A STUDY ON SCHOOL TRIP MODE CHOICE IN CHIANG RAI CITY AREA USING A MULTINOMIAL LOGIT REGRESSION APPROACH

CHANYANUCH PANGDERM

MASTER OF BUSINESS ADMINISTRATION
IN
INTERNATIONAL LOGISTICS AND
SUPPLY CHAIN MANAGEMENT

SCHOOL OF MANAGEMENT
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ABSTRACT

This study investigates school trip mode choice behavior among senior high school students in Mueang Chiang Rai District, Thailand, with a focus on environmental conditions, particularly adverse weather, that influence transportation decisions. Given Chiang Rai's unique geographic and climatic context, characterized by seasonal haze and limited transport infrastructure, understanding students' commuting preferences is critical for designing sustainable and equitable school transportation systems. This research collected data from 472 student respondents across six extra-large schools using structured questionnaires. The analysis employed both Multinomial Logit (MNL) regression and Exploratory Factor Analysis (EFA) to examine the relationship between travel behavior and influencing factors.

The findings reveal motorcycles as the most common mode under normal weather conditions, while adverse weather significantly reduces their use, with a corresponding increase in private vehicle and school bus usage. Key determinants of mode choice include household vehicle ownership, income, travel distance, waiting time, and perceived safety. The EFA identified latent variables such as convenience, environmental satisfaction, and transport reliability that further shape behavior.

These insights suggest the need for resilient school transport policies that address equity and environmental sustainability. Strategies such as expanding formal school bus services, improving weather-protected infrastructure, and promoting active travel for short-distance students are recommended. The study highlights the importance of integrating behavioral modeling with local policy to improve transport accessibility for students in secondary urban regions of Thailand.

Keywords: Adverse Weather, Urban, School Trip, Mode Choice, Multinomial Logit, Chiang Rai

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CHAPTER 1

INTRODUCTION

1.1 Background

Transportation plays a critical role in facilitating economic activity, social mobility, and global trade (Park et al., 2019). However, traditional transportation systems are highly dependent on fossil fuels and significantly contribute to environmental degradation, air pollution, and climate change (Chandrasekaran et al., 2016). The growing awareness of these environmental challenges has led to increased emphasis on the need for transportation systems that are not only efficient and accessible but also equitable and environmentally sustainable. In response to the escalating impacts of climate change and environmental deterioration, the United Nations (UN) is an international organization founded in 1945 and composed of 193 member states, has taken a leadership role in promoting sustainable development. In 2015, all UN member states adopted the 2030 Agenda for Sustainable Development, a comprehensive framework designed to guide global development efforts toward peace, prosperity, and environmental protection.

Central to this agenda are the 17 Sustainable Development Goals (SDGs), which call for a coordinated global partnership to address the most pressing challenges faced by both developed and developing countries (United Nations, 2023). Among the United Nations Sustainable Development Goals (UNSDGs), Goal 11: Sustainable Cities and Communities, illustrated in Figure 1.1, emphasizes the importance of making urban areas inclusive, safe, resilient, and sustainable. A key component of this goal is the development of safe, affordable, accessible, and sustainable transport systems for all, particularly for vulnerable groups such as women, children, persons with disabilities, and the elderly. The goal also stresses the need to reduce the adverse environmental impact of cities, including managing air pollution and ensuring access to green public spaces (Sharifi et al., 2021).

Source United Nations (2023)

Figure 1.1 The Sustainable Development Goals (SDGs)

Sustainable transportation is thus closely linked to the achievement of broader development objectives, including improved public health, enhanced quality of life, and environmental preservation. Transportation planning that aligns with these goals requires a deep understanding of travel behavior, the patterns, and choices individuals make regarding their travel. Travel behavior encompasses a wide range of factors such as the purpose of travel, mode choice, travel time, frequency, cost, and distance. Understanding these patterns is essential for developing transportation policies that support sustainability, accessibility, and equity (Mwale et al., 2022). One critical area of travel behavior is the mode choice for school trips, which involves selecting the most appropriate form of transport for students commuting to and from school. This decision is influenced by a complex interplay of individual, household, and contextual factors. These include the distance to school, availability and accessibility of different transportation modes, safety concerns, parental preferences, travel costs, and environmental awareness (Ho & Mulley, 2013; Lin & Chang, 2010; Whalen et al., 2013).

For instance, the availability of dedicated school buses or public transit options, such as vans or buses, can significantly impact students' mode choices. The convenience and reliability of these modes and factors such as distance and travel time influence students' decisions to use them. Additionally, individual and household characteristics, such as the presence of a personal vehicle or parental preferences, can also shape mode choice decisions (Ashalatha et al., 2013). Understanding students' mode choice preferences and behavior can inform transportation planning and policymaking to create safer and more efficient school transportation systems. By promoting sustainable modes of transportation, such as walking, cycling, or using public transit, policymakers can reduce traffic congestion, promote physical activity, and improve air quality around schools (Giles-Corti et al., 2016; Sá et al., 2017; Sallis et al., 2016).

This research selected the study area as Chiang Rai Province in northernmost Thailand. This province often encounters dust pollution, such as PM dust that comes from domestic and international combustion, which will be significantly affected at some period every year. In addition, travel is not as convenient as in the country's capital or major economic cities. This research conducted a study with a target group of high school students at extra-large schools in Mueang Chiang Rai District, Chiang Rai Province. Understanding the mode choice behaviors of this group is critical for designing transportation strategies that address their specific needs while aligning with broader sustainability goals.

Therefore, investigating the factors influencing mode choice for school trips is essential for designing effective transportation strategies that cater to the unique needs of students by considering factors such as accessibility, cost, safety, and environmental sustainability. Policymakers and transportation planners can develop initiatives that encourage the use of sustainable modes of transportation, improve the overall quality and sustainability of the transportation system in the region, to ensure that the travel experience for students, including people of all ages, is safer and more efficient.

1.2 Research Objective

Objective 1: To explore the transport modes selection to the school of high school students in Muang Chiang Rai district, Chiang Rai province.

Objective 2: To explore the factors associated with commuting behavior to school among high school students in Muang Chiang Rai district, Chiang Rai province.

Objective 3: Suggest a policy to promote the transportation system to develop sustainable, more efficient, and safer transportation.

1.3 Research Questions

Question 1: How do high school students in Muang Chiang Rai district select their mode of transportation to school?

Question 2: What factors affect the selection of transport modes by high school students in Mueang Chiang Rai district, Chiang Rai province?

Question 3: What policy measures can be implemented in the transportation system to enhance sustainability, efficiency, and safety?

1.4 Research Gap

Although there is research on the choice of modes of transport in various contexts, there appears to be a research gap in the study of students' choice of school travel mode, especially on the choice of school travel mode in Chiang Rai, Thailand. Select a mode and identify the challenges or opportunities that may arise specifically in the region. It will help gain valuable insights for transportation planning and policymaking.

1.5 Expected Outcomes

1.5.1 Able to understand the travel modes selection to the school of high school students in Muang Chiang Rai District, Chiang Rai Province.

1.5.2 Able to understand the factors associated with commuting behavior to the school of high school students in Muang Chiang Rai District.

1.5.3 Able to suggest a policy to promote the transportation system to develop sustainable, more efficient, and safer transportation.

1.6 Scope of Study

This research explores the behavior of the school trip selection of students in extra-large schools in Mueang Chiang Rai, Chiang Rai. Data was collected through a questionnaire targeting high school students. This study examined the actual preferences of students and the factors involved in deciding on different modes of travel. Focusing on studying and developing future transportation policies to promote sustainable transportation to increase safety and convenience in terms of accessibility, cost, and public transportation travel time. Support factors that influence travel decisions and passenger behavior.

1.7 Conceptual Framework

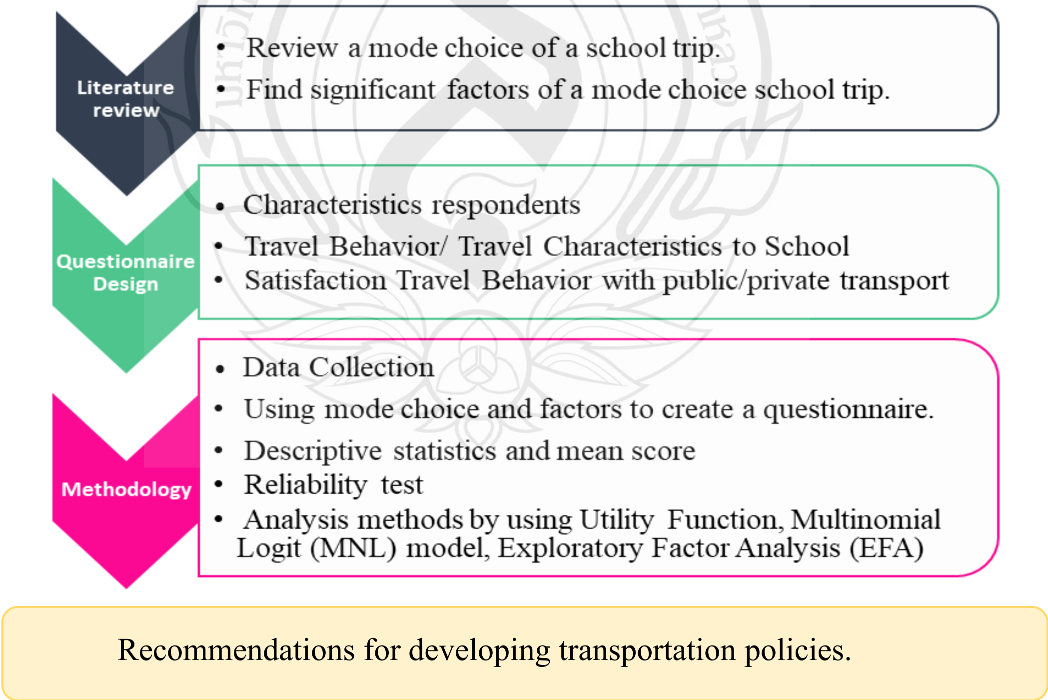

Figure 1.2 Conceptual Framework

CHAPTER 2

LITERATURE REVIEW

2.1 Transportation Management and Sustainability

The intersection of transportation management and sustainability has garnered significant scholarly attention in recent decades, driven by growing concerns over climate change, urban congestion, resource depletion, and social equity. As cities expand and transportation demand intensifies, sustainable transportation management has emerged as a critical paradigm for achieving long-term environmental, economic, and societal well-being (Stefaniec et al., 2021). Contemporary research increasingly frames transportation sustainability through the lens of the Triple Bottom Line, emphasizing the need to simultaneously address environmental integrity, economic viability, and social equity (Stefaniec et al., 2020). This framework has influenced the design and evaluation of transportation policies and systems, encouraging decision-makers to move beyond cost-benefit analysis and incorporate broader sustainability performance measures. For example, lifecycle assessment models are increasingly employed to capture emissions and resource use across transportation activities, from infrastructure construction to vehicle disposal (Chester & Horvath, 2009).

Technological innovation has been a transformative driver in the evolution of sustainable transport management. The integration of intelligent transport systems (ITS), big data analytics, and connected vehicle technologies has enabled real-time traffic optimization, dynamic demand forecasting, and multimodal coordination, leading to substantial reductions in fuel consumption and emissions(Agureev et al., 2017; Zhu et al., 2019). Moreover, automation and electrification are reshaping the vehicle landscape, with electric vehicles (EVs) and autonomous mobility-on-demand (AMoD) services promising to decrease reliance on fossil fuels and reduce urban congestion, although their net environmental benefit remains contingent on energy mix and policy design (Mourtakos et al., 2022; Turan et al., 2020).

Freight transportation, a traditionally carbon-intensive sector, has also seen a shift toward more sustainable management practices. Horizontal logistics cooperation, where companies share infrastructure and transport capacity, has been shown to enhance both economic efficiency and environmental outcomes (Verstrepen et al., 2009). Urban transportation planning is another crucial area where sustainability principles are increasingly applied. Cities worldwide are investing in active transport infrastructure, such as bicycle lanes and pedestrian-friendly zones, to encourage modal shifts away from private car use (Pojani & Stead, 2015). The integration of public transportation with micromobility solutions like bike-sharing and e-scooters further supports sustainable travel behaviors, though these innovations must be carefully regulated to ensure safety, accessibility, and system efficiency (Shaheen & Cohen Adam, 2019). Despite these advancements, critical challenges persist. The rapid pace of technological change raises questions about digital equity, privacy, and system interoperability.

Moreover, tensions between sustainability goals, such as reducing emissions versus maintaining economic competitiveness, often complicate policy implementation. As such, future research must address these trade-offs through interdisciplinary approaches that integrate engineering, behavioral science, and public policy (Verlinghieri & Schwanen, 2020). In summary, the literature on transportation management and sustainability underscores the need for integrated, data-driven, and equity-focused strategies. As the field continues to evolve, greater emphasis on system-level thinking, cross-sector collaboration, and the inclusion of diverse stakeholder perspectives will be essential for developing transportation systems that are resilient, inclusive, and aligned with global sustainability targets.

2.1.1 Sustainable Transportation Planning

Although definitions of a sustainable transportation system vary, there is growing agreement that sustainability should encompass both system effectiveness and its impact on economic development, environmental health, and social well-being. Integrating sustainability assessment into the planning process can guide decision-making and support regional sustainability goals (Jeon et al., 2013). Integrated transportation planning approaches, which incorporate multiple modes of transportation and land use considerations (Wegener, 2004), have gained prominence.

For example, Transit-Oriented Development (TOD) typically aims to achieve three key transportation objectives: (1) reduce the total number of motorized trips, a process often referred to as trip degeneration; (2) increase the proportion of trips made by nonmotorized means, such as walking or cycling; and (3) for the motorized trips that do occur, shorten travel distances and boost vehicle occupancy rates by promoting transit, paratransit, and ride-sharing. By reducing reliance on private cars and encouraging alternative travel modes, TOD is expected to mitigate many of the negative impacts of car-dependent societies, including those identified by Lichfield (1995), Dittmar (1995), Cervero and Kockelman (1997). Multi-modal transportation systems that integrate various modes, such as buses, trains, bicycles, and pedestrian infrastructure, have also emerged as effective solutions to be an effective way to ease the negative environmental effects of transportation (Dong et al., 2020).

2.1.2 Green Logistics

Green logistics has emerged as a framework encompassing environmentally conscious practices aimed at minimizing the overall ecological footprint of logistics operations (Karaman et al., 2020). Strategies such as efficient routing and shipment consolidation can significantly reduce transportation distances and associated emissions (Rodrigue et al., 2008). Enhanced collaboration within logistics networks, such as shared distribution centers and synchronized delivery schedules, further improves resource efficiency and reduces waste (Jiang et al., 2022). Additionally, green supply chain management practices, including reverse logistics and sustainable procurement, are vital to promoting sustainability across transportation and logistics activities (Dev et al., 2020).

2.1.3 Alternative Fuel Technologies

The adoption of alternative fuel technologies in transportation holds promise for reducing greenhouse gas emissions and dependence on fossil fuels. Electric vehicles (EVs) have gained significant attention due to their zero-emission operation and advancements in battery technology. Infrastructure development, including charging stations and battery-swapping networks, is crucial for supporting widespread EV adoption (Zhang et al., 2020). Hydrogen fuel cell vehicles offer another viable option, as they produce only water vapor emissions. However, challenges related to hydrogen production, distribution, and storage need to be addressed (Zhang et al., 2022). Biofuels derived from renewable sources also offer potential alternatives to conventional fuels, but their scalability and sustainability require careful consideration (Rajendra Prasad Reddy et al., 2022).

2.1.4 Policy Interventions for Sustainable Transportation

Government regulations and policy interventions play a vital role in driving sustainable transportation practices. Incentives, such as tax breaks and subsidies for electric vehicles or renewable fuel production, can stimulate the adoption of sustainable transportation technologies (Rajendra Prasad Reddy et al., 2022). Carbon pricing mechanisms, including emissions trading schemes and carbon taxes, can internalize the environmental costs of transportation and incentivize emissions reduction(Goulder & Hafstead, 2013). Public transportation investments, such as expanding and improving public transit systems can encourage modal shifts and reduce congestion and emissions (Wong et al., 2020).

2.1.5 Assessing the Sustainability Performance of Transportation Systems

Measuring and evaluating the sustainability performance of transportation systems is crucial for making informed decisions and tracking progress. Metrics and indicators specific to transportation sustainability, such as vehicle miles traveled (VMT), emissions per passenger mile, and mode share, can provide insights into transportation's environmental, social, and economic aspects (Litman, 2019). Life cycle assessment (LCA) is a valuable tool for assessing the holistic environmental impacts (Guo et al., 2023).

2.2 Commuting to School

Commuting to school, referring to daily travel between students' homes and their educational institutions, has become a significant topic in transport research due to its implications for urban planning, public health, environmental sustainability, and social equity. Over recent decades, dramatic shifts in school travel behavior have been observed. For example, McDonald et al. (2011) provided a comprehensive analysis of school travel patterns in the United States using data from the National Household Travel Survey (NHTS). The study compared travel behavior from 1969 to 2009, documenting a dramatic decline in active travel, particularly walking, alongside a substantial increase in car use. Using a binary logit model, the authors examined how trip characteristics, child demographics, and household variables influenced the decision to walk to school. The paper's findings can be useful in monitoring progress toward the goal of increasing walking and biking to school by 50% within 5 years, as set by the White House Task Force on Childhood Obesity. Their findings underscore a major shift toward automobility, driven by increased trip distances, parental concerns, and evolving residential patterns. Expanding on this, McDonald (2012) investigated gender differences in school travel across the NHTS from 1977 and 2009. Employing a multinomial logit model, the study revealed persistent gender disparities in school mode choices, even after controlling individual and household-level covariates. Girls were found to be less likely than boys to engage in independent and active modes such as walking or biking. The study also highlighted regional variation and the importance of cultural norms, safety perceptions, and parental restrictions in shaping these differences issues which are even more pronounced in many non-Western contexts. In South Asia.

Lodhi et al. (2022) conducted a gender-based analysis of school travel in Abbottabad, Pakistan, revealing a significant preference among boys for bicycles and public transport, while girls were more likely to be accompanied in private vehicles. Using descriptive statistics, chi-square tests, and t-tests, the study identified distinct differences in travel behavior and satisfaction with public transport. An index was constructed to assess overall satisfaction, underscoring the need for transport and urban planning to consider gender-sensitive approaches, particularly in contexts where cultural constraints on female mobility persist. Parental decision-making is another critical determinant of school travel mode.

Zuniga (2012) examined parental attitudes toward active school travel in Denver, Colorado, using qualitative methods. Through semi-structured interviews with 65 parents, the study identified two major coping strategies, including barrier elimination and barrier negotiation, that parents employed in response to perceived challenges such as safety, weather, and time constraints. These themes were analyzed using NVivo 8.0 and provided actionable insights into how interventions could be tailored to increase active travel participation. Similarly, Faulkner et al. (2010)

explored parental decision-making processes in Toronto through interviews with 37 parents from diverse socio-economic backgrounds. Thematic analysis revealed a two-stage decision framework: parents first evaluated the feasibility of walking or biking, then assessed the trade-offs with motorized modes. The study emphasized that improving physical infrastructure alone may be insufficient without addressing parental concerns about safety, time, and social norms. To promote active school travel, structured interventions such as the Walking School Bus (WSB) have gained attention.

Nikitas et al. (2019) synthesized existing literature and employed thematic analysis to explore parental motivations and barriers to WSB adoption. Their research identified six key thematic dimensions: logistics, safety, trust, health and well-being, emotional engagement, and educational opportunities, as central to the success of WSB initiatives. The study provided policy recommendations for enhancing the appeal and scalability of WSB programs, particularly in car-dependent urban environments. In the South Asian context, where informal transport systems are common, Dias et al. (2022) analyzed school travel in Kandy, Sri Lanka, using multinomial and mixed logit models. The study examined a wide range of school travel modes, including walking, public transport, school buses and vans, motorcycles, private vehicles, and three-wheelers, and assessed the role of gender, age, income, distance, and school type in shaping mode choice. The findings highlighted the need for regulatory oversight of informal modes such as private school vans and called for policies to encourage enrollment in neighborhood schools to reduce congestion and improve accessibility. Their research offers context-specific insights that can inform the development of more equitable and efficient school transport systems in developing cities.

While international research has advanced our understanding of school commuting patterns, there is a growing need to contextualize these insights within local realities, especially in low- and middle-income countries (LMICs) such as Thailand. In particular, the northern province of Chiang Rai presents a unique context characterized by a mixture of urban, peri-urban, and rural settlements, where infrastructure, geography, and socio-economic conditions play a critical role in shaping students' travel behavior. In Thailand, the reliance on motorcycles for school travel, especially in rural areas, is markedly higher than in many Western contexts. Due to limited public transport coverage and the absence of safe pedestrian and cycling infrastructure, many students are either driven by parents or operate motorcycles themselves, despite being underage. This phenomenon raises serious concerns regarding traffic safety, legal enforcement, and child independence (Kaewkluengklom et al., 2017). Unlike contexts where walking and cycling are actively promoted through interventions like the Walking School Bus, Thai students in rural provinces often face long distances, poor road conditions, and a lack of supervised or collective transport systems.

Furthermore, parental decision-making in the Thai context is influenced not only by safety concerns but also by economic constraints and cultural values related to familial responsibility (Nanthawong et al., 2024). In areas such as Chiang Rai, where many households rely on agriculture and daily-wage labor, parents may not have the flexibility to accompany children to school or invest in safer travel alternatives. Faulkner et al. (2010) and Zuniga (2012) have shown, parental perceptions and capabilities are key determinants of mode choice; however, in Thailand, such perceptions are compounded by systemic limitations in infrastructure and governance. Gender also plays a significant role. As in Lodhi et al. (2022), Thai female students often experience restricted mobility due to safety fears and social norms, leading to increased reliance on parents or family members for transportation. This is particularly true for secondary school girls in rural areas, where personal autonomy is limited compared to boys. Despite these constraints, national and local data on gender disparities in school travel in Thailand remain scarce, indicating a research gap with practical implications for equitable transport planning.

Moreover, school choice is often determined by factors beyond geographic proximity, such as perceived school quality, reputation, or specialized academic programs. Dias et al. (2022) highlighted how school selection can exacerbate congestion and extend trip lengths, which is evident in Chiang Rai as well, where students frequently bypass neighborhood schools in favor of more prestigious institutions in city centers. This contributes to higher rates of private vehicle use during peak hours, intensifying urban traffic and carbon emissions. Addressing these challenges requires an integrated policy framework that includes infrastructure investment, education on road safety, enforcement of traffic laws, and localized transport planning that prioritizes accessibility and inclusivity. Importantly, data-driven approaches such as discrete choice modeling, GIS mapping of school catchment areas, and household travel survey tools effectively employed in the literature reviewed can be adapted for use in Thailand to better understand the determinants of mode choice and to evaluate the effectiveness of interventions.

Overall, the various literature reviews demonstrate that school commuting is influenced by a complex interplay of demographic, socio-economic, cultural, and infrastructural factors. While research from high-income countries provides important theoretical frameworks, studies from the Asia side, including Thailand, reveal the need for locally tailored strategies that address informal transport, gender inequity, and disparities in access to nearby schools, especially in semi-rural provinces like Chiang Rai, which demand attention to local socio-cultural, infrastructural, and institutional dynamics. Literature underscores the need for a multi-scalar approach that links household-level decisions to broader patterns of urban development and mobility governance. Bridging these global and local perspectives is essential for designing inclusive, safe, and sustainable school transport systems. There are additional displays in Table 2.1.

Table 2.1 Previous studies on commuting to school

Years	Reference	Country	Travel modes	Methods
2011	McDonald et al.	United States	Walk Car	Binary Logit Model
2012	McDonald.	United States	Walk Biking Other modes	Multinomial Logit (MNL) Model
2022	Lodhi et al.	Abbottabad, Pakistan	Bicycles Public transport Private vehicles	Descriptive statistics Chi-square tests t-tests

Table 2.1 (continued)

Years	Reference	Country	Travel modes	Methods
2012	Zuniga	Denver, Colorado, USA	Active school travel modes	Qualitative methods Semi-structured interviews
2010	Faulkner et al.	Toronto, Canada	Walking Bicycle Motorized modes	Thematic analysis Semi-structured interviews
2019	Nikitas et al.	Multiple contexts	Walking School Bus	Thematic analysis Literature synthesis
2022	Dias et al.	Kandy, Sri Lanka	Walking Public transport School buses School vans Private vehicles Three-wheelers Motorcycles	Multinomial Logit (MNL) Model Mixed Logit Models
2017	Kaewkluengklom et al.	Thailand	Motorcycles Other modes	Descriptive statistics Chi-square tests t-tests
2024	Nanthawong et al.	Thailand	Public transport Other modes	Structural Equation Model

2.3 Travel Behavior

Travel behavior among school-aged children is shaped by a complex interplay of socio-demographic, environmental, institutional, and psychological factors. Gender has emerged as a salient determinant in several studies, though findings vary by region and context. Mitra and Buliung (2015) reported no significant association between gender and school travel mode in their Canadian sample, whereas Lodhi et al. (2022), in their study of schoolchildren in Abbottabad, Pakistan, observed pronounced gender-based differences. Boys were found to undertake more trips, and girls reported lower satisfaction with public transport, suggesting that built environment factors may disproportionately affect female students' mobility. Schlossberg et al. (2006) emphasize that school siting decisions and the surrounding built environment are pivotal in influencing students' travel patterns, underlining the importance of designing walkable and safe neighborhoods to foster active travel.

Chaudhry and Elumalai. (2020) contributed to this discourse by examining students' mode choice behavior in the Indian context, finding that female students are more likely to use passive transport modes. Their study also revealed significant exposure to particulate matter across different transport modes, with three-wheeler users experiencing the highest exposure, raising public health concerns regarding transport equity. In Beijing, Zhang et al. (2017) found that car ownership, poor active travel infrastructure, and parental convenience strongly influence private car use for school trips. Similarly, Li and Zhao (2015) reported that socioeconomic status and institutional factors, such as China's population and education policies, drive disparities in mode choice and travel distance among junior secondary school students. Students from suburban areas endure longer commutes due to the uneven distribution of high-quality schools, and car ownership appears to further entrench modal inequalities. Beyond social and economic variables, safety and institutional support also play crucial roles.

Ikeda et al. (2020) examined school travel policy in Auckland, New Zealand, identifying traffic safety as a primary concern. They advocate for infrastructure improvements, such as safe crossings, and educational programs like Travelwise to support active travel. However, the study noted that children from lower socioeconomic backgrounds may require additional institutional support to access equitable and sustainable travel options. Weather is another exogenous factor with a measurable influence on travel behavior. Ma et al. (2019) and Rong et al. (2022) highlighted the effects of weather conditions, including air quality, temperature, wind, and humidity, on students' mode choice decisions. On days with poor air quality or inclement weather, students are more likely to shift from active travel to public or private motorized modes, indicating the need for climate-responsive transportation planning.

2.3.1 Travel Behavior under Adverse Conditions

Adverse environmental conditions are increasingly recognized as a key factor in determining travel behavior, particularly as cities around the world face mounting challenges from climate variability and extreme weather events. Environmental disruptions, including both short-term weather anomalies and chronic atmospheric stressors, can have significant implications for daily mobility patterns, mode choice, and transport system performance (Koetse & Rietveld, 2009). These effects are especially pronounced in contexts where infrastructure resilience is limited and modal alternatives are constrained, such as in low- and middle-income countries (LMICs) and secondary cities (Priya Uteng & Turner, 2019). Adverse weather conditions are commonly defined in transport literature as environmental phenomena that deviate from normal climatic expectations and hinder travel safety, efficiency, and comfort. These conditions include, but are not limited to, heavy rainfall, strong winds, fog, snow, extreme temperatures, and reduced visibility (Saneinejad et al., 2012).

More recently, air pollution, particularly elevated concentrations of fine particulate matter, has been increasingly recognized within this category due to its atmospheric nature and direct impact on mobility decisions (Xu et al., 2021). While traditionally excluded from meteorological classifications, air pollution shares key behavioral characteristics with adverse weather, such as reducing the desirability of active travel modes and increasing the perceived risk of exposure for vulnerable users (Angell & Potoglou, 2022). As such, adverse weather is best understood not only through physical metrics but also in terms of its social and behavioral consequences on the transportation system (Ma et al., 2021). Empirical research has consistently demonstrated that adverse weather influences a wide range of travel behaviors. Rain and snow have been shown to reduce the use of active modes such as walking and cycling, particularly when protective infrastructure is lacking or when users perceive elevated risk (Böcker et al., 2016). Wind and extreme temperatures can similarly discourage outdoor travel or prompt shifts to more enclosed modes (Mirzaei et al., 2021).

In urban settings, poor weather conditions are also associated with longer travel times, increased congestion, and decreased service reliability for public transport (Zhou et al., 2017). These outcomes often lead to behavioral adaptations such as rescheduling trips, modifying routes, or switching modes. Importantly, these adjustments are not equally accessible to all travelers (Thondoo et al., 2020). Individuals with access to private vehicles or flexible schedules may adapt more easily, whereas others, especially students, the elderly, or low-income commuters, may face disproportionate disruptions and exposure (Delbosc & Currie, 2011). School travel offers a particularly relevant lens through which to examine the impact of adverse weather, as students typically have fixed schedules and may rely on modes that are highly sensitive to environmental variability, such as walking or motorcycles (Blanchette et al., 2021).

Where formal school transport services are unavailable, many students remain dependent on informal or unsafe travel arrangements, amplifying their vulnerability during environmental disturbances. Despite growing awareness of these dynamics, there remains a paucity of research focusing on how adverse weather affects school travel behavior in peripheral urban areas and developing regions. Much of the existing literature is concentrated in high-income metropolitan contexts, where infrastructure and data availability support more detailed modeling (Böcker et al., 2013). In contrast, border cities and secondary urban centers, often characterized by fragmented transport networks and seasonal climatic extremes, remain underexplored. Addressing this gap, the present study investigates school travel behavior under both normal and adverse weather conditions in Chiang Rai, Thailand, a region marked by monsoonal rainfall, transboundary haze pollution, and limited modal alternatives. In doing so, it contributes to a more nuanced understanding of climate-sensitive mobility and highlights the need for resilient and equitable transport planning in vulnerable urban settings.

2.3.2 Factors Affecting Travel Behavior

Travel behavior is a complex outcome shaped by a combination of individual attributes, household characteristics, built environment features, and broader societal factors. Age, gender, and income levels have been shown to significantly influence transport mode choice, travel frequency, and distance. For instance, Wang and Akar (2021) found that gender differences persist in active travel, with women less likely to walk or bike due to safety and time constraints, while younger individuals are more inclined toward sustainable modes. Household income and vehicle ownership further determine travel mode, as evidenced by Chen et al. (2020), who revealed that higher-income households tend to rely more on private vehicles, whereas lower-income groups are often constrained to public or non-motorized modes. Built environment characteristics, such as land use diversity, connectivity, and access to transit, also significantly impact travel behavior.

Xu et al. (2020) demonstrated that individuals residing in mixed-use, walkable neighborhoods were more likely to engage in active transport modes, emphasizing the role of urban design in promoting sustainable mobility. Similarly, traveling distance to key destinations like schools and workplaces can dictate mode choice. Using data from a metropolitan region in India, Singla et al. (2022) highlighted that shorter trip distances and compact neighborhood designs strongly encouraged walking and cycling, especially among schoolchildren. Weather and environmental conditions are additional influencing factors. According to Khatun and Yamamoto (2021), poor weather conditions, such as heavy rain or high humidity, deter individuals from using active modes, shifting preferences toward more sheltered or motorized options. Furthermore, psychological and perceptual variables, such as safety concerns and travel time reliability, play a critical role.

A study by Kim and Lee (2021) showed that perceived safety from traffic and crime is a key determinant in encouraging walking, particularly among children and elderly populations. Importantly, institutional and policy-level factors also contribute to shaping travel behavior. Shen et al. (2022) examined how transportation policies aimed at reducing car dependency, such as congestion pricing, transit subsidies, and active travel infrastructure, can successfully shift mode choice behavior when well-integrated with land use planning. Moreover, educational and cultural norms, especially in Asian contexts, influence school commuting choices, as students and parents often prioritize academic quality over proximity, leading to longer travel distances (Li et al., 2023).

2.4 Travel Mode Selection

Parental attitudes play a crucial role in influencing younger teens' mode choices for transportation, with socioeconomic and demographic variables being less significant statistically. Attitudinal variables are essential predictors of mode choice. In densely populated areas, walking and bicycling are more prevalent. Crime adversely affects public transit choices for younger teens (Woldeamanuel, 2016). In Abbottabad, Pakistan, there are notable gender-based differences in mode choice preferences and travel characteristics for educational trips. Girls tend to prefer family cars and have more negative views on public transport compared to boys, who are more inclined toward using motorcycles, public transport, and ride-hailing services (Lodhi et al., 2022). Research in Mexico City highlights transport-related inequalities among older adults, particularly concerning income class, gender, and access to public transportation. It stresses the importance of understanding transport-related exclusion in the Global South and among different societal groups, providing insights applicable to other global cities (Villena-Sanchez et al., 2022). A shift in mode choice for school trips has been observed, with a decline in active modes of transport leading to health issues, environmental concerns, congestion, and safety risks due to increased vehicle use. This highlights the importance of understanding the factors that influence mode choice and accompaniment decisions for school trips (Ermagun et al., 2015).

Tourist transport mode choices at destinations are significantly influenced by travel time, cost, party composition, trip purpose, fitness level, knowledge about long-distance travel, mobility options at the destination, and weather conditions. Tourists show inelasticity to travel cost changes, prioritizing transit service quality over price (Bursa et al., 2022). Residential preferences strongly impact travel behavior, even in homogeneous neighborhoods, leading to differences in daily mode use. Inner-city neighborhoods encourage even car-preferring households to use alternative modes of transport. Urban planning policies should adapt to the needs and preferences of future residents to attract a diverse population, as new inner-city areas tend to draw residents from other inner-city locations rather than suburban areas (Jarass & Scheiner, 2018). In the context of Thailand, several studies have explored mode choice selection in both urban and regional settings. Arreeras et al. (2020) conducted a study on factors affecting mode selection in accessing railway stations in Nakhon Ratchasima, emphasizing the critical role of private vehicle availability, travel convenience, and trip purpose in shaping access mode decisions among intercity rail users. Their findings highlight how proximity, infrastructure quality, and personal mobility resources significantly influence modal selection, particularly in semi-urban and peri-urban environments, paralleling the patterns observed among school commuters in border cities such as Chiang Rai.

Complementing this, Chansuk et al. (2022) utilized exploratory and confirmatory factor analysis to evaluate behavioral shifts in the wake of COVID-19, focusing on domestic tourism in Thailand. The study demonstrated how latent variables such as health concerns, perceived risk, and accessibility influence travel choices, reinforcing the value of multi-dimensional analytical approaches to understand evolving mobility behaviors. These studies emphasize the methodological and contextual relevance of using quantitative tools such as MNL and factor analysis to record nuanced transport decisions.

2.5 Multinomial Logit Regression in Mode Choice Study

Travel behavior modeling has evolved significantly through the development and refinement of discrete choice models and emerging machine learning techniques. Southworth (1981) laid important groundwork by calibrating multinomial logit (MNL) models to analyze travel mode and destination choices using a disaggregate database. His research extended traditional practices by incorporating socio-economic characteristics to assess household trip-making behavior for work, shopping, and recreation purposes. By stratifying car-owning households based on income and employment structures, the study revealed that travel time values and demand elasticities could be meaningfully interpreted at a regional level, with model significance validated through likelihood ratio testing at the 99% confidence level. Building on such foundations, Li (2011) proposed a semi-parametric approach to discrete choice analysis that addresses the limitations of the conventional MNL model, particularly its reliance on the Gumbel distribution. This alternative model allowed for heteroscedastic variance and used a transformation-based method to link travel attribute combinations to choice probabilities via an unspecified sensitivity function, capturing varied traveler responses to cost changes. Empirical validation using Danish value-of-time datasets demonstrated improved model flexibility and explanatory depth. In parallel, Salas et al. (2022) explored the predictive power of machine learning (ML) techniques, such as neural networks, in comparison to classical logit models for travel mode choice. While ML models exhibited superior predictive accuracy, especially in the presence of taste heterogeneity.

The study affirmed the enduring value of logit models for their interpretability and explanatory capabilities. The integration of both approaches supports enhanced decision-making in transport policy by balancing predictive performance with theoretical insight. Further enriching the discourse, Tay et al. (2011) introduced a cluster-based framework to understand tour complexity, trip chaining, and mode choice among non-workers. Using data from the Space-Time Activity Research (STAR) in Halifax, Canada, they identified five behavioral clusters and applied Poisson, ordered probit, and MNL models to capture travel patterns across different socio-demographic profiles. The study emphasized the critical role of urban form and daily activity structure in shaping travel decisions, particularly for non-work trips, and highlighted the necessity of robust choice set development before model estimation.

Collectively, these studies illustrate the multifaceted nature of travel behavior modeling and underscore the need for continuous methodological innovation to better capture the complexity of individual travel choices in diverse urban contexts. Previous studies on travel mode choice perspectives are represented in Table 2.2.

Table 2.2 Previous studies on travel mode choice perspective

Years	Reference	Country	Travel modes	Methods
2015	Mitra et al.	Toronto, Canada	Walk Transit School bus Car	Multinomial Logit (MNL) Model
2015	Ermagun et al.	Tehran, Iran	Walk Auto drive School bus Public transport	Three-Level Nested Logit (NL) Multinomial Logit (MNL) Model
2015	Thrane	Norway	Private car Air Transport Public transport	Multinomial Logit (MNL) Model
2018	Singh et al.	Kanpur, India	Walk Bicycle Cycle-rickshaw School bus Tempo/auto Family vehicle	Multinomial Logit (MNL) Model
2019	Ma et al.	Beijing, China	Walking Bicycle Public transport Car	Multinomial Probit (MNP) Model Multinomial Logit (MNL) Model
2019	Zhou et al.	State of Western Australia	Car Bus Air transport	Multinomial Logit (MNL) Model Nested Logit Models
2019	Zhou et al.	State of Western Australia	Car Bus Air transport	Multinomial Logit (MNL) Model Nested Logit Models

Table 2.2 (continued)

Years	Reference	Country	Travel modes	Methods
2020	Chaudhry et al.	India	Two-wheeler Passenger car Three-wheeler School bus Active school transport	Multinomial Logit (MNL) Model
2020	Chaudhry et al.	India	Two-wheeler Passenger car Three-wheeler School bus Active school transport	Multinomial Logit (MNL) Model
2020	Tang et al.	Hangzhou, China	Walk Bike or e-bike Bus Subway Automobile Others	Multinomial Logit (MNL) Model
2021	Liang et al.	Milan, Italy	Public transport Private car Multimodal transport Active transport	Multinomial Logit (MNL) Model Random Forest (RF) Support Vector Machine (SVM)
2022	Dias et al.	Kandy, Sri Lanka	Walking Public bus School bus School van Private vehicle	Multinomial Logit (MNL) Model Mixed Logit Models

Table 2.2 (continued)

Years	Reference	Country	Travel modes	Methods
2022	Paul et al.	Dhaka, Bangladesh	Non-motorized vehicle On-demand vehicle Private vehicle Public transport Walk	Multinomial Logit (MNL) Model
	Present study	Senior high school	Active transport Motorcycles School bus Private	Factor Analysis Multinomial Logit (MNL) Model

CHAPTER 3

METHODOLOGY

3.1 Study Area

Chiang Rai province, located in northern Thailand, is a diverse region encompassing urban, suburban, and rural areas. The study area in Figure 3.1 is a Muang Chiang Rai district in Chiang Rai Province which is one of the 18 most populous districts in Chiang Rai Province with an area of 1,216 km² with a total population of 125,340 people out of an entire Chiang Rai Province of 785,252 people (Chiang Rai Provincial Community Development Office, 2019) Investigating mode selection for school trips in Muang Chiang Rai district has a unique and intriguing context to understand transportation preferences and decision-making processes among students and their parents or guardians.

This district presents a range of transportation options for school trips, including walking, cycling, motorbiking, public transit, and private vehicles. The target group selected to study is an extra-large school in Mueang Chiang Rai District, focusing on mode selection within this district, to shed light on the factors that influence transportation decisions for school trips in this specific geographic context. This includes exploring the significance of various attributes such as travel distance, travel time, cost considerations, safety perceptions, convenience, and Environmental concerns.

(a) (b)

Figure 3.1 The Chiang Rai Province (a) and Mueang Chiang Rai District (b)

The study area, there are 18 schools that teach at the senior high school level, have shown in Table 3.1. And there are extra-large schools to meet the target group, with 6 schools. Namely, the schools are CRPAO School (A), Samakkhi Witthayakhom School (B), Chiang Rai Municipality School 6 (C), Damrongrat Songkro School (D), Chiang Rai Vidhayakhome School (E), and Sahasartsuksa School (F) illustrated in Figure 3.2.

Table 3.1 Schools that teach at the senior high school level in Muamg Chiang Rai, Chiang Rai

No.	**School**	**Locality**	**School Level**	**Total (Senior high school)**	**Total**
1.	CRPAO School	Rop Wiang	Primary School – High School	1468	3263
2.	Samakkhi Witthayakhom School	Wiang	High School	1,752	3113
3.	Chiang Rai Municipality School 6	Rim Kok	High School	1600	3000
4.	Damrongrat Songkhro School	Wiang	High School	1,314	2639

Table 3.1 (continued)

No.	School	Locality	School Level	Total (Senior high school)	Total
5.	Sahasartsuksa School	Rim Kok	Kindergarten – High School	489	2468
6.	Chiang Rai Vitthayakhom School	Wiang	Pre-Kindergarten – High School	614	1948
7.	Mengrai Maharat Wittayakhom School	Nang Lae	High School	419	1006
8.	Santi Wittaya School	Rop Wiang	Pre-Kindergarten – High School	208	968
9.	Municipal School 5 Den Ha	Rop Wiang	High School	200	800
10.	Chiang Rai International Christian School	Ban Du	Primary School – High School	142	568
11.	Huay Sak Wittayakhom School	Huay Sak	High School	192	508
12.	Chulabhorn Science High School, Chiang Rai	Rop Wiang	High School	430	430
13.	Triam Udom Suksa Pattanakarn School, Chiang Rai	Rop Wiang	High School	180	415
14.	TaweeSC Wittaya School	Pa O Don Chai	High School	141	313
15.	Samakkhi Wittayakom 2 School	Rop Wiang	High School	114	276
16.	Donchai Wittayakhom School	Pa O Don Chai	High School	70	266

Table 3.1 (continued)

No.	School	Locality	School Level	Total (Senior high school)	Total
17.	Chiang Rai International School	Rim Kok	Kindergarten – High School	30	242
18.	Chiang Rai Panyanukul School	Pa O Don Chai	Kindergarten – High School	123	123

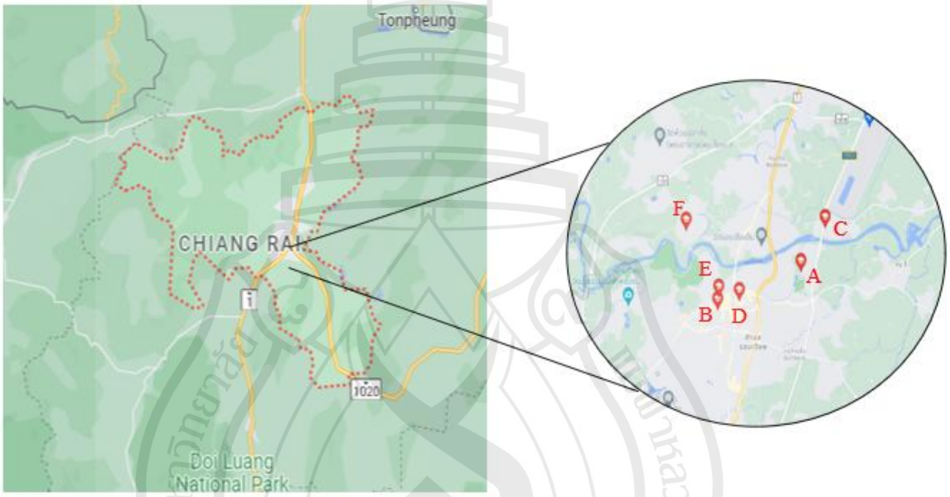

Figure 3.2 The selected School to study in Chiang Rai

Additionally, the study will examine the role of demographic factors, trip characteristics, and parental preferences in shaping mode selection behavior. Understanding mode selection for school trips in the Chiang Rai district has implications for transportation planning and policy development. It can provide valuable insights into the transportation needs of students and their families, helping inform initiatives to improve the accessibility, safety, and sustainability of school transportation services. The findings from this study can contribute to the development of tailored interventions and strategies that promote efficient and environmentally friendly modes of transport, enhance student mobility, and reduce traffic congestion in the district.

3.2 Sample Size and Data Collection

Based on data collected from all the school provides education up to the senior high school level in Mueang Chiang Rai, Chiang Rai. This research was chosen to study schools with extra-large sizes. The school sizes in Thailand were categorized into 4 groups based on the number of students: small, medium, large, and extra-large. Small schools have a minimum of 119 students, medium schools have 120 to 719 students, large schools have 720 to 1,679 students, and extra-large schools have 1,680 students or more (Office of the Basic Education Commission Ministry of Education, 2021) There are a total of 18 high schools in Mueang Chiang Rai district the school provides education up to the senior high school level and has only 6 extra-large schools namely CRPAO School with 3263 students, Samakkhi Witthayakhom School with 3,113 students, Chiang Rai Municipality School 6 with 3,000 students, Damrongrat Songkhro School with 2,639 students, Sahasartsuksa School with 2,468 students, and Chiang Rai Vidhayakhome School with 1,948 students illustrated in Figure 3.3.

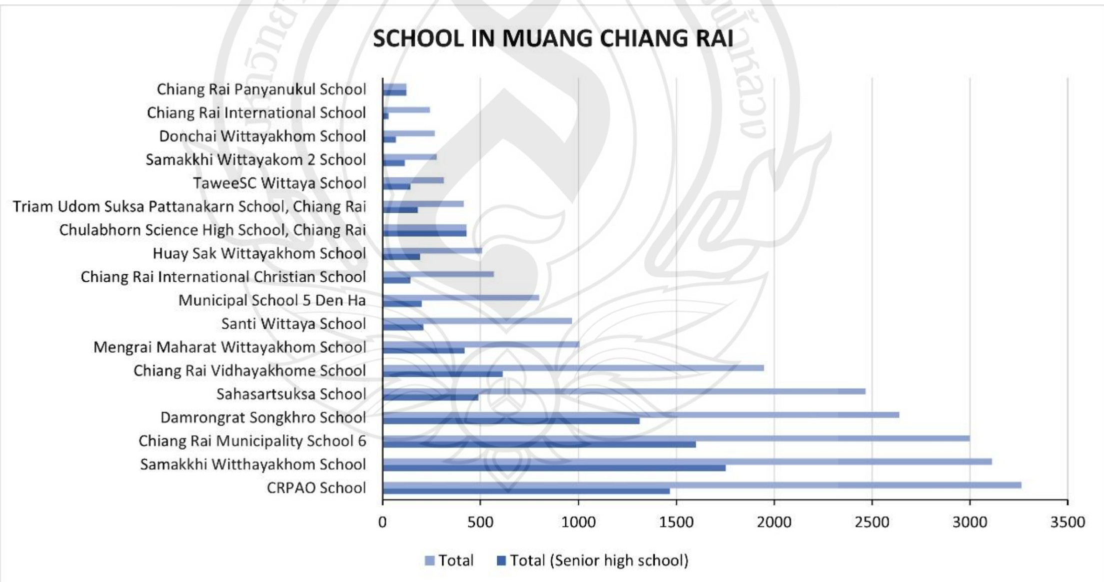

Figure 3.3 The total number of high school levels in Mueang Chiang Rai District

From a case study, a selection study was conducted among senior high school students in 6 extra-large schools with a total of 9032 students. The sample size for the study was determined using the formula of Taro Yamane as Equation 1 (Taro Yamane, 1973). By taking the number of all students in 6 schools to calculate the sample population to know the total number must be used.

$$n = \frac{N}{1 + Ne^2} \quad \text{(Eq. 1)}$$

Where N represents the population size, n denotes the sample size, and e is the margin of error, equal to 0.05, and when e^2, the value is 0.0025. Data collection was carried out through on-site surveys administered directly within each selected school. A random sampling technique was employed to select senior high school students, and responses were recorded using paper-based survey forms. The result is needed to survey 384 students using a questionnaire. Ultimately, a total of 472 valid responses were collected, exceeding the minimum sample size requirement and thereby enhancing the robustness of the dataset. Any questionnaires with incomplete or missing information were removed during the data cleaning process to ensure statistical reliability. The data collection was conducted from January to February 2024, during the regular academic term, which coincided with typical seasonal weather variations, including haze and occasional rainfall events in the Chiang Rai region.

After that, the number of students at the high school level of all 6 schools will be calculated to determine how many questionnaires we must collect from each school. The result is the percentage of students to be analyzed from each school is as follows: Samakkhi Witthayakhom School 24% (75 students), Chiang Rai Municipality School 6 22% (68 students), CRPAO School 20% (63 students), Damrongrat Songkro School 18% (56 students), Chiang Rai Vidhayakhome School 9% (27 students), and Sahasartsuksa School 7% (21 students), as shown in Figure 3.4. The data collected from the questionnaire can then be analyzed further.

Where N represents the population size, n denotes the sample size, and e is the margin of error. Data collection was carried out through on-site surveys administered directly within each selected school. A random sampling technique was employed to select senior high school students, and responses were recorded using paper-based survey forms. Ultimately, a total of 472 valid responses were collected, exceeding the minimum sample size requirement and thereby enhancing the robustness of the dataset. Any questionnaires with incomplete or missing information were removed during the data cleaning process to ensure statistical reliability. The data collection was conducted from January to February 2024, during the regular academic term, which coincided with typical seasonal weather variations, including haze and occasional rainfall events in the Chiang Rai region.

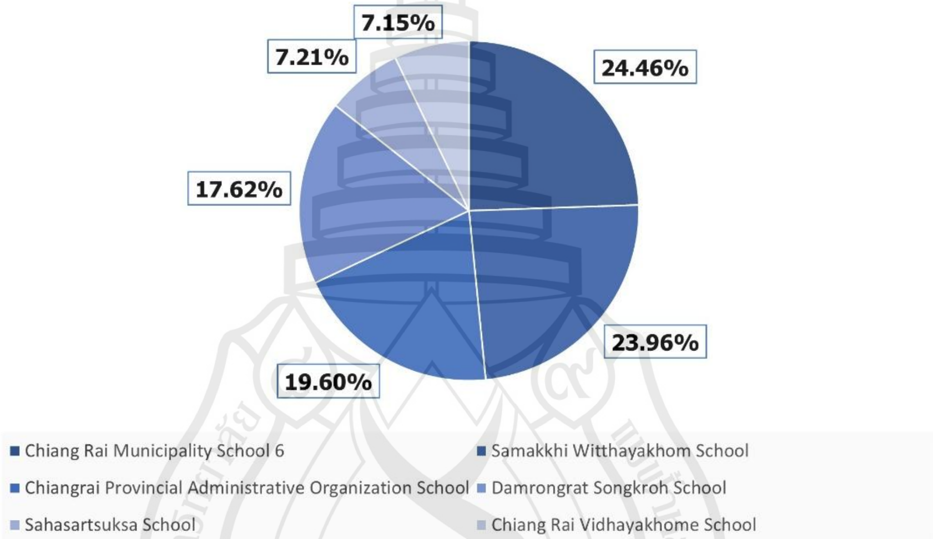

Figure 3.4 Target group of student respondents across six extra-large schools in Mueang Chiang Rai district

3.3 Questionnaire Design

The questionnaire has been designed to study the mode choice of transportation by senior high school students to travel to school and the various factors related to the selection of transportation modes. The questionnaire has been developed in Thai and English to accommodate the diversity of nationalities. The questionnaire consists of 3 main sections. (1) Characteristics of Respondents, including variables such as gender, age, grade level, household income, vehicle ownership, household size, occupation of parents, and residential location. (2) Travel Behavior/Travel Characteristics to School, includes questions regarding the selection of transportation modes to school, distance, time, cost, and waiting time for public transportation in normal and abnormal weather conditions. This section identifies the preferred transportation mode for traveling to school. (3) Satisfaction with Travel Behavior includes questions related to the level of satisfaction with various aspects of traveling to school, including private and public transportation modes. This section will be evaluated for both private and public transportation modes.

Overall, the questionnaire has been developed to understand the travel behavior of high school students and the factors influencing their selection of transportation modes. It is hoped that the results of this study will contribute to the development of effective transportation policies and strategies to improve the transportation system for students.

3.4 Pilot Test

Prior to the main data collection, a pilot test was conducted with 50 high school students from one of the selected extra-large schools in Mueang Chiang Rai District to validate the reliability and internal consistency of the questionnaire instrument. The pilot sample represented approximately 10.6% of the minimum required sample size (n=472), exceeding the recommended 10% threshold for pilot studies in social science research, and respondents were selected using convenience sampling from students who met the same inclusion criteria as the main study but were excluded from the final data collection to avoid response contamination. The pilot test specifically focused on validating the reliability of Section 3 of the questionnaire, which measures students' satisfaction with school transport services using 19 variables rated on a 5-point Likert scale, including factors such as ease of boarding, driver behavior, driving quality, punctuality, scheduling frequency, ticket system, fare pricing, vehicle characteristics, cleanliness, accessibility, and safety.

The reliability analysis revealed Cronbach’s alpha coefficient of 0.947 for the 19-item satisfaction scale, indicating excellent internal consistency that substantially exceeds the commonly accepted thresholds of 0.70 for exploratory research and 0.80 for confirmatory studies, with all individual items demonstrating adequate item-total correlations (r > 0.30) and no items requiring removal. The excellent Cronbach's alpha value provided confidence that the satisfaction scale would yield consistent and reliable measurements in the full study, and the pilot test revealed no significant issues with question comprehension, response time, or administration procedures, validating the survey methodology for deployment to the full sample of 472 respondents across the six selected schools without modifications.

3.5 Analysis Methods

3.5.1 Utility Function

In the research on mode choice for school trips in Chiang Rai, a utility function can be utilized to understand and analyze the decision-making behavior of students and their parents or guardians. The utility function will help capture the preferences and relative desirability associated with different transportation modes available for school trips. The utility function in this research can take the form: U (mode 1, mode 2, ..., mode n) where U represents the utility, and $mode_1$, $mode_2$, ..., $mode_n$ represent the different transportation modes under consideration (e.g., walking, cycling, motorbike, public transit, private vehicle). Several mode choice examples are proposed. Discrete choice models assume that a n decision-maker (n = 1, …, Q), who must choose between i alternative, assigns to each alternative a U_{in} utility function was specified was as Equation 2.

$$U_{in} = V_{in} + \varepsilon_{in} \tag{Eq. 2}$$

Where V_{iq} is a deterministic term and ε_{iq} is the random term of the utility function. V_{iq} can have different specifications (Train, 2009; Ortúzar & Willumsen, 2011; Greene & Hensher, 2010; Dias et al., 2022). However, the utility function is part of the Multinomial Logit Model, which is the main tool of this research.

3.5.2 Multinomial Logit Model (MNL)

The Multinomial Logit (MNL) model is a commonly used statistical technique for analyzing mode choice behavior in transportation research, including studying mode choice for school trips in Muang Chiang Rai, Chiangrai. The MNL model (Eq. 3) allows for the estimation of the probability of choosing a specific mode from a set of alternatives based on the attributes or characteristics of each mode. In this research, use the MNL model is employed to understand the factors that influence mode choice for school trips and estimate the probabilities of selecting different transportation modes from the target group that make rational choices by maximizing their utility, which is derived from the attributes associated with each mode.

$$P_{in} = \frac{e^{Vin}}{\sum_{j=1}^{j} e^{Vj}\, n} \qquad \text{(Eq. 3)}$$

The formulation of a classic multinomial logit model. In this work, a more advanced modeling solution is used to investigate the respondents' heterogeneity to demonstrate that the P_{iq} probability that a q decision-maker chooses i alternative assuming that random terms in Eq. 3 follow Gumbel distributions with mean 0 and variance π2/6 and these are independent and homoscedastic and have been widely used to investigate how the same factors can have different impacts on several decision-makers (Train, 2009; Dias et al., 2022).

The estimation of the MNL model involves fitting the model to observed mode choice data using techniques such as Maximum Likelihood Estimation (MLE). The estimated coefficients provide insights into the impact of each attribute on mode choice behavior and can be used to predict mode choice probabilities for different scenarios or policy interventions, and the parameters of the multinomial logistic regression model are calibrated using the Statistical Package for Social Sciences (SPSS) (Tay et al., 2011).

3.5.3 Exploratory Factor Analysis (EFA)

To uncover the underlying structure of observed variables associated with travel behavior determinants, Exploratory Factor Analysis (EFA) was applied as a multivariate technique for dimensionality reduction. EFA is especially effective in identifying latent constructs by examining correlations among a large set of observed indicators, thereby simplifying complex data structures without imposing prior assumptions about the number or structure of latent factors (Fabrigar & Wegener, 2012). Before performing EFA, the adequacy of the dataset was assessed using the Kaiser-Meyer-Olkin (KMO) measure and Bartlett's Test of Sphericity. A KMO value exceeding 0.60 and a statistically significant Bartlett's test ($p < 0.05$) confirmed the suitability of the data for factor analysis (Kaiser, 1974). Principal Axis Factoring (PAF) was employed as the extraction method because it is more appropriate for non-normally distributed data, which is often the case in transportation survey research (Costello, 2005). To enhance interpretability, the extracted factors were rotated using the Varimax rotation method, an orthogonal technique that maximizes the variance of factor loadings and facilitates clearer factor delineation. Factors with eigenvalues greater than 1.0 were retained in line with Kaiser's criterion, and items with factor loadings below 0.40 were excluded to ensure clarity and reliability in the resulting factor structure (Black & Babin, 2019). The latent factors were labeled based on theoretical coherence and the shared characteristics of grouped variables, typically aligned with service quality, vehicle comfort, travel safety, and accessibility dimensions. These extracted factors were subsequently utilized in further analyses, such as regression modeling and structural equation modeling, to assess their influence on travel mode choice and broader mobility behaviors.

3.6 Ethical Considerations

The authors have completed the ethics examination, obtained the certificate, which is shown in the Appendix, and this thesis was conducted under the Declaration of Helsinki and approved by the Institutional Review Board of the Mae Fah Luang University Ethics Committee on Human Research protocol no. EC 24058-12. Accordingly, all participants were fully informed about the nature and purpose of the study, and the participation was entirely voluntary. The researchers ensured that all survey data would remain confidential and anonymous, thereby safeguarding the privacy and rights of all respondents.

CHAPTER 4

RESEARCH RESULTS

4.1 Pre-test and Post-test Results

Before conducting the main survey, a pre-test was administered with 30 respondents to evaluate the clarity, reliability, and appropriateness of the questionnaire items. The pre-test ensured that the questions were easily understood and relevant to the study objectives. Based on the feedback, minor adjustments were made to wording and structure to improve comprehensibility. For reliability analysis, Cronbach's alpha was employed. The pre-test yielded alpha coefficients above the acceptable threshold of 0.70 for all constructs, indicating good internal consistency. This confirmed that the instrument was reliable for data collection. Following data collection, a post-test reliability check was conducted using the full dataset. The Cronbach's alpha values remained consistently above 0.70 across all dimensions, reaffirming the stability and reliability of the measurement tool. This indicated that the questionnaire was effective in capturing the factors influencing school trip mode choice in Chiang Rai.

4.2 Sample Characteristics

The demographic profile of the respondents demonstrates a clear gender imbalance, with female students comprising 70.3% of the sample, compared to 29.7% male students. This may suggest a higher participation rate of female students in the survey or reflect the actual gender distribution in the study population. Age distribution is relatively even across the upper secondary school spectrum: 10.4% of students are 15 years old, 29.9% are 16 years old, 29.0% are 17 years old, and 30.7% are 18 years old. This indicates that the sample adequately represents all relevant age groups within senior high school.

With respect to grade level, students in Grade 10 constitute the largest proportion (39.8%), followed by Grade 12 (31.1%) and Grade 11 (29.0%). This balanced distribution across grades reduces the likelihood of bias towards a specific academic year. In terms of financial capacity, measured by weekly pocket money, nearly half of respondents (48.9%) receive less than 500 THB, while 43.4% receive between 500–1,000 THB. Only a small minority receive higher amounts, with 5.5% reporting 1,001–1,500 THB, and just 1.1% receiving 1,501–2,000 THB and more than 2,000 THB per week. These figures suggest that most students have limited personal financial resources, which may influence their mode choice for school travel.

Parental employment status shows that 87.7% of respondents have at least one parent engaged in the workforce, while 12.3% report otherwise. Household income distribution further highlights socioeconomic disparities: nearly half of the households (48.3%) earn less than 30,000 THB per month, while 24.4% earn between 30,001–40,000 THB, and 11.7% fall in the 40,001–50,000 THB range. Higher-income households are less common, with only 6.4% reporting 50,001–60,000 THB and 9.3% earning more than 60,000 THB.

In terms of household composition, families with 3–4 members are the most common (53.2%), followed by 5–6 members (29.4%). Smaller households with fewer than 3 people are relatively rare (5.1%), while larger households exceeding 6 members represent 12.3%. This distribution indicates that the majority of students live in medium-sized nuclear families, which is consistent with demographic patterns in many Thai urban contexts.

Table 4.1 Demographic information of participants. (n = 472)

Items	**Sub-categories**	**Frequency**	**Percentage**
Gender	Male	140	29.7
	Female	332	70.3
Age	15 years old	49	10.4
	16 years old	141	29.9
	17 years old	137	29
	18 years old	145	30.7
Grade	Grade 10	188	39.8
	Grade 11	137	29
	Grade 12	147	31.1
Pocket money per week*	< 500 THB	231	48.9
	500 – 1,000 THB	205	43.4
	1,001 – 1,500 THB	26	5.5
	1,501 – 2,000 THB	5	1.1
	> 2,000 THB	5	1.1
Parents working status	Do	414	87.7
	Don’t	58	12.3
Household monthly income	< 30,000 THB	228	48.3
	30,001 – 40,000 THB	115	24.4
	40,001 – 50,000 THB	55	11.7
	50,001 – 60,000 THB	30	6.4
	> 60,000 THB	44	9.3
Family member	< 3 people	24	5.1
	3 - 4 people	251	53.2
	5 - 6 people	139	29.4
	> 6 people	58	12.3
Household car ownership	Yes	401	85
	No	71	15
Household motorcycle ownership	Yes	446	94.5
	No	26	5.5

Table 4.1 (continued)

Items	Sub-categories	Frequency	Percentage
Current residence	Urban	293	62.1
	Suburban	179	37.9

Source The Siam Commercial Bank Public Company Limited, n.d.

Note * 1 USD ≈ 35.00 THB

4.3 Mode Choice Preference Under Weather Conditions

The analysis of students' travel mode preferences under varying weather conditions, illustrated in Figure 4.1, reveals distinct behavioral shifts, underscoring the influence of environmental factors on school commuting choices. Under normal weather conditions, motorcycles emerge as the most frequently used mode, accounting for 36.9% of trips. This predominance reflects the widespread appeal of two-wheeled vehicles in facilitating short- to mid-distance school travel due to their affordability and maneuverability. However, motorcycle usage exhibits a marked decline to 26.7% during adverse weather conditions, suggesting heightened sensitivity to the safety and comfort challenges posed by inclement weather. In contrast, school bus usage demonstrates notable stability, maintaining a consistent share of 33.7% regardless of weather. This indicates the school bus system's perceived reliability and structured nature, which likely insulates it from weather-related disruptions.

Interestingly, active transport, including walking and cycling, shows a marginal increase from 13.8% to 14.2% in adverse weather. This counterintuitive pattern may be attributed to students residing within proximity to their schools, for whom walking remains the most practical and least affected mode of travel. Meanwhile, private vehicle use experiences a substantial surge from 15.7% under normal conditions to 25.4% during adverse weather. This shift suggests that households with access to private cars are more likely to pivot toward safer and more sheltered travel alternatives during unfavorable conditions. These findings underscore the significance of weather as a determinant of modal choice and highlight broader issues of transport equity. Students from households lacking access to flexible or resilient transport options may face greater vulnerability to environmental disruptions, thereby reinforcing the need for inclusive and weather-resilient school transport planning.

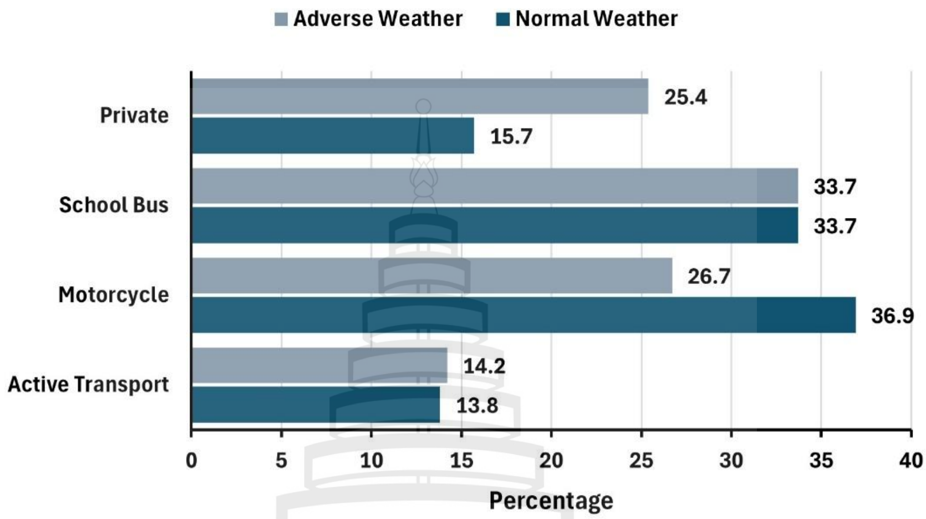

Figure 4.1 Travel mode choice distribution preferences in normal and adverse conditions.

4.4 Travel Behavior Characteristics of Normal and Adverse Weather Conditions

4.4.1 Travel Behavior Characteristics in Normal Weather Conditions

The total distance traveled to school under normal weather conditions revealed significant differences among students. As can be seen from Figure 4.2, many students (32.6%) reported traveling more than 15 kilometers to school, indicating that many students live in remote areas. It's possible that either schools near their residences do not offer high school education, or personal preferences for their school. Students who traveled between 1–5 kilometers accounted for 21.6%, while 17.6% traveled 5–10 kilometers, and 13.1% traveled 10–15 kilometers. Noteworthy, only 15% of students traveled less than 1 kilometer, indicating that few students live in the vicinity of their school.

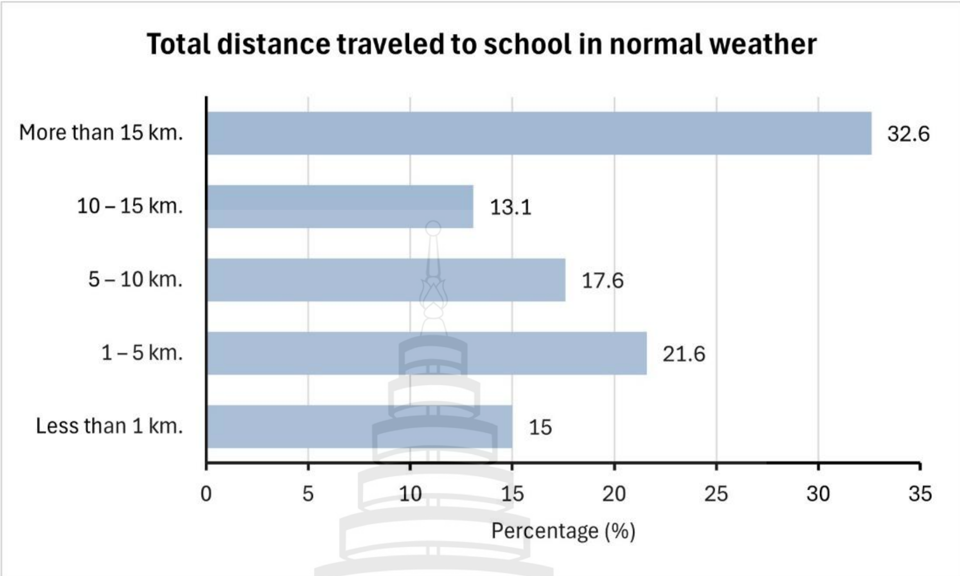

Figure 4.2 The total distance traveled to school in normal weather

Travel time from students' residences to the nearest pick-up point under normal weather conditions, shown in Figure 4.3, reveals key insights into accessibility and first-mile connectivity. A substantial majority (44.7%) reported travel times of less than 5 minutes, indicating that many students live close to designated pick-up locations, which supports convenience and encourages consistent use of school transport services. Meanwhile, 21.6% needed 6–10 minutes, and 12.1% required 11–15 minutes, showing a moderate level of accessibility. However, 14.4% of students spent more than 20 minutes reaching the pick-up point, suggesting gaps in equitable access, particularly for those in more remote or underserved areas.

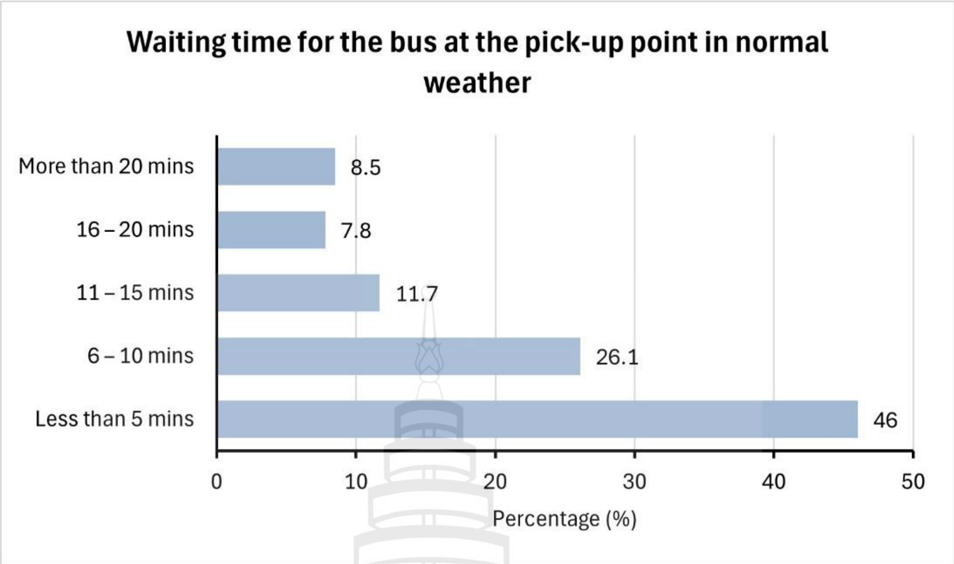

Figure 4.3 The travel time from residence to the nearest pick-up point in normal weather

The waiting time for the bus at the pick-up point under normal weather conditions in Figure 4.4 revealed that most students experience relatively short waiting durations. Specifically, 46% of students wait less than 5 minutes, indicating a generally efficient scheduling and pick-up coordination. An additional 26.1% report waiting between 6 and 10 minutes, while 11.7% experience waiting times of 11 to 15 minutes. Longer waits are less common, with 7.8% waiting between 16 and 20 minutes, and only 8.5% reporting waits exceeding 20 minutes. These results suggest that while the majority of students benefit from timely bus arrivals, a small proportion still face extended waiting periods, which may affect their travel satisfaction and perception of reliability. Improvements in schedule adherence and route optimization could help reduce these delays and enhance the overall efficiency of school transport services.

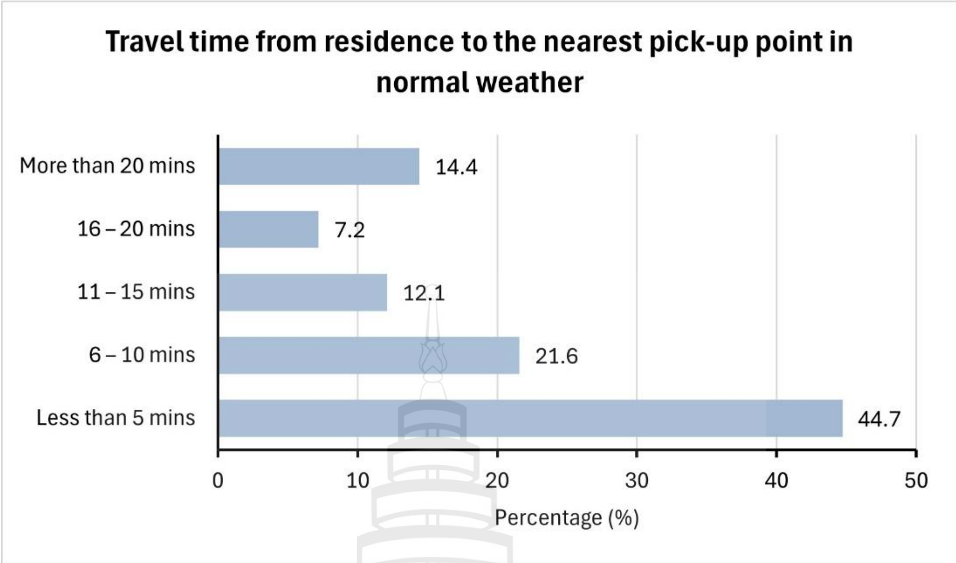

Figure 4.4 The waiting time for the bus at the pick-up point in normal weather

The total travel time to school under normal weather conditions, illustrated in Figure 4.5, indicates that most students have relatively moderate commuting durations. Approximately 33.1% of students reported a travel time between 11 and 20 minutes, making it the most common duration. This is followed by 26.3% who travel for less than 10 minutes, suggesting that a significant portion of students live close to school or have access to efficient transport options. On the other hand, 18.2% of students spend more than 40 minutes commuting, and 9.3% report travel times between 31 and 40 minutes, indicating that some students experience extended travel durations. These findings highlight disparities in school accessibility, which may be influenced by residential location, transport availability, and infrastructure quality, and emphasize the need for targeted interventions to alleviate excessive travel burdens for specific student groups.

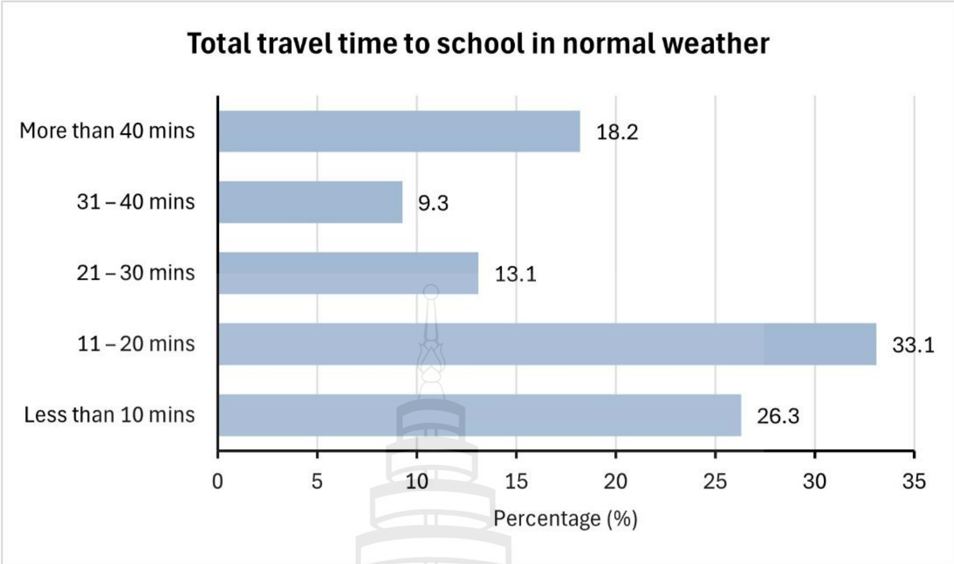

Figure 4.5 The Total travel time to school in normal weather

The total travel expenses per month revealed in Figure 4.6 varied financial burdens among students. The largest group, accounting for 29.9%, reported spending less than 100 baht monthly, suggesting either proximity to school or access to free or low-cost transport. Meanwhile, 28.2% of students incur expenses between 1,001 and 1,500 baht, indicating reliance on costlier transport options, such as private services. About 20.3% and 18% spend 101–500 baht and 501–1,000 baht, respectively, representing moderate expenditure levels. Only 3.6% of students spend more than 1,500 baht monthly, reflecting significant financial strain likely associated with long distances or high-cost transportation.

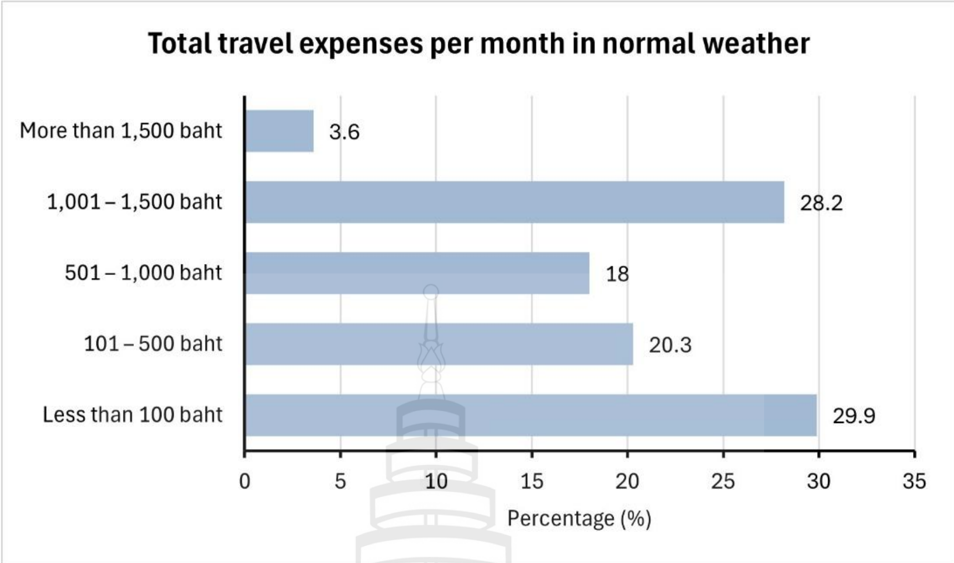

Figure 4.6 The Total travel expenses per month in normal weather

The transfer frequency to school per trip, shown in Figure 4.7 that most students (93.2%) have only a single transfer or travel directly without changing modes. This indicates that most school trips are relatively straightforward and do not involve complex multimodal routes. A small proportion of students, 5.3%, report needing two transfers, while only 1.5% require three or more. These findings suggest that for most students, school commutes are simple and likely more time-efficient and less stressful. However, the minority who face multiple transfers may experience greater travel time and potential delays, highlighting the need for improved transport connectivity and planning for those students.

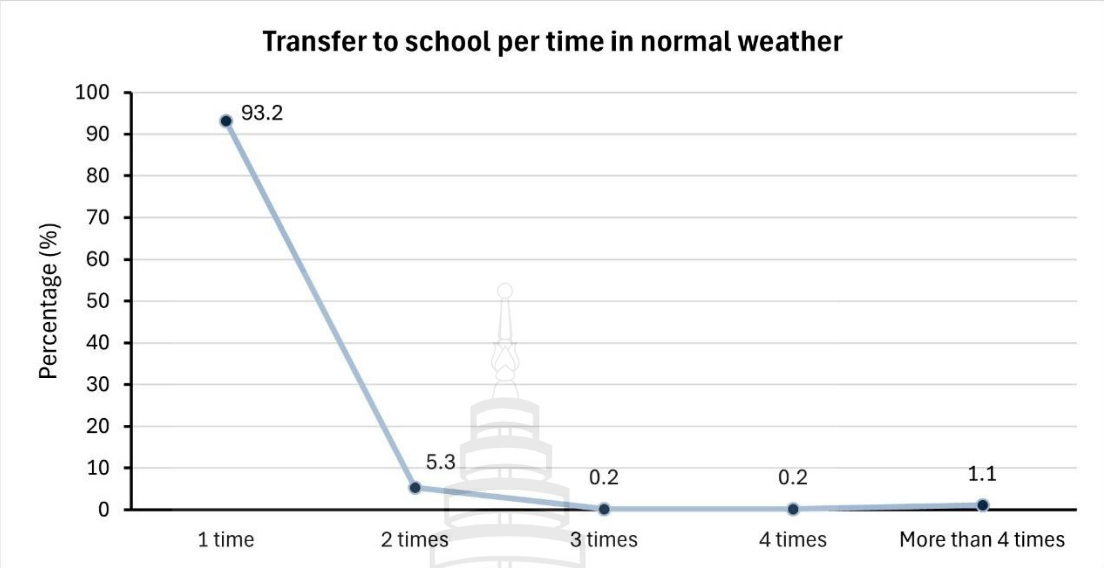

Figure 4.7 The transfer to school per time in normal weather

4.4.2 Travel Behavior Characteristics in Adverse Weather Conditions

The total distance traveled to school under adverse weather conditions is revealed in Figure 4.8, with a skew toward longer commutes. Approximately one-third of students (31.1%) travel more than 15 kilometers, indicating a substantial reliance on transportation infrastructure for educational access. Conversely, 17.4% of students reside less than 1 kilometer from school, suggesting walkability for a minority. Distances between 1 and 15 kilometers are distributed relatively evenly, with 19.3% traveling 1–5 km, 14.2% traveling 5–10 km, and 17.8% traveling 10–15 km. This distribution highlights a diverse spatial dispersion of student residences and reinforces the need for multimodal and resilient transport options, particularly during adverse weather when accessibility challenges may be amplified.

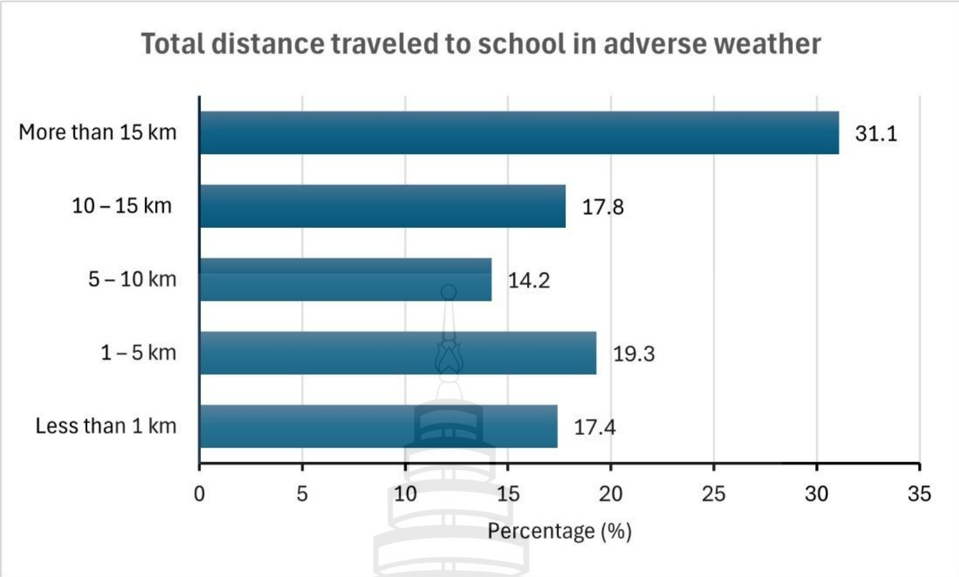

Figure 4.8 The total distance traveled to school in adverse weather

In adverse weather conditions, the travel time from residence to the nearest pick-up point, shown in Figure 4.9, demonstrates a distribution skewed toward shorter durations, though with a notable portion experiencing moderate delays. A significant 41.5% of students report travel times of less than 5 minutes, suggesting that many reside in areas with convenient access to pick-up locations even during inclement weather. Meanwhile, 21.2% and 13.3% of students report travel times of 6–10 minutes and 11–15 minutes, respectively. However, 8.1% and 15.9% report longer access durations of 16–20 minutes and over 20 minutes, respectively. These figures suggest that while many students maintain relatively easy access to school transport, inclement weather also poses additional obstacles for students in terms of punctuality, convenience, and transportation options.

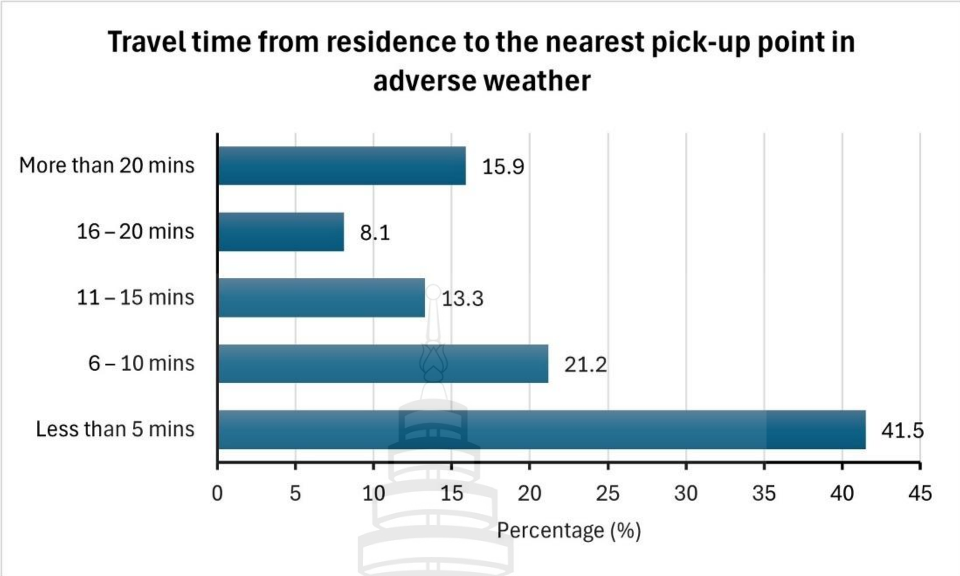

Figure 4.9 The travel time from residence to the nearest pick-up point in adverse weather

Under adverse weather conditions, the distribution of waiting times at pick-up points in Figure 4.10 reveals moderate variability, with a considerable proportion of students still experiencing minimal delays. Specifically, 40.5% of students report waiting less than 5 minutes, indicating efficient scheduling or close coordination between students and school bus services. However, 23.1% and 14.4% experience waiting times between 6–10 minutes and 11–15 minutes, respectively, which could become uncomfortable or unsafe in inclement weather. Notably, 9.3% and 12.7% of students report longer waiting times of 16–20 minutes and over 20 minutes, respectively. These delays highlight the potential impact of weather on bus punctuality and suggest the need for improved service reliability and shelter infrastructure at pick-up points to enhance student safety and travel satisfaction during poor weather conditions.

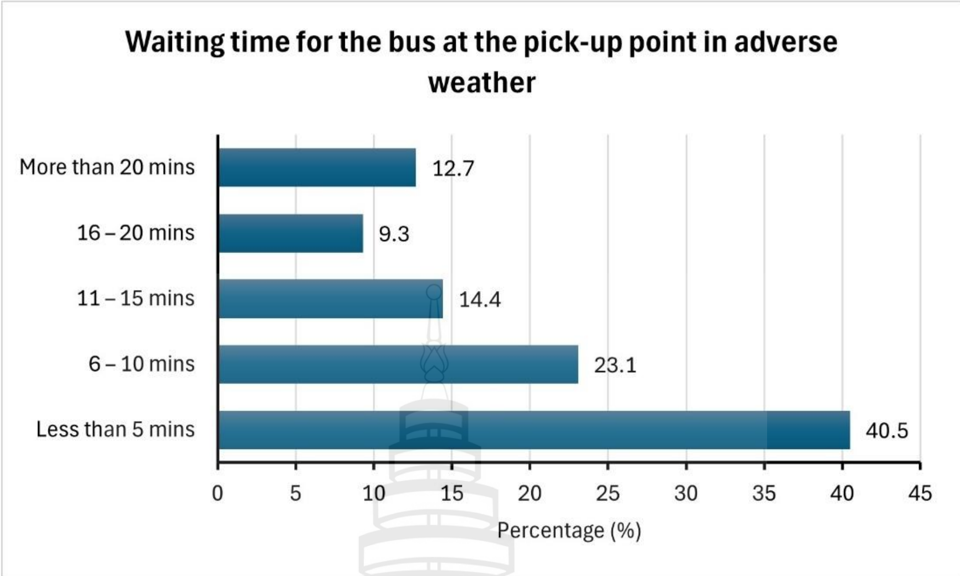

Figure 4.10 The waiting time for the bus at the pick-up point in adverse weather

Under adverse weather conditions, total travel time to school demonstrates a clear pattern of increase, suggesting significant sensitivity of the student commute to adverse conditions. While 19.3% of students reported travel times of less than 10 minutes, the majority experienced considerably longer durations. Specifically, 25.4% of respondents indicated travel times between 11 and 20 minutes, 18.2% between 21 and 30 minutes, and 24.6% exceeded 40 minutes. Only 12.5% reported travel times of 31 to 40 minutes, as illustrated in Figure 4.11. These findings indicate that inclement weather conditions contribute to delays in school commutes, likely due to reduced transport speed, increased congestion, and the need for more cautious driving behavior. The results highlight the need for robust transport planning that accounts for weather variability to ensure timely and reliable school travel for students.

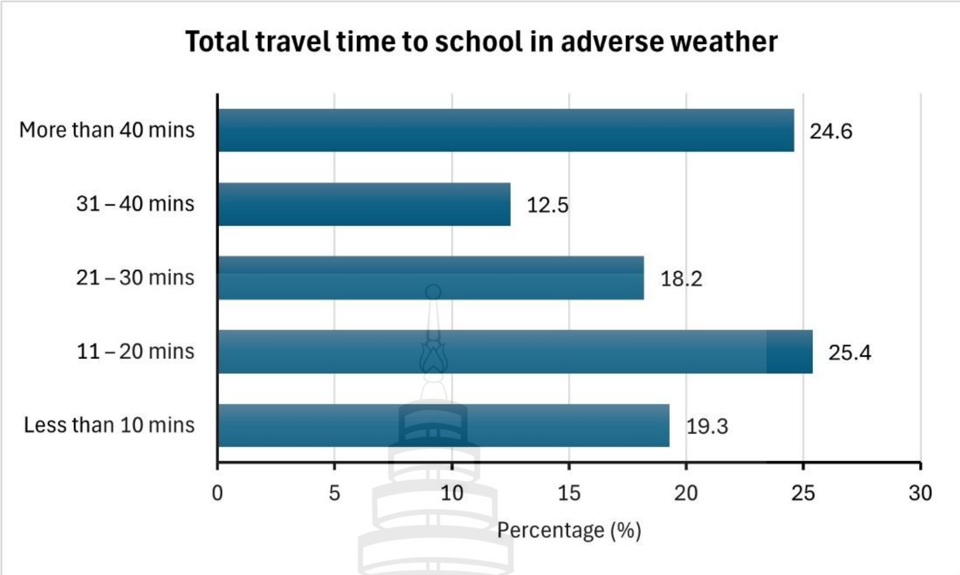

Figure 4.11 The travel time to school in adverse weather

The distribution of monthly travel expenses under adverse weather conditions is illustrated in Figure 4.12, a dual pattern of affordability and financial strain among students. While 31.4% of respondents spent less than 100 baht, suggesting continued reliance on low-cost transportation modes or turning to travel in an active mode, e.g., walking, a notable 28.2% reported monthly expenses between 1,001 and 1,500 baht, indicating a shift toward more secure or private transport alternatives during inclement weather. Mid-range expenditures of 101–500 baht and 501–1,000 baht each accounted for 18.4% of respondents, reflecting a balanced reliance on moderately priced services. Only 3.6% of students reported expenses exceeding 1,500 baht, pointing to a small segment of the population with high travel costs. These findings underscore the economic disparities in transport resilience, highlighting how adverse weather may disproportionately impact students with limited financial means by constraining their modal options.

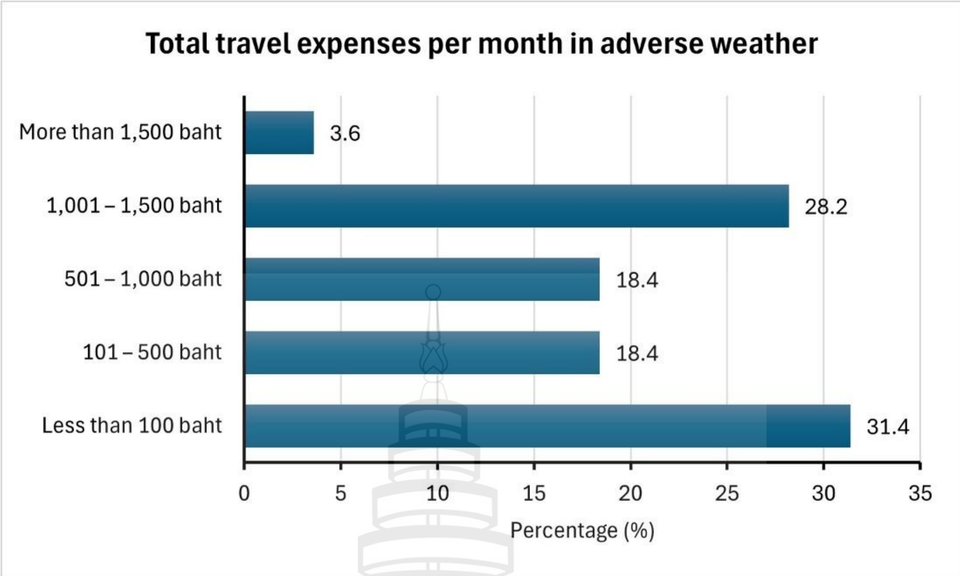

Figure 4.12 The total travel expenses per month in adverse weather

The transfer to school commute under adverse weather conditions is shown in Figure 4.13. Although many students (93.0%) reported making only one transfer during their journey, the impact of bad weather may exacerbate difficulties for those who need to transfer multiple times. Adverse weather can increase waiting times, reduce the reliability and frequency of transportation services, and create safety risks at transfer points. For students who transfer two or more times (approximately 6.9%), these conditions may lead to longer overall travel times, increased physical discomfort, and greater exposure to hazardous environments. Consequently, students facing multiple transfers are potentially more vulnerable during adverse weather, which may affect their punctuality and willingness to use certain modes of transportation.

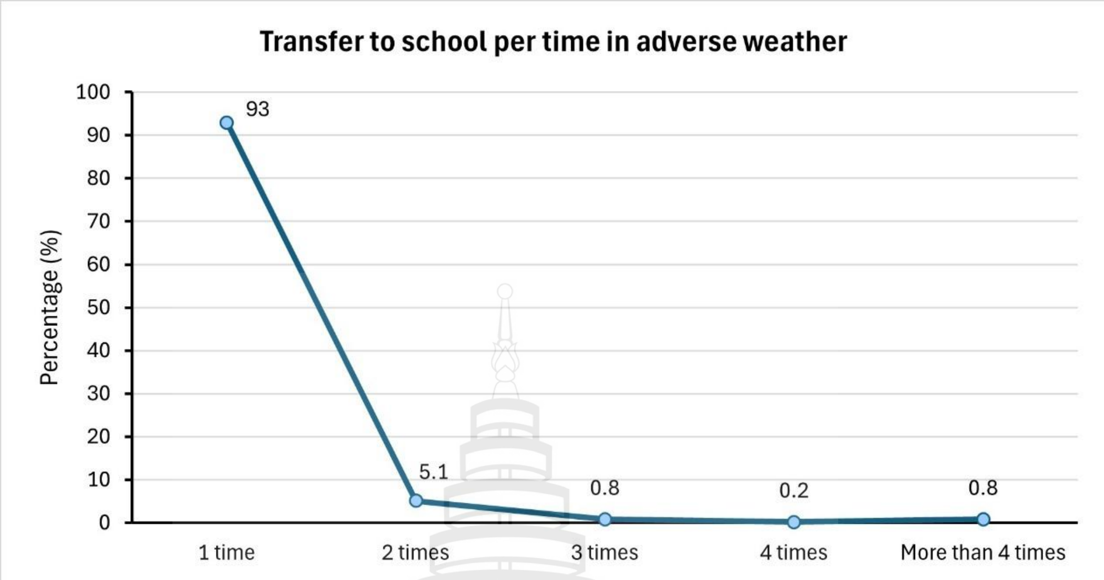

Figure 4.13 The transfer to school per time in adverse weather

4.4.3 Travel Behavior Characteristics in Normal Versus Adverse Weather Conditions

The distribution of travel distances to school under normal and adverse weather conditions, shown in Figure 4.14, reveals notable shifts in student commuting patterns. Under normal weather, 15.0% of students travel less than one kilometer to school, increasing to 17.6% during adverse weather conditions. This rise suggests that students residing close to school maintain or slightly increase their likelihood of walking or using short-distance modes, potentially due to the reduced dependence on external transport services. In contrast, the proportion of students traveling moderate distances, specifically 1–5 km and 5–10 km are decreases from 21.6% to 19.3% and from 17.6% to 14.2%, respectively. These declines may reflect behavioral adaptations, such as choosing different pick-up points or avoiding non-essential travel during poor weather. Meanwhile, the share of students traveling 10–15 km rises from 13.1% to 17.8%, possibly indicating re-routed or elongated trips due to road conditions, traffic, or service disruptions. Interestingly, the proportion of students commuting over 15 km remains relatively consistent (32.6% vs. 31.1%), suggesting that those with long-distance commutes are less flexible in their mode or route choices, regardless of weather. These findings point to differentiated impacts of adverse weather based on travel distance, highlighting the vulnerability of mid-distance commuters and the relative resilience of both short- and long-distance student travelers. Addressing these disparities may require targeted interventions such as enhanced route planning, shelter infrastructure, or real-time service updates during adverse weather conditions.

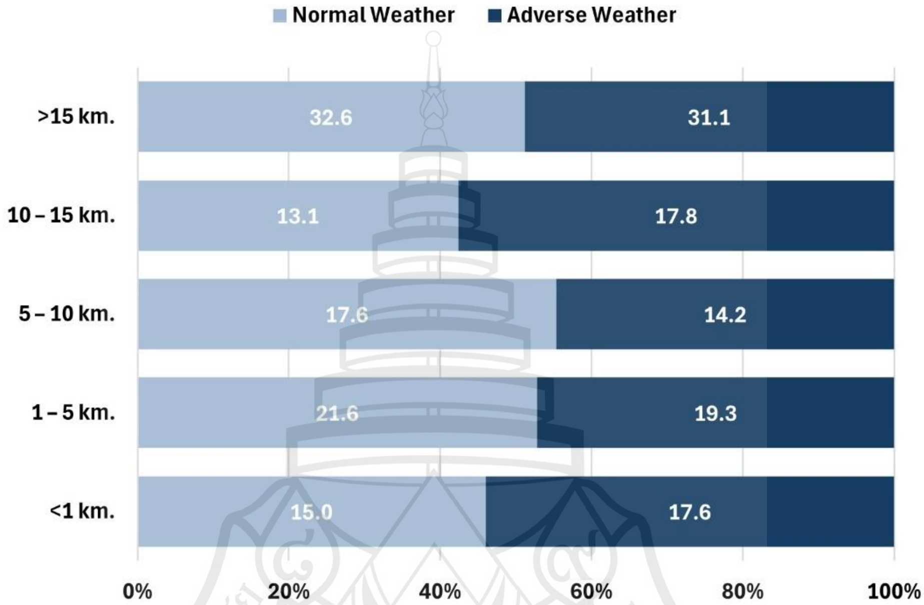

Figure 4.14 The travel distance to school in normal versus adverse weather

The analysis of travel times from students' residences to the nearest pick-up points under normal and adverse weather conditions, illustrated in Figure 4.15. Under normal weather, 44.7% of students reach the pick-up point within five minutes, indicating a high level of spatial accessibility. However, during adverse weather, this proportion decreases slightly to 41.5%, suggesting that inclement conditions may either impede direct access or encourage students to seek safer, although more distant, boarding points. The proportion of students requiring 6–10 minutes remains relatively stable (21.6% to 21.2%), highlighting resilience in moderate accessibility ranges. Notably, the share of students requiring longer travel times (11–15 minutes, 16–20 minutes, and >20 minutes) increases across all categories during adverse conditions. Particularly, students traveling more than 20 minutes rose from 14.4% to 15.9%, reflecting weather-induced spatial displacement. These findings highlight latent vulnerabilities in school transport accessibility, emphasizing the need for enhanced first-mile infrastructure and adaptive transport services during adverse environmental events.

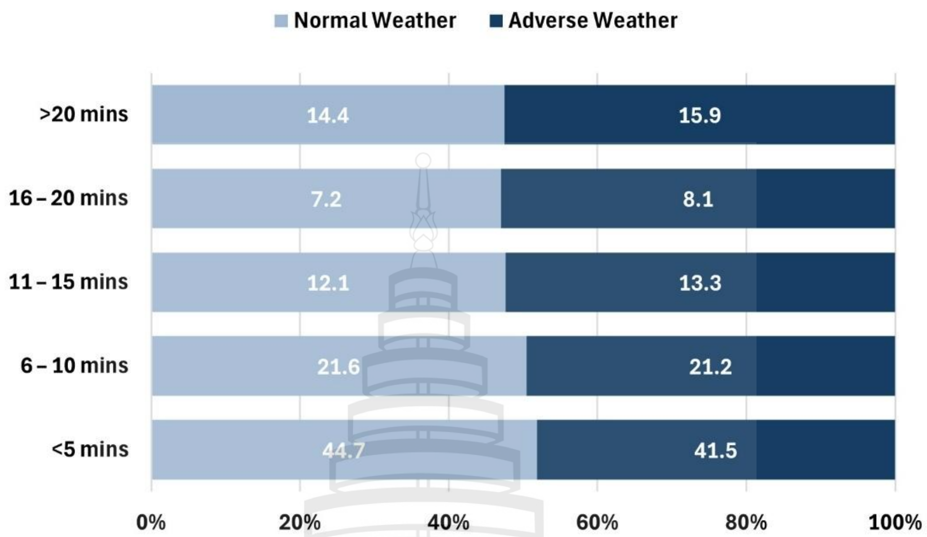

Figure 4.15 The travel time from the residence to the nearest pick-up point in normal versus adverse weather

Figure 4.16 presents the distribution of waiting times for the bus at the pick-up point under normal and adverse weather conditions. Under normal weather, 46% of students wait less than five minutes, indicating high operational efficiency and punctuality of the transport system. However, during adverse weather, this proportion drops to 40.5%, highlighting weather-induced service disruptions. Similarly, the share of students waiting 6–10 minutes declines from 26.1% to 23.1%. In contrast, longer waiting times increase across all categories. Notably, students waiting more than 20 minutes rise from 8.5% to 12.7%, representing a substantial 50% relative increase. Additionally, the proportion waiting 11–15 minutes and 16–20 minutes also rises, reflecting systemic delays caused by adverse environmental conditions, such as traffic congestion, reduced vehicle speed, or route adjustments. These findings suggest that inclement weather significantly deteriorates transport service reliability, underscoring the need for adaptive scheduling and infrastructure improvements to enhance resilience in student commuting patterns.

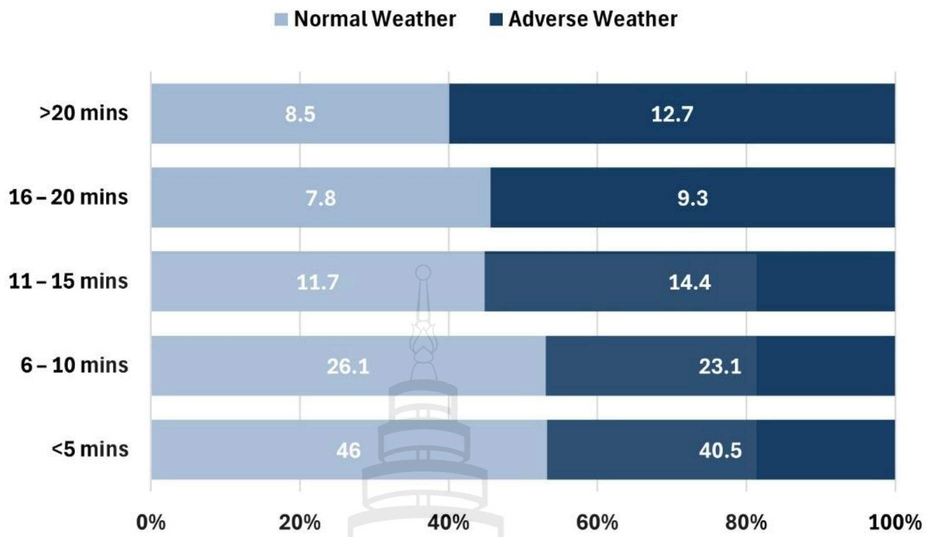

Figure 4.16 The waiting time for the bus at the pick-up point distribution in normal versus adverse weather

Total travel time to school under different weather conditions, as illustrated in Figure 4.17, reveals that under normal weather conditions, a substantial proportion of students (59.4%) experience relatively short commutes, with 26.3% traveling less than 10 minutes and 33.1% between 11–20 minutes. This suggests that, under typical circumstances, most school journeys are efficient, likely supported by stable transport modes and reliable scheduling. However, when weather conditions deteriorate, the proportion of students traveling under 20 minutes drops significantly to 44.7%, a reduction of nearly 15 percentage points. This reduction signals delays and increased inefficiencies in travel systems, potentially due to traffic congestion, reduced vehicle speeds, and changes in modal choice (e.g., avoidance of motorcycles or active transport). Interestingly, the percentage of students traveling between 21–30 minutes and beyond increases under adverse weather. The 21–30 minutes category rises from 13.1% to 18.2%, while those traveling more than 40 minutes palpably increased from 18.2% to 24.6%. These changes in travel time length indicate a systematic expansion of travel time to school in the face of environmental constraints, which may reflect rerouting, a shift in travel mode to slower but safer alternatives (e.g., from motorcycle to school bus), or increased waiting times for public or private transportation.

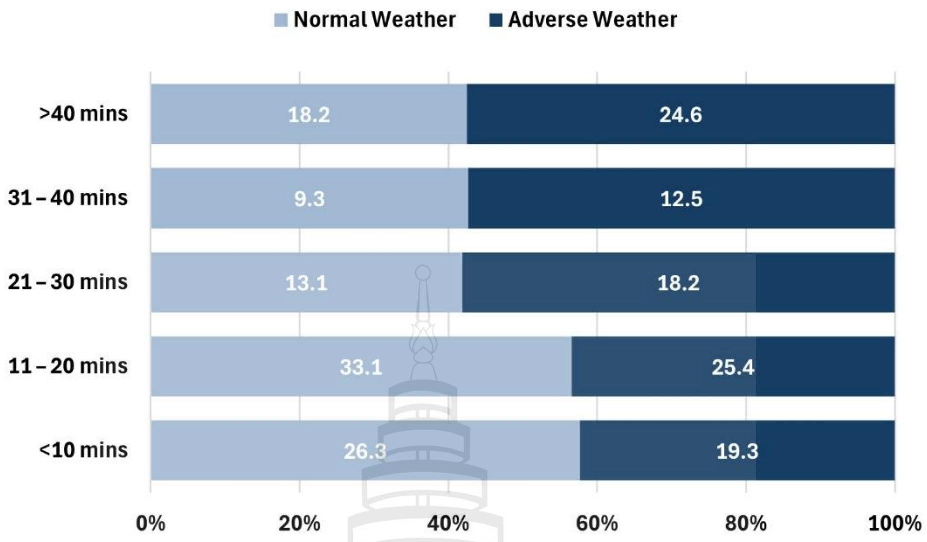

Figure 4.17 The total travel time to school in normal versus adverse weather

The distribution of total travel expenses per month under normal and adverse weather conditions is presented in Figure 4.18, which indicates a generally stable cost structure, with minor fluctuations across expenditure categories. Under normal weather conditions, 29.9% of students spend less than 100 baht monthly on school travel. This proportion rises slightly to 31.4% during adverse weather, suggesting that a segment of students. These people are likely to choose to walk or decide to travel with their parents, so they are not greatly affected by the costs caused by weather conditions and remain largely unaffected by weather-induced costs. Conversely, the share of students spending between 101–500 baht decreases from 20.3% to 18.4%, potentially reflecting a temporary shift to either cost-free travel alternatives (such as carpooling with family) or the postponement of travel during adverse weather. Interestingly, the proportions of students in the 501–1,000 baht and 1,001–1,500 baht expenditure brackets remain unchanged or slightly increase, with both seeing a modest rise to 18.4% and 28.2%, respectively, under adverse weather. This stability suggests that many students continue relying on consistent travel modes such as school buses or private transport, regardless of weather conditions, absorbing additional costs associated with delays or detours. The proportion of students incurring the highest expenses, more than 1,500 baht, remains constant at 3.6%, indicating that those in this category are likely committed to high-cost transport modes (e.g., daily private car use) and are unaffected by short-term environmental changes. These results imply that while the majority of students maintain consistent monthly travel expenses, adverse weather may impose a slight financial burden on those dependent on mid-range paid services, underscoring the need for equitable and weather-resilient school transport subsidies or policies.

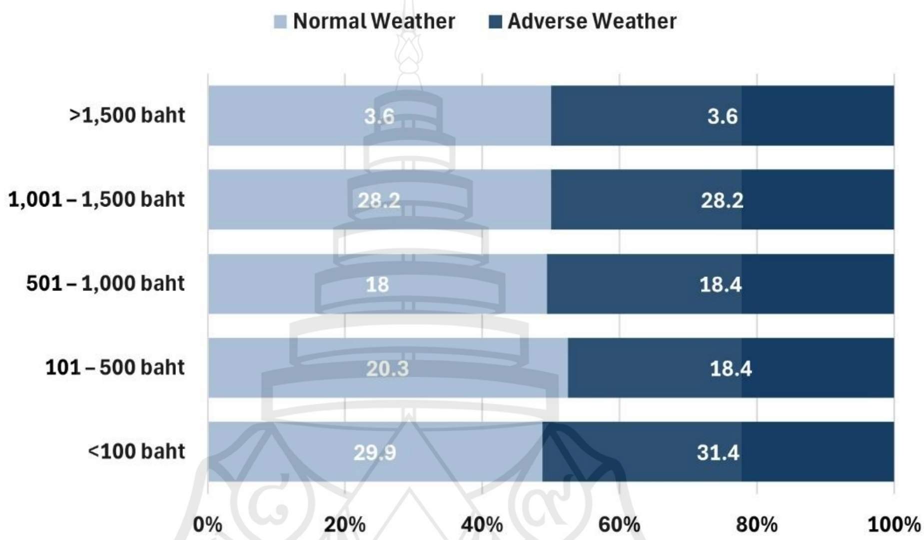

Figure 4.18 The total travel expenses per month in normal versus adverse weather

Transfers to school per trip under different weather conditions in Figure 4.19 offer a nuanced understanding of student mobility efficiency with environmental variability. Under normal weather conditions, 93.2% of students require only one trip, suggesting a largely direct or streamlined school travel pattern that benefits from coherent route planning, accessible transit infrastructure, or widespread private mobility solutions. The fact that this figure marginally declines to 93.0% under adverse weather implies a high degree of structural resilience in the transport system to school. However, more telling are the subtle shifts in the higher-frequency transfer categories. The share of students requiring three trips increases significantly from 0.2% in normal conditions to 0.8% in adverse weather, a fourfold rise. Though the absolute numbers remain low, this relative surge reflects a potential vulnerability in transport continuity for a specific subset of the student population. That may indicate service disruptions, route changes due to weather conditions, or reduced service frequencies, necessitating additional modal transitions. In the context of student well-being and punctuality, even small increments in trip complexity can introduce psychological fatigue, temporal uncertainty, and reduced accessibility. In transfers involving four trips or more, while uncommon, exhibit a mild contraction under adverse weather, more than 4 trips drop from 1.1% to 0.8%. This could suggest two contrasting behavioral or systemic adaptations: either a withdrawal from such burdensome travel during adverse conditions, possibly through school absenteeism or alternative remote arrangements, or a substitution effect, where longer, segmented commutes are replaced by more consolidated or private travel modes in response to inclement weather challenges. Furthermore, the marginal decline in two-trip journeys (from 5.3% to 5.1%) may signal a minor optimization or reconfiguration of routes during adverse conditions, potentially aided by parental intervention, dynamic routing policies, or informal carpool networks. While this change is statistically slight, it could reflect broader strategies aimed at minimizing multimodality in favor of reliability.

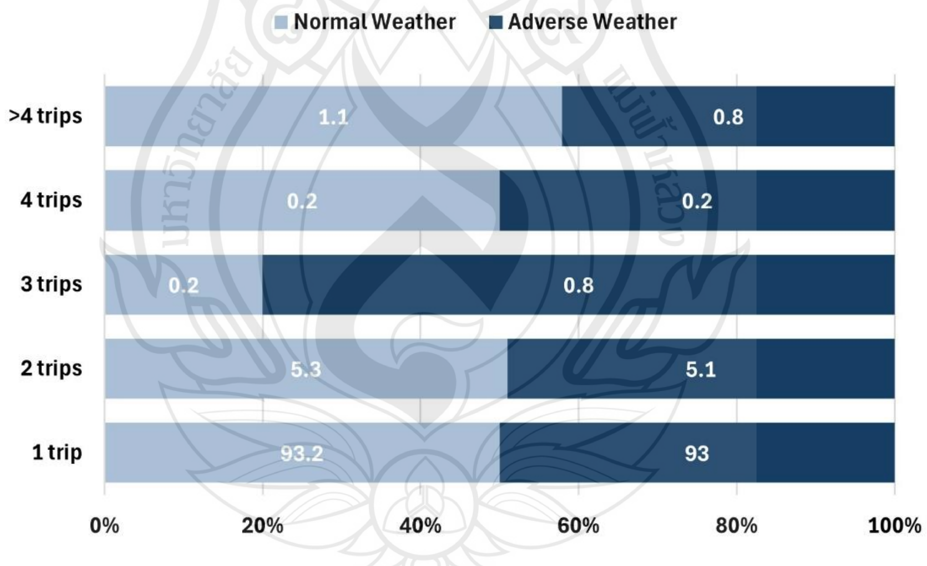

Figure 4.19 Transfer during the trip to school distribution in normal versus adverse weather

4.4.4 Summary of Travel Behavior Under Normal and Adverse Weather Conditions

The comparative analysis reveals significant behavioral adaptations between normal and adverse weather conditions with important implications for transportation planning in Chiang Rai. Adverse weather triggers systematic modal shifts toward more protected transportation modes, with motorcycle usage declining substantially from 36.9% to 26.7% due to safety and comfort concerns, while private vehicle usage increases dramatically from 15.7% to 25.4% as households with car access buffer against weather disruptions. School bus usage demonstrates remarkable stability (33.7% in both conditions), reinforcing its role as a weather-resilient transport solution.

Weather conditions significantly affect travel efficiency, with students experiencing longer travel times (>40 minutes) increasing from 18.2% to 24.6%, and extended waiting times at pick-up points (>20 minutes) rising from 8.5% to 12.7%, indicating systematic delays and service disruptions. Cost structures remain relatively stable, though slight increases in higher-cost categories during adverse weather may create additional financial burden for economically disadvantaged families. The analysis reveals three critical patterns: motorcycle users show highest weather vulnerability while school bus users demonstrate greatest resilience; households with diverse vehicle ownership exhibit superior adaptive capacity; and increased delays highlight insufficient weather-protected infrastructure.

These findings underscore the need for climate-responsive transportation planning, including expanded school bus services, improved weather-resistant infrastructure at pick-up points, and targeted support for disadvantaged students lacking access to weather-resilient transport alternatives.

4.5 Model Validity

4.5.1 Normal Weather Conditions

Table 4.2 presents the model fitting statistics and diagnostic measures for the Multinomial Logit (MNL) model under normal weather conditions. The model demonstrates strong explanatory capability, as evidenced by a substantial likelihood ratio chi-square value ($\chi^2 = 620.966$, df = 36, $p < 0.001$), indicating that the final model significantly outperforms the null (intercept-only) model. The goodness-of-fit statistics reveal mixed but interpretable results: while the Pearson chi-square test suggests a significant misfit ($p < 0.001$), the deviance statistic is non-significant ($p = 1.000$), implying an acceptable model fit when overdispersion is not a major concern. Pseudo R-square measures further support the model's robustness, with Cox and Snell (0.732), Nagelkerke (0.791), and McFadden (0.507) values all exceeding commonly accepted thresholds, particularly McFadden's R^2 surpassing 0.4, which is rare for discrete choice models and indicates excellent explanatory strength. The model classification accuracy (72.7%) also substantiates the model's predictive reliability, especially for school bus and motorcycle users. These results validate the suitability of the MNL approach for analyzing school travel mode choice behavior under stable environmental conditions and offer a strong foundation for comparative analysis against adverse weather scenarios.

Table 4.2 Model fitting, Goodness-of-fit, Pseudo r-square, Classification in normal weather conditions information

Model fitting						
	Model Fitting Criteria			**Likelihood Ratio Tests**		
Model	**AIC**	**BIC**	**-2 Log Likelihood**	**Chi-Square**	**df**	**Sig.**
Intercept Only	1231.253	1243.724	1225.253			
Final	682.287	844.409	604.287	620.966	36	< 0.001

Table 4.2 (continued)

Model fitting						
Model	**Model Fitting Criteria**			**Likelihood Ratio Tests**		
	AIC	**BIC**	**-2 Log Likelihood**	**Chi-Square**	**df**	**Sig.**
Goodness-of-Fit						
	Chi-Square	df	Sig.			
Pearson	2397.524	1374	< 0.001			
Deviance	604.287	1374	1.000			
Pseudo R-Square						
Cox and Snell	Nagelkerke	McFadden				
0.732	0.791	0.507				

Table 4.3 details the results of likelihood ratio tests assessing the significance of individual variables influencing travel mode choice under normal weather conditions. All examined variables demonstrate statistically significant effects ($p < 0.05$ or $p < 0.01$), affirming their importance in shaping mode selection. Among the socio-demographic factors, grade level (χ^2 = 15.102, p = 0.002) and household monthly income (χ^2 = 16.056, p = 0.001) are noteworthy, reflecting how academic progression and economic resources critically impact transport autonomy and modal flexibility. Family structure variables, including family member count (χ^2 = 25.367, $p < 0.001$), further underscore the role of household logistics in school commuting. Vehicle ownership variables both car (χ^2 = 14.531, p = 0.002) and motorcycle (χ^2 = 32.040, $p < 0.001$) exert particularly strong influences, highlighting mobility resource disparities. Spatial-temporal trip attributes, such as travel distance (χ^2 = 45.525, $p < 0.001$), waiting time at pick-up points (χ^2 = 11.597, p = 0.009), and overall travel cost (χ^2 = 13.007, p = 0.005), significantly explain mode preference variance, confirming the multidimensional nature of school commuting behavior. These findings collectively validate the integrated socio-demographic, economic, and spatial

framework applied in the modeling, offering policy-relevant insights for designing interventions that promote equitable and sustainable school transport systems.

Table 4.3 Likelihood testing results for normal weather conditions

Effect	Likelihood Ratio Tests		
	Chi-Square	**df**	**Sig.**
Intercept	97.294	3	< 0.000***
Grade	15.102	3	0.002**
Household monthly income	16.056	3	0.001**
Family member	25.367	3	< 0.000***
Household car ownership	14.531	3	0.002**
Household motorcycle ownership	32.040	3	< 0.000***
Number of people traveling to school	107.820	3	< 0.000***
Current residence	21.054	3	< 0.000***
Travel distance	45.525	3	< 0.000***
Travel time to the nearest pick-up point	15.265	3	0.002**
Waiting time at the pick-up point	11.597	3	0.009**
Travel time	44.528	3	< 0.000***
Travel cost	13.007	3	0.005**

Note ** p-value < 0.01, *** p-value < 0.001

4.5.2 Adverse Weather Conditions

Table 4.4 presents the model fitting criteria, goodness-of-fit tests, and pseudo R-square values for the Multinomial Logit (MNL) model applied to school commuting mode choice under adverse weather conditions. The model fitting statistics indicate robust performance. The Final Model achieves a -2 Log Likelihood value of 766.138, significantly lower than the Intercept-Only model (1269.107), with a substantial chi-square difference of 502.968 ($p < 0.001$), confirming that the inclusion of explanatory variables meaningfully improves model fit over the null model. The goodness-of-fit assessment reveals a Pearson chi-square value of 1996.565 (df = 1374, $p < 0.001$), indicating a statistically significant departure from perfect fit. However, the Deviance statistic (766.138, df = 1374, p = 1.000) suggests an excellent fit between the model and the observed data, as a high p-value reflects no significant deviation. This pattern aligns with the expectation for MNL models where the Deviance is often prioritized over the Pearson chi-square in assessing fit quality, particularly in cases with categorical data and large sample sizes.

Regarding pseudo-R-square metrics, the Cox and Snell value is 0.655, the Nagelkerke value is 0.703, and McFadden's R-square is 0.396. These values suggest moderate to strong explanatory power, especially McFadden's R^2, which exceeds the 0.2–0.4 benchmark commonly accepted for discrete choice models. Collectively, these results confirm that the model captures a substantial portion of the variance in mode choice behavior under adverse conditions. Furthermore, the relatively high Nagelkerke R^2 indicates strong predictability, reinforcing the model's suitability for informing policy interventions targeting resilient student mobility strategies during environmental disruptions.

Table 4.4 Model fitting, Goodness-of-Fit, Pseudo-R-square, in adverse weather conditions information

			Model fitting			
Model	**Model Fitting Criteria**			**Likelihood Ratio Tests**		
	AIC	**BIC**	**-2 Log Likelihood**	**Chi-Square**	**df**	**Sig.**
Intercept Only	1275.107	1287.578	1269.107			
Final	844.138	1006.260	766.138	502.968	36	< 0.001
			Goodness-of-Fit			
	Chi-Square	df	Sig.			
Pearson	1996.565	1374	< 0.001			
Deviance	766.138	1374	1.000			
			Pseudo R-Square			
Cox and Snell	Nagelkerke	McFadden				
0.655	0.703	0.396				

Table 4.5 presents the likelihood ratio tests for variables affecting school commuting mode choice under adverse weather conditions. The results highlight that several socio-demographic and travel-related factors significantly influence students' modal preferences when weather deteriorates. Household car ownership ($\chi^2 = 33.250$, $p < 0.001$) and the number of people traveling to school ($\chi^2 = 91.939$, $p < 0.001$) emerge as the most statistically powerful determinants, underscoring the critical role of private mobility resources and travel group composition in adapting to environmental constraints. Travel distance ($\chi^2 = 40.825$, $p < 0.001$) and total travel time ($\chi^2 = 41.425$, $p < 0.001$) also exhibit strong effects, indicating that longer journeys exacerbate vulnerability during adverse conditions, possibly encouraging shifts toward safer or more enclosed modes such as private vehicles or school buses. Interestingly, age ($\chi^2 = 14.362$, $p = 0.002$) and parents' working status ($\chi^2 = 9.997$, $p = 0.019$) become significant under adverse conditions, suggesting that older students and dual-income families are more adaptive in modifying their travel behavior. Variables related to spatial access, such as travel time to the nearest pick-up point and waiting time at pick-up points, also show significance, reflecting operational disruptions and heightened travel uncertainty in inclement weather. Collectively, these findings reinforce that adverse weather amplifies existing transport inequities and infrastructural vulnerabilities.

Table 4.5 Likelihood ratio in adverse weather condition tests.

Effect	Likelihood Ratio Tests		
	Chi-Square	**df**	**Sig.**
Intercept	73.528	3	< 0.000***
Age	14.362	3	0.002**
Parents working status	9.997	3	0.019*
Household monthly income	8.878	3	0.031*
Family member	18.571	3	< 0.000***
Household car ownership	33.250	3	< 0.000***
Household motorcycle ownership	18.026	3	< 0.000***
Number of people traveling to school	91.939	3	< 0.000***
Current residence	33.936	3	< 0.000***

Table 4.5 (continued)

Effect	Likelihood Ratio Tests		
	Chi-Square	**df**	**Chi-Square**
Travel distance	40.825	3	< 0.000***
Travel time to the nearest pick-up point	17.240	3	0.001**
Waiting time at the pick-up point	13.720	3	0.003**
Travel time	41.425	3	< 0.000***

Note * p-value < 0.05, ** p-value < 0.01, *** p-value < 0.001

Building upon the robust model fitting results and the significance of key determinants identified in the likelihood testing, the subsequent analysis delves deeper into the specific behavioral influences that drive school travel mode choices under varying environmental conditions. The multinomial logit regression models provide granular insights into how individual, household, and spatial factors interact to shape mobility preferences among high school students. By comparing estimated coefficients across normal and adverse weather scenarios, the study captures the dynamic nature of school commuting behavior, uncovering both stable predictors and context-sensitive adaptations. The next section presents a detailed interpretation of the multinomial regression outputs, highlighting how weather variability accentuates existing transport inequalities and shifts modal dependencies. These findings serve as a foundation for proposing targeted policy interventions aimed at enhancing the resilience, safety, and inclusivity of school transport systems, particularly in climatically vulnerable urban areas such as Chiang Rai.

4.6 Multinomial Logit Regression Model

4.6.1 Normal Weather Conditions

Table 4.6 presents the Multinomial Logit (MNL) coefficients for three alternatives: active transport, motorcycle, and school bus, relative to the reference category, private car. All standard errors are robust; Wald χ^2 indicates joint significance ($p < 0.001$). Pseudo-$R^2 = 0.507$ and an overall hit-rate of 72.7 % confirm excellent explanatory power for a behavioral model. Notably, household car ownership exhibits a remarkably strong positive association across all modes, particularly for active transport (β = 3.09, Odds = 21.96) and school bus use (β = 2.84, Odds = 17.12). This suggests that households with car access possess greater flexibility in facilitating modal options beyond private cars, possibly due to greater household mobility resources or differential parental decision-making for school commutes. Conversely, household motorcycle ownership is associated negatively with motorcycle use, an unexpected outcome that may reflect preference for private cars where motorcycle access exists but is deprioritized in favorable weather.

Travel distance is a consistent negative predictor for active transport (β = -1.94, Odds = 0.14) and motorcycles (β = -0.53, Odds = 0.59), aligning with existing literature that longer distances diminish the feasibility of non-motorized travel and increase dependence on mechanized transport. Additionally, family size positively influences school bus selection, reflecting logistical efficiencies when multiple children travel to the same institution. Importantly, current residence (urban/suburban) significantly influences active transport (β = 2.20, Odds = 9.04) and school bus choice (β = 1.01, Odds = 2.75), suggesting spatial disparities in mode availability and infrastructural access. Meanwhile, travel time to pick-up points and waiting times also emerge as critical behavioral determinants, particularly impacting the decision between private and public modes. These results reinforce the multi-dimensional interplay between household attributes, spatial accessibility, and travel behavior under stable environmental conditions.

Table 4.6 Multinomial logit regression estimated models in normal weather conditions

Mode	Variable	Normal Weather			
		Estimate	**S.E.**	**t-statistic**	**Odds**
Active Transport	Constant	5.69	2.63	4.69*	
	Grade	0.54	0.31	3.00	1.71
	Household monthly income	-0.62	0.20	9.99**	0.54
	Family member	0.70	0.33	4.40*	2.01
	Household car ownership	3.09	1.21	6.53*	21.96
	Household motorcycle ownership	-1.69	1.30	1.69	0.19
	Number of people traveling to school	-2.97	0.58	26.08***	0.05
	Current residence	2.20	0.64	11.89**	9.04
	Travel distance	-1.94	0.34	32.03***	0.14
	Travel time to the nearest pick-up point	0.29	0.26	1.28	1.34
	Waiting time at the pick-up point	-0.61	0.25	6.05*	0.54
	Travel time	-0.17	0.43	0.15	0.85
	Travel cost	-0.79	0.27	8.32**	0.46
Motorcycle	Constant	9.52	2.31	16.96***	
	Grade	0.83	0.23	13.09***	2.28
	Household monthly income	-0.50	0.14	12.51***	0.61
	Family member	-0.21	0.25	0.68	0.81
	Household car ownership	3.04	1.15	6.93**	20.79
	Household motorcycle ownership	-4.79	1.32	13.18***	0.01
	Number of people traveling to school	-2.75	0.43	41.88***	0.06

Table 4.6 (continued)

Mode	Variable	Normal Weather			
		Estimate	S.E.	t-statistic	Odds
Motorcycle	Current residence	0.24	0.48	0.25	1.27
	Travel distance	-0.53	0.21	6.13*	0.59
	Travel time to the nearest pick-up point	0.13	0.15	0.74	1.14
	Waiting time at the pick-up point	-0.25	0.16	2.24	0.78
	Travel time	0.01	0.25	0.00	1.01
	Travel cost	-0.44	0.17	6.51*	0.64
School Bus	Constant	-9.54	2.30	17.19***	
	Grade	0.22	0.22	0.96	1.24
	Household monthly income	-0.34	0.14	5.62*	0.71
	Family member	0.70	0.25	7.66**	2.01
	Household car ownership	2.84	1.12	6.38*	17.12
	Household motorcycle ownership	0.22	0.69	0.10	1.24
	Number of people traveling to school	1.10	0.53	4.33*	3.01
	Current residence	1.01	0.45	5.11*	2.75
	Travel distance	-0.31	0.22	1.95	0.73
	Travel time to the nearest pick-up point	-0.38	0.14	7.21**	0.69
	Waiting time at the pick-up point	0.15	0.15	0.92	1.16
	Travel time	1.24	0.23	29.30***	3.46
	Travel cost	0.05	0.17	0.07	1.05

Note The private is the reference category, * p-value < 0.05, ** p-value < 0.01, *** p-value < 0.001

4.6.2 Adverse Weather Conditions

Table 4.7 presents the Multinomial Logit (MNL) regression results analyzing factors influencing school commuting mode choice during adverse weather conditions, using private vehicle use as the baseline category. The model elucidates how socio-demographic attributes, household mobility resources, and spatial-temporal variables differentially affect students' travel decisions under environmental stress, offering critical insights into climate-sensitive mobility patterns. Household car ownership emerges as the most powerful predictor across all alternative modes—active transport, motorcycle, and school buswith exceptionally high odds ratios (Odds > 22). This result confirms that private vehicle access substantially enhances modal flexibility, serving as a vital buffer against environmental disruptions. In particular, students from car-owning households are significantly more capable of substituting to safer or more resilient modes, aligning with established literature that underscores car ownership as a key enabler of adaptive travel behavior under adverse conditions.

Conversely, household motorcycle ownership exerts a strong negative influence on motorcycle mode choice (β = -3.66, Odds = 0.03), substantially deterring two-wheeled vehicle use during inclement weather. This finding reflects heightened risk perception among students and guardians regarding motorcycle safety in hazardous environmental contexts, reinforcing safety concerns commonly associated with motorcycle commuting, especially in rain or haze conditions prevalent in Chiang Rai. Spatial factors also display critical behavioral effects. Travel distance significantly decreases the likelihood of choosing active transport (β = -1.29, Odds = 0.28) and motorcycle usage (β = -0.22, Odds = 0.81), indicating that greater distances exacerbate the limitations of exposed or informal travel modes during adverse weather. Moreover, travel time to the nearest pick-up point and waiting time at the pick-up point negatively affect active transport choices, illustrating increased discomfort and reliability concerns as decisive factors discouraging exposure to inclement conditions. Socio-demographic variables further reveal context-sensitive behavioral adaptations. Age is positively associated with motorcycle use (β = 0.59, Odds = 1.81), suggesting that older students possess greater autonomy and willingness to maintain independent travel despite weather adversities. Meanwhile, parents' working status becomes significant for school bus choice (β = 1.04, Odds =

2.84), indicating that students from dual-income households may prefer structured, supervised transport services when parental logistical support is constrained during work hours.

Current residence, whether urban or suburban, significantly influences mode selection. Urban students exhibit a substantially higher likelihood of choosing active transport (β = 1.96, Odds = 7.13) and school bus (β = 1.81, Odds = 6.13) relative to suburban counterparts, highlighting spatial inequities in infrastructure access and service availability. This result emphasizes the critical role of urban form and density in supporting climate-resilient student mobility. Moreover, temporal dynamics are crucial. Longer travel times to school during adverse weather further discourage motorcycle use (β = -0.39, Odds = 0.68) but increase the reliance on structured transport modes like the school bus (β = 0.76, Odds = 2.13). These findings suggest that adverse conditions systematically exacerbate time inefficiencies in less resilient transport options, motivating a shift toward organized services despite potential cost or scheduling inconveniences.

Table 4.7 Multinomial logit regression estimated models in adverse weather conditions

Mode	Variable	Adverse weather			
		Estimate	**S.E.**	**t-statistic**	**Odds**
Active Transport	Constant	-1.72	2.15	0.64	
	Age	0.33	0.21	2.50	1.39
	Parents working status	-0.68	0.70	0.94	0.51
	Household monthly income	-0.21	0.16	1.81	0.81
	Family member	0.50	0.27	3.50	1.64
	Household car ownership	3.81	1.12	11.48**	45.07
	Household motorcycle ownership	-0.38	0.95	0.16	0.68
	Number of people traveling to school	-1.41	0.43	10.84**	0.24

Table 4.7 (continued)

Mode	Variable	Adverse weather			
		Estimate	**S.E.**	**t-statistic**	**Odds**
Active Transport	Current residence	1.96	0.51	14.98***	7.13
	Travel distance	-1.29	0.23	30.03***	0.28
	Travel time to the nearest pick-up point	0.33	0.21	2.57	1.39
	Waiting time at the pick-up point	-0.60	0.21	7.80**	0.55
	Travel time	-0.13	0.25	0.26	0.88
Motorcycle	Constant	2.52	2.05	1.52	
	Age	0.59	0.16	13.58***	1.81
	Parents working status	-0.32	0.49	0.43	0.73
	Household monthly income	-0.33	0.12	7.02**	0.72
	Family member	-0.32	0.22	2.09	0.73
	Household car ownership	3.85	1.09	12.60***	47.15
	Household motorcycle ownership	-3.66	1.27	8.34**	0.03
	Number of people traveling to school	-1.49	0.32	21.14***	0.23
	Current residence	0.77	0.40	3.76	2.16
	Travel distance	-0.22	0.16	1.95	0.81
	Travel time to the nearest pick-up point	0.16	0.13	1.48	1.17
	Waiting time at the pick-up point	-0.08	0.14	0.37	0.92
	Travel time	-0.39	0.18	4.80*	0.68

Table 4.7 (continued)

Mode	Variable	Adverse weather			
		Estimate	**S.E.**	**t-statistic**	**Odds**
School Bus	Constant	-12.05	2.01	35.91***	
	Age	0.23	0.16	2.04	1.25
	Parents working status	1.04	0.49	4.53*	2.84
	Household monthly income	-0.24	0.12	3.94*	0.78
	Family member	0.45	0.21	4.40*	1.56
	Household car ownership	3.13	1.08	8.38**	22.96
	Household motorcycle ownership	-0.33	0.66	0.26	0.72
	Number of people traveling to school	1.83	0.39	21.93***	6.25
	Current residence	1.81	0.37	23.98***	6.13
	Travel distance	-0.27	0.17	2.71	0.76
	Travel time to the nearest pick-up point	-0.35	0.13	7.74**	0.70
	Waiting time at the pick-up point	0.19	0.13	2.05	1.21
	Travel time	0.76	0.18	18.65***	2.13

Note The private is the reference category, * p-value < 0.05, ** p-value < 0.01, *** p-value < 0.001

Significant mode choice influencing factors in both conditions. Table 4.8 presents the comparison of significant factors influencing school travel behavior under normal and adverse weather conditions, revealing notable differences. Under normal weather conditions, factors such as gender, monthly household income, family size, private vehicle ownership (both car and motorcycle), the number of people traveling to school, current residence, total distance to school, travel time to the nearest pick-up point, waiting time for the bus, total travel time, and total travel expenses significantly affect travel behavior. In contrast, under adverse weather conditions, age and father's working status emerge as significant factors, alongside household income, family size, vehicle ownership, number of people traveling to school, current residence, total distance to school, travel time to the pick-up point, waiting time for the bus, and total travel time. This indicates that while several factors consistently influence travel behavior across weather conditions, adverse weather introduces additional socio-demographic determinants such as age and parental employment status, reflecting the adaptability of travel behavior to changing environmental conditions.

Table 4.8 Significant mode choice influencing factors in the model

Variable	**Normal weather**	**Adverse weather**
Age	✕	✓
Grade	✓	✕
Parents working status	✕	✓
Household monthly income	✓	✓
Family member	✓	✓
Household car ownership	✓	✓
Household motorcycle ownership	✓	✓
Number of people traveling to school	✓	✓
Current residence	✓	✓
Travel distance	✓	✓
Travel time to the nearest pick-up point	✓	✓
Waiting time at the pick-up point	✓	✓
Travel time	✓	✓
Travel cost	✓	✕

Note ✓ is included in the model and ✕ is excluded from the model

4.7 Model Classification and Accuracy

The classification in normal and adverse weather conditions in Table 4.9 demonstrates varying levels of prediction accuracy across different travel modes. Under normal weather conditions, the model shows the highest classification accuracy for school bus users (83.0%), followed by motorcycle users (77.6%) and active transport users (64.6%), with the lowest accuracy observed for private vehicle users (45.9%). In adverse weather conditions, school bus users continue to exhibit the highest classification accuracy (79.2%), while active transport and motorcycle users show moderate accuracy levels (64.2% and 67.5%, respectively), and private vehicle users display improved accuracy (58.3%) compared to normal weather. The overall classification accuracy decreases slightly from 72.7% in normal weather to 68.6% in adverse weather, indicating that weather conditions may influence the model's predictive performance, particularly for private vehicle usage. This suggests that adverse weather introduces additional variability in travel behavior, affecting the consistency of mode choice predictions.

Table 4.9 Classification of observed and predicted values in normal weather and adverse weather conditions

Observed	**Predicted**				
	Active Transport	**Motorcycle**	**School Bus**	**Private**	**Percent Correct**
Normal weather conditions					
Active Transport	42	21	1	1	64.60%
Motorcycle	14	135	12	13	77.60%
School Bus	1	11	132	15	83.00%
Private	0	17	23	34	45.90%
Overall Percentage	12.10%	39.00%	35.60%	13.30%	72.70%

Table 4.9 (continued)

Observed	Predicted				
	Active Transport	Motorcycle	School Bus	Private	Percent Correct
Adverse weather conditions					
Active Transport	43	18	1	5	64.20%
Motorcycle	8	85	11	22	67.50%
School Bus	4	12	126	17	79.20%
Private	3	21	26	70	58.30%
Overall Percentage	12.30%	28.80%	34.70%	24.20%	68.60%

4.8 Exploratory Factor Analysis (EFA) of Students' Perceptions toward School Transport Services

To explore the underlying structure of students' perceptions regarding school transportation services, an Exploratory Factor Analysis (EFA) was conducted using Principal Component Analysis (PCA) with Varimax rotation. The goal of the analysis was to identify latent dimensions that influence students' evaluations of various transport-related attributes.

4.8.1 Sampling Adequacy and Suitability of Data

Before performing EFA, the Kaiser-Meyer-Olkin (KMO) measure and Bartlett's Test of Sphericity were used to assess the appropriateness of the dataset for factor extraction. The KMO value was 0.955, which exceeds the recommended threshold of 0.90, indicating excellent sampling adequacy. Additionally, Bartlett's Test of Sphericity was significant ($\chi^2 = 8139.086$, df = 171, $p < 0.001$), confirming that the correlation matrix was not an identity matrix and that the data were suitable for factor analysis.

4.8.2 Total Variance Explained

Table 4.10 has two components with eigenvalues greater than 1 were extracted, following the Kaiser criteria. Together, these two components explained 68.546% of the total variance in the data. The first component accounted for 37.936%, while the second explained 30.611%, which together provided a sufficient cumulative variance for interpreting the data in social sciences.

The cumulative variance of 68.546% represents a good to excellent level of explanation in social science research. In social and behavioral sciences, variance explained between 60-70% is considered good, while anything above 70% is considered excellent (Hair et al., 2018; Tabachnick et al., 2018). Our result of 68.5% falls within the upper range of "good" and approaches "excellent" standards. This assessment is further supported by transportation behavior studies, where similar variance levels are commonly accepted. For example, 65.2% variance in their mode choice factor analysis Chaudhry and Elumalai (2020), 63.8% variance in their tourism transport behavior study Tang et al. (2020), and 66.4% variance in their railway access mode study (Arreeras et al., 2020b).

The 68.5% variance indicates that our two-factor model captures approximately two-thirds of the systematic variation in students' perceptions of school transport services. This level of explanation provides sufficient foundation for understanding the underlying structure of transport service evaluation (Costello & Osborne, 2005). Moreover, achieving 68.5% variance with only two factors demonstrates a highly parsimonious solution, which is preferable to models with many factors explaining marginally higher variance, as it provides clearer theoretical interpretation while maintaining substantial explanatory power (Fabrigar & Wegener, 2012).

This level of variance explanation is appropriate for several reasons. Transportation mode choice involves numerous unmeasured factors such as personal preferences, cultural influences, and situational variables, making 100% variance explanation unrealistic. Additionally, survey-based data inherently contains measurement error, limiting maximum achievable variance explanation. The two-factor solution provides clear, interpretable dimensions (System Efficiency and Onboard Comfort) that align with transportation service quality theory. Studies in similar domains report comparable variance levels, including public transport satisfaction studies at 60-75% (Mouwen, 2015), school travel behavior research at 58-72% (McDonald et al., 2011b), and mode choice factor analyses at 62-69% (Eriksson et al., 2013). Therefore, the 68.546% cumulative variance provides sufficient explanation for interpreting the underlying dimensions of student transport service perceptions and supports reliable factor-based analysis in subsequent modeling stages.

Table 4.10 Total Variance Explained

Total Variance Explained									
Component	**Initial Eigenvalues**			**Extraction Sums of Squared Loadings**			**Rotation Sums of Squared Loadings**		
	Total	**% of Variance**	**Cumulative %**	**Total**	**% of Variance**	**Cumulative %**	**Total**	**% of Variance**	**Cumulative %**
1	11.623	61.174	61.174	11.623	61.174	61.174	7.208	37.936	37.936
2	1.401	7.372	68.546	1.401	7.372	68.546	5.816	30.611	68.546

4.8.3 Interpretation of Factors

The rotated component matrix revealed two distinct factors that group related variables according to student perceptions:

Factor 1: System and Operational Efficiency

This factor reflects students' perceptions of the broader operational aspects of school transportation services. High-loading variables include fare pricing, stop cleanliness, engine type, number of seats, punctuality, accessibility, and safety. This suggests that students evaluate the transport system based on cost-efficiency, reliability, and general service quality.

Factor 2: Onboard Environment and Comfort

This factor pertains to the comfort and physical experience during travel. It includes variables such as seat cleanliness, driver behavior, ease of boarding, temperature, and interior conditions. These aspects reflect the students' day-to-day experience while being transported, highlighting the role of sensory and behavioral factors in satisfaction.

4.8.4 Summary of Extracted Factors

Table 4.11 shows two factors that provide a comprehensive understanding of the dimensions students consider when evaluating their school transport experience. While Factor 1 relates to infrastructure and service performance, Factor 2 focuses on comfort, cleanliness, and environmental conditions inside the vehicle.

Table 4.11 Summary of Extracted Factors

Factor	Label	High-Loading Variables (Factor Loadings)
1	System and Operational Efficiency	Fare of public transportation (0.844), Cleanliness of stops (0.842), Engine type (0.807), Number of seats (0.784), Punctuality (0.773), Accessibility (0.723), Safety (0.715), Size of vehicles (0.703), Ticket system (0.690), Exterior (0.658), Scheduling (0.655)
2	Onboard Environment and Comfort	Cleanliness of seats (0.827), Seat position (0.792), Cleanliness of vehicles (0.783), Driver behavior (0.706), Driving quality (0.699), Odor and temperature (0.677), Ease of boarding (0.670), Interior condition (0.636)

CHAPTER 5

CONCLUSION AND DISCUSSION

5.1 Discussion

This study investigated the school trip mode choice behavior among high school students in Mueang Chiang Rai District using a multinomial logit (MNL) regression model and exploratory factor analysis. The findings offer crucial insights into how demographic, socio-economic, environmental, and trip-related factors shape students' decisions in selecting a mode of transport for their daily commute under both normal and adverse weather conditions.

This section discusses the findings of the study concerning its three primary objectives:

1. To explore the transport modes selected by high school students in Mueang Chiang Rai District.
2. To investigate the factors associated with commuting behavior to school.
3. To propose policy recommendations that support the development of a more sustainable, efficient, and safer transportation system.

The discussion integrates a comparative analysis of student travel behavior under normal and adverse weather conditions and links findings to broader implications for transportation planning and policy.

Objective 1: Explore the Transport Modes Selected by High School Students

The study found that motorcycles are the dominant mode of travel under normal weather conditions, representing 36.9% of trips. This reflects the high rate of motorcycle ownership in Thai households, especially in semi-urban settings like Chiang Rai. School buses were the second most used mode (33.7%), offering a structured, institutional option that supports students' travel needs consistently across weather types.

However, during adverse weather conditions, a shift in preferences was observed. Motorcycle usage declined significantly (to 26.7%), suggesting concerns over safety and comfort. Private car usage increased to 25.4%, reflecting greater reliance on enclosed and weather-resistant transport options. Interestingly, school bus usage remained relatively stable, indicating its value as a dependable mode regardless of environmental challenges. This comparison highlights that mode choice is highly sensitive to weather conditions. Students and families with access to more resilient transport options (e.g., cars) are better able to adapt to adverse weather. In contrast, those dependent on vulnerable modes like motorcycles face limitations, revealing disparities in transport security and flexibility.

Objective 2: To Investigate the Factors Associated with Commuting Behavior

The study employed a Multinomial Logit (MNL) regression model and Exploratory Factor Analysis (EFA) to identify key variables influencing school mode choice. The MNL model revealed that: Household vehicle ownership (both motorcycle and car) significantly increased the probability of using private or semi-private transport, household income, travel distance, and waiting time were also statistically significant predictors, gender played a role, with female students more likely to use passive or supervised modes such as school buses or family cars, the analysis under adverse weather conditions showed that students' travel time and cost increased, particularly for those with long distances or multiple transfers. These students were more exposed to delays and discomfort, reinforcing the connection between environmental vulnerability and modal accessibility.

EFA provided further insights into underlying dimensions that affect mode choice decisions, identifying factors such as perceived safety and convenience, Environmental satisfaction, Comfort, and reliability of transport services. These latent variables reflect psychological and experiential dimensions of travel, not just structural factors. For instance, even if a mode is affordable or available, students may avoid it due to perceived inconvenience or safety concerns, especially in adverse weather.

Objective 3: To Suggest Policy Recommendations for Sustainable, Efficient, and Safe School Transportation

Based on the findings, several policy interventions are recommended to improve the current school transportation system: Expand and subsidize school bus services, especially for low-income or remote-area students, to ensure equitable access to safe and reliable transport, enhance infrastructure resilience, such as installing weather shelters at pick-up points and maintaining reliable timetables during adverse weather, to reduce student vulnerability, promote non-motorized modes (e.g., walking, cycling) through safe routes, pedestrian crossings, and protected bike lane particularly for students living within short distances of school, implement support mechanisms such as transport subsidies or vouchers for students from economically disadvantaged households to reduce inequalities in modal access, encourage collaboration between schools and local government to optimize travel routes, reduce congestion, and improve overall transport safety near school zones.

The findings of this study are consistent with previous research in several respects. Similar to (Dias et al., 2022; Lodhi et al., 2022), the results indicate that safety concerns play a crucial role in influencing students' mode choice, particularly under adverse weather conditions, where the use of motorcycles significantly declines while private vehicles and school buses become more prevalent. This aligns with the observations of Dias et al. (2022) in Kandy, Sri Lanka, who also reported that inclement weather leads to a modal shift toward enclosed and more reliable transport options.

Furthermore, the influence of household vehicle ownership and income on mode choice corroborates the findings of Lodhi et al. (2022) and Chen et al. (2020), who highlighted the significance of socio-economic status in determining access to private vehicles and shaping travel decisions. However, this study extends prior research by explicitly demonstrating how environmental satisfaction and perceived convenience, identified through exploratory factor analysis, also play a role in shaping travel behavior, a dimension that was less emphasized in earlier studies.

Moreover, while international studies often focus on large metropolitan contexts, the present research contributes to the literature by providing evidence from a secondary city in northern Thailand, where transportation infrastructure, cultural attitudes, and economic diversity present unique challenges. These contextual insights support the argument of Faulkner et al. (2010) and Zuniga (2012) that parental decision-making and localized infrastructure constraints are critical factors requiring further policy attention.

5.2 Conclusion

This study successfully addressed its three research objectives by providing empirical insights into school mode choice in a secondary urban setting of Thailand.

Objective 1: The results clearly demonstrate distinct mode preference patterns under normal versus adverse weather conditions. Motorcycles dominate in normal weather, but school buses and private vehicles are preferred during adverse weather, reflecting a weather-sensitive modal shift.

Objective 2: The study identified key determinants of travel behavior, including demographic and socioeconomic factors, transport accessibility, and perceptions of safety and reliability. The integration of MNL modeling and EFA provided a robust framework for understanding the multifaceted nature of mode choice.

Objective 3: The findings support several policy recommendations: Expand school bus programs to offer safe and reliable alternatives, particularly in underserved suburban and rural areas, improve infrastructure resilience, such as sheltered waiting areas and real-time service updates, to enhance the reliability of public and school transport during adverse weather, Promote active transport for short-distance commutes by developing safer pedestrian and cycling infrastructure around schools, implement equity-based subsidies to support students from low-income households with school transport costs, Raise awareness through education campaigns about safe and sustainable travel behavior for students and their families.

In conclusion, school travel behavior in Chiang Rai is highly influenced by environmental conditions, socioeconomic disparities, and infrastructure limitations. The study highlights the importance of data-driven, inclusive transport planning that considers local context and climate sensitivity. Through strategic interventions, it is possible to enhance the efficiency, equity, and sustainability of school transportation systems not only in Chiang Rai but in other developing urban regions facing similar challenges.

5.3 Policy Implications

The findings of this study offer several implications for policy and planning. First, the substantial reliance on motorcycles among students necessitates targeted interventions to improve road safety, particularly during the monsoon and haze seasons. Traffic education, enforcement of helmet use, and designated student drop-off areas can mitigate risks associated with two-wheeler travel.

Second, the consistent use of school buses across weather conditions suggests a strategic opportunity for expanding and enhancing formal student transportation services. Policymakers should consider subsidizing school bus operations, particularly for students in remote or low-income households, to promote equitable access to safe and reliable transport.

Third, the fluctuation in mode use during adverse weather conditions indicates a lack of infrastructure resilience. Investments in weather-proof shelters at pick-up points, real-time service information systems, and contingency route planning can reduce delays and improve user satisfaction. Moreover, integrating climate-responsive design into transport planning is essential for addressing the impacts of seasonal weather variability in northern Thailand.

Fourth, the relatively low-cost burden of school travel for a portion of the sample contrasts with high expenditures for others, revealing economic disparities. Transportation subsidies for disadvantaged students may reduce financial strain and promote school attendance during challenging weather conditions.

Lastly, a long-term strategy should include investments in pedestrian and cycling infrastructure around schools to foster active transport modes. Initiatives such as safe routes to school, walking school buses, and community-based supervision programs can enhance the appeal and safety of these modes, contributing to both health and environmental goals.

However, some of the policy recommendations drawn from this study are presented in general terms rather than as detailed action plans. For example, suggestions for expanding school bus services highlight important directions for improving student mobility but do not provide specifics regarding implementation strategies, funding sources, operational management, or budget allocation. As a result, while the recommendations indicate potential solutions, they may require further refinement and feasibility assessment before being adopted into practice.

5.4 Limitations and Future Work

While the study provides a comprehensive analysis of school mode choice in Chiang Rai, it has several limitations. The sample was studied only for students in the Chiang Rai city area. The results may not be applicable to other areas, as this research does not cover students in rural or mountainous areas who may have different travel problems. Furthermore, the analysis is based on self-reported data. The data from the questionnaire may be biased because students may respond based on their personal memories or feelings. Moreover, some factors that may not be considered, such as the influence of culture or personal beliefs on travel method choice, have not been studied, and the impact of school or government policies has not been thoroughly analyzed.

Future research should broaden the scope beyond Chiang Rai city to include rural and mountainous regions, as well as other provinces, to capture more diverse travel behaviors and improve the generalizability of results. To reduce bias from self-reported data, studies should also adopt multiple data collection methods, such as direct observation and in-depth interviews with students, parents, school administrators, and policymakers. Incorporating additional factors, including school policies and the influence of social media, would further enrich the analysis of determinants shaping school travel choices. Longitudinal designs could additionally capture seasonal variations and the long-term impacts of infrastructure or policy interventions.

From a methodological perspective, this study employed the Multinomial Logit (MNL) model, which is widely used but constrained by the Independence of Irrelevant Alternatives (IIA) assumption and limited ability to account for unobserved heterogeneity. Future research should therefore explore more advanced models such as Nested Logit, Mixed Logit, or Error Component Logit to relax these assumptions and provide greater behavioral accuracy. Integrating meteorological monitoring alongside survey data would further strengthen the alignment of travel behavior with specific weather conditions, enhancing the robustness of future analyses.

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APPENDIX A

QUESTIONNAIRE SURVEY

Section 1: Characteristics of Respondents

1. Gender
   - ☐ Male
   - ☐ Female

2. Age
   - ☐ 15 years old
   - ☐ 16 years old
   - ☐ 17 years old
   - ☐ 18 years old

3. Grade
   - ☐ Grade 10
   - ☐ Grade 11
   - ☐ Grade 12

4. Pocket money per week (THB)
   - ☐ < 500 THB
   - ☐ 500 – 1,000 THB
   - ☐ 1,001 – 1,500 THB
   - ☐ 1,501 – 2,000 THB
   - ☐ > 2,000 THB

5. Parents' working status
   - ☐ Do
   - ☐ Don't

6. Household monthly income
   - ☐ < 30,000 THB
   - ☐ 30,001 – 40,000 THB
   - ☐ 40,001 – 50,000 THB
   - ☐ 50,001 – 60,000 THB
   - ☐ > 60,000 THB

7. Family member
   - ☐ < 3 people
   - ☐ 3 - 4 people
   - ☐ 5 - 6 people
   - ☐ > 6 people

8. Household car ownership
   - ☐ Yes
   - ☐ No

9. Household motorcycle ownership
   - ☐ Yes
   - ☐ No

10. Number of people traveling to school
    - ☐ Traveling alone
    - ☐ More than 1 person traveling together

11. Current residence
    - ☐ Urban
    - ☐ Suburban

12. Residence near a public transportation point
    - ☐ Yes
    - ☐ No

Section 2: Travel Behavior/ Travel Characteristics in Normal & Adverse Weather Conditions to School

1. Travel mode to school
   - ☐ Active Transport
   - ☐ Motorcycle
   - ☐ School bus
   - ☐ Private

2. Total distance traveled to school
   - ☐ Less than 1 km
   - ☐ 1 – 5 km
   - ☐ 5 – 10 km
   - ☐ 10 – 15 km
   - ☐ More than 15 km

3. Travel time from residence to the nearest pick-up point
   - ☐ Less than 5 mins
   - ☐ 6 – 10 mins
   - ☐ 11 – 15 mins
   - ☐ 16 – 20 mins
   - ☐ More than 20 mins

4. Waiting time for the bus at the pick-up point
   - ☐ Less than 5 mins
   - ☐ 6 – 10 mins
   - ☐ 11 – 15 mins
   - ☐ 16 – 20 mins
   - ☐ More than 20 mins

5. Total travel time to school
   - ☐ Less than 10 mins
   - ☐ 11 – 20 mins
   - ☐ 21 – 30 mins
   - ☐ 31 – 40 mins
   - ☐ More than 40 mins

6. Total travel expenses per month
   - ☐ Less than 100 baht
   - ☐ 101 – 500 baht
   - ☐ 501 – 1,000 baht
   - ☐ 1,001 – 1,500 baht
   - ☐ More than 1,500 baht

7. Transfer to school per time
   - ☐ 1 time
   - ☐ 2 times
   - ☐ 3 times
   - ☐ 4 times
   - ☐ More than 4 times

Section 3: Satisfaction with Public Transport

	Variables	1	2	3	4	5
1	Easy get-in/get-off the vehicles					
2	Driver behavior					
3	Driving quality					
4	Punctuality of travel time					
5	Public transport scheduling and service frequency					
6	Ticket system					
7	Fare of public transportation					
8	Engine type of vehicles e.g. Electrical system, gas system, oil system					
9	Size of vehicles					
10	Exterior of the vehicle					
11	Interior condition of the vehicle					
12	Cleanliness of vehicles					
13	Cleanliness of the seats					
14	Number of seats					
15	Position seat					
16	Odor and temperature					
17	Cleanliness of stops					
18	Public transport accessibility					
19	Travel safety and security					

APPENDIX B

LIKELIHOOD RATIO TESTS

Table B1 Normal Weather Condition

Effect	Model Fitting Criteria			Likelihood Ratio Tests		
	AIC of Reduced Model	BIC of Reduced Model	-2 Log Likelihood of Reduced Model	Chi-Square	df	Sig.
Intercept	773.581	923.232	701.581	97.294	3.000	0.000
Grade	691.390	841.041	619.390	15.102	3.000	0.002
Household monthly income	692.344	841.995	620.344	16.056	3.000	0.001
Family member	701.654	851.305	629.654	25.367	3.000	0.000
Household car ownership	690.819	840.470	618.819	14.531	3.000	0.002
Household motorcycle ownership	708.327	857.979	636.327	32.040	3.000	0.000
Number of people traveling to school	784.107	933.759	712.107	107.82	3.000	0.000
Current residence	697.341	846.993	625.341	21.054	3.000	0.000
Travel distance	721.812	871.464	649.812	45.525	3.000	0.000
Travel time to the nearest pick-up point	691.552	841.203	619.552	15.265	3.000	0.002

Table B1 (continued)

Effect	Model Fitting Criteria			Likelihood Ratio Tests		
	AIC of Reduced Model	BIC of Reduced Model	-2 Log Likelihood of Reduced Model	Chi-Square	df	Sig.
Waiting time at the pick-up point	687.884	837.535	615.884	11.597	3.000	0.009
Travel time	720.815	870.467	648.815	44.528	3.000	0.000
Travel cost	689.294	838.946	617.294	13.007	3.000	0.005

Note The chi-square statistic is the difference in -2 log-likelihoods between the final model and a reduced model. The reduced model is formed by omitting an effect from the final model. The null hypothesis is that all parameters of that effect are 0.

Table B2 Adverse Weather Condition

Effect	Model Fitting Criteria			Likelihood Ratio Tests		
	AIC of Reduced Model	BIC of Reduced Model	-2 Log Likelihood of Reduced Model	Chi-Square	df	Sig.
Intercept	911.666	1061.317	839.666	73.528	3.000	0.000
Age	852.500	1002.152	780.500	14.362	3.000	0.002
Father working status	848.135	997.787	776.135	9.997	3.000	0.019
Total family income	847.016	996.667	775.016	8.878	3.000	0.031
Total population in family	856.709	1006.360	784.709	18.571	3.000	0.000
Private car ownership	871.389	1021.040	799.389	33.250	3.000	0.000
Household motorcycle ownership	856.164	1005.815	784.164	18.026	3.000	0.000
Number of people traveling to school	930.077	1079.729	858.077	91.939	3.000	0.000
Current residence	872.074	1021.725	800.074	33.936	3.000	0.000
Time required to travel from residence to the nearest pick-up point	855.378	1005.030	783.378	17.240	3.000	0.001

Table B2 (continued)

Effect	Model Fitting Criteria			Likelihood Ratio Tests		
	AIC of Reduced Model	BIC of Reduced Model	-2 Log Likelihood of Reduced Model	Chi-Square	df	Sig.
Total time spent waiting for the bus at the pick-up point	851.858	1001.510	779.858	13.720	3.000	0.003
Total time to school	879.563	1029.215	807.563	41.425	3.000	0.000

Note The chi-square statistic is the difference in -2 log-likelihoods between the final model and a reduced model. The reduced model is formed by omitting an effect from the final model. The null hypothesis is that all parameters of that effect are 0.

APPENDIX C

CERTIFICATE OF APPROVAL

The Mae Fah Luang University Ethics Committee on Human Research
333 Moo 1, Thasud, Muang, ChiangRai 57100
Tel: (053) 917-170 to 71 Fax: (053) 917-170 E-mail: rec.human@mfu.ac.th

CERTIFICATE OF APPROVAL

COA: 121/2024 **Protocol No: EC 24058-12**

Title: A Study on School Trip Mode Choice in Chiang Rai City Area Using A Multinomial Logit Regression Approach

Principal Investigator: Miss. Chanyanuch Pangderm

School: Management

Funding support: Funds to support research studies (Mae Fah Luang University Postgraduate Office)

Approval:

1) Research protocol — Version 2 Date May 9, 2024
2) Information sheet and informed consent documents — Version 2 Date May 9, 2024
3) Questionnaire — Version 2 Date May 9, 2024
4) Principal investigator and Co-investigators
   - Miss. Chanyanuch Pangderm
   - Assistant Professor Tosporn Arreeras, Ph.D.

The aforementioned documents have been reviewed and approved by the Mae Fah Luang University Ethics Committee on Human Research 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)

Date of Approval: June 3, 2024

Date of Expiration: June 2, 2025

Frequency of Continuing Review: 1 year

(Assoc. Prof., Maj. Gen. Sangkae Chamnanvanakij, M.D.)

Chairperson of the Mae Fah Luang Ethics Committee on Human Research

The Mae Fah Luang University Ethics Committee on Human Research
333 Moo 1, Thasud, Muang, ChiangRai 57100
Tel: (053) 917-170 to 71 Fax: (053) 917-170 E-mail: rec.human@mfu.ac.th

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

1. Strictly conduct the research as required by the protocol.
2. Use only the information sheet, consent form, questionnaire, case record form and advertisement bearing the MFU EC stamp of approval.
3. Submit a progress report (AP 05/2024) for continuing review and for renewing the approval within 30 days before expiration date.
4. When there are changes of the protocol, the investigator must submit an amendment report (AP 06/2024) with amended protocol for MFU EC approval before implementing any changes in the research (unless those changes are required urgently for the safety of the research subjects).
5. When there is any unanticipated problem or serious adverse event, the investigator must submit a safety report (AP 07/2024) as set forth in the ICH-GCP.
6. When there is any deviation or non-compliance with the approved protocol, the investigator must submit a protocol deviation/non-compliance report (AP 08/2024).
7. When the research is complete or terminated, the investigator must submit a closing report (AP 09/2024).

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

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

....

(Miss. Chanyanuch Pangderm)

Date ......6/6/24......

APPENDIX D

CERTIFICATE OF ETHICAL CONSIDERATIONS

คณะกรรมการจริยธรรมการวิจัยในคน มหาวิทยาลัยธรรมศาสตร์
สาขาแพทยศาสตร์

ประกาศนียบัตรฉบับนี้ให้ไว้เพื่อแสดงว่า

ชัญญานุช ปางเดิม

ได้ผ่านการอบรมหลักสูตร GCP online training (Computer-based)

“แนวทางการปฏิบัติการวิจัยทางคลินิกที่ดี (ICH-GCP:E6(R2))”

ประกาศนียบัตรฉบับนี้มีผลตั้งแต่วันที่ 14 มีนาคม 2567 ถึงวันที่ 14 มีนาคม 2569

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ประธานคณะกรรมการจริยธรรมการวิจัยในคน
มหาวิทยาลัยธรรมศาสตร์ สาขาแพทยศาสตร์

(รองศาสตราจารย์ แพทย์หญิงทิพาพร ธาระวานิช)
รองคณบดีฝ่ายวิจัยและนวัตกรรม

APPENDIX E

PUBLICATION PAPER OF JOURNAL

future transportation

MDPI

Article

Modeling School Commuting Mode Choice Under Normal and Adverse Weather Conditions in Chiang Rai City

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Abstract

This study investigates the factors influencing school trip mode choice among senior high school students in the Chiang Rai urban area, Chiang Rai, Thailand, under normal and adverse weather conditions. Utilizing data from 472 students across six extra-large urban schools, a Multinomial Logit (MNL) regression model was applied to examine the effects of socio-demographic attributes, household vehicle ownership, travel distance, and spatial variables on mode selection. The results revealed notable modal shifts during adverse weather, with motorcycle usage decreasing and private vehicle reliance increasing, while school bus usage remained stable, highlighting its role as a resilient transport option. Car ownership emerged as a strong enabler of modal flexibility, whereas students with limited access to private transport demonstrated reduced adaptability. Additionally, increased waiting and travel times during adverse conditions underscored infrastructure and service vulnerabilities, particularly for mid-distance travelers. The findings suggest an urgent need for transport policies that promote inclusive and climate-resilient mobility systems, particularly in the context of Chiang Rai, including expanded school bus services, improved first-mile connectivity, and enhanced pedestrian infrastructure. This study contributes to the literature by addressing environmental variability in school travel behavior and offers actionable insights for sustainable transport planning in secondary cities and border regions.

Keywords: adverse weather; urban; school trip; mode choice; multinomial logit; Chiang Rai

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1. Introduction

Transportation is fundamental to everyday life, functioning as a critical mechanism for human mobility, goods distribution, and economic advancement. However, contemporary transportation systems demonstrate significant dependence on fossil fuel consumption, contributing substantially to environmental degradation, atmospheric pollution, and climatic alterations [1–3]. This paradigm has generated increased awareness regarding the necessity for innovative transport solutions that minimize adverse environmental impacts while optimizing operational efficiency, accessibility, and social equity. The United Nations (UN), comprising 193 member states, adopted the 2030 Agenda for Sustainable Development in 2015, outlining 17 goals [4,5]. Among them, SDG 11 emphasizes the creation of inclusive, safe, resilient, and sustainable urban environments [6]. This comprehensive objective encompasses the advancement of sustainable transportation systems, addressing the mobility requirements of vulnerable demographics, implementing effective pollution management strategies, and establishing accessible green environmental spaces [7]. It should therefore respond to the requirements of all population groups, including school-aged children.

In this context, the choice of student transport modes under diverse weather conditions has become an important research topic, necessitating insightful studies of the everyday travel behavior and overall transport systems of the study area. Understanding individuals' patterns and choices regarding transportation and commuting is crucial for effective transportation planning and sustainable development. Such research involves factors such as weather conditions, mode of transportation, travel distance, cost, travel time, frequency, and even purpose. The mode choice for school travel is crucial as it is influenced by students' overall travel behavior and transportation patterns. Understanding the factors that affect mode choice for school trips is essential for developing policies and initiatives that promote safe, efficient, and sustainable school travel. Research has identified various factors influencing this decision-making process, including proximity to school, availability and accessibility of transportation options, travel time, cost considerations, safety concerns, and environmental factors [8–10]. For example, the availability of dedicated school buses or public transit options significantly impacts students' mode choices, with convenience and reliability, along with distance and travel time, playing crucial roles. Additionally, individual and household characteristics, such as the presence of a personal vehicle, can influence mode choice decisions [11]. Understanding these preferences and behaviors can inform transportation planning and policymaking, leading to the creation of safer and more efficient school transportation systems. By promoting sustainable modes of transportation, such as walking, cycling, or using public transit, policymakers can reduce traffic congestion, promote physical activity, and improve air quality around schools [12–14].

This research focuses on Chiang Rai province, a border city located in northern Thailand, which offers a unique and compelling context for examining school travel behavior due to its distinctive geographic, environmental, and socio-transport characteristics. Unlike Thailand's capital or economically dominant urban centers, Chiang Rai represents a secondary city with evolving urbanization patterns, limited public transportation infrastructure, and high dependence on informal and private transport modes, particularly motorcycles. These characteristics render it an ideal setting to investigate the complexities of school trip mode choice, especially under environmentally adverse conditions. Chiang Rai frequently experiences adverse environmental conditions, including seasonal haze from agricultural burning (PM2.5) and heavy rainfall during the monsoon season, which significantly disrupt travel reliability and safety. These environmental stressors, combined with a lack of resilient mobility infrastructure, create a highly relevant context for analyzing behavioral shifts in school travel under normal and adverse conditions. Additionally, several extra-large secondary schools within the urban core provide access to a diverse and sizable student population, enabling a robust statistical analysis of mode choice patterns. By selecting the Chiang Rai urban area in Chiang Rai province as the study area, this research not only addresses a critical knowledge gap in transport behavior literature related to climatically vulnerable and infrastructure-constrained regions but also generates insights with broader applicability to similarly situated secondary cities across Southeast Asia.

2. Literature Review

2.1. Travel Behavior Under Adverse Conditions

Adverse environmental conditions are increasingly recognized as a key factor in determining travel behavior, particularly as cities around the world face mounting challenges from climate variability and extreme weather events. Environmental disruptions, including both short-term weather anomalies and chronic atmospheric stressors, can have significant implications for daily mobility patterns, mode choice, and transport system performance [15]. These effects are especially pronounced in contexts where infrastructure resilience is limited and modal alternatives are constrained, such as in low- and middle-income countries (LMICs) and secondary cities [16]. Adverse weather conditions are commonly defined in the transport literature as environmental phenomena that deviate from normal climatic expectations and hinder travel safety, efficiency, and comfort. These conditions include, but are not limited to, heavy rainfall, strong winds, fog, snow, extreme temperatures, and reduced visibility [17]. More recently, air pollution, particularly elevated concentrations of fine particulate matter, has been increasingly recognized within this category due to its atmospheric nature and direct impact on mobility decisions [18]. While traditionally excluded from meteorological classifications, air pollution shares key behavioral characteristics with adverse weather, such as reducing the desirability of active travel modes and increasing the perceived risk of exposure for vulnerable users [19]. As such, adverse weather is best understood not only through physical metrics but also in terms of its social and behavioral consequences on the transportation system [20].

Empirical research has consistently demonstrated that adverse weather influences a wide range of travel behaviors. Rain and snow have been shown to reduce the use of active modes such as walking and cycling, particularly when protective infrastructure is lacking or when users perceive elevated risk [21]. Wind and extreme temperatures can similarly discourage outdoor travel or prompt shifts to more enclosed modes [22]. In urban settings, poor weather conditions are also associated with longer travel times, increased congestion, and decreased service reliability for public transport [23]. These outcomes often lead to behavioral adaptations such as rescheduling trips, modifying routes, or switching modes. Importantly, these adjustments are not equally accessible to all travelers [24]. Individuals with access to private vehicles or flexible schedules may adapt more easily, whereas others, especially students, the elderly, or low-income commuters, may face disproportionate disruptions and exposure [25].

School travel offers a particularly relevant lens through which to examine the impact of adverse weather, as students typically have fixed schedules and may rely on modes that are highly sensitive to environmental variability, such as walking or motorcycles [26]. Where formal school transport services are unavailable, many students remain dependent on informal or unsafe travel arrangements, amplifying their vulnerability during environmental disturbances. Despite growing awareness of these dynamics, there remains a paucity of research focusing on how adverse weather affects school travel behavior in peripheral urban areas and developing regions [27]. Most existing studies are situated in high-income metropolitan contexts, with limited attention given to high-school students in secondary cities who face distinctive infrastructural and environmental vulnerabilities. This study fills this gap by jointly examining the travel behavior of high-school students under normal and adverse weather conditions in Chiang Rai, a secondary city in northern Thailand. In doing so, it contributes to a more nuanced understanding of climate-sensitive mobility and highlights the need for resilient and equitable transport planning in vulnerable urban settings.

2.2. Commuting to School

Parents' choices of school travel modes are primarily influenced by considerations of convenience and safety, with behavioral costs and time constraints playing pivotal roles in their decision-making process [28]. The observed trend of a sharp increase in driving children to school since 1969, juxtaposed with a decline in walking, highlights the evolving dynamics of school commuting habits, where high school students' reliance on driving has declined due to various factors, while school trips continue to represent a significant portion of American children's travel [29]. Moreover, gender disparities emerge, with males exhibiting a higher likelihood of walking and biking to school compared to females, a trend exacerbated by stronger parental mobility restrictions on females which consequently impact travel behavior [30]. Further delineating factors influencing school transport mode choices, Dias et al. [31] revealed the impact of gender, age, income, school type, and distance, with male students exhibiting preferences for public buses, walking, and private vehicles, while older students were found to be more inclined toward walking and school buses. Additionally, their study highlighted preferences among national or provincial school students for school buses over private vehicles, with distance to school significantly affecting all school transport modes. Addressing factors influencing car use, Zhang et al. [32] emphasized the impact of car ownership, the quality of the walking environment, and rush hour dynamics, alongside preferences for walking among students in core zones and increased public transit usage with proximity to stations. Furthermore, Minh Ngoc et al. [33] emphasized the significance of factors such as location, gender, age, and population density in school traffic crashes, which are particularly prevalent in urban areas and among females in Can Tho, Vietnam, necessitating a redesign of the road infrastructure for motorcycle users' safety. Lastly, Li et al. [34] elucidated the prevalence of active school travel among primary students in Shenzhen, attributing it to high-intensity land development and the significant influence of built environment factors on children's choice of transportation.

2.3. Travel Mode Preferences

Parental attitudes play a crucial role in influencing younger teens' mode choices for transportation, with socioeconomic and demographic variables being statistically less significant. Attitudinal variables are essential predictors of mode choice. In densely populated areas, walking and bicycling are more prevalent. Crime adversely affects public transit choices for younger teens [35]. In Abbottabad, Pakistan, there are notable gender-based differences in mode choice preferences and travel characteristics for educational trips. Girls tend to prefer family cars and have more negative views regarding public transport compared to boys, who are more inclined toward using motorcycles, public transport, and ride-hailing services [36]. Research in Mexico City highlighted transport-related inequalities among older adults, particularly concerning income class, gender, and access to public transportation. That study stressed the importance of understanding transport-related exclusion in the Global South and among different societal groups, providing insights applicable to other global cities [37]. A shift in mode choice for school trips has been observed, with a decline in active modes of transport leading to health issues, environmental concerns, congestion, and safety risks due to increased vehicle use. This underscores the need to understand factors influencing mode choice and accompaniment decisions for school trips [38]. Tourist transport mode choices at destinations are significantly influenced by travel time, cost, party composition, trip purpose, fitness level, knowledge about long-distance travel, mobility options at the destination, and weather conditions. Tourists show inelasticity to travel cost changes, prioritizing transit service quality over price [39]. Residential preferences strongly impact travel behavior, even in homogeneous neighborhoods, leading to differences in daily mode use. Inner-city neighborhoods encourage even car-preferring households to use alternative modes of transport. Urban planning policies should adapt to the needs and preferences of future residents to attract a diverse population, as new inner-city areas tend to draw residents from other inner-city locations rather than suburban areas [40]. In the context of Thailand, several studies have explored mode choice selection in both urban and regional settings. Arreeras et al. [41] conducted a study on factors affecting mode selection in terms of accessing railway stations in Nakhon Ratchasima, emphasizing the critical role of private vehicle availability, travel convenience, and trip purpose in shaping access mode decisions among intercity rail users. Their findings highlighted how proximity, infrastructure quality, and personal mobility resources significantly influence modal selection, particularly in semi-urban and peri-urban environments, paralleling the patterns observed among school commuters in border cities such as Chiang Rai. Complementing this, Chansuk et al. [42] utilized exploratory and confirmatory factor analysis to evaluate behavioral shifts in the wake of COVID-19, focusing on domestic tourism in Thailand. Their study demonstrated how latent variables such as health concerns, perceived risk, and accessibility influence travel choices, reinforcing the value of multi-dimensional analytical approaches in efforts to understand evolving mobility behaviors. These studies emphasized the methodological and contextual relevance of using quantitative tools such as MNL and factor analysis to record nuanced transport decisions. Previous studies on school commuting and travel mode choice perspectives are represented in Table 1.

Table 1. Previous studies on school commuting and travel mode choice perspective.

Years	Reference	Country	Travel Modes	Methods
2015	[43]	Toronto, Canada	Walk Transit School bus Car	Multinomial Logit (MNL) Model
2015	[44]	Tehran, Iran	Walk Auto drive School bus Public transport	Three-Level Nested Logit (NL) Multinomial Logit (MNL) Model
2015	[45]	Norway	Private car Air Transport Public transport	Multinomial Logit (MNL) Model
2018	[46]	Kanpur, India	Walk Bicycle Cycle-rickshaw School bus Tempo/auto Family vehicle	Multinomial Logit (MNL) Model
2019	[47]	Beijing, China	Walking Bicycle Public transport Car	Multinomial Probit (MNP) Model Multinomial Logit (MNL) Model
2019	[48]	State of Western Australia	Car Bus Air transport	Multinomial Logit (MNL) Model Nested Logit Models
2020	[49]	India	Two-wheeler Passenger car Three-wheeler School bus Active school transport	Multinomial Logit (MNL) Model

Table 1. *Cont.*

Years	Reference	Country	Travel Modes	Methods
2020	[50]	Hangzhou, China	Walk Bike or e-bike Bus Subway Automobile Others	Multinomial Logit (MNL) Model
2021	[51]	Milan, Italy	Public transport Private car Multimodal transport Active transport	Multinomial Logit (MNL) Model Random Forest (RF) Support Vector Machine (SVM)
2022	[31]	Kandy, Sri Lanka	Walking Public bus School bus School van Private vehicle	Multinomial Logit (MNL) Model Mixed Logit Models
2022	[52]	Dhaka, Bangladesh	Non-motorized vehicle On-demand vehicle Private vehicle Public transport Walk	Multinomial Logit (MNL) Model
	Present study	Chiang Rai, Thailand	Active transport Motorcycles School bus Private	Descriptive analysis, Multinomial Logit (MNL) Model

3. Methodology

3.1. Study Area

Chiang Rai Province in northern Thailand is a diverse region encompassing urban, suburban, and rural areas. The study area is Chiang Rai district, which is an urban area of Chiang Rai Province, one of the 18 most populous districts in Chiang Rai Province, with an area of 1216 km^2 and a total population of 125,340 people out of 785,252 people in Chiang Rai Province in total [53]. The Chiang Rai urban area provides a unique and intriguing context to understand transportation mode choices and decision-making processes among students and their parents or guardians concerning mode selection for school trips. This study presents a range of transportation options for school trips, including active transport, motorcycles, school buses, and private vehicles. The mode choice study's focus was on "extra-large" schools in the Chiang Rai urban area. This setting was chosen to shed light on the factors influencing transportation decisions for school trips in this specific geographic context, exploring the significance of various attributes such as travel distance, travel time, cost considerations, safety perceptions, convenience, and environmental concerns.

3.2. Sample and Data Collection

The target population for this study comprised senior high school students enrolled in extra-large schools within the Chiang Rai urban area. In the Thai education system, school sizes are officially classified into four categories: small, medium, large, and extra-large, based on student enrollment numbers. An extra-large school is defined as having more than 1680 students [54]. Based on this criterion, six schools qualified and were selected for inclusion in the study [55]. The distribution of the senior high school population and the corresponding sample size across these schools is presented in Table 2. The required sample size was calculated using Taro Yamane's formula [56], as shown in Equation (1), with margin of error e set at 0.05. The calculation was based on the total senior high school student population across the six identified schools, yielding a minimum required sample size of 380 students.

$$n = \frac{N}{1 + Ne^2} \quad (1)$$

where N represents the population size, n denotes the sample size, and e is the margin of error. Data collection was carried out through on-site surveys administered directly within each selected school. A random sampling technique was employed to select senior high school students, and responses were recorded using paper-based survey forms. Ultimately, a total of 472 valid responses were collected, exceeding the minimum sample size requirement and thereby enhancing the robustness of the dataset. Any questionnaires with incomplete or missing information were removed during the data cleaning process to ensure statistical reliability. The data collection was conducted from January to February 2024, during the regular academic term, which coincided with typical seasonal weather variations including haze and occasional rainfall events in the Chiang Rai region.

Table 2. Sample in the study.

Item	Extra-Large School	Senior High School (Year 2023)	Sample in the Study		
		Population	Percent	Designed	Actual
A	Chiang Rai Municipality School 6	1752	24.46	93	95
B	Samakkhi Witthayakhom School	1600	23.96	91	93
C	Chiang Rai Provincial Administrative Organization School	1468	19.6	74	90
D	Damrongrat Songkroh School	1314	17.62	67	73
E	Sahasartsuksa School	614	7.21	27	74
F	Chiang Rai Vidhayakhome School	489	7.15	27	48
	Total	7486	100	380	472

3.3. Instrument Design

The questionnaire was developed to investigate the mode choice behavior of senior high school students for commuting to school, along with the factors influencing transportation mode selection. The instrument was designed based on an extensive review of relevant literature and adapted from associated research to ensure construct validity. To accommodate the diverse nationalities of participants, the questionnaire was prepared in both Thai and English languages. The questionnaire was developed in English and translated into Thai using a forward–backward translation method to ensure conceptual accuracy. Discrepancies were resolved through expert review. A pilot test with 30 students was conducted to assess clarity, resulting in minor revisions before full implementation. Ethical approval for the study was obtained from the Mae Fah Luang University Ethics Committee on Human Research. The questionnaire comprised two primary sections. The first section collected respondent demographic characteristics, including gender, age, grade level, weekly pocket money, parents' employment status, monthly household income, number of family members, household car ownership, household motorcycle ownership, number of people commuting to school together, type of current residence, and proximity to public transportation points. The second section focused on travel behavior and travel characteristics related to travel distance, access time, and waiting time; these data were obtained through self-reported responses using predefined categorical intervals. Household vehicle ownership (car and motorcycle) was recorded as binary variables. While geospatial data collection was not implemented, self-reporting allowed for practical and context-relevant measurement within the school setting.

In this study, respondents were asked to identify their predominant mode of school travel under two distinct environmental scenarios, i.e., normal weather and adverse weather conditions, from a set of four discrete alternatives: active transport, motorcycle, school bus, and private vehicle. Each participant selected a single, most frequently used mode per condition, consistent with discrete choice modeling conventions, thereby enabling robust Multinomial Logit (MNL) estimation. The questionnaire was designed to capture context-sensitive behavioral shifts, with adverse weather being defined as periods characterized by either heavy rainfall or elevated PM2.5 haze levels, both of which are recurrent in Chiang Rai's monsoon and agricultural burning seasons. Rather than relying on specific meteorological events, the survey invited students to reflect on their usual mode choices under such conditions, based on lived experience and perception. This approach ensured consistency in survey administration while allowing for a comparative assessment of travel behavior under climatologically relevant stressors.

3.4. Multinomial Logit Model (MNL)

In this study, the Multinomial Logit Model (MNL) was employed to investigate the determinants influencing individuals' mode choice behavior [57,58]. The MNL framework assumed that each traveler would select the alternative that offered the highest utility among a finite set of discrete travel modes [59], while this study evaluated four primary travel modes: active transport, motorcycle, school bus, and private vehicle. The MNL assumed that each alternative i had an associated utility U_{in} which consisted of a systematic (observable) component V_{in} and a random (unobservable) component ε_{in}, decomposed into two components, as represented in Equation (2):

$$U_{in} = V_{in} + \varepsilon_{in} \tag{2}$$

The systematic component V_{in} was typically modeled as a linear function of observed attributes of the alternative and characteristics of the decision-maker (Equation (3)):

$$V_{in} = \beta\prime X_{in} \tag{3}$$

where β is a vector of parameters to be estimated and X_{in} is a vector of explanatory variables concerning the utility associated with a particular travel mode. Assuming the error terms ε_{in} were independently and identically distributed with a Gumbel distribution led to the closed-form choice probability expression (Equation (4)):

$$P_{in} = \frac{exp(V_{in})}{\sum_{j=1}^{J} exp(V_{jn})} \tag{4}$$

where P_{in} is the probability that individual n selects alternative i among J available modes. This formulation offered significant computational simplicity and allowed for straightforward estimations using maximum likelihood techniques. While the MNL model assumes independence of irrelevant alternatives (IIA), it offers straightforward interpretability and is suitable for modeling school travel behavior in exploratory contexts. It enabled the quantification of how socio-demographic factors (e.g., income, vehicle ownership) and trip attributes (e.g., travel time, travel cost) systematically influenced the probability of selecting each mode. Moreover, it facilitated the estimation of elasticities and marginal effects, providing critical insights for transport policy and infrastructure planning [59]. The overall research framework guiding this analytical process is presented in Figure 1.

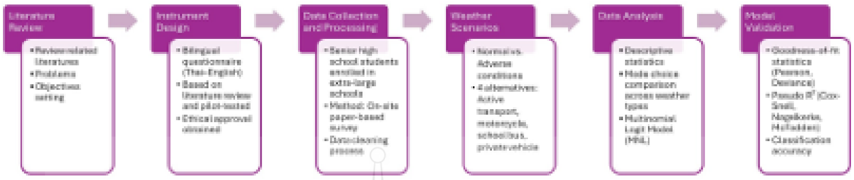

Figure 1. Research framework.

4. Results

4.1. Sample Characteristics

The demographic profiles of the 472 respondents in Table 3 revealed key insights into their socio-economic backgrounds, which were likely to influence their travel behavior. The sample was predominantly female (70.3%), with students mostly aged between 16 and 18 years, reflecting the typical age range for senior high school levels. The distribution across grades was relatively balanced, with a slight concentration in Grade 10 (39.8%), suggesting that younger students were more represented in the survey. In terms of economic factors, nearly half of the students reported receiving less than 500 THB (14 USD) in weekly pocket money, highlighting potential financial constraints that could impact transportation choices. Interestingly, despite the modest pocket money, a significant proportion of students came from households where both parents were employed (87.7% for both mothers and fathers), indicating dual-income families. However, household incomes varied considerably, with almost half of the earnings being below 30,000 THB (857 USD) monthly, suggesting economic diversity within the sample. Household composition and vehicle ownership further reflected socioeconomic conditions. Most families consisted of 3–4 members, which may have influenced the shared transportation dynamics. High rates of motorcycle ownership (94.5%) and substantial car ownership (85%) indicated strong access to private vehicles, potentially reducing reliance on public transportation. Additionally, most students resided in urban areas (62.1%), which likely offered greater access to diverse transportation modes compared to their suburban counterparts (37.9%). Collectively, these demographic and socio-economic factors provided a nuanced understanding of the respondents, offering a foundational context for analyzing travel behavior and mode choice decisions in subsequent sections of the study.

Table 3. Demographic information of participants. (n = 472).

Items	Sub-Categories	Frequency	Percentage
Gender	Male	140	29.7
	Female	332	70.3
Age	15 years old	49	10.4
	16 years old	141	29.9
	17 years old	137	29
	18 years old	145	30.7
Grade	Grade 10	188	39.8
	Grade 11	137	29
	Grade 12	147	31.1
Pocket money per week *	<500 THB	231	48.9
	500–1000 THB	205	43.4
	1001–1500 THB	26	5.5
	1501–2000 THB	5	1.1
	>2000 THB	5	1.1

Table 3. *Cont.*

Items	Sub-Categories	Frequency	Percentage
Parents working status	Do	414	87.7
	Don't	58	12.3
Household monthly income	<30,000 THB	228	48.3
	30,001–40,000 THB	115	24.4
	40,001–50,000 THB	55	11.7
	50,001–60,000 THB	30	6.4
	>60,000 THB	44	9.3
Family member	<3 people	24	5.1
	3–4 people	251	53.2
	5–6 people	139	29.4
	>6 people	58	12.3
Household car ownership	Yes	401	85
	No	71	15
Household motorcycle ownership	Yes	446	94.5
	No	26	5.5
Current residence	Urban	293	62.1
	Suburban	179	37.9

* 1 USD ≈ 35.00 THB.

4.2. *Mode Choice Preference Under Weather Conditions*

The analysis of travel mode preferences revealed notable shifts due to weather variability, as represented in Figure 2. Under normal conditions, motorcycle usage dominated at 36.9%, reflecting the popularity of two-wheeled transport for short- to mid-distance school trips. However, this proportion significantly decreased to 26.7% during adverse weather, indicating sensitivity to safety and comfort risks. School bus usage remained stable at 33.7% across both conditions, highlighting its resilience and reliability. Active transport slightly increased from 13.8% to 14.2%, likely representing students living within close proximity to school who continued to walk despite unfavorable weather. Conversely, private vehicle use rose substantially from 15.7% to 25.4% under adverse conditions, suggesting that families with private car access switched to safer travel options. These shifts emphasized the critical role of structured transport services and the inequities in modal flexibility during environmental disruptions.

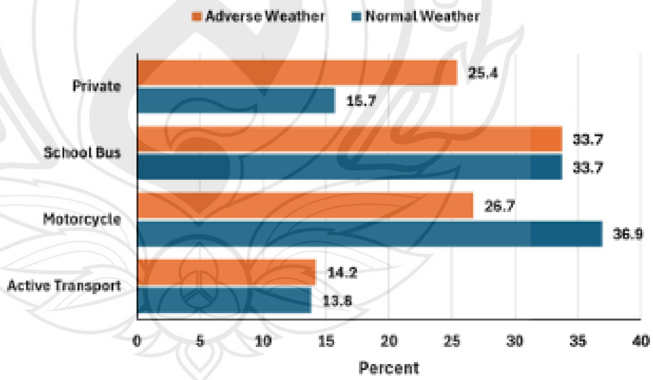

Figure 2. Travel mode preferences under normal and adverse weather conditions.

4.3. Monthly Travel Cost Analysis

The analysis of monthly travel costs in Figure 3 shows that the majority of students incurred low expenses, with 29.9% spending less than 100 THB (3 USD) under normal weather, rising slightly to 31.4% during adverse weather. Mid-range spenders 101–500 THB (3–14 USD) decreased from 20.3% to 18.4%, suggesting possible travel consolidation or mode shifts to maintain affordability. Costs in the 501–1000 THB (14–29 USD) and 1001–1500 THB (29–43 USD) ranges remained stable, indicating resilience among students using structured or private transport. Only 3.6% of students consistently spent over 1500 THB (43 USD) monthly, reflecting long-distance or premium transport reliance. Overall, while most students' travel expenses were stable, adverse weather slightly increased cost burdens for moderate spenders, highlighting the need for affordable and weather-resilient school transport options.

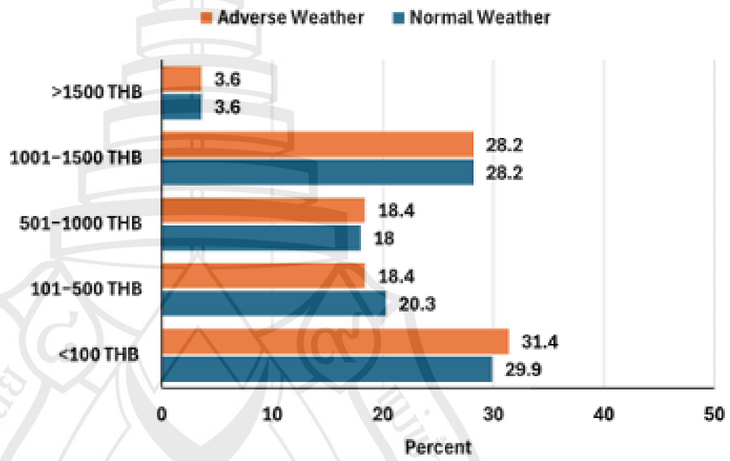

Figure 3. Monthly travel cost distribution under weather conditions.

4.4. Trip Characteristics of Normal and Adverse Weather Conditions

4.4.1. Travel Time from Residence to Nearest Pick-Up Point

Our analysis of travel times from students' residences to the nearest pick-up points under normal and adverse weather conditions is illustrated in Figure 4. Under normal weather, 44.7% of students reached the pick-up point within five minutes, indicating a high level of spatial accessibility. However, during adverse weather, this proportion decreased slightly to 41.5%, suggesting that inclement conditions may have either impeded direct access or encouraged students to seek safer, although more distant, boarding points. The proportion of students requiring 6–10 min remained relatively stable (21.6% to 21.2%), highlighting resilience in moderate accessibility ranges. Notably, the share of students requiring longer travel times (11–15 min, 16–20 min, and >20 min) increased across all categories during adverse conditions. Particularly, the proportion of students traveling more than 20 min rose from 14.4% to 15.9%, reflecting weather-induced spatial displacement.

These findings highlight latent vulnerabilities in school transport accessibility, emphasizing the need for enhanced first-mile infrastructure and adaptive transport services during adverse environmental events.

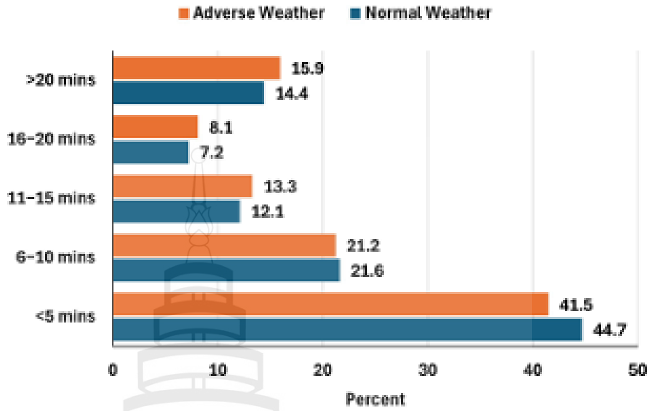

Figure 4. Travel time from residence to the nearest pick-up point under normal and adverse weather conditions.

4.4.2. Waiting Time Pick-Up Point

Figure 5 presents the distribution of waiting times for the bus at pick-up points under normal and adverse weather conditions. Under normal weather, 46% of students waited less than five minutes, indicating high operational efficiency and punctuality of the transport system. However, during adverse weather, this proportion dropped to 40.5%, highlighting weather-induced service disruptions. Similarly, the share of students waiting 6–10 min declined from 26.1% to 23.1%. In contrast, longer waiting times increased across all categories. Notably, the proportion of students waiting more than 20 min rose from 8.5% to 12.7%, representing a substantial 50% relative increase. Additionally, the proportion waiting 11–15 min and 16–20 min also rose, reflecting systemic delays caused by adverse environmental conditions, such as traffic congestion, reduced vehicle speed, or route adjustments. These findings suggest that inclement weather significantly deteriorates transport service reliability, underscoring the need for adaptive scheduling and infrastructure improvements to enhance resilience in student commuting patterns.

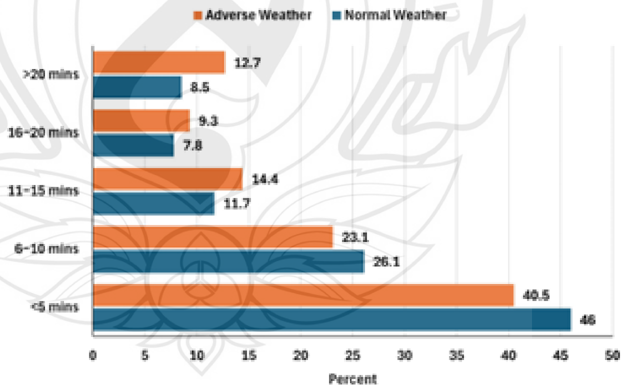

Figure 5. Waiting time at the pick-up point under normal and adverse weather conditions.

4.4.3. Travel Time to School

Total travel time to school under different weather conditions, as illustrated in Figure 6, revealed that under normal weather conditions, a substantial proportion of students (59.4%) experienced relatively short commutes, with 26.3% traveling less than 10 min and 33.1% between 11–20 min. This suggested that, under typical circumstances, most school journeys were efficient, likely supported by stable transport modes and reliable scheduling. However, when weather conditions deteriorated, the proportion of students traveling under 20 min dropped significantly to 44.7%, a reduction of nearly 15 percentage points. This reduction signaled delays and increased inefficiencies in travel systems, potentially due to traffic congestion, reduced vehicle speeds, and changes in modal choice (e.g., avoidance of motorcycles or active transport). Interestingly, the percentage of students traveling between 21–30 min and beyond increased under adverse weather. The 21–30 min category rose from 13.1% to 18.2%, while those traveling more than 40 min palpably increased from 18.2% to 24.6%. These changes in travel time length indicated a systematic expansion of travel time to school in the face of environmental constraints, which may reflect rerouting, a shift in travel mode to slower but safer alternatives (e.g., from motorcycle to school bus), or increased waiting times for public or private transportation.

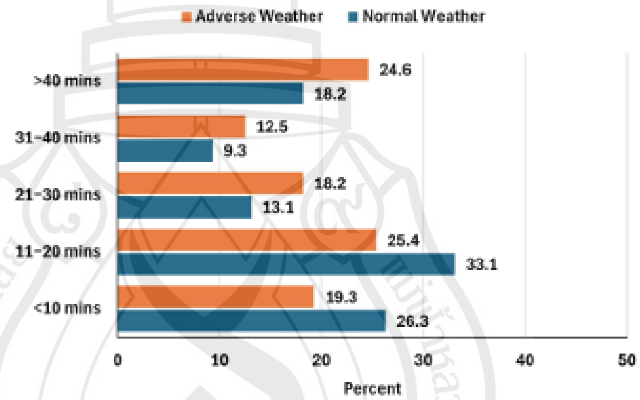

Figure 6. Travel time to school under normal and adverse weather conditions.

4.4.4. Transfers During the Trip to School

Data concerning transfers to school per trip under different weather conditions, as shown in Figure 7, offer a nuanced understanding of student mobility efficiency with environmental variability. Under normal weather conditions, 93.2% of students required only one trip, suggesting a largely direct or streamlined school travel pattern that benefited from coherent route planning, accessible transit infrastructure, or widespread private mobility solutions. The fact that this figure marginally declined to 93.0% under adverse weather implied a high degree of structural resilience in the transport system to school. However, more telling were the subtle shifts in the higher-frequency transfer categories. The share of students requiring three trips increased significantly from 0.2% in normal conditions to 0.8% in adverse weather, a fourfold rise. Though the absolute numbers remained low, this relative surge reflected a potential vulnerability in transport continuity for a specific subset of the student population. That may indicate service disruptions, route changes due to weather conditions, or reduced service frequencies, necessitating additional modal transitions. In the context of student well-being and punctuality, even small increments in trip complexity can introduce psychological fatigue, temporal uncertainty, and reduced accessibility. Transfers involving four trips or more, while uncommon, exhibited a mild contraction under adverse weather, i.e., from 1.1% to 0.8%. This could suggest two contrasting behavioral or systemic adaptations: either a withdrawal from such burdensome travel during adverse conditions, possibly through school absenteeism or alternative remote arrangements, or a substitution effect, where longer, segmented commutes were replaced by more consolidated or private travel modes in response to inclement weather challenges. Furthermore, the marginal decline in two-trip journeys (from 5.3% to 5.1%) may signal a minor optimization or reconfiguration of routes during adverse conditions, potentially aided by parental intervention, dynamic routing policies, or informal carpool networks. While this change was statistically slight, it could reflect broader strategies aimed at minimizing multimodality in favor of reliability.

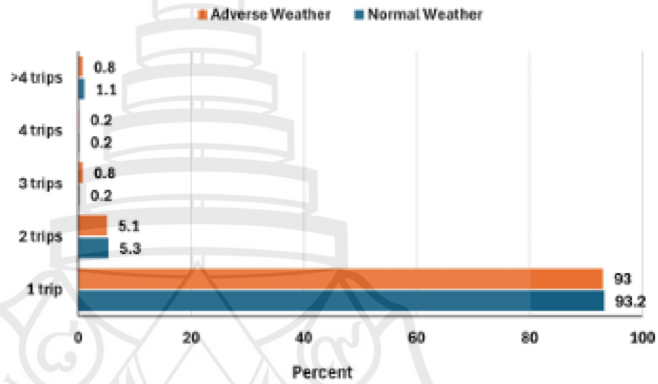

Figure 7. Number of modal transfers required for school trip under normal and adverse weather conditions.

4.5. Model Validity

4.5.1. Normal Weather Conditions

Table 4 presents the model fitting statistics and diagnostic measures for the Multinomial Logit (MNL) model under normal weather conditions. The model demonstrates strong explanatory capabilities, as evidenced by a substantial likelihood ratio chi-square value (χ^2 = 620.966, df = 36, p < 0.001), indicating that the final model significantly outperformed the null (intercept-only) model. The goodness-of-fit statistics revealed mixed but interpretable results: while the Pearson chi-square test suggested a significant misfit (p < 0.001), the deviance statistic was non-significant (p = 1.000), implying an acceptable model fit when overdispersion was not a major concern. Pseudo R-square measures further supported the model's robustness, with the Cox and Snell (0.732), Nagelkerke (0.791), and McFadden (0.507) values all exceeding commonly accepted thresholds, particularly McFadden's R^2, which surpassed 0.4; this is rare for discrete choice models and indicated excellent explanatory strength [59–61]. The model classification accuracy (72.7%) also substantiated the model's predictive reliability, especially for school bus and motorcycle users. These results validate the suitability of the MNL approach for analyzing school travel mode choice behavior under stable environmental conditions and offer a strong foundation for comparative analyses against adverse weather scenarios.

Table 4. Model fitting, Goodness-of-fit, Pseudo r-square, Classification in normal weather conditions information.

Model Fitting						
Model	**Model Fitting Criteria**			**Likelihood Ratio Tests**		
	AIC	**BIC**	**−2 Log Likelihood**	**Chi-Square**	**df**	**Sig.**
Intercept Only	1231.253	1243.724	1225.253			
Final	682.287	844.409	604.287	620.966	36	<0.001
Goodness-of-Fit						
	Chi-Square	df	Sig.			
Pearson	2397.524	1374	<0.001			
Deviance	604.287	1374	1.000			
Pseudo R-Square						
Cox and Snell	Nagelkerke	McFadden				
0.732	0.791	0.507				

Table 5 details the results of likelihood ratio tests assessing the significance of individual variables influencing travel mode choice under normal weather conditions. All examined variables demonstrated statistically significant effects ($p < 0.05$ or $p < 0.01$), affirming their importance in shaping mode selection. Among the socio-demographic factors, grade level ($\chi^2 = 15.102$, $p = 0.002$) and household monthly income ($\chi^2 = 16.056$, $p = 0.001$) are noteworthy, reflecting how academic progression and economic resources critically impact transport autonomy and modal flexibility. Family structure variables, including family member count ($\chi^2 = 25.367$, $p < 0.001$), further underscore the role of household logistics in school commuting. Vehicle ownership variables—both car ($\chi^2 = 14.531$, $p = 0.002$) and motorcycle ($\chi^2 = 32.040$, $p < 0.001$)—exerted particularly strong influences, highlighting mobility resource disparities. Spatial-temporal trip attributes, such as travel distance ($\chi^2 = 45.525$, $p < 0.001$), waiting time at pick-up points ($\chi^2 = 11.597$, $p = 0.009$), and overall travel cost ($\chi^2 = 13.007$, $p = 0.005$), significantly explained mode preference variance, confirming the multidimensional nature of school commuting behavior. These findings collectively validate the integrated socio-demographic, economic, and spatial framework applied in the modeling, offering policy-relevant insights for designing interventions that promote equitable and sustainable school transport systems. To ensure the robustness of the estimated parameters, multicollinearity diagnostics were conducted using the Variance Inflation Factor (VIF). All variables included in the model exhibited VIF values below 2.5, indicating no critical multicollinearity issues [62].

Table 5. Likelihood testing results for normal weather conditions.

Effect	**Likelihood Ratio Tests**		
	Chi-Square	**df**	**Sig.**
Intercept	97.294	3	<0.000 ***
Grade	15.102	3	0.002 **
Household monthly income	16.056	3	0.001 **
Family member	25.367	3	<0.000 ***
Household car ownership	14.531	3	0.002 **
Household motorcycle ownership	32.040	3	<0.000 ***
Number of people traveling to school	107.820	3	< 0.000 ***
Current residence	21.054	3	< 0.000 ***
Travel distance	45.525	3	< 0.000 ***

Table 5. *Cont.*

Effect	Likelihood Ratio Tests		
	Chi-Square	**df**	**Sig.**
Travel time to the nearest pick-up point	15.265	3	0.002 **
Waiting time at the pick-up point	11.597	3	0.009 **
Travel time	44.528	3	<0.000 ***
Travel cost	13.007	3	0.005 **

** p-value < 0.01, *** p-value < 0.001.

4.5.2. Adverse Weather Conditions

Table 6 presents the model fitting criteria, goodness-of-fit tests, and pseudo R-square values for the Multinomial Logit (MNL) model applied to school commuting mode choice under adverse weather conditions. The model fitting statistics indicated robust performance. The Final Model achieved a −2 Log Likelihood value of 766.138, significantly lower than the Intercept-Only model (1269.107), with a substantial chi-square difference of 502.968 ($p < 0.001$), confirming that the inclusion of explanatory variables meaningfully improved model fit over the null model. The goodness-of-fit assessment revealed a Pearson chi-square value of 1996.565 (df = 1374, $p < 0.001$), indicating a statistically significant departure from perfect fit. However, the Deviance statistic (766.138, df = 1374, $p = 1.000$) suggested an excellent fit between the model and the observed data, as a high p-value reflects no significant deviation. This pattern aligns with the expectation for MNL models, where Deviance is often prioritized over Pearson chi-square in assessing fit quality, particularly in cases with categorical data and large sample sizes.

Table 6. Model fitting, Goodness-of-Fit, Pseudo-R-square, in adverse weather conditions information.

Model Fitting						
Model	**Model Fitting Criteria**			**Likelihood Ratio Tests**		
	AIC	**BIC**	**−2 Log Likelihood**	**Chi-Square**	**df**	**Sig.**
Intercept Only	1275.107	1287.578	1269.107			
Final	844.138	1006.260	766.138	502.968	36	<0.001
Goodness-of-Fit						
	Chi-Square	df	Sig.			
Pearson	1996.565	1374	<0.001			
Deviance	766.138	1374	1.000			
Pseudo R-Square						
Cox and Snell	Nagelkerke	McFadden				
0.655	0.703	0.396				

Regarding pseudo R-square metrics, the Cox and Snell value was 0.655, the Nagelkerke value was 0.703, and McFadden's R-square was 0.396. These values suggest moderate to strong explanatory power, especially McFadden's R^2, which exceeded the 0.2–0.4 benchmark commonly accepted for discrete choice models [59–61]. Collectively, these results confirm that the model captured a substantial portion of the variance in mode choice behavior under adverse conditions. Furthermore, the relatively high Nagelkerke R^2 indicated strong predictability, reinforcing the model's suitability for informing policy interventions targeting resilient student mobility strategies during environmental disruptions.

Table 7 presents the likelihood ratio tests for variables affecting school commuting mode choice under adverse weather conditions. The results highlight that several socio-demographic and travel-related factors significantly influenced students' modal preferences when weather deteriorated. Household car ownership (χ^2 = 33.250, p < 0.001) and the number of people traveling to school (χ^2 = 91.939, p < 0.001) emerged as the most statistically powerful determinants, underscoring the critical role of private mobility resources and travel group composition in adapting to environmental constraints. Travel distance (χ^2 = 40.825, p < 0.001) and total travel time (χ^2 = 41.425, p < 0.001) also exhibited strong effects, indicating that longer journeys exacerbate vulnerability during adverse conditions, possibly encouraging shifts toward safer or more enclosed modes such as private vehicles or school buses. Interestingly, age (χ^2 = 14.362, p = 0.002) and parents' working status (χ^2 = 9.997, p = 0.019) became significant under adverse conditions, suggesting that older students and dual-income families are more adaptive in modifying their travel behavior. Variables related to spatial access, such as travel time to the nearest pick-up point and waiting time at pick-up points, also showed significance, reflecting operational disruptions and heightened travel uncertainty in inclement weather. Collectively, these findings reinforce that adverse weather amplifies existing transport inequities and infrastructural vulnerabilities.

Table 7. Likelihood ratio in adverse weather condition tests.

Effect	Likelihood Ratio Tests		
	Chi-Square	**df**	**Sig.**
Intercept	73.528	3	<0.000 ***
Age	14.362	3	0.002 **
Parents working status	9.997	3	0.019 *
Household monthly income	8.878	3	0.031 *
Family member	18.571	3	<0.000 ***
Household car ownership	33.250	3	<0.000 ***
Household motorcycle ownership	18.026	3	<0.000 ***
Number of people traveling to school	91.939	3	<0.000 ***
Current residence	33.936	3	<0.000 ***
Travel distance	40.825	3	<0.000 ***
Travel time to the nearest pick-up point	17.240	3	0.001 **
Waiting time at the pick-up point	13.720	3	0.003 **
Travel time	41.425	3	<0.000 ***

* p-value < 0.05, ** p-value < 0.01, *** p-value < 0.001.

Building upon the robust model fitting results and the significance of key determinants identified in the likelihood testing, the subsequent analysis delves deeper into the specific behavioral influences that drive school travel mode choices under varying environmental conditions. The multinomial logit regression models provide granular insights into how individual, household, and spatial factors interact to shape mobility preferences among high school students. By comparing estimated coefficients across normal and adverse weather scenarios, the study captures the dynamic nature of school commuting behavior, uncovering both stable predictors and context-sensitive adaptations. The next section presents a detailed interpretation of the multinomial regression outputs, highlighting how weather variability accentuates existing transport inequalities and shifts modal dependencies. These findings serve as a foundation for proposing targeted policy interventions aimed at enhancing the resilience, safety, and inclusivity of school transport systems, particularly in climatically vulnerable urban areas such as Chiang Rai.

4.6. Multinomial Logit Model

4.6.1. Normal Weather Condition

Table 8 presents the Multinomial Logit (MNL) coefficients for three alternatives—active transport, motorcycle, and school bus, relative to the reference category, i.e., private car. All standard errors were robust; Wald χ^2 indicated joint significance ($p < 0.001$). Pseudo-R^2 = 0.507 and an overall hit-rate of 72.7% confirm excellent explanatory power for a behavioral model. Notably, household car ownership exhibited a remarkably strong positive association across all modes, particularly for active transport (β = 3.09, Odds = 21.96) and school bus use (β = 2.84, Odds = 17.12). This suggested that households with car access possessed greater flexibility in facilitating modal options beyond private cars, possibly due to greater household mobility resources or differential parental decision-making for school commutes. Conversely, household motorcycle ownership was associated negatively with motorcycle use, an unexpected outcome that may reflect preference for private cars where motorcycle access existed but was deprioritized in favorable weather.

Travel distance was a consistent negative predictor for active transport (β = −1.94, Odds = 0.14) and motorcycles (β = −0.53, Odds = 0.59), aligning with existing literature stating that longer distances diminish the feasibility of non-motorized travel and increase dependence on mechanized transport. Additionally, family size positively influenced school bus selection, reflecting logistical efficiencies when multiple children traveled to the same institution. Importantly, current residence (urban/suburban) significantly influenced active transport (β = 2.20, Odds = 9.04) and school bus choice (β = 1.01, Odds = 2.75), suggesting spatial disparities in mode availability and infrastructural access. Meanwhile, travel time to pick-up points and waiting times also emerged as critical behavioral determinants, particularly impacting the decision between private and public modes. These results reinforce the multi-dimensional interplay between household attributes, spatial accessibility, and travel behavior under stable environmental conditions.

Table 8. Multinomial logit regression estimated models in normal weather conditions.

Mode	Variable	Normal Weather			
		Estimate	S.E.	t-Statistic	Odds
Active Transport	Constant	5.69	2.63	4.69 *	
	Grade	0.54	0.31	3.00	1.71
	Household monthly income	−0.62	0.20	9.99 **	0.54
	Family member	0.70	0.33	4.40 *	2.01
	Household car ownership	3.09	1.21	6.53 *	21.96
	Household motorcycle ownership	−1.69	1.30	1.69	0.19
	Number of people traveling to school	−2.97	0.58	26.08 ***	0.05
	Current residence	2.20	0.64	11.89 **	9.04
	Travel distance	−1.94	0.34	32.03 ***	0.14
	Travel time to the nearest pick-up point	0.29	0.26	1.28	1.34
	Waiting time at the pick-up point	−0.61	0.25	6.05 *	0.54
	Travel time	−0.17	0.43	0.15	0.85
	Travel cost	−0.79	0.27	8.32 **	0.46
Motorcycle	Constant	9.52	2.31	16.96 ***	
	Grade	0.83	0.23	13.09 ***	2.28
	Household monthly income	−0.50	0.14	12.51 ***	0.61
	Family member	−0.21	0.25	0.68	0.81
	Household car ownership	3.04	1.15	6.93 **	20.79
	Household motorcycle ownership	−4.79	1.32	13.18 ***	0.01
	Number of people traveling to school	−2.75	0.43	41.88 ***	0.06
	Current residence	0.24	0.48	0.25	1.27
	Travel distance	−0.53	0.21	6.13 *	0.59
	Travel time to the nearest pick-up point	0.13	0.15	0.74	1.14
	Waiting time at the pick-up point	−0.25	0.16	2.24	0.78
	Travel time	0.01	0.25	0.00	1.01
	Travel cost	−0.44	0.17	6.51 *	0.64

Table 8. *Cont.*

Mode	Variable	Normal Weather			
		Estimate	S.E.	t-Statistic	Odds
School Bus	Constant	−9.54	2.30	17.19 ***	
	Grade	0.22	0.22	0.96	1.24
	Household monthly income	−0.34	0.14	5.62 *	0.71
	Family member	0.70	0.25	7.66 **	2.01
	Household car ownership	2.84	1.12	6.38 *	17.12
	Household motorcycle ownership	0.22	0.69	0.10	1.24
	Number of people traveling to school	1.10	0.53	4.33 *	3.01
	Current residence	1.01	0.45	5.11 *	2.75
	Travel distance	−0.31	0.22	1.95	0.73
	Travel time to the nearest pick-up point	−0.38	0.14	7.21 **	0.69
	Waiting time at the pick-up point	0.15	0.15	0.92	1.16
	Travel time	1.24	0.23	29.30 ***	3.46
	Travel cost	0.05	0.17	0.07	1.05

The private is the reference category, * p-value < 0.05, ** p-value < 0.01, *** p-value < 0.001.

4.6.2. Adverse Weather Conditions

Table 9 presents the Multinomial Logit (MNL) regression results analyzing factors influencing school commuting mode choice during adverse weather conditions, using private vehicle use as the baseline category. The model elucidates how socio-demographic attributes, household mobility resources, and spatial-temporal variables differentially affect students' travel decisions under environmental stress, offering critical insights into climate-sensitive mobility patterns. Household car ownership emerged as the most powerful predictor across all alternative modes active transport, motorcycle, and school bus with exceptionally high odds ratios (Odds > 22). This result confirms that private vehicle access substantially enhances modal flexibility, serving as a vital buffer against environmental disruptions. In particular, students from car-owning households were significantly more capable of substituting to safer or more resilient modes, aligning with established literature that underscores car ownership as a key enabler of adaptive travel behavior under adverse conditions.

Table 9. Multinomial logit regression estimated models in adverse weather conditions.

Mode	Variable	Adverse Weather			
		Estimate	S.E.	t-Statistic	Odds
Active Transport	Constant	−1.72	2.15	0.64	
	Age	0.33	0.21	2.50	1.39
	Parents working status	−0.68	0.70	0.94	0.51
	Household monthly income	−0.21	0.16	1.81	0.81
	Family member	0.50	0.27	3.50	1.64
	Household car ownership	3.81	1.12	11.48 **	45.07
	Household motorcycle ownership	−0.38	0.95	0.16	0.68
	Number of people traveling to school	−1.41	0.43	10.84 **	0.24
	Current residence	1.96	0.51	14.98 ***	7.13
	Travel distance	−1.29	0.23	30.03 ***	0.28
	Travel time to the nearest pick-up point	0.33	0.21	2.57	1.39
	Waiting time at the pick-up point	−0.60	0.21	7.80 **	0.55
	Travel time	−0.13	0.25	0.26	0.88

Table 9. *Cont.*

Mode	Variable	Adverse Weather			
		Estimate	S.E.	t-Statistic	Odds
Motorcycle	Constant	2.52	2.05	1.52	
	Age	0.59	0.16	13.58 ***	1.81
	Parents working status	−0.32	0.49	0.43	0.73
	Household monthly income	−0.33	0.12	7.02 **	0.72
	Family member	−0.32	0.22	2.09	0.73
	Household car ownership	3.85	1.09	12.60 ***	47.15
	Household motorcycle ownership	−3.66	1.27	8.34 **	0.03
	Number of people traveling to school	−1.49	0.32	21.14 ***	0.23
	Current residence	0.77	0.40	3.76	2.16
	Travel distance	−0.22	0.16	1.95	0.81
	Travel time to the nearest pick-up point	0.16	0.13	1.48	1.17
	Waiting time at the pick-up point	−0.08	0.14	0.37	0.92
	Travel time	−0.39	0.18	4.80 *	0.68
School Bus	Constant	−12.05	2.01	35.91 ***	
	Age	0.23	0.16	2.04	1.25
	Parents working status	1.04	0.49	4.53 *	2.84
	Household monthly income	−0.24	0.12	3.94 *	0.78
	Family member	0.45	0.21	4.40 *	1.56
	Household car ownership	3.13	1.08	8.38 **	22.96
	Household motorcycle ownership	−0.33	0.66	0.26	0.72
	Number of people traveling to school	1.83	0.39	21.93 ***	6.25
	Current residence	1.81	0.37	23.98 ***	6.13
	Travel distance	−0.27	0.17	2.71	0.76
	Travel time to the nearest pick-up point	−0.35	0.13	7.74 **	0.70
	Waiting time at the pick-up point	0.19	0.13	2.05	1.21
	Travel time	0.76	0.18	18.65 ***	2.13

The private is the reference category, * p-value < 0.05, ** p-value < 0.01, *** p-value < 0.001.

Conversely, household motorcycle ownership exerted a strong negative influence on motorcycle mode choice ($\beta = -3.66$, Odds = 0.03), substantially deterring two-wheeled vehicle use during inclement weather. This finding reflects heightened risk perception among students and guardians regarding motorcycle safety in hazardous environmental contexts, reinforcing safety concerns commonly associated with motorcycle commuting, especially in rain or haze conditions prevalent in Chiang Rai. Spatial factors also displayed critical behavioral effects. Travel distance significantly decreased the likelihood of choosing active transport ($\beta = -1.29$, Odds = 0.28) and motorcycle usage ($\beta = -0.22$, Odds = 0.81), indicating that greater distances exacerbate the limitations of exposed or informal travel modes during adverse weather. Moreover, travel time to the nearest pick-up point and waiting time at the pick-up point negatively affected active transport choices, illustrating increased discomfort and reliability concerns as decisive factors discouraging exposure to inclement conditions. Socio-demographic variables further revealed context-sensitive behavioral adaptations. Age was positively associated with motorcycle use ($\beta = 0.59$, Odds = 1.81), suggesting that older students possess greater autonomy and willingness to maintain independent travel despite weather adversities. Meanwhile, parents' working status became significant for school bus choice ($\beta = 1.04$, Odds = 2.84), indicating that students from dual-income households may prefer structured, supervised transport services when parental logistical support is constrained during work hours.

Current residence, whether urban or suburban, significantly influences mode selection. Urban students exhibited a substantially higher likelihood of choosing active transport ($\beta = 1.96$, Odds = 7.13) and school bus ($\beta = 1.81$, Odds = 6.13) relative to their suburban counterparts, highlighting spatial inequities in infrastructure access and service availability. This result emphasizes the critical role of urban form and density in supporting climate-resilient student mobility. Moreover, temporal dynamics are crucial. Longer travel times to school during adverse weather further discouraged motorcycle use ($\beta = -0.39$, Odds = 0.68) but increased reliance on structured transport modes like the school bus ($\beta = 0.76$, Odds = 2.13). These findings suggest that adverse conditions systematically exacerbate time inefficiencies in less resilient transport options, motivating a shift toward organized services despite potential cost or scheduling inconveniences.

Table 10 presents a comparison of significant factors influencing school travel behavior under normal and adverse weather conditions, revealing notable differences. Under normal weather conditions, factors such as gender, monthly household income, family size, private vehicle ownership (both car and motorcycle), the number of people traveling to school, current residence, total distance to school, travel time to the nearest pick-up point, waiting time for the bus, total travel time, and total travel expenses significantly affected travel behavior. In contrast, under adverse weather conditions, age and father's working status emerged as significant factors, alongside household income, family size, vehicle ownership, number of people traveling to school, current residence, total distance to school, travel time to the pick-up point, waiting time for the bus, and total travel time. This indicated that while several factors consistently influenced travel behavior across weather conditions, adverse weather introduced additional socio-demographic determinants such as age and parental employment status, reflecting the adaptability of travel behavior to changing environmental conditions.

Table 10. Significant mode choice influencing factors in the model.

Variable	Normal Weather	Adverse Weather
Age		○
Grade	○	
Parents working status		○
Household monthly income	○	○
Family member	○	○
Household car ownership	○	○
Household motorcycle ownership	○	○
Number of people traveling to school	○	○
Current residence	○	○
Travel distance	○	○
Travel time to the nearest pick-up point	○	○
Waiting time at the pick-up point	○	○
Travel time	○	○
Travel cost	○	

○ is included in the model.

4.7. Model Classification and Accuracy

The classification in normal and adverse weather conditions in Table 11 demonstrates varying levels of prediction accuracy across different travel modes. Under normal weather conditions, the model showed the highest classification accuracy for school bus users (83.0%), followed by motorcycle users (77.6%) and active transport users (64.6%), with the lowest accuracy observed for private vehicle users (45.9%). In adverse weather conditions, school bus users continued to exhibit the highest classification accuracy (79.2%), while active transport and motorcycle users showed moderate accuracy levels (64.2% and 67.5%, respectively), and private vehicle users displayed improved accuracy (58.3%) compared to normal weather. The overall classification accuracy decreased slightly from 72.7% in normal weather to 68.6% in adverse weather, indicating that weather conditions may have influenced the model's predictive performance, particularly for private vehicle usage. This suggests that adverse weather introduces additional variability in travel behavior, affecting the consistency of mode choice predictions.

Table 11. Classification of observed and predicted values in normal weather and adverse weather conditions.

Observed	Predicted				
	Active Transport	Motorcycle	School Bus	Private	Percent Correct
Normal Weather Conditions					
Active Transport	42	21	1	1	64.60%
Motorcycle	14	135	12	13	77.60%
School Bus	1	11	132	15	83.00%
Private	0	17	23	34	45.90%
Overall Percentage	12.10%	39.00%	35.60%	13.30%	72.70%
Adverse weather conditions					
Active Transport	43	18	1	5	64.20%
Motorcycle	8	85	11	22	67.50%
School Bus	4	12	126	17	79.20%
Private	3	21	26	70	58.30%
Overall Percentage	12.30%	28.80%	34.70%	24.20%	68.60%

5. Discussion

This study provides critical insights into the dynamics of school commuting mode choices among senior high school students in Chiang Rai, Thailand, under both normal and adverse weather conditions. By employing a Multinomial Logit (MNL) modeling approach, the research reveals how socio-demographic characteristics, household mobility resources, spatial factors, and travel-related attributes collectively influence mode selection, and how these relationships shift when environmental conditions deteriorate.

Under normal weather conditions, the findings highlight the predominant reliance on motorcycles and the significant role of household vehicle ownership in facilitating diverse mobility choices. Car ownership, in particular, was found to substantially enhance flexibility in selecting non-private vehicle modes such as active transport and school bus usage. This outcome aligns with prior research indicating that households with greater mobility resources can better tailor mode choice decisions to optimize convenience, safety, and cost-efficiency. Furthermore, shorter travel distances, urban residence, and lower travel costs significantly encourage the adoption of active and shared transport modes. These results reinforce the established understanding that proximity to school and favorable built environment characteristics are key enablers of sustainable commuting behaviors.

Conversely, during adverse weather conditions, the analysis illustrated a distinct behavioral adaptation among students and their households. Private vehicle usage notably increased, reflecting a risk-averse response to environmental stressors. Motorcycle usage declined sharply, corroborating concerns about the safety vulnerabilities of two-wheeled travel under inclement conditions. The role of household car ownership became even more pronounced, underscoring how access to resilient mobility options acts as a crucial buffer against external disruptions. These findings are consistent with studies that emphasize the magnified role of private vehicles in contexts of climatic uncertainty and inadequate public transport resilience.

Spatial factors, particularly travel distance and travel time to pick-up points, exerted stronger effects under adverse conditions. The MNL results indicate that under adverse weather, a one-minute decrease in travel time to the nearest pick-up point increased the odds of choosing the school bus by approximately 1.43 times ($\beta = -0.35$, $p < 0.01$). Furthermore, students from households with car ownership were 22.96 times more likely to opt for the school bus during adverse weather, underscoring how mobility resources influence adaptive modal shifts. These findings suggest that improving first-mile connectivity such as safe walkways or feeder services could facilitate a measurable shift from motorcycle use to safer, enclosed travel modes during inclement conditions. While school buses maintained consistent usage (~33.7%) across weather scenarios, indicating relative stability, their share remained moderate. Thus, while buses offers a more resilient alternative than motorcycles during adverse weather, their capacity constraints and limited coverage must be addressed before promoting them as a universally viable solution.

Socio-demographic attributes also exhibited context-dependent influences. Age emerged as a significant predictor under adverse weather, with older students demonstrating greater independence in motorcycle use despite environmental risks. Meanwhile, parents' working status influenced school bus reliance, suggesting that dual-income households are more likely to prefer structured, reliable transport options when parental support for school commuting is constrained. This socio-economic mediation of mode choice underlines the broader theme of transport disadvantage during adverse conditions, a concern increasingly recognized in transport equity research.

This study contributes to the transport literature by emphasizing that school commuting behaviors are not static but highly responsive to environmental variability. Moreover, it demonstrates that environmental disruptions disproportionately impact students lacking access to resilient mobility resources, amplifying underlying socio-economic and spatial inequalities. The findings advocate for urgent policy interventions aimed at enhancing transport system resilience, particularly by improving first- and last-mile connectivity, expanding access to reliable school transport services, and ensuring safe infrastructure for vulnerable road users. These insights are particularly relevant for secondary cities like Chiang Rai, where rapid urbanization and limited public transport systems expose systemic vulnerabilities that may be exacerbated by climate change and environmental instability.

6. Conclusions

This study examined the factors influencing school commuting mode choice among senior high school students in Chiang Rai, Thailand, under both normal and adverse weather conditions. Utilizing a Multinomial Logit (MNL) modeling approach, the research elucidates how socio-demographic attributes, household vehicle ownership, spatial factors, and travel-related characteristics collectively shape students' transport decisions, and how these determinants dynamically adjust in response to environmental variability. The results demonstrate that car ownership significantly enhances modal flexibility, serving as a key enabler of adaptive commuting behavior during adverse weather. In contrast, motorcycle reliance declines sharply under inclement conditions, reflecting heightened risk sensitivity. Spatial factors such as travel distance and access time to pick-up points were also found to critically influence mode shifts, particularly amplifying transport inequities between urban and suburban students. Socio-economic variables, including parental working status and household income, emerged as important contextual factors mediating travel choices, especially during environmental disruptions. These findings advance the current understanding of climate-sensitive travel behavior in secondary cities, a domain traditionally underrepresented in transport research dominated by metropolitan case studies. By highlighting the interplay between mobility resource availability, spatial accessibility, and socio-environmental vulnerability, this study offers critical insights into the structural barriers to resilient and equitable school transport systems in rapidly urbanizing regions.

The policy implications are clear: enhancing school transport resilience requires investments in inclusive and accessible mobility infrastructure, particularly first-mile connectivity improvements, the expansion of reliable school bus services, and safer environments for active transport. Such interventions are essential not only for improving the safety and efficiency of school travel but also for promoting broader goals of social equity, urban resilience, and sustainable development. In conclusion, this research underscores the necessity for transport policies that are sensitive to environmental variability and socio-spatial disparities, particularly in Chiang Rai and other similarly vulnerable secondary cities. Future research should extend these findings by incorporating longitudinal data to capture behavioral adaptations over time and by exploring integrated modeling approaches that account for multimodal trip chains and heterogeneous user preferences under varying climatic scenarios. By doing so, transport planning can be better informed to foster inclusive, resilient, and sustainable mobility systems for all urban residents.

7. Limitations and Future Work

This study has several limitations. First, the use of cross-sectional, self-reported survey data may have introduced recall bias, suggesting that future research should consider longitudinal or real-time tracking methods. Second, the focus on senior high school students from extra-large urban schools limited generalizability; broader samples covering younger students and suburban or rural areas are recommended. Third, adverse weather was treated as a single category without distinguishing between specific environmental stressors, which future research could disaggregate. Lastly, supply-side factors such as service quality or parental interventions were not examined and merit deeper investigation. Expanding methodological approaches and interdisciplinary collaborations will be essential to enrich understanding and develop more resilient and inclusive school transport systems. Additionally, adverse weather was measured based on respondent-reported behavioral recall rather than linked to real-time meteorological data, which may have introduced perception-based variability. Additionally, this study used a standard MNL model, which assumed IIA; although widely used, this model may not have captured unobserved heterogeneity. Future studies should consider integrating meteorological monitoring to more precisely align travel behavior with specific weather episodes and adopt Mixed Logit or Nested Logit approaches for improved behavioral fidelity respectively.

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