THB per month and only a small minority (2.7%) earning more than 50,000 THB. This economic distribution highlights potential vulnerabilities to rising transport costs, particularly during an air quality crisis. Regarding marital status, 83.5% of respondents were unmarried, again underscoring a young, possibly student-heavy population. Vehicle ownership was relatively high at 82.3%, although the majority held motorcycle licenses (56.4%) rather than private car licenses (40.6%). This suggests a mobility pattern dominated by two-wheeled transport, a common feature in many Southeast Asian secondary cities where affordability and accessibility shape transport choices. These demographic trends provide essential context for interpreting the model estimates and behavioral responses reported later in the study. The socioeconomic composition of the sample, predominantly young, low-income, and motorcycle-reliant, directly informs how individuals respond to environmental hazards such as air pollution. A detailed breakdown of respondent characteristics is provided in Table 2.

Table 2. Respondent characteristics.

Item	Value: Description	Count	Percent
Total of respondents		406	100
Gender	1: Male	127	31.3
	2: Female	259	63.8
	3: Others	20	4.9
Age (years)	1: <21	109	26.8
	2: 21–30	240	59.1
	3: 31–40	22	5.4
	4: 41–50	25	6.2
	5: 51–60	10	2.5
Monthly income (THB)	1: <10,000	219	53.9
	2: 10,001–15,000	38	9.4
	3: 15,000–20,000	82	20.2
	4: 20,001–30,000	37	9.1
	5: 30,001–40,000	11	2.7
	6: 40,001–50,000	8	2.0
	7: >50,001	11	2.7

Table 2. *Cont.*

Item	Value: Description	Count	Percent
Marital status	1: Unmarried	339	83.5
	2: Married	37	9.1
	3: Not mentioned	30	7.4
Vehicle ownership	0: No	72	17.7
	1: Yes	334	82.3
Holding motorcycle driving license	0: No	177	43.6
	1: Yes	229	56.4
Holding private car driving license	0: No	241	59.4
	1: Yes	165	40.6

Note: 32.435 THB = 1 USD (Bank of Thailand, 27 September 2024).

4.2. Analysis of Travel Distributions

Travel behavior patterns were analyzed across five key dimensions during non-air quality crisis (N-AQC) and air quality crisis (AQC) periods: travel time, travel cost, travel frequency, travel distance, and travel mode distributions. The analysis revealed significant shifts in travel patterns between these periods, reflecting adaptations in response to air quality conditions. Each distribution was examined to identify changes in modal preferences and travel characteristics that emerged during an air quality crisis.

4.2.1. Travel Time Distributions

Based on the travel time distribution data in Figure 2, the most significant change occurs in motorcycle usage, with an 8% increase for trips lasting 11–20 min during an air quality crisis. This suggests a shift towards shorter motorcycle trips when air quality deteriorates. Alternatives also see a marked increase, with a 5% rise in the same 11–20 min range, indicating a greater preference for using alternatives for short trips during an air quality crisis. Private car use shows a modest 2% decrease for trips in the 21–30 min range, while public transport experiences a slight 1 percentage point increase for 11–20 min journeys. These patterns collectively suggest that during an air quality crisis, residents of Chiang Rai tend to opt for shorter trips, with a particular preference for motorcycles and alternatives for shorter distances.

4.2.2. Travel Cost Distribution

The travel cost distributions reveal several notable shifts in commuter behavior. As demonstrated in Figure 3, the most significant change is observed in motorcycle usage, where trips costing less than 50 THB decreased 5%, indicating a drop in all motorcycle trips. This substantial reduction in low-cost motorcycle journeys suggests a shift away from this mode for shorter trips during an air quality crisis. An increase of 2–3% in private car use in the 101–150 THB range during an air quality crisis indicates a potential shift towards longer or different car trips. Public transport usage decreased marginally (1–2%) across all cost categories, reflecting a general reduction in public transit use. Interestingly, alternative transport experienced a small increase of 2–3% in the 101–150 THB range, suggesting some commuters may be opting for alternatives during an air quality crisis. Overall, these changes point to a general trend of slightly higher travel costs across most modes during an air quality crisis, with the most pronounced shift being away from motorcycle trips.

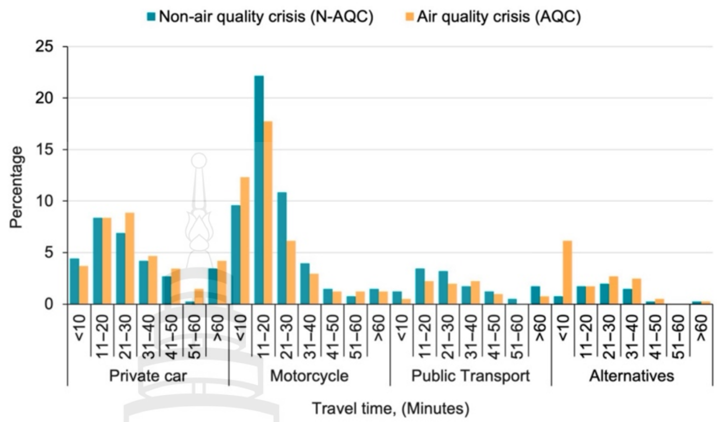

Figure 2. Travel time distributions.

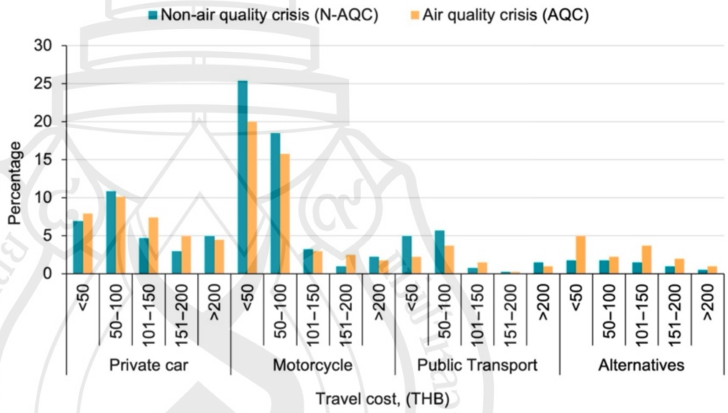

Figure 3. Travel cost distribution.

4.2.3. Travel Frequency Changes

The shifts in travel frequency behavior are shown in Figure 4, particularly in lower-frequency travel categories. Private car use in the 2–3 trips per week category increases 5%, while motorcycle use in the same category shows an even greater increase, by 8 percent. Public transport experiences a modest rise of 2% for 2–3 trips per week. However, the most striking change is observed in alternative transportation. The percentage of people using alternatives for 1 trip per week jumps from near 0% to 5%, and for 2–3 trips per week it increases from 1% to 4%. These trends indicate a general reduction in travel frequency during an air quality crisis, especially for private vehicles, coupled with a substantial increase in the use of alternatives. This shift suggests that residents are adapting their travel behaviors in response to air quality crisis, likely prioritizing essential trips and perceived safer travel options during periods of high air pollution.

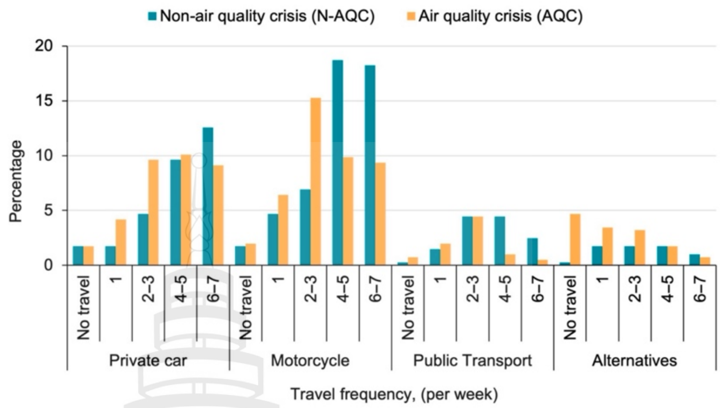

Figure 4. Travel frequency changes.

4.2.4. Travel Distance Changes

The statistic of travel distance reveals several notable shifts in behavior. As shown in Figure 5, the most significant change is observed in motorcycle usage for longer trips (>5 km), which decreases by approximately 11% during air quality crisis. Conversely, alternatives for shorter trips (<5 km) see a substantial increase of around 6%. Motorcycle use for shorter trips shows a modest increase of about 3% points, while private car use for short distances also rises by roughly 4%. These shifts indicate a clear tendency towards reduced exposure during longer trips and increased use of alternatives for shorter distances when air quality is poor. The data suggest that residents adapt their travel behaviors in response to air quality crisis, prioritizing shorter trips and exploring alternatives to minimize their exposure to pollutants.

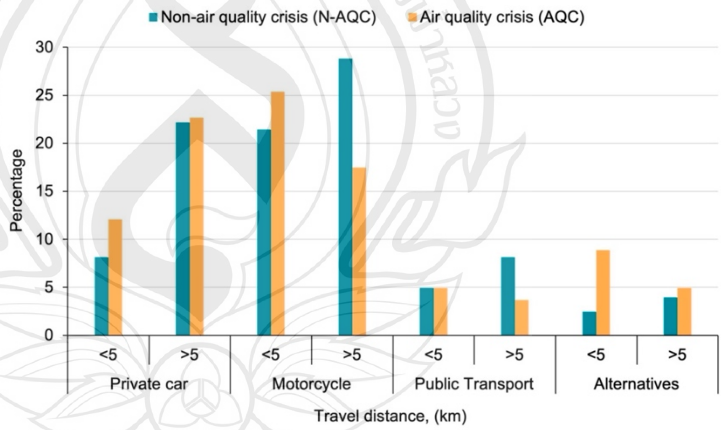

Figure 5. Travel distance distribution.

4.2.5. Travel Mode Distributions

Analysis of travel mode selection in Chiang Rai, Thailand, as shown in Table 3, reveals significant shifts during an air quality crisis compared to a non-air quality crisis. Private car usage increased by 4.40% points to 34.70%, indicating a preference for enclosed transportation during an air quality crisis. Motorcycle usage saw the largest decrease, dropping 7.30% points to 42.90%, likely due to increased pollution exposure. Public transport usage declined by 4.50% points to 8.60%, possibly reflecting concerns about shared spaces. Notably, alternatives experienced the most substantial increase, rising 7.40% points to 13.80%, suggesting adaptive behavior among residents seeking flexible or less exposed travel options. The "Alternatives" category combines transportation modes with varying air pollution exposure profiles. In Chiang Rai, walking and biking constitute small portions of overall mode share, necessitating their combination with other alternative modes for adequate statistical analysis. Preliminary examination indicated taxi-based services showed proportionally larger increases during air quality crisis compared to active transportation, though sample constraints prevented robust conclusions. This suggests a preference for enclosed alternatives that minimize pollutant exposure, demonstrating that air quality significantly influences mode choices toward enclosed transportation during an air quality crisis.

Table 3. Travel mode distributions.

Travel Mode	Percentage	
	N-AQC	**AQC**
Private car	30.30	34.70
Motorcycle	50.20	42.90
Public transport	13.10	8.60
Alternatives	6.40	13.80

Note: N-AQC is non-air quality crisis; AQC is air quality crisis.

4.3. Mode Choice for Non-Air Quality Crisis (N-AQC)

4.3.1. Likelihood Ratio Tests and Collinearity Matrix (N-AQC)

The likelihood ratio tests reveal that all examined factors significantly influence travel mode choice under a non-air quality crisis in Chiang Rai, Thailand ($p < 0.05$), as shown in Table 4. The test results demonstrate high statistical significance ($p < 0.001$). The most influential factors include holding a private car driving license, holding a motorcycle driving license, vehicle ownership, travel cost, and income. Other significant factors encompass travel time, healthcare effects, gender, age, financial effects, and marital status. The high chi-square values and low p-values (all $p \leq 0.038$) suggest these variables are Thistrong predictors of mode choice in a non-air quality crisis. The collinearity matrix presented in Table 5 confirms the statistical robustness of the model. Pearson correlation analysis demonstrates that all pairs of independent variables maintain correlation coefficients below 0.80, effectively ruling out significant multicollinearity concerns [42]. Among the observed relationships, three moderate correlations emerge: age and income (r = 0.562), travel time and cost (r = 0.462), and income and holding a private car driving license (r = 0.411). All other variable pairs exhibit weak correlations (r < 0.5), indicating their relative independence. This statistical independence of predictor variables establishes a sound methodological foundation, enabling reliable analysis of travel behavior patterns both under non-air quality crisis and during air quality crisis.

Table 4. Likelihood ratio tests of non-air quality crisis (N-AQC).

Effect	Chi-Square	df	Sig.
Intercept	15.011	3	0.002 **
Gender	13.772	3	0.003 **
Age	11.660	3	0.009 **
Monthly income	17.954	3	<0.000 ***
Marital status	8.407	3	0.038 *
Vehicle ownership	24.308	3	<0.000 ***
Holding a motorcycle driving license	31.509	3	<0.000 ***
Holding a private car driving license	36.885	3	<0.000 ***
Effect on healthcare	16.341	3	0.001 **
Effect on finance	9.509	3	0.023 *
Travel time	16.703	3	0.001 **
Travel cost	20.630	3	<0.000 ***

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 5. Collinearity matrix of independent variable for non-air quality crisis (N-AQC).

	X_G	X_A	X_{MI}	X_{MS}	X_{VO}	X_{MCDL}	X_{PCDL}	X_{EH}	X_{EF}	X_{TT}	X_{TC}
X_G	-										
X_A	−0.112	-									
X_{MI}	−0.149	0.562	-								
X_{MS}	−0.075	0.177	0.074	-							
X_{VO}	−0.107	0.180	0.119	−0.076	-						
X_{MCDL}	−0.043	0.072	0.048	−0.023	0.294	-					
X_{PCDL}	−0.153	0.360	0.411	0.005	0.187	0.111	-				
X_{EH}	0.109	0.066	0.040	−0.081	−0.046	0.028	0.053	-			
X_{EF}	0.034	0.000	−0.027	−0.004	−0.084	0.031	−0.048	0.185	-		
X_{TT}	−0.068	0.189	0.126	0.023	0.051	0.015	0.196	−0.009	−0.066	-	
X_{TC}	−0.072	0.202	0.214	0.047	0.076	−0.058	0.185	−0.002	−0.073	0.462	-

Note: X_G: gender, X_A: Age, X_{MI}: monthly income, X_{MS}: marital status, X_{VO}: vehicle ownership, X_{MCDL}: holding a motorcycle driving license, X_{PCDL}: holding a private car driving license, X_{EH}: effect on healthcare, X_{EF}: effect on finance, X_{TT}: travel time, X_{TC}: travel cost.

4.3.2. Multinomial Logit Model Parameter Estimates and Utility Function (N-AQC)

A multinomial logit model analysis was conducted to examine travel mode choice behavior under a non-air quality crisis, with private car designated as the reference category, as presented in Table 6. The model revealed several significant socioeconomic and travel-related factors influencing mode choice across different transportation options. The utility function for mode choice during non-air quality crisis (N-AQC) was specified as Equation (5).

$$U_{N-AQC} = \alpha X_G + \beta X_A + \gamma X_{MI} + \delta X_{MS} + \varepsilon X_{VO} + \zeta X_{MCDL} + \eta X_{PCDL} + \theta X_{EH} + \iota X_{EF} + \kappa X_{TT} + \lambda X_{TC} + c \quad (5)$$

Here, the variables represent X_G: gender, X_A: age, X_{MI}: monthly income, X_{MS}: marital status, X_{VO}: vehicle ownership, X_{MCDL}: holding a motorcycle driving license, X_{PCDL}: holding a private car driving license, X_{EH}: effect on healthcare, X_{EF}: effect on finance, X_{TT}: travel time, and X_{TC}: travel cost.

Table 6. MNL parameter estimates of non-air quality crisis model (N-AQC).

Mode	Variable	Coef.	Sig.	Odds Ratio
Motorcycle	Intercept	2.832	0.002 **	
	Gender (X_G)	0.019	0.944	1.019
	Age (X_A)	0.058	0.780	1.059
	Monthly income (X_{MI})	−0.454	***	0.635
	Marital status (X_{MS})	−0.475	0.046 *	0.622
	Vehicle ownership (X_{VO})	−0.331	0.474	0.718
	Holding motorcycle driving license (X_{MCDL})	1.252	***	3.496
	Holding private car driving license (X_{PCDL})	−1.776	***	0.169
	Effect on healthcare (X_{EH})	0.867	0.047 *	2.379
	Effect on finance (X_{EF})	0.180	0.588	1.197
	Travel time (X_{TT})	−0.097	0.344	0.907
	Travel cost (X_{TC})	−0.477	***	0.621
Public transport	Intercept	−0.375	0.746	
	Gender (X_G)	1.248	0.001 **	3.485
	Age (X_A)	0.857	0.002 **	2.356
	Monthly income (X_{MI})	−0.475	0.005 **	0.622
	Marital status (X_{MS})	−0.681	0.048 *	0.506
	Vehicle ownership (X_{VO})	−2.045	***	0.129
	Holding motorcycle driving license (X_{MCDL})	−0.392	0.355	0.676
	Holding private car driving license (X_{PCDL})	−1.346	0.003 **	0.260
	Effect on healthcare (X_{EH})	−1.030	0.067	0.357
	Effect on finance (X_{EF})	1.200	0.006 **	3.321
	Travel time (X_{TT})	0.388	0.003 **	1.474
	Travel cost (X_{TC})	−0.427	0.025 *	0.652
Alternatives	Intercept	1.396	0.335	
	Gender (X_G)	0.431	0.381	1.539
	Age (X_A)	0.452	0.206	1.572
	Monthly income (X_{MI})	−0.236	0.210	0.790
	Marital status (X_{MS})	−1.111	0.039 *	0.329
	Vehicle ownership (X_{VO})	−1.797	0.003 **	0.166
	Holding motorcycle driving license (X_{MCDL})	−0.457	0.395	0.633
	Holding private car driving license (X_{PCDL})	−2.045	0.001 **	0.129
	Effect on healthcare (X_{EH})	−1.056	0.093	0.348
	Effect on finance (X_{EF})	0.869	0.108	2.386
	Travel time (X_{TT})	0.027	0.868	1.027
	Travel cost (X_{TC})	0.141	0.481	1.152

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; reference mode: private car.

The analysis of motorcycle usage revealed that income has a significant negative effect ($\alpha = -0.454$), indicating that higher-income individuals are less likely to choose motorcycles over private cars. License possession showed contrasting effects—holding a motorcycle license significantly increased the likelihood of motorcycle use ($\beta = 1.252$), while possession of a car license decreased it ($\gamma = -1.776$). Travel cost demonstrated a negative relationship with motorcycle choice ($\delta = -0.477$), suggesting cost sensitivity among motorcycle users. For public transport, gender and age emerged as significant positive factors, with females ($\varepsilon = 1.248$) and older individuals ($\zeta = 0.857$) showing higher probabilities of choosing this mode. Income exhibited a negative relationship with public transport use ($\alpha = -0.475$), while travel time showed a positive effect ($\theta = 0.388$), possibly reflecting the reliability of scheduled services for longer journeys. Vehicle ownership was found to significantly decrease public transport use ($\eta = -2.045$). Regarding alternative modes, marital status showed a significant negative effect ($\iota = -1.111$). Both vehicle ownership ($\eta = -1.797$) and possession of a car license ($\gamma = -2.045$) were found to substantially decrease the likelihood of choosing alternative transportation modes. The findings align with previous studies on mode choice behavior in Southeast Asian contexts. This comprehensive analysis provides valuable insights into the factors influencing travel mode choices under a non-air quality crisis, establishing a baseline for comparison with behavior during an air quality crisis. The model's results highlight the complex interplay between socioeconomic characteristics, travel attributes, and mode choice decisions.

4.3.3. Model Fitting and Predictive Accuracy of Non-Air Quality Crisis Model (N-AQC)

The model fitting results for the multinomial logistic regression (MNL) under non-air quality crisis (N-AQC) conditions are summarized in Table 7. The model fitting criteria indicated that the final model (AIC = 746.099; BIC = 890.328) performed substantially better than the intercept model (AIC = 939.296; BIC = 951.316), suggesting an improved fit with the inclusion of explanatory variables. The decrease in −2 Log Likelihood from 933.296 to 674.099 further supported this improvement. The likelihood ratio test revealed a statistically significant chi-square value of 259.197 with 33 degrees of freedom ($p < 0.001$), confirming that the predictors significantly contributed to explaining mode choice behavior during non-crisis periods [10,43].

Table 7. Model summary of multinomial logistic regression for non-air quality crisis (N-AQC).

Model Info	Model Fitting Criteria	Likelihood Ratio Tests	Goodness-of-Fit	Pseudo R-Square
Model (N-AQC)	AIC: 939.296 (Intercept) 746.099 (Final) BIC: 951.316 (Intercept) 890.328 (Final) −2 Log Likelihood: 933.296 (Intercept) 674.099 (Final)	Chi-Square: 259.197 df: 33 Sig.: 0.000 ***	Pearson Chi-Square: 1306.169 df: 1182 $p = 0.007$ Deviance: 674.099 df: 1182 $p = 1.000$	Cox and Snell: 0.472 Nagelkerke: 0.525 McFadden: 0.278

Note: *** $p < 0.001$.

In terms of goodness-of-fit, the deviance statistic was 674.099 with a p-value of 1.000, indicating an excellent model fit with no significant deviation from the saturated model. However, the Pearson chi-square value of 1306.169 (df = 1182, $p = 0.007$) suggested a marginal lack of fit, which could be attributed to the large sample size or data sparsity in certain categories [44]. The model's explanatory power, assessed through pseudo R-square statistics, showed acceptable levels: Cox and Snell $R^2 = 0.472$, Nagelkerke $R^2 = 0.525$, and McFadden $R^2 = 0.278$. These values indicate that the model accounted for approximately 47% to 53% of the variance in mode choice [41].

The classification results in Table 8 evaluated the predictive accuracy of the model. The overall correct classification rate was 67.5%, indicating that the model correctly predicted two-thirds of the respondents' travel mode choices under non-crisis conditions. The highest predictive accuracy was observed for motorcycle users at 83.3%, followed by private car users at 65.9%. In contrast, the model performed less effectively in predicting public transport users (35.8%) and those choosing alternative modes (15.4%). These findings suggest that while the model performs well for dominant travel modes, further refinement may be necessary to improve predictive performance for less frequently used or more heterogeneous modes [45,46].

Table 8. Percentage correct for non-air quality crisis (N-AQC).

	Classification				
Observed	**Private Car**	**Motorcycle**	**Public Transport**	**Alternatives**	**Percent Correct**
Private car	81	38	2	2	65.90%
Motorcycle	24	170	10	0	83.30%
Public transport	7	26	19	1	35.80%
Alternatives	6	12	4	4	15.40%
Overall Percentage	29.10%	60.60%	8.60%	1.70%	67.50%

4.4. Mode Choice for Air Quality Crisis (AQC)

4.4.1. Likelihood Ratio Tests and Collinearity Matrix (AQC)

The Likelihood ratio tests, as presented in Table 9, indicate that holding a private car driving license, travel frequency, travel time, and vehicle ownership are the most influential predictors. The test results demonstrate high statistical significance ($p < 0.001$). Monthly income, travel cost, and financial impacts of the air quality crisis also significantly affect mode choice. Notably, possession of a motorcycle license was not statistically significant. The collinearity matrix presented in Table 10 confirms the statistical soundness of the model through Pearson correlation analysis. The analysis reveals that no pairs of independent variables exceed the correlation coefficient threshold of 0.80, effectively addressing multicollinearity concerns [42]. The strongest observed correlation exists between travel time and cost (r = 0.559), while moderate correlations are identified between monthly income and private car license ownership (r = 0.411) and between vehicle ownership and motorcycle license possession (r = 0.294). All other variable pairs demonstrate weak correlations (r < 0.5), indicating their relative independence. These statistical relationships, particularly those involving vehicle access and travel characteristics, illuminate the significant role of socioeconomic factors in shaping travel behavior during periods of air quality crisis. The robust model structure, characterized by significant predictors and minimal variable interdependence, provides a reliable framework for understanding mode choice dynamics during an air quality crisis in this urban context.

Table 9. Likelihood ratio tests of air quality crisis (AQC).

Effect	Chi-Square	df	Sig.
Intercept	22.067	3	<0.000 ***
Monthly income	16.396	3	<0.000 ***
Vehicle ownership	19.720	3	<0.000 ***
Holding motorcycle driving license	18.502	3	<0.000 ***
Holding private car driving license	42.441	3	<0.000 ***
Effect on finance	11.451	3	0.010 *
Travel time	28.396	3	<0.000 ***
Travel cost	17.775	3	<0.000 ***
Travel frequency	41.544	3	<0.000 ***

Note: * $p < 0.05$, *** $p < 0.001$.

Table 10. Collinearity matrix of independent variables for air quality crisis (AQC).

	X_{MI}	X_{VO}	X_{MCDL}	X_{PCDL}	X_{EF}	X_{TT}	X_{TC}	X_{TF}
X_{MI}	-							
X_{VO}	0.119	-						
X_{MCDL}	0.048	0.294	-					
X_{PCDL}	0.411	0.187	0.111	-				
X_{EF}	−0.027	−0.084	0.031	−0.048	-			
X_{TT}	0.161	0.114	0.074	0.215	−0.102	-		
X_{TC}	0.215	0.079	−0.041	0.177	−0.068	0.559	-	
X_{TF}	0.161	0.224	0.112	0.154	−0.018	0.264	0.140	-

Note: X_{MI} : monthly income, X_{VO} : vehicle ownership, X_{MCDL} : holding a motorcycle driving license, X_{PCDL} : holding a private car driving license, X_{EF} : effect on finance, X_{TT} : travel time, X_{TC} : travel cost, X_{TF} : travel frequency.

4.4.2. Multinomial Logit Model Parameter Estimates and Utility Function (AQC)

An MNL model analysis was conducted to examine travel mode choice behavior during an air quality crisis, with private car serving as the reference category, as presented in Table 11. The model identified several significant factors that influence mode choice during an air quality crisis. The utility function for mode choice during an air quality crisis (AQC) was specified as Equation (6).

$$U_{AQC} = \alpha X_{MI} + \beta X_{VO} + \gamma X_{MCDL} + \delta X_{PCDL} + \varepsilon X_{EF} + \zeta X_{TT} + \eta X_{TC} + \theta X_{TF} + c \quad (6)$$

Table 11. MNL parameter estimates of air quality crisis model (AQC).

Mode	Variable	Coef.	Sig.	Odds Ratio
Motorcycle	Intercept	1.814	0.002 **	
	Monthly income (X_{MI})	−0.386	***	0.680
	Vehicle ownership (X_{VO})	0.352	0.422	1.423
	Holding motorcycle driving license (X_{MCDL})	1.087	***	2.967
	Holding private car driving license (X_{PCDL})	−1.886	***	0.152
	Effect on finance (X_{EF})	0.540	0.097	1.715
	Travel time (X_{TT})	−0.326	0.002 **	0.722
	Travel cost (X_{TC})	−0.282	0.041 *	0.755
	Travel frequency (X_{TF})	0.147	0.252	1.158
Public transport	Intercept	1.539	0.039 *	
	Monthly income (X_{MI})	−0.400	0.040 *	0.670
	Vehicle ownership (X_{VO})	−1.318	0.010 *	0.268
	Holding motorcycle driving license (X_{MCDL})	−0.315	0.511	0.730
	Holding private car driving license (X_{PCDL})	−1.398	0.006 **	0.247
	Effect on finance (X_{EF})	1.304	0.005 **	3.685
	Travel time (X_{TT})	0.337	0.025 *	1.400
	Travel cost (X_{TC})	−0.226	0.283	0.797
	Travel frequency (X_{TF})	−0.413	0.036 *	0.662
Alternatives	Intercept	2.798	***	
	Monthly income (X_{MI})	−0.058	0.652	0.944
	Vehicle ownership (X_{VO})	−1.159	0.011 *	0.314
	Holding motorcycle driving license (X_{MCDL})	0.086	0.828	1.090
	Holding private car driving license (X_{PCDL})	−1.101	0.009 **	0.332
	Effect on finance (X_{EF})	1.109	0.006 **	3.030
	Travel time (X_{TT})	−0.384	0.012 *	0.681
	Travel cost (X_{TC})	0.418	0.015 *	1.520
	Travel frequency (X_{TF})	−0.849	***	0.428

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; reference mode: private car.

Here, the variables represent X_{MI} : monthly income, X_{VO} : vehicle ownership, X_{MCDL} : holding a motorcycle driving license, X_{PCDL} : holding a private car driving license, X_{EF} : effect on finance, X_{TT} : travel time, X_{TC} : travel cost, and X_{TF} : travel frequency.

The analysis of motorcycle usage during air quality crisis revealed that income maintains a significant negative effect ($\alpha = -0.386$), indicating that higher-income individuals are less likely to choose motorcycles over private cars. License possession continued to show contrasting effects; holding a motorcycle license remained positively significant ($\gamma = 1.087$), while possession of a car license decreased motorcycle utility ($\delta = -1.886$). Both travel time ($\zeta = -0.326$) and costs ($\eta = -0.282$) emerged as significant deterrents during air quality crisis conditions, suggesting increased sensitivity to these factors during an air quality crisis.

For public transport, income demonstrated a persistent negative influence ($\alpha = -0.400$), while vehicle ownership substantially reduced its utility ($\beta = -1.318$). Notably, financial considerations showed heightened importance during the air quality crisis ($\varepsilon = 1.304$), suggesting that economic factors become more crucial in mode choice decisions during these periods. Travel frequency exhibited a negative association ($\theta = -0.413$), indicating that frequent travelers were less likely to opt for public transport during air quality crisis conditions. Alternative modes revealed distinct patterns during the air quality crisis, with financial effects showing a significant positive influence ($\varepsilon = 1.109$), while travel frequency demonstrated a strong negative relationship ($\theta = -0.849$). Vehicle ownership maintained its negative influence ($\beta = -1.159$) on the choice of alternatives. Interestingly, travel time ($\zeta = -0.384$) and travel costs ($\eta = 0.418$) showed opposing effects during air quality crisis conditions, suggesting a complex trade-off between these factors in mode choice decisions.

These findings highlight the significant shifts in travel mode choice behavior during an air quality crisis, particularly in how individuals weigh various factors such as financial impacts, travel characteristics, and personal resources in their transportation decisions. The differential coefficient patterns between N-AQC and AQC periods suggest the presence of implicit interaction effects between environmental conditions and behavioral determinants. For instance, the emergence of travel frequency as significant only during AQC periods (coefficients ranging from −0.849 to 0.147 across modes), as shown in Table 11, while demographic variables lose significance, indicates that environmental stressors fundamentally alter decision-making processes. The results provide valuable insights for transportation planning and policy development during an air quality crisis.

4.4.3. Model Fitting and Predictive Accuracy of Air Quality Crisis Model (AQC)

The model fitting results for the multinomial logistic regression (MNL) under air quality crisis (AQC) conditions are presented in Table 12. The reduction in AIC from 967.119 (intercept) to 745.348 (final model), and in BIC from 979.138 to 853.520, indicates that the model with predictors performs substantially better. Similarly, the drop in −2 Log Likelihood from 961.119 to 691.348 supports an improved model fit. The likelihood ratio test reported a significant chi-square value of 269.771 with 24 degrees of freedom ($p < 0.001$), suggesting that the final model provides a significantly better fit than the null model [35,47]. Regarding model adequacy, the deviance statistic was 669.272 with a non-significant p-value ($p = 1.000$), indicating no significant deviation from the saturated model. Additionally, the Pearson chi-square (1054.790, df = 1047, $p = 0.427$) further supports a good overall fit (Louviere, Hensher, & Swait, 2000) [48]. The pseudo R-square values Cox and Snell $R^2 = 0.485$, Nagelkerke $R^2 = 0.532$, and McFadden $R^2 = 0.273$ indicate56moderate explanatory power of the model, with Nagelkerke R^2 exceeding the commonly accepted threshold of 0.5 for behavioral models [49,50].

Table 12. Model summary of multinomial logistic regression for air quality crisis (AQC).

Model Info	Model Fitting Criteria	Likelihood Ratio Tests	Goodness-of-Fit	Pseudo R-Square
Model (AQC)	AIC: 967.119 (Intercept) 745.348 (Final) BIC: 979.138 (Intercept) 853.520 (Final) −2 Log Likelihood: 961.119 (Intercept) 691.348 (Final)	Chi-Square: 269.771 df: 24 Sig.: 0.000 ***	Pearson Chi-Square: 1054.790 df: 1047 $p = 0.427$ Deviance: 669.272 df: 1047 $p = 1.000$	Cox and Snell: 0.485 Nagelkerke: 0.532 McFadden: 0.273

Note: *** $p < 0.001$.

Table 13 presents the model's classification accuracy. An overall correct prediction rate of 63.8% was achieved, indicating that nearly two-thirds of actual mode choices were correctly classified. The highest prediction accuracy occurred for motorcycle users (81.0%), followed by private car users (64.5%). In contrast, the model showed weaker predictive accuracy for public transport (17.1%) and alternative modes (37.5%). This distribution of accuracy suggests that while the model is effective in capturing dominant travel behaviors, it may require further refinement or additional variables to improve prediction for less frequently chosen modes [51,52].

Table 13. Percentage correct for air quality crisis (AQC).

	Classification				
Observed	**Private Car**	**Motorcycle**	**Public Transport**	**Alternatives**	**Percent Correct**
Private car	91	37	4	9	64.50%
Motorcycle	24	141	2	7	81.00%
Public transport	8	13	6	8	17.10%
Alternatives	10	23	2	21	37.50%
Overall Percentage	32.80%	52.70%	3.40%	11.10%	63.80%

The analysis revealed significant differences in mode choice factors between non-air quality crisis (N-AQC) and air quality crisis (AQC) periods in Chiang Rai, Thailand, as shown in Table 14. Core economic and operational variables, including monthly income, vehicle ownership, driving licenses, travel time, and travel cost, remained significant across both conditions. However, demographic factors (gender, age, and marital status) were only significant during non-air quality crisis, while travel frequency emerged as significant exclusively during air quality crisis. This shift in significant variables suggests that environmental conditions substantially alter commuters' mode choice decision-making processes, with economic considerations maintaining importance regardless of air quality conditions. These findings provide valuable insights for developing targeted transportation policies that can adapt to varying air quality conditions.

Table 14. Significant variables in non-air quality crisis and air quality crisis models.

Variable	Significance in N-AQC Model	Significance in AQC Model	Interpretation
Gender	○		Significant only during non-air quality crisis
Age	○		Relevant for mode choice only in non-air quality crisis
Monthly income	○	○	Key factor influencing mode choice in both periods
Marital status	○		Only significant under non-air quality crisis
Vehicle ownership	○	○	Consistently significant; access to a vehicle strongly affects mode selection
Holding motorcycle driving license	○	○	Strong predictor for motorcycle use in both periods
Holding private car driving license	○	○	Influences private car and alternative mode decisions in both periods
Effect on healthcare	○		Perceived health impact mattered only during non-air quality crisis
Effect on finance	○	○	Financial concern significantly affects decisions in both scenarios
Travel time	○	○	Travel duration influences choice across both periods
Travel cost	○	○	Cost remains a significant determinant under all air quality conditions
Travel frequency		○	Becomes significant only during air quality crisis, indicating crisis-driven behavior change

Note: N-AQC is non-air quality crisis; AQC is air quality crisis; ○ is statistically significant ($p < 0.05$).

4.5. *The Predicted Probabilities of Transportation Mode*

Tables 15 and 16 present the predicted probabilities of transportation mode choices during non-air quality crisis and air quality crisis in Chiang Rai, Thailand. Transport mode preferences are strongly influenced by socioeconomic and demographic factors. Motorcycles emerge as the dominant mode of transport, particularly favored by younger individuals and lower-income groups. Private car usage increases significantly with income levels, while public transport becomes more prevalent among older age groups. Travel characteristics also play a key role, with longer journeys associated with higher public transport use and higher travel costs linked to increased private car usage. Vehicle ownership and possession of driving licenses strongly correlate with respective mode choices, with non-vehicle owners showing greater reliance on public transport. These findings reflect typical transportation patterns observed in Southeast Asian urban contexts, characterized by high motorcycle dependency among certain demographic groups.

For predicted probabilities of transportation mode choices during the air quality crisis in Chiang Rai, socioeconomic factors, particularly monthly income levels, significantly influence transportation preferences, with higher-income groups demonstrating a strong preference for private cars while lower-income groups predominantly rely on motorcycles. Vehicle ownership and licensing status also play crucial roles in mode selection, with license holders typically choosing their respective vehicle types and non-vehicle owners showing higher public transport usage. Travel characteristics emerge as important determinants—longer journey durations correlate with increased public transport use, while shorter journeys associate with higher motorcycle usage, and higher travel costs lead to greater utilization of alternative modes. The frequency of travel impacts mode selection, with regular commuters showing stronger preferences for private cars while occasional travelers demonstrate more varied choices. Additionally, the financial impact of the air quality crisis notably influences transportation decisions, where individuals reporting financial effects show distinct changes in their choices, including reduced private car usage and increased utilization of both public transport and alternative modes, demonstrating how economic constraints during an environmental crisis can significantly reshape transportation behavior.

Table 15. The predicted probabilities of transportation mode during non-air quality crisis (%).

	Private Car	Motorcycle	Public Transport	Alternatives
Gender				
Male	32	60	4	4
Female	28	54	12	6
Others	21	41	32	7
Age (years)				
<21	33	59	4	4
21–30	29	56	9	5
31–40	24	50	19	7
41–50	18	40	33	8
51–60	12	28	51	9
Monthly income (THB)				
<10,000	20	64	11	5
10,001–15,000	28	57	10	5
15,000–20,000	38	49	8	6
20,001–30,000	48	40	6	6
30,001–40,000	59	31	5	5
40,001–50,000	69	23	3	5
>50,001	77	16	2	4
Marital status				
Unmarried	27	57	10	6
Married	38	51	7	3
Not mentioned	51	43	5	1
Vehicle ownership				
No	17	42	28	13
Yes	32	57	7	4
Holding motorcycle driving license				
No	39	37	15	9
Yes	21	70	6	3
Holding private car driving license				
No	17	67	9	7
Yes	53	36	8	3
Effect on healthcare				
No	32	29	25	15
Yes	28	60	8	4
Effect on finance				
No	31	57	7	4
Yes	23	51	18	8
Travel time (Minutes)				
<10	28	63	4	5
10–20	29	60	7	5
21–30	29	56	10	5
31–40	29	51	15	6
41–50	29	45	21	6
51–60	27	38	29	5
>60	25	32	39	5
Travel cost (THB)				
<50	20	66	10	3
50–100	29	57	9	5
101–150	38	47	8	8
151–200	47	36	7	11
>200	54	26	5	15

Note: The predicted probabilities were calculated using the MNL model presented in Table 6. When generating predictions for each variable of interest, all other quantitative variables were held constant at their respective mean values, while categorical variables were fixed at their modal values.

Table 16. The predicted probabilities of transportation mode during air quality crisis (%).

	Private Car	Motorcycle	Public Transport	Alternatives
Monthly income (THB)				
<10,000	29	54	8	8
10,001–15,000	36	47	7	10
15,000–20,000	44	39	6	12
20,001–30,000	52	31	5	13
30,001–40,000	59	24	4	14
40,001–50,000	65	18	3	14
>50,001	70	13	2	15
Vehicle ownership				
No	32	29	17	22
Yes	37	49	6	8
Holding motorcycle driving license				
No	47	31	10	12
Yes	29	58	5	8
Holding private car driving license				
No	23	60	8	10
Yes	62	25	5	9
Effect on finance				
No	42	44	5	8
Yes	26	46	12	16
Travel time (Minutes)				
<10	26	57	3	14
10–20	32	51	5	12
21–30	38	44	8	10
31–40	44	36	12	8
Travel time (Minutes)				
41–50	47	28	18	6
51–60	49	21	26	4
>60	47	15	36	3
Travel cost (THB)				
<50	32	55	8	5
50–100	36	47	7	9
101–150	40	39	6	15
151–200	41	30	5	23
>200	40	22	4	34
Travel frequency (per weeks)				
No travel	24	20	11	45
1	32	32	10	26
2–3	37	43	8	13
4–5	38	51	5	6
6–7	51	20	12	16

Note: The predicted probabilities were calculated using the MNL model presented in Table 11. When generating predictions for each variable of interest, all other quantitative variables were held constant at their respective mean values, while categorical variables were fixed at their modal values.

The analysis of travel mode choices in Chiang Rai reveals distinct shifts between non-air quality crisis and air quality crisis. During an air quality crisis, private car usage decreased among higher-income groups (from 77 to 70%), while motorcycle dependency reduced among lower-income groups (from 64 to 54%). Public transport usage also declined, particularly among non-vehicle owners (from 28 to 17%). These changes indicate four key impacts of the air quality crisis: reduced overall mobility, preference for enclosed transport modes, increased health considerations, and stronger economic influences on travel decisions. These findings contribute to understanding environmental crisis impacts on travel behavior in Southeast Asian contexts, particularly in areas with high motorcycle dependency.

5. Discussion

5.1. Key Finding

The analysis revealed significant modal shifts in travel behavior during air quality crisis in Chiang Rai, Thailand, with private car usage increasing from 30.30% to 34.70% and motorcycle usage decreasing from 50.20% to 42.90%, while public transport declined from 13.10% to 8.60% and alternative modes increased substantially from 6.40% to 13.80%, indicating a clear preference for enclosed transportation during air quality crisis. Factors influencing mode choice differed between crisis and non-crisis periods, with socioeconomic variables including monthly income, vehicle ownership, and driving licenses remaining significant across both periods, while demographic factors such as gender, age, and marital status were only significant during non-crisis periods, and travel frequency emerged as a crucial determinant specifically during the air quality crisis. Economic factors became more influential during crisis periods, with financial impacts particularly pronounced among lower-income groups who shifted from private vehicles to public transport or alternative modes, while travel characteristics showed varying impacts across periods, with shorter trips becoming more prevalent during crisis and increased sensitivity to travel time and cost, particularly among motorcycle users, reflecting attempts to minimize pollution exposure.

5.2. Policy Implication

The analysis revealed significant modal shifts in travel behavior during an air quality crisis in Chiang Rai, Thailand. Specifically, private car usage increased from 30.30% to 34.70%, while motorcycle usage decreased from 50.20% to 42.90%. Public transport usage declined from 13.10% to 8.60%, and alternative modes (e.g., walking, biking, e-hailing) rose notably from 6.40% to 13.80%. These shifts highlight a clear preference for enclosed transportation during an air quality crisis, driven by concerns over pollutant exposure. Socioeconomic factors such as monthly income, vehicle ownership, and driving license status remained consistently influential across both the non-air quality crisis and air quality crisis. In contrast, demographic variables (gender, age, marital status) were significant only in non-crisis periods, while travel frequency emerged as a critical determinant specifically during air quality crises. These findings underscore the role of economic and behavioral adaptation in response to environmental stress and support the need for responsive transportation policies that can ensure mobility, safety, and equity during environmental crises.

Importantly, this study aligns with the United Nations Sustainable Development Goals (SDGs) [53], particularly SDG 11: Sustainable Cities and Communities, by providing actionable insights into how urban transport systems can become more resilient and inclusive in the face of environmental challenges. The findings also contribute to SDG 3: Good Health and Well-being by addressing how transport behaviors interact with public health risks from air pollution.

5.2.1. Low-Emission Public Transport Fleet Transition

The observed shift toward enclosed modes during air quality crisis conditions necessitates a phased transition to low-emission public transport, particularly targeting the Song-Teaw (mini-bus) fleet. Implementation should begin with installing air filtration systems in existing vehicles, followed by gradually replacing the fleet with electric alternatives through subsidized purchase programs [54]. The primary beneficiaries would be lower-income groups (53.9% of respondents earning <10,000 THB monthly) who rely heavily on public transportation during a crisis. To contextualize these income levels, 10,000 THB (approximately 308 USD) represents the minimum wage threshold in Thailand. For reference, typical local transportation costs in Chiang Rai include motorcycle taxi fares of 20–40 THB (0.60–1.25 USD) per trip, Song-Teaw (mini-bus) fares of 10–15 THB (0.30–0.45 USD), private car fuel costs of approximately 35–40 THB (1.08–1.23 USD) per liter of gasoline, and monthly motorcycle maintenance averaging 500–800 THB (15–25 USD). These transportation expenses can represent 15–25% of monthly income for the lowest-income respondents, making them particularly sensitive to mode choice decisions during an air quality crisis when health considerations may conflict with economic constraints [55].

5.2.2. Integrated Air Quality Monitoring and Transportation Information System

The finding that travel frequency becomes a significant factor during air quality crisis indicates the need for improved information systems to support decision-making. A comprehensive approach involving air quality monitoring stations integrated with transportation information platforms would enable travelers to make informed decisions during pollution events. Real-time air quality information has been shown to significantly influence travel decisions during pollution events in Beijing [56]. Such systems reduce health impacts through behavioral adaptation, with potential healthcare cost savings through decreased respiratory admissions during pollution events. Implementation would require inter-agency coordination within existing governance frameworks as documented in analyses of energy and environmental policy coordination in ASEAN countries [57].

5.2.3. Financial Support Mechanisms for Sustainable Mode Shifts

The analysis revealed significant financial influences on mode choice during an air quality crisis. Financial intervention strategies could include air quality-responsive fare systems with public transport fare reductions during severe pollution events, targeted transportation vouchers for lower-income households, and incentive programs for businesses providing alternative transportation options. Income levels significantly influence travel behavior during air pollution events [20]. Such measures would particularly benefit the 17.7% of respondents without vehicle ownership [58].

5.2.4. Active Transportation Infrastructure with Air Pollution Protection

The significant increase in alternative usage (from 6.4% to 13.8%) during an air quality crisis indicates substantial potential for growth with appropriate protective infrastructure. Infrastructure development could include separated bicycle and pedestrian pathways with vegetative barriers, enclosed air-filtered waiting areas at transportation nodes, and targeted subsidy programs for electric micromobility options. Vegetation barriers can reduce particulate matter exposure by 15–30% for active transportation users [58]. These measures would benefit the 68.2% of student respondents [24].

5.3. Limitations and Future Work

Several methodological limitations warrant acknowledgment. The probability sampling approach resulted in significant demographic skewing, with overrepresentation of younger respondents (85.9% under 30 years) and students (68.2%) compared to Chiang Rai's general population [32]. This bias limits generalizability to older adults and working professionals. The cross-sectional design and reliance on stated preferences introduce potential recall bias regarding pre-crisis travel patterns. Methodologically, separate multinomial logit models lacked explicit interaction terms between environmental conditions and individual characteristics. The aggregation of taxi services and active transportation into the "Alternatives" category potentially masked distinct behavioral responses due to different pollution exposure profiles.

Future research should address these limitations through several approaches. Methodological improvements should incorporate explicit interaction terms to capture how environmental conditions moderate relationships between socioeconomic characteristics and mode choice. Mixed-method sampling strategies combining probability and non-probability techniques would improve demographic representation. Longitudinal studies tracking behavioral changes over multiple air quality crisis seasons would provide insights into adaptation patterns and the sustainability of behavioral changes. Alternative-specific data collection enabling comprehensive modeling of all transportation options is recommended. Future studies should examine taxi services and active transportation modes separately, investigate policy intervention effectiveness, and explore emerging transportation technologies and remote work options in addressing air quality crisis challenges.

6. Conclusions

This study examined travel mode choice adaptations during an air quality crisis in Chiang Rai, Thailand, revealing significant behavioral shifts toward enclosed transportation modes and shorter trips during the air quality crisis. The findings demonstrate systematic changes in transportation preferences, with motorcycle usage decreasing from 50.2% to 42.9% while private car usage increased from 30.3% to 34.7% during crisis periods. Financial considerations became increasingly influential in mode choice decisions during an environmental crisis, particularly among the younger, student-dominated sample population. While sample demographics limit generalizability to older adults and working professionals, the results provide valuable insights into an important demographic segment representing future transportation users. The research contributes to understanding how environmental crises impact urban mobility patterns and emphasizes the importance of integrating environmental and socioeconomic factors in transportation planning. The findings indicate that effective crisis-period transportation policies must address both infrastructure limitations and socioeconomic barriers to mode switching. Incorporating broader demographic representation will be essential for developing comprehensive transportation policies that can effectively respond to the air quality crisis across all population segments. The study establishes a foundation for creating more resilient urban transportation systems capable of adapting to environmental challenges while addressing equity considerations in policy development.

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References

1. Wang, D.; Zhou, M. The Built Environment and Travel Behavior in Urban China: A Literature Review. *Transp. Res. D Transp. Environ.* **2017**, *52*, 574–585. [CrossRef]
2. United Nations Environment Programme. *Air Pollution in Asia and the Pacific: Science-Based Solutions*; UNEP: Nairobi, Kenya, 2019; ISBN 9789280737257.
3. Cohen, A.J.; Brauer, M.; Burnett, R.; Anderson, H.R.; Frostad, J.; Estep, K.; Balakrishnan, K.; Brunekreef, B.; Dandona, L.; Dandona, R.; et al. Estimates and 25-Year Trends of the Global Burden of Disease Attributable to Ambient Air Pollution: An Analysis of Data from the Global Burden of Diseases Study 2015. *Lancet* **2017**, *389*, 1907–1918. [CrossRef] [PubMed]
4. World Health Organization. *WHO Global Air Quality Guidelines: Particulate Matter (PM2.5 and PM10), Ozone, Nitrogen Dioxide, Sulfur Dioxide and Carbon Monoxide*; World Health Organization: Geneva, Switzerland, 2021.
5. Reid, J.S.; Hyer, E.J.; Johnson, R.S.; Holben, B.N.; Yokelson, R.J.; Zhang, J.; Campbell, J.R.; Christopher, S.A.; Di Girolamo, L.; Giglio, L.; et al. Observing and Understanding the Southeast Asian Aerosol System by Remote Sensing: An Initial Review and Analysis for the Seven Southeast Asian Studies (7SEAS) Program. *Atmos. Res.* **2013**, *122*, 403–468. [CrossRef]
6. Phosri, A.; Ueda, K.; Phung, V.L.H.; Tawatsupa, B.; Honda, A.; Takano, H. Effects of Ambient Air Pollution on Daily Hospital Admissions for Respiratory and Cardiovascular Diseases in Bangkok, Thailand. *Sci. Total Environ.* **2019**, *651*, 1144–1153. [CrossRef]
7. Pimonsree, S.; Vongruang, P. Impact of Biomass Burning and Its Control on Particulate Matter over a City in Mainland Southeast Asia during a Smog Episode. *Atmos. Environ.* **2018**, *195*, 196–209. [CrossRef]
8. Pollution Control Department Thailand State of Pollution Report 2022. Available online: https://www.pcd.go.th/ebook/book17/Pollutiin.html (accessed on 4 November 2024).
9. Phopluechai, R.; Arreeras, T.; Jia, X.; Phonsitthangkun, S.; Arreeras, S.; Prommakhot, S. Examining Factors Affected to Travel Decision During Air Pollution Crisis in Chiang Rai Using Exploratory Factor Analysis. In Proceedings of the 2024 ASU International Conference in Emerging Technologies for Sustainability and Intelligent Systems (ICETSIS), Manama, Bahrain, 28–29 January 2024; pp. 1602–1606.
10. Long, J.S.; Freese, J. *Regression Models for Categorical Dependent Variables Using STATA*; Stata Press: College Station, TX, USA, 2001; Volume 7.
11. Withers, S.D. Categorical Data Analysis. In *International Encyclopedia of Human Geography: Volume 1–12*; Elsevier: Amsterdam, The Netherlands, 2009; Volume 1–12, pp. V1-456–V1-462, ISBN 9780080449104.
12. Pojani, D.; Stead, D. Sustainable Urban Transport in the Developing World: Beyond Megacities. *Sustainability* **2015**, *7*, 7784–7805. [CrossRef]
13. Tian, G.; Ewing, R.; White, A.; Hamidi, S.; Walters, J.; Goates, J.P.; Joyce, A. Traffic Generated by Mixed-Use Developments: Thirteen-Region Study Using Consistent Measures of Built Environment. *Transp. Res. Rec.* **2015**, *2500*, 116–124. [CrossRef]
14. Tainio, M.; de Nazelle, A.J.; Götschi, T.; Kahlmeier, S.; Rojas-Rueda, D.; Nieuwenhuijsen, M.J.; de Sá, T.H.; Kelly, P.; Woodcock, J. Can Air Pollution Negate the Health Benefits of Cycling and Walking? *Prev. Med.* **2016**, *87*, 233–236. [CrossRef] [PubMed]
15. Pangderm, C.; Arreeras, T.; Jia, X. Modeling School Commuting Mode Choice Under Normal and Adverse Weather Conditions in Chiang Rai City. *Future Transp.* **2025**, *5*, 101. [CrossRef]
16. Meena, K.K.; Taneja, R.; Agarwal, A. Impact of Air Pollution on Informed Decision-Making for Choice of a Travel Mode. In Proceedings of the 2024 16th International Conference on Communication Systems and Networks, Comsnets 2024, Bengaluru, India, 3–7 January 2024.
17. Li, W.; Kamargianni, M. Air Pollution and Seasonality Effects on Mode Choice in China. *Transp. Res. Rec.* **2017**, *2634*, 101–109. [CrossRef]
18. Luo, R.; Fan, Y.; Yang, X.; Zhao, J.; Zheng, S. The Impact of Social Externality Information on Fostering Sustainable Travel Mode Choice: A Behavioral Experiment in Zhengzhou, China. *Transp. Res. Part A Policy Pract.* **2021**, *152*, 127–145. [CrossRef]
19. Kim, S.; Ko, Y.; Jang, K. Air Pollution, Perceived Health Risk, and Trip Decision-Making: Environmental Justice Considerations. *Cities* **2024**, *149*, 104949. [CrossRef]
20. Kim, S.; Ko, Y.; Jang, K. Role of Income on Travel Behavior in Polluted Air. *J. Transp. Health* **2023**, *33*, 101705. [CrossRef]
21. Dabirinejad, S.; Habibian, M.; Khorsandi, B. Exploring Impacts of Perceived and Actual Air Pollution on Commuters' Mode Choice. *Transp. Res. D Transp. Environ.* **2024**, *135*, 104359. [CrossRef]
22. Ercan, T.; Onat, N.C.; Keya, N.; Tatari, O.; Eluru, N.; Kucukvar, M. Autonomous Electric Vehicles Can Reduce Carbon Emissions and Air Pollution in Cities. *Transp. Res. D Transp. Environ.* **2022**, *112*, 103472. [CrossRef]
23. Meena, K.K.; Bairwa, D.; Agarwal, A. A Machine Learning Approach for Unraveling the Influence of Air Quality Awareness on Travel Behavior. *Decis. Anal. J.* **2024**, *11*, 100459. [CrossRef]
24. Zhao, P.; Li, S.; Li, P.; Liu, J.; Long, K. How Does Air Pollution Influence Cycling Behaviour? Evidence from Beijing. *Transp. Res. D Transp. Environ.* **2018**, *63*, 826–838. [CrossRef]
25. Xu, Y.; Liu, Y.; Chang, X.; Huang, W. How Does Air Pollution Affect Travel Behavior? A Big Data Field Study. *Transp. Res. D Transp. Environ.* **2021**, *99*, 103007. [CrossRef]

26. Ben-Akiva, M.E.; Lerman, S.R. *Discrete Choice Analysis: Theory and Application to Travel Demand*; MIT Press: Cambridge, MA, USA, 1985; Volume 9, ISBN 0262022176.
27. Hensher, D.A.; Rose, J.M.; Greene, W.H. Applied Choice Analysis: A Primer. Applied Choice Analysis; Cambridge University Press: Cambridge, UK, 2015; ISBN 131630034X.
28. Bhat, C.R. A Multi-Level Cross-Classified Model for Discrete Response Variables. *Transp. Res. Part B Methodol.* **2000**, *34*, 567–582. [CrossRef]
29. Hagenauer, J.; Helbich, M. A Comparative Study of Machine Learning Classifiers for Modeling Travel Mode Choice. *Expert Syst. Appl.* **2017**, *78*, 273–282. [CrossRef]
30. De Vos, J.; Schwanen, T.; van Acker, V.; Witlox, F. Travel and Subjective Well-Being: A Focus on Findings, Methods and Future Research Needs. *Transp. Rev.* **2013**, *33*, 421–442. [CrossRef]
31. Li, S.; Liu, Y.; Purevjav, A.O.; Yang, L. Does Subway Expansion Improve Air Quality? *J. Environ. Econ. Manag.* **2019**, *96*, 213–235. [CrossRef]
32. National Statistical Office of Thailand Population and Housing Census 2024. Available online: https://chiangrai.nso.go.th/reports-publications/provincial-statistics-report/chiang-rai-province-statistical-report.html (accessed on 4 November 2024).
33. Pollution Control Department Air Quality and Noise Management Bureau Annual Report 2023. Available online: https://www.pcd.go.th/publication/33068/ (accessed on 4 November 2024).
34. Yamane, T. *Statistics: An Introductory Analysis*; Harper and Row: New York, NY, USA, 1973.
35. Abdullah, M.; Dias, C.; Muley, D.; Shahin, M. Exploring the Impacts of COVID-19 on Travel Behavior and Mode Preferences. *Transp. Res. Interdiscip. Perspect.* **2020**, *8*, 100255. [CrossRef]
36. Chansuk, C.; Arreeras, T.; Chiangboon, C.; Phonmakham, K.; Chotikool, N.; Buddee, R.; Pumjampa, S.; Yanasoi, T.; Arreeras, S. Using Factor Analyses to Understand the Post-Pandemic Travel Behavior in Domestic Tourism through a Questionnaire Survey. *Transp. Res. Interdiscip. Perspect.* **2022**, *16*, 100691. [CrossRef]
37. Rahman, M.L.; Baker, D. Modelling Induced Mode Switch Behaviour in Bangladesh: A Multinomial Logistic Regression Approach. *Transp. Policy* **2018**, *71*, 81–91. [CrossRef]
38. van Buuren, S.; Groothuis-Oudshoorn, K. Mice: Multivariate Imputation by Chained Equations in R. *J. Stat. Softw.* **2011**, *45*, 1–7. [CrossRef]
39. Arreeras, T.; Chongutsah, S.; Asada, T.; Arimura, M. Factors Affecting Mode Choice in Accessing Railway Station Study in Nakhon Ratchasima. *Transp. Res. Procedia* **2020**, *48*, 3457–3468. [CrossRef]
40. Liu, C.; Susilo, Y.O.; Karlström, A. The Influence of Weather Characteristics Variability on Individual's Travel Mode Choice in Different Seasons and Regions in Sweden. *Transp. Policy* **2015**, *41*, 147–158. [CrossRef]
41. McFadden, D. *Conditional Logit Analysis of Qualitative Choice Behavior*; Scholarly Communication & Information Policy University of California Berkeley Library: Berkeley, CA, USA, 1972.
42. Co, N.J.S.; Dimaculangan, K.F.; Peralta, M.H.T. Effects of Covid-19 Pandemic on Mode Choice Behavior of Working Filipinos in Metro Manila. *Asian Transp. Stud.* **2023**, *9*, 100101. [CrossRef]
43. Hosmer, D.W.; Lemeshow, S.; Sturdivant, R.X. *Applied Logistic Regression: Third Edition*; John Wiley & Sons: Hoboken, NJ, USA, 2013.
44. Menard, S. *Logistic Regression: From Introductory to Advanced Concepts and Applications*; Sage: Thousand Oaks, CA, USA, 2014.
45. Train, K.E. *Discrete Choice Methods with Simulation*; Cambridge University Press: Cambridge, UK, 2009; ISBN 1139480375.
46. Washington, S.; Karlaftis, M.G.; Mannering, F.; Anastasopoulos, P. *Statistical and Econometric Methods for Transportation Data Analysis*; Chapman and Hall/CRC: Boca Raton, FL, USA, 2020; ISBN 0429244010.
47. Greene, W.H. The Econometric Approach to Efficiency Analysis. In *The Measurement of Productive Efficiency and Productivity Growth*; Fried, H.O., Knox Lovell, C.A., Schmidt, S.S., Eds.; Oxford Academic: Oxford, UK, 2008; pp. 92–250.
48. Louviere, J.J.; Hensher, D.A.; Swait, J.D. Stated Choice Methods: Analysis and Applications. Cambridge University Press: Cambridge, UK, 2000; ISBN 1107717515.
49. Gaudry, M.; Domencich, T.A.; McFadden, D. Urban Travel Demand: A Behavioral Analysis. *Can. J. Econ.* **1977**, *10*, 724. [CrossRef]
50. de Dios Ortúzar, J.; Willumsen, L.G. *Modelling Transport*; Wiley: Hoboken, NJ, USA, 2011; ISBN 9781119993520.
51. Gärling, T.; Fujii, S. Travel Behavior Modification: Theories, Methods, and Programs. In *The Expanding Sphere of Travel Behaviour Research*; Emerald: Leeds, UK, 2009; pp. 97–128.
52. Buehler, R.; Pucher, J. Demand for Public Transport in Germany and the USA: An Analysis of Rider Characteristics. *Transp. Rev.* **2012**, *32*, 541–567. [CrossRef]
53. United Nations. The 17 Sustainable Development Goals (SDGs). Available online: https://sdgs.un.org/goals (accessed on 12 February 2025).
54. Dhar, S.; Pathak, M.; Shukla, P.R. Electric Vehicles and India's Low Carbon Passenger Transport: A Long-Term Co-Benefits Assessment. *J. Clean. Prod.* **2017**, *146*, 139–148. [CrossRef]

55. Yin, H.; Pizzol, M.; Xu, L. External Costs of PM2.5 Pollution in Beijing, China: Uncertainty Analysis of Multiple Health Impacts and Costs. *Environ. Pollut.* **2017**, *226*, 356–369. [CrossRef]
56. Liu, T.; He, G.; Lau, A. Avoidance Behavior against Air Pollution: Evidence from Online Search Indices for Anti-PM2.5 Masks and Air Filters in Chinese Cities. *Environ. Econ. Policy Stud.* **2018**, *20*, 325–363. [CrossRef]
57. Shi, X. The Future of ASEAN Energy Mix: A SWOT Analysis. *Renew. Sustain. Energy Rev.* **2016**, *53*, 672–680. [CrossRef]
58. Abhijith, K.V.; Kumar, P. Field Investigations for Evaluating Green Infrastructure Effects on Air Quality in Open-Road Conditions. *Atmos. Environ.* **2019**, *201*, 132–147. [CrossRef]

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