IMPACT OF THE COVID-19 PANDEMIC ON TRAVEL MODE CHOICES AND FATAL CRASH RATES

FINAL PROJECT REPORT

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16. Abstract

The COVID-19 pandemic caused unprecedented disruptions to human mobility and transportation systems worldwide, significantly altering travel behavior and mode choices. This study investigates these changes within the Pacific Northwest region of the United States, encompassing a mix of urban and rural contexts with diverse socio- demographic characteristics. Using survey data from 807 respondents, we analyze transportation patterns before and during the pandemic, focusing on shifts in mode shares and probabilities of switching travel modes. The analysis incorporates McNemar's test, logistic regression, and latent class analysis (LCA) to evaluate the extent of these shifts and identify key influencing factors. The results reveal a substantial reduction in public transport usage, reflecting heightened concerns over health risks and limited operational capacity during the pandemic. In contrast, there was a notable increase in the use of private vehicles and active transportation modes, such as walking and cycling.

Demographic variables, including age, income, employment status, and gender, played significant roles in shaping travel behavior, with younger and lower-income individuals exhibiting higher probabilities of mode change. The latent class analysis highlighted distinct behavioral clusters, indicating that travel behavior responses were not uniform across populations. A logistic regression model further underscored the importance of pre-pandemic travel habits, socio-economic conditions, and pandemic-related concerns in influencing mode choice decisions.

Additionally, traffic safety outcomes showed notable variations, with overall crash rates decreasing during the lockdowns but fatality rates rising due to riskier driving behaviors, such as speeding on roads. Crash patterns varied across urban and rural areas, with urban crashes experiencing a slight decline in proportion, while rural crashes increased.

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SI* (MODERN METRIC) CONVERSION FACTORS

APPROXIMATE CONVERSIONS TO SI UNITS				
Symbol	**When You Know**	**Multiply By**	**To Find**	**Symbol**
		LENGTH		
in	inches	25.4	millimeters	mm
ft	feet	0.305	meters	m
yd	yards	0.914	meters	m
mi	miles	1.61	kilometers	km
		AREA		
in^2	square inches	645.2	square millimeters	mm^2
ft^2	square feet	0.093	square meters	m^2
yd^2	square yard	0.836	square meters	m^2
ac	acres	0.405	hectares	ha
mi^2	square miles	2.59	square kilometers	km^2
		VOLUME		
fl oz	fluid ounces	29.57	milliliters	mL
gal	gallons	3.785	liters	L
ft^3	cubic feet	0.028	cubic meters	m^3
yd^3	cubic yards	0.765	cubic meters	m^3
		NOTE: volumes greater than 1000 L shall be shown in m^3		
		MASS		
oz	ounces	28.35	grams	g
lb	pounds	0.454	kilograms	kg
T	short tons (2000 lb)	0.907	megagrams (or "metric ton")	Mg (or "t")
		TEMPERATURE (exact degrees)		
^oF	Fahrenheit	5 (F-32)/9 or (F-32)/1.8	Celsius	^oC
		ILLUMINATION		
fc	foot-candles	10.76	lux	lx
fl	foot-Lamberts	3.426	candela/m^2	cd/m^2
		FORCE and PRESSURE or STRESS		
lbf	poundforce	4.45	newtons	N
lbf/in^2	poundforce per square inch	6.89	kilopascals	kPa
APPROXIMATE CONVERSIONS FROM SI UNITS				
Symbol	**When You Know**	**Multiply By**	**To Find**	**Symbol**
		LENGTH		
mm	millimeters	0.039	inches	in
m	meters	3.28	feet	ft
m	meters	1.09	yards	yd
km	kilometers	0.621	miles	mi
		AREA		
mm^2	square millimeters	0.0016	square inches	in^2
m^2	square meters	10.764	square feet	ft^2
m^2	square meters	1.195	square yards	yd^2
ha	hectares	2.47	acres	ac
km^2	square kilometers	0.386	square miles	mi^2
		VOLUME		
mL	milliliters	0.034	fluid ounces	fl oz
L	liters	0.264	gallons	gal
m^3	cubic meters	35.314	cubic feet	ft^3
m^3	cubic meters	1.307	cubic yards	yd^3
		MASS		
g	grams	0.035	ounces	oz
kg	kilograms	2.202	pounds	lb
Mg (or "t")	megagrams (or "metric ton")	1.103	short tons (2000 lb)	T
		TEMPERATURE (exact degrees)		
^oC	Celsius	1.8C+32	Fahrenheit	^oF
		ILLUMINATION		
lx	lux	0.0929	foot-candles	fc
cd/m^2	candela/m^2	0.2919	foot-Lamberts	fl
		FORCE and PRESSURE or STRESS		
N	newtons	0.225	poundforce	lbf
kPa	kilopascals	0.145	poundforce per square inch	lbf/in^2

*SI is the symbol for the International System of Units. Appropriate rounding should be made to comply with Section 4 of ASTM E380.
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EXECUTIVE SUMMARY

The COVID-19 pandemic caused significant disruptions to transportation systems and drastically changed the way people traveled around the world. This study focuses on the Pacific Northwest region of the United States, including both urban and rural areas with a wide variety of populations and transportation demands. By analyzing survey responses from 807 individuals, the research explores travel modes before and during the pandemic, examining how people's choices in transportation changed and what influenced these shifts.

The findings reveal a decrease in public transportation use, as people were concerned about the risks of infection and faced limited public transportation services. Meanwhile, more people turned to private vehicles or active transportation modes such as biking and walking. Demographic factors like age, annual income, employment status, and gender played key roles in these changes. For instance, younger and lower-income individuals were more likely to change their travel mode in comparison to older or higher-income groups.

To better understand these changes, the study used advanced methods like McNemar's test, logistic regression, and latent class analysis (LCA). The LCA showed that not everyone responded to the pandemic in the same way. Different groups of people had different transportation-related behaviors based on their own circumstances.

These results show the need for flexible and adaptive transportation policies. Improving public transportation safety, expanding cycling and walking infrastructure, and addressing the needs of vulnerable groups are essential steps for building a transportation system that works for everyone. The study also emphasizes the importance of designing systems that can handle crises such as public health emergencies while ensuring they remain fair and sustainable.

Beyond mobility shifts, traffic safety trends exhibited complex patterns. While overall crash rates declined in 2020 due to reduced travel demand, fatal crashes saw an increase, particularly in 2021 and 2023. This increase aligns with reports of riskier driving behaviors, such as excessive speeding on less congested roads. Data from crash statistics also indicate fluctuations in injury severity, with suspected serious and minor injuries remaining stable, but an increase in high-risk crash factors such as aggressive and distracted driving after lockdowns. Moreover, crash distributions between urban and rural areas shifted, with rural crashes representing a larger proportion during the pandemic, likely due to changes in travel demand and enforcement patterns.

This research provides valuable insights for policymakers and transportation planners, helping them understand how travel behaviors shifted during the pandemic and how these changes might continue affecting patterns in the future. It offers practical recommendations for creating transportation networks that can adapt to challenges, meet the needs of diverse communities, and support long-term sustainability and resilience.

CHAPTER 1. INTRODUCTION

1.1. Overview

In March 2020, the outbreak of the coronavirus 2019 (COVID-19) was declared a pandemic. This was followed by a response that has had significant impact on all aspects of life including economic and social activities. The work-at-home, business closure, and travel restrictions significantly disrupted the nation's transportation reducing travel to significantly lower levels especially during the second quarter of 2020. While the reduced vehicle travel miles (VMT) during most of 2020 would have reduced the risk of collisions, recent statistics in the US show a considerable increase in fatal crashes in the nine months that followed the travel restriction in 2020 (April 2020-December 2020) compared to the same period in previous years. The U.S. Department of Transportation's National Highway Traffic Safety Administration NHTSA's early estimates show that 38,680 people died in motor vehicle traffic crashes in 2020. This is the largest number of fatalities since 2007. Preliminary data from the Federal Highway Administration (FHWA) shows that while VMT in 2020 decreased by approximately 13.2-percent compared to 2019, the fatality rate for 2020 was 23.4-percent higher than that for 2019 (1.37 fatalities per 100 million VMT in 2020 up from 1.11 fatalities per 100 million VMT in 2019). NHTSA's analysis shows that the main behaviors that drove this increase include impaired driving, speeding, and failure to wear a seat belt (NHTSA 2021).

In May 2020, the National Police Foundation published a fact sheet based on their examination of traffic crashes and fatalities from an initial sample of five states: Florida, Iowa, Ohio, Massachusetts, and Missouri. The fact sheet states: "While the number of traffic and fatal crashes decreased across the states, fatality rates increased across each state during April and in parts of March compared to 2019 data. These data may suggest a probable increase in behaviors that should cause concern among policymakers, including what appears to be an increase in excessive speed and reckless driving among motorists." It also adds that "early anecdotal information suggested that reduced traffic congestion on the roads was due to stay-at-home orders as well as businesses that are either closed or running on reduced operations. Consequently, increased maneuverability and absence of drivers on the roads may be incentivizing higher speeds and reduced control while driving. This assessment suggests that it is important for drivers to remain even more vigilant and practice greater safety while driving in order to reduce the potentially devastating outcomes from this emerging trend." (National Police Foundation, 2020).

Several studies have attempted to identify factors that may have contributed to such a sharp increase in fatal crash rates during the pandemic. Vingilis et al (2020) identified several factors that might have contributed to the reported increase in fatal crash rate including increased risky behaviors as a result of less congested roadways and reduced law enforcement presence. Increased alcohol sales and use have been reported among the characteristics of the pandemic. Liu et al., (2020) attributed the increased use of alcohol to the reported increase in stress, anxiety, and depression among several population groups. Carter (2020) reported that the proportion of speeding-related crashes and fatalities had increased during the pandemic lockdown in North Carolina. Lockwood et al., (2020) reported similar results in Virginia.

1.2. Study Objectives

This project builds on the outcome of previous CSET research that has been conducted focusing on documenting the characteristics of fatal crash rates for RITI communities in Idaho (Abdel-Rahim, 2022). The project goals were to examine the impact of the COVID-19 pandemic on fatal crash rates for RITI communities in Idaho and identify factors that might have contributed to such impact in fatal crash rates. The project had the following three objectives: 1) to assess how the COVID-19 pandemic has impacted travel behavior for different RITI communities in the Pacific Northwest, 2) to determine how the pandemic impacted fatal crash rates for roads that serve RITI communities in Idaho, and 3) to identify measures that RITI communities could take to offset the impact of the COVID pandemic on roadway safety.

1.3. Report Organization

A literature review focused on the pandemic and its impact to choosing mode of travel and traffic safety is provided in Chapter 2. In Chapter 3, a brief discussion of the data collection process and analysis methods are described. The results and analysis from these methods are shared in Chapter 4. Lastly, in Chapter 5, the study conclusions and a discussion of future work in this area are provided.

CHAPTER 2. LITERATURE REVIEW

The COVID-19 pandemic significantly disrupted mobility around the world, leading to deep and widespread changes in travel behavior and choice of travel mode. Public health measures such as social distancing, travel restrictions, and lockdowns not only required immediate limitations and constraints on movement but also forced individuals to rearrange their transportation preferences. Safety and hygiene concerns became crucial priorities, overshadowing traditional concerns such as convenience and cost. These shifts resulted in a significant decline in using public transportation, which was often anticipated as a high-risk option, and an increased reliance on private cars and active modes such as cycling and walking. This behavioral shift highlights the role of psychological factors, especially the fear of infection, in shaping transportation mode choices during the pandemic (Chan et al., 2020, Dong et al., 2021, Abdullah et al., 2020).

Surveys conducted across different global regions provide detailed findings into these shifts in mobility modes. In Pakistan, for example, individuals shifted from motorbikes to active modes for shorter distances, while avoiding public transportation for longer trips. This change highlights the effect of safety concerns and perceived risk on travel mode choices (Abdullah et al., 2021). Similarly, a study in Poland showed significant reductions in travel times across all demographic groups, because of changes in the purpose of travel, household size, and fear of the COVID-19 pandemic. These results show how dependent factors, including family responsibilities and employment status, collaborate with psychological concerns to influence travel (Borkowski et al., 2021). Moreover, a study in the Netherlands showed that the pandemic increased long-term trends such as working from home and active travel, with a substantial percentage of remote workers planning to continue working from home post-pandemic. In addition to that, many individuals reported an increased plan to walk or use bikes more frequently, indicating a broader shift toward active travel modes (De Haas et al., 2020).

In the United States, data from the American Time Use Survey exposed that participation in outdoor travel and activities decreased significantly during COVID-19 and had not fully returned to levels before the pandemic by 2022. However, there was a remarkable increase in time spent on active travel modes, such as cycling and walking, as well as an increase in online purchasing (Shi and Goulias, 2024). In the same way, panel data from the Czech Republic showed an increase in remote work and online shopping, accompanied by a reduction in traditional trips to workplaces and retail locations. Interestingly, while the frequency and purpose of the trips changed, the average share of modals for shopping and commuting remained relatively stable, showing that the influence of the pandemic was more obvious in the characteristics of the trips than in the preferences of the modes (Folt`ynov´a and Bruuha, 2024).

Public transportation systems were directly impacted by the pandemic, undergoing a significant decrease in passenger numbers due to safety concerns and risk perception (Barbieri, et al., 2020 and Barbieri, et al., 2021). In Gda´nsk, Poland, 90% of respondents reduced their use of public transport, with only 75% planning to return post-pandemic (Przybylowski et al., 2021). In Tehran, ride-sharing services demonstrated notable resilience, complementing public transportation and taxis but showing no significant correlation with the use of private cars. This trend highlighted the importance of targeted decision-makers to rebuild confidence in public transportation systems, such as improving safety measures, ensuring cleanliness, and effectively applying these efforts to the public (Karimi et al., 2024).

Regional differences and trip lengths influenced travel behavior during COVID-19. In the UAE, short-distance travel returned to pre-pandemic levels, medium-distance travel decreased, and long-distance travel increased compared to pre-pandemic levels (Hamad et al., 2024). In Australia, private car usage resumed for shopping and recreational purposes as restrictions eased, but public transport continued to struggle due to persistent safety concerns (Beck and Hensher, 2020). These regional differences highlight the need for policy-making that addresses the unique challenges and preferences of different travelers.

Demographic and socioeconomic factors also played a vital role in shaping mobility changes during the pandemic. Gender, employment status, income, and car ownership appeared as significant predictors of mode choice. For instance, low-income people relied heavily on public transport, while university students and private-sector employees preferred ridesharing (Karimi et al., 2024). In a school transportation study, parents' education level, household income, and child age affected behavioral changes during the pandemic (Chang et. al.,2024). Women exhibited a higher usage of ride-sharing services, particularly in the post-pandemic period. These results highlight the impacts of the pandemic on diverse demographic groups and the importance of designing equitable and inclusive transportation policies.

The pandemic also profoundly reshaped travel purposes and daily routines. In urban areas like Istanbul and Thessaloniki in Greece, non-commuting trips increased as walking became a dominant mode of travel (Shakibaei et al., 2021, Politis et al., 2021). These shifts reflect a re-evaluation of travel priorities during the pandemic and emphasize the importance of adaptive transportation systems capable of meeting evolving needs.

Regarding the effect of the pandemic on traffic congestion, the COVID-19 pandemic led to unprecedented reductions in traffic congestion across the globe, primarily because of strict travel restrictions and lockdown measures (Li et al., 2021; Xu et al., 2022). These changes had significant impacts on traffic speed, flow, and density, all of which are interconnected elements that influence road safety (Choi & Ewing, 2021). As vehicle mobility declined, so did congestion, which in turn contributed to a reduction in road traffic collisions (RTCs). However, the reduction in congestion also created new challenges, particularly in relation to increased speeding, as empty road lanes encouraged drivers to accelerate (Zhao et al., 2024).

Studies indicate that worldwide vehicle mobility decreased by more than 50% during the pandemic of COVID-19, with Asian countries experiencing reductions ranging from 50% to 60% (Yasin et al., 2021), and European countries seeing even more substantial declines of 55% to 80% (Bucsky, 2020; Droj et al., 2023; Hadjidemetriou et al., 2020; Saladié et al., 2020a; Simunek et al., 2021). These reductions were not limited to private car usage but also affected public transportation, which saw a global decline of 60% to 80% during the peak of the pandemic, particularly in the months of March through May 2020 (Gragera Lladó et al., 2021; Lapatinas, 2020). In regions like Latin America and the Caribbean, public transport usage plummeted by up to 90%, while car trips in Europe decreased by 65% to 80%, further contributing to a global reduction in traffic congestion (Medimorec et al., 2020).

The variation in traffic reduction was influenced by several factors, including the type and function of roads, urban versus rural settings, local jurisdictional policies, and the types of vehicles on the road. The decline in traffic congestion, while improving road safety by reducing collisions, also led to negative economic consequences. With fewer people using public transportation due to fears of virus transmission, the reliance on private cars increased, exacerbating congestion once restrictions were eased. For example, in India, over 90% of public transport users reported feeling unsafe due to the potential risk of infection, compared to just 13% of private car users (Pawar et al., 2020). As countries began to lift restrictions, traffic congestion began to rise again, particularly in urban areas.

While the pandemic's effects on traffic congestion have been widespread, the relationship between vehicle travel distance and RTCs remains a critical factor. Reduced congestion did not eliminate the risks associated with road travel, as speed and driver behavior became more critical in determining traffic safety outcomes.

Concerning the driving performance and the effect of COVID-19 on it, the COVID-19 pandemic has led to significant changes in driving behavior, with several studies highlighting a shift toward more dangerous driving habits because of reduced traffic volume and the unique circumstances created by lockdowns. Understanding these changes in driving performance is crucial for addressing road safety during and after the pandemic (Katrakazas et al., 2021).

One of the most notable trends observed during the lockdowns was an increase in risky driving behaviors, particularly speeding, harsh acceleration, and harsh braking. Research conducted in Greece and Saudi Arabia found that the reduction in traffic volume led to an increase in these dangerous driving habits, as fewer vehicles on the road allowed for higher speeds and more aggressive driving. This phenomenon was accompanied by a rise in the use of mobile cellphones while driving, further increasing the risk of distractions and RTCs (Gupta et al., 2021; Sekadakis et al., 2021; Tucker & Marsh, 2021).

Teenager drivers exhibited significant changes in their driving behavior during the pandemic. A study on teenager driving in the US showed that driving time and distance decreased by around 35% during the lockdown (Stavrinos et al., 2020). However, this reduction was less pronounced in older people, those with jobs, and ethnic minorities. In contrast, adolescents with more social tendencies showed greater decreases in their driving activity. Despite the overall reduction in driving, studies from the US indicated that distracted driving persisted, although the frequency of distraction-related RTCs decreased by 43% in Louisiana. Notably, there was a slight increase in the number of injuries among drivers using mobile phones during this period, suggesting that while the overall traffic volume decreased, distracted driving remained a significant concern (Barnes et al., 2020).

With respect to the effect of COVID-19 on RTCs, RTCs are influenced by various factors, including traffic volume, human behavior, vehicle design, road infrastructure, and environmental conditions (Choudhary et al., 2024). During the COVID-19 pandemic, several of these factors were directly impacted by travel restrictions, leading to significant changes in RTCs across the world.

While road infrastructure, vehicle design, and environmental conditions largely remained unchanged during the pandemic, the reduction in traffic volume and the presence of empty road lanes had a notable effect on human behavior and, consequently, on RTCs rates. With fewer vehicles on the road, many countries saw a significant decline in RTCs. This reduction in collisions was primarily attributed to the decrease in traffic volume, which led to fewer opportunities for accidents. However, the extent of this reduction varied significantly by country and the type of roadways involved. The Table 2-1 shows the reduction in RTCs in different countries.

However, it is important to note that the reduction in RTCs was not uniform across all types of roads or all regions. The type and function of the roadway, along with the specific travel restrictions in place, influenced the degree of reduction in collisions. In some regions, such as urban areas with major highways, traffic volume remained higher compared to more rural areas, where lockdowns led to a more significant reduction in RTCs.

Overall, while the reduction in traffic volume during the COVID-19 pandemic contributed to a global decrease in RTCs, the variations in the extent of the reduction reflect the complex interplay between traffic volumes, road types, and regional policies. The pandemic provided an opportunity to observe how significantly RTCs are influenced by changes in human behavior and traffic patterns.

Table 2-1. Reduction in road traffic collision in different countries

Reference	Location	Reduction in RTCs
Europe		
(Briefing, 2020)	Germany	23%
(Briefing, 2020)	France	74%
(Briefing, 2020)	Czech Republic	28%
(Jefferies et al., 2021)	Northen Ireland	29% to 53%
(Saladié et al., 2020)	Spain	67%
(Valent, 2022)	Italy	70%
(Sekadakis et al., 2021)	Greece	42%
(Oguzoglu, 2020)	Turkey	30% to 60%
Other		
(Yasin, 2023)	United Arab Emirates	33.5%
(Sedain & Pant, 2021)	Nepal	48%
(Chand et al., 2021)	Australia	50% to 60 %
(Barnes et al., 2020; Hughes et al., 2021; Pishue, 2020)	USA	11% to 58%

While the overall number of RTCs globally decreased during the COVID-19 pandemic due to travel restrictions and reduced traffic volumes, the severity of those collisions did not follow the same trend. In many cases, although the absolute number of RTC fatalities declined, the relative percentage of serious injuries and deaths increased. This paradox can be due to several factors, including increased speeds, empty lanes, and reduced law enforcement presence during the lockdown periods.

For example, in Missouri, USA, the decrease in RTCs during the mandated lockdown was accompanied by a reduction in mild injuries, but serious and fatal injuries remained relatively unchanged. This suggests that while fewer collisions occurred overall, those that did take place were more likely to result in severe outcomes (Yasin et al., 2021). The increase in speed, a key factor behind this trend, has been identified as a major contributor to fatal collisions during the pandemic. With fewer vehicles on the road, drivers were more likely to speed, leading to an increased likelihood of severe accidents. Empty lanes and reduced law enforcement also created an environment conducive to risky driving behavior, further exacerbating the severity of accidents.

In terms of statistics, the ratio of fatal crashes to all crashes saw dramatic increases in several cities. For instance, in Madrid, Spain, the ratio of fatal crashes increased by 470%, while Chicago and New York saw increases of 292% and 167%, respectively (Yasin et al., 2021). Similarly, the fatality rate in the United States rose by 14% per mile driven in March 2020, and by 37% in April 2020, both of which were attributed to excessive speeding. Trauma center data also supports these findings, with a significant increase in the injury severity of patients admitted during the lockdown. The proportion of patients with an Injury Severity Score (ISS) above nine increased from 35% before the lockdown to about 63% during the lockdown (Rajput et al., 2021).

While the overall number of RTC fatalities declined in some countries, the severity of the injuries and fatalities that did occur remained a critical concern. In Greece, for example, fatal accidents declined by 41%, severe injuries by 8%, and mild injuries by 42% (Katrakazas et al., 2020). Australia also saw a decrease in the number of fatal crashes by 10% in 2020 compared to the prior three years, although this trend varied by jurisdiction (Soltani et al., 2023). Similarly, New York City and France experienced reductions in fatal collisions, with decreases of 35% and 56%, respectively, in April 2020 compared to the same month in 2019 (Alkhudhairy & Aldhalemi, 2023). These findings highlight a key concern during the pandemic: while fewer collisions occurred overall, the severity of the accidents that did take place was much higher. This emphasizes the importance of addressing the underlying causes of severe accidents, such as speeding and risky driving behavior, in post-pandemic road safety policies.

Finally, the COVID-19 pandemic significantly impacted RTCs worldwide, leading to varied outcomes in terms of injuries and fatalities. Many countries experienced a reduction in RTCs due to lockdown measures, which restricted mobility and reduced traffic volume. However, despite the overall decline in incidents, changes in driver behavior contributed to increased crash severity in some regions. The decrease in congestion encouraged risky driving practices such as speeding, which heightened the severity of injuries among road users (Ziakopoulos et al., 2025).

In most countries, the lockdown period led to a notable decline in traffic-related deaths and injuries (Sedain & Pant, 2021). For instance, Spain recorded a 62% reduction in fatalities on rural roads, which translated to a 10% drop in deaths among vulnerable road users such as pedestrians and cyclists (Briefing, 2020). Similarly, in Northern Ireland, pedestrian fatalities decreased by 24%, motorcyclist deaths by 16%, and passenger deaths by 38% (Statistics, 2023). Australia also saw reductions in road deaths, with pedestrian fatalities dropping by 20%, motorcyclist deaths by 12%, and passenger deaths by 11% (Soltani et al., 2023). However, an exception was observed among cyclists, whose fatalities rose by 29%, likely due to the increased adoption of cycling as a primary mode of transport during the pandemic (Soltani et al., 2023).

Conversely, some countries reported an increase in road fatalities despite the overall reduction in traffic. In April 2020, Slovakia experienced a 50% rise in traffic-related deaths, while Denmark saw an increase of 9% compared to April 2019 (Francke, 2022). Similar trends were noted in the Netherlands and Sweden, where road deaths increased by 6%, even though no formal lockdown measures were in place (Francke, 2022). In the Czech Republic, the number of vulnerable road user deaths rose by 27%, with cyclist fatalities surging by 86% and motorcyclist deaths by 50% (Yasin et al., 2021). The differences in fatality trends across countries can be attributed to several factors, including variations in lockdown measures, road infrastructure, traffic enforcement, and driving behavior. Vulnerable road users, such as pedestrians, cyclists, and motorcyclists, were disproportionately affected due to their exposure to high-speed vehicles in less congested road conditions. The findings highlight the importance of adaptive road safety policies, stricter speed enforcement, and improved infrastructure to mitigate the adverse effects of reduced traffic volume on crash severity.

CHAPTER 3. METHODS

This section outlines the detailed approach to investigating the impact of COVID-19 on travel behavior and mode choices in the Pacific Northwest region of the United States. The methodology consists of three subsections: (1) Data Source, (2) Statistical Analysis, and (3) Modeling with regard to choosing of travel mode before and after pandemic. The survey, in its entirety, is provided in the Appendix.

3.1. Data Source

3.1.1. Study Area

The Pacific Northwest region of the United States was selected as the study area due to its geographic diversity and varying transportation systems. This region includes urban cities such as Seattle and Portland and rural communities, providing a wide spectrum of socio-demographic and transportation characteristics to analyze. The urban and rural areas mix also offers insights into how travel behavior shifts under different infrastructures.

3.1.2. Survey Design and Sample

An online company, Qualtrics, was used to create and distribute the survey. The company was hired to find respondents who met specific criteria set by the researchers, including a minimum of 800 participants, at least 20% from each targeted state, and respondents aged 18 or older. Before distribution, the survey was reviewed and approved by the university's Institutional Review Board (IRB).

The survey, conducted in May 2023, included multiple-choice, single-choice, and matrix-style questions, along with one open-ended question asking for respondents' zip codes. The timing of the survey assumed that participants could accurately recall their travel habits before the pandemic and would perceive the pandemic as largely over at the time of their responses.

A total of 807 responses were collected, Qualtrics performed a thorough data review to remove low-quality responses, such as incomplete answers, repetitive responses, or duplicates. No time limit was imposed for completing the survey.

3.2. Statistical Analysis

3.2.1. Descriptive Statistics

Descriptive statistics were used to provide a comprehensive overview of the data. Frequencies and percentages were calculated to summarize the distribution of demographic variables, travel modes, and changes in travel patterns. These statistics offered insights into the characteristics of the sample and the extent of mode changes before and during the pandemic.

3.2.2. McNemar's Test

McNemar's test was applied to assess the significance of changes in travel modes before and during the pandemic. This non-parametric test is suitable for paired nominal data and was used to analyze individual respondents' mode choice shifts. As this study investigated paired responses from the same individuals before and after COVID-19, the Chi-Square test of independence was not used as it assumes the tested samples are independent. Similarly, the Wilcoxon Signed-Rank test and paired t-test were not suitable for this analysis because they are designed for continuous or ordinal data, whereas travel mode choices are categorical in nature. The McNemar's test is used in this study to determine whether the observed changes in travel behavior, such as a shift from public transport to private vehicles, were statistically significant.

3.2.3. Cross-Tabulation

Cross-tabulation analysis was conducted to explore the shifts that take place between each two categories of travel modes. This method identified patterns and trends across different travel modes. It provided a detailed comparison between different travel modes before and during the pandemic as a pairwise comparison. Moreover, cross-tabulation allowed for direct observation of changing between each mode, such as the extent to which public transport users switched to private vehicles or active travel modes.

3.2.4. Limitations of Statistical Analysis

While the statistical methods provide valuable insights, it is important to acknowledge certain limitations. The reliance on self-reported data may introduce recall bias, as participants might not accurately remember their travel behavior before the pandemic. Additionally, the sample may not fully represent the population of the Pacific Northwest region, particularly in terms of rural and underserved communities. Lastly, the analysis does not explicitly account for external factors such as economic conditions, infrastructure changes, or government policies that may have influenced travel behavior during the pandemic.

3.3. Modeling choosing of travel mode before and after pandemic

3.3.1. Logistic Regression Analysis

A logistic regression model was developed to investigate the relationship between mode changes and socio-demographic characteristics further. The dependent variable was defined as whether a participant changed their primary mode of travel during the pandemic (yes/no). Independent variables included demographic factors such as age, gender, education level, household size, and employment status. This analysis helped identify key predictors of mode change, providing a deeper understanding of the factors influencing travel behavior during the pandemic. For instance, the logistic regression model assessed whether individuals in certain age groups were more likely to shift from public transport to private vehicles, or whether employment status influenced the likelihood of adopting active travel modes. Odds ratios and confidence intervals were calculated to measure the strength and significance of these relationships.

3.3.2. Latent Class Analysis (LCA)

Latent Class Analysis (LCA) was used to identify unobserved subgroups within the population based on their travel behavior and mode choice patterns. LCA grouped respondents into distinct classes based on shared characteristics and behaviors, such as frequent travelers who shifted to private vehicles or occasional travelers who adopted walking or cycling. These classes were analyzed to understand their demographic profiles and the factors driving their behavior during the pandemic.

The LCA approach allowed for the identification of patterns that were not apparent through descriptive statistics or regression analysis. For example, it helped to reveal whether certain classes were more sensitive to perceived health risks or whether others prioritized convenience and accessibility in their travel decisions.

CHAPTER 4. RESULTS AND ANALYSIS

This section includes the following subsections: (1) Socio-Demographic characteristics of respondents; (2) the effect of COVID-19 on choosing travel modes; (3) the relationship between the respondent characteristics and the ability of changing mode of travel; and (4) Latent Class analysis.

4.1. Socio-Demographic Characteristics of Respondents

This subsection shows the demographic characteristics of the survey respondents, providing an overview of their distribution across different socio-demographic factors such as gender, age, marital status, racial category, educational level, expected annual income, employment status, and vehicle ownership as shown in Table 4.1. It is crucial to understand these demographics for contextualizing the observed changes in travel behavior and mode choices during the COVID-19 pandemic. The geographic distribution of respondents shows a strong representation from Washington (53.00%), followed by Oregon (34.70%) and Idaho (12.30%) as shown in Figure 4.1. Most of the participants reported living in urban areas (65.18%), with 28.62% residing in rural areas and 6.20% in suburban areas as shown in Figure 4.2. This distribution reflects the mix of urban and rural populations in the Pacific Northwest region, providing a diverse sample for analysis.

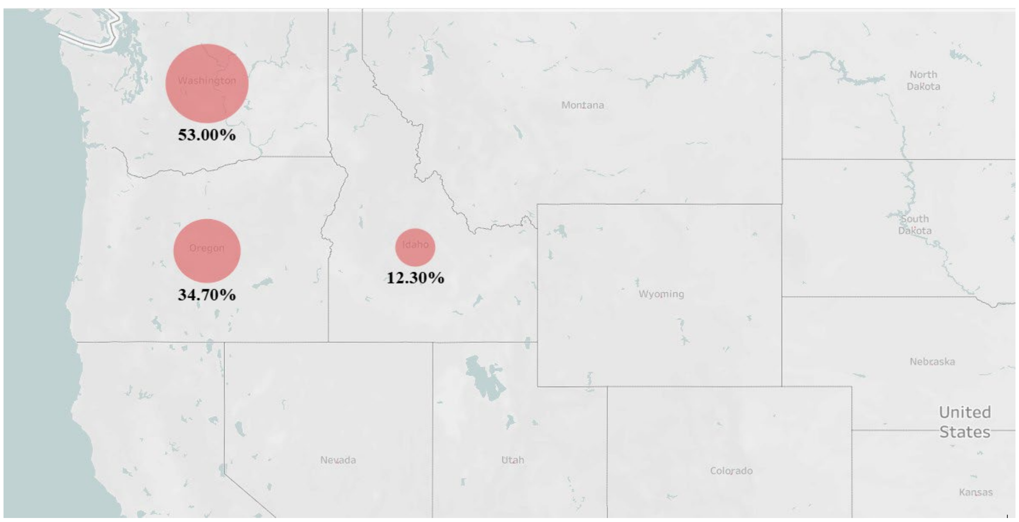


Figure 4-1. Percent of Respondents in Each State

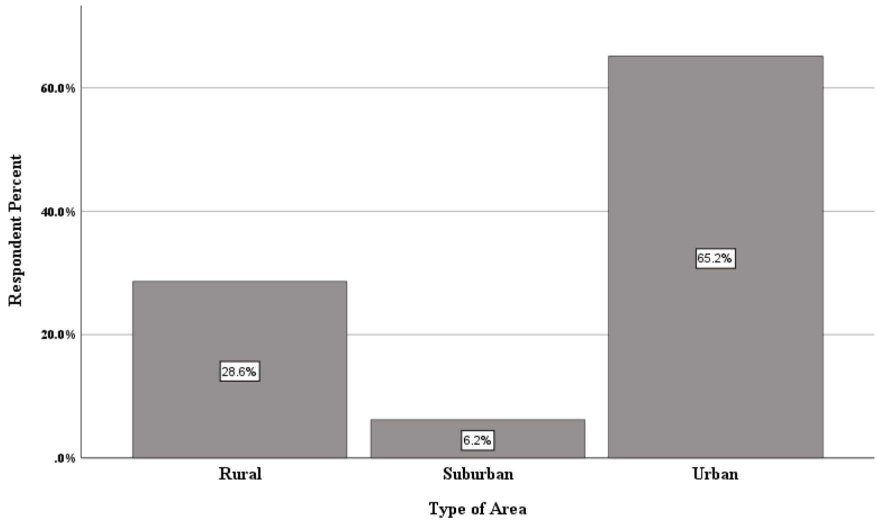


Figure 4-2. Type of Living Area for Respondents

In terms of gender, female respondents comprised the majority (70.90%), while males accounted for 27.50%. A small percentage identified as non-binary (1.10%) or preferred not to disclose their gender (0.50%). This gender distribution highlights a predominance of female participation in the study, which may influence the analysis of travel behavior trends. The age distribution reveals that respondents aged 36 to 49 years old represented the largest group (42.38%), followed by those aged 26 to 35 years old (26.89%). Younger participants aged 18 to 25 years old accounted for 11.03%, while older age groups, including 50 to 64 years old (12.89%) and over 65 years old (6.82%), were less prevalent. This age spread provides a balanced representation of working-age individuals and those at different stages of life, which could influence their travel choices.

The marital status of respondents was diverse, with nearly half (49.19%) identifying as married or legally paired. Single respondents made up 21.44%, while those in long-term committed partnerships represented 13.88%. Smaller proportions were divorced (10.66%), separated (2.23%), or widowed (2.60%). This variation in marital status helps capture the impact of household composition on travel behavior during the pandemic.

Regarding the racial categories, most of respondents identified as White/Caucasian (79.80%). Minority groups included Hispanic/Latino (5.58%), Asian (5.20%), Black/African American (3.84%), and American Indian/Alaskan Native (2.60%). Native Hawaiian/Pacific Islander participants accounted for 1.12%, and 1.86% identified as “Other.” This racial composition aligns with the demographic profile of the Pacific Northwest region but also emphasizes the need to account for potential disparities in access to transportation.

Educational levels varied widely among respondents. High school graduates and individuals with some college but no degree each represented approximately 24.29% of the sample, while bachelor’s degree holders accounted for 20.94%. Smaller proportions held associate degrees (9.79%), master’s degrees (9.05%), and trade/vocational qualifications (5.95%). Those with doctorate and professional degrees were least represented at 1.24% and 0.74%, respectively. This range of educational levels offers insights into how education may shape perceptions and choices related to transportation during the pandemic.

Annual income distribution showed that 40.27% of respondents earned less than $50,000, with 22.18% in the $50,000 to $74,999 range. Higher-income ranges were represented as follows: $75,000 to $99,999 (12.76%), $100,000 to $149,999 (14.13%), and $150,000 or higher (7.19%). A small percentage (3.47%) preferred not to disclose their income. These variations in income provide an understanding of economic constraints that may have influenced travel mode decisions during COVID-19.

Employment status was dominated by full-time employees (47.83%), followed by unemployed individuals (18.09%) and part-time workers (13.75%). Retirees (8.92%), students (2.85%), and others (8.55%) accounted for smaller proportions of the sample. This distribution reflects the diversity of employment situations, which likely influenced the necessity and frequency of travel during the pandemic.

Table 4-1. Demographic Frequency Summary for Respondents Sample

Variable	Categories	Percent	Variable	Categories	Percent
Gender	Male	27.5%	Educational level	Associate degree	9.79%
	Female	70.9%		Bachelor's Degree	20.94%
	Other	1.6%		Did not graduate high school	3.35%
Age Group	18 to 25 years old	11.03%		Doctorate Degree	1.24%
	26 to 35 years old	26.89%		High school diploma or equivalent (GED)	24.66%
	36 to 49 years old	42.38%		Master's Degree	9.05%
	50 to 64 years old	12.89%		Professional Degree	0.74%
	Older than 65 years old	6.81%		Some colleges, no degree	24.29%
Marital status	Divorced	10.66%		Trade / Vocational Training / Technical Degree	5.94%
	Single	21.44%	Expected Annual Income	Less than $50,000	40.27%
	Married/Legally paired	49.19%		$50,000 to $74,999	22.18%
	In a long-term committed partnership	13.88%		$75,000 to $99,999	12.76%
	Separated	2.23%		$100,000 to $149,999	14.13%
	Widowed	2.60%		$150,000 or higher	7.19%

Variable	Categories	Percent	Variable	Categories	Percent
Racial category	American Indian/Alaskan Native	2.60%		Prefer not to answer	3.47%
	Asian	5.20%		Employed, full time	47.83%
	Black/African American	3.84%	Employment Status	Employed, part time	13.75%
	Hispanic/Latino	5.58%		Retired	8.92%
	Native Hawaiian/Pacific Islander	1.12%		Unemployed	18.09%
	White/Caucasian	79.80%		Student	2.85%
	Other	1.86%		Other	8.55%

4.2. Effect of COVID-19 on the Mode Choice

The COVID-19 pandemic has had an impact on the mode of transportation people use for their daily, primary trips. Restrictions imposed by authorities and the personal fear of infection have led to a substantial shift in travel behavior. This section analyzes the mode share changes and explores the modal shifts based on statistical tests and graphical comparisons. Figure 4.3 illustrates the changes in

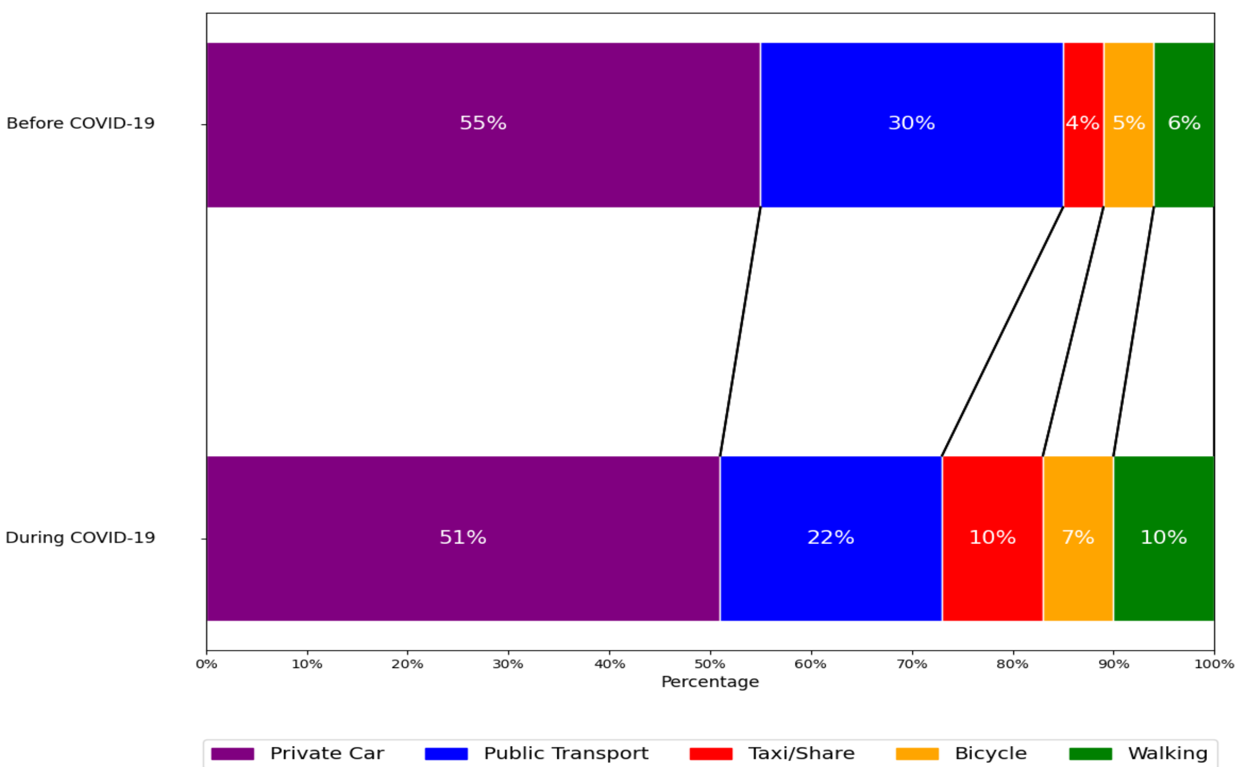


Figure 4-3. Mode of Travel Before and During COVID-19

travel mode shares before and during COVID-19. Before the pandemic, most respondents (55%) used private cars as their primary mode of travel. During COVID-19, this share slightly decreased to 51%, indicating small shifts away from private car use. Public transport showed a substantial decline, dropping from 30% pre-COVID to 22% during the pandemic. This is consistent with global trends where fear of infection and restrictions on public transport usage significantly reduced its patronage. In contrast, the use of taxis or ride-sharing services slightly increased from 4% before the pandemic to 10%, reflecting a preference for more isolated travel options compared to public transit during the pandemic. The share of active modes, including walking and cycling, increased during COVID-19. Walking rose from 6% to 10%, and bicycle use increased from 5% to 7%. These shifts can be attributed to a combination of factors, including the need for safer, socially distanced travel options and the encouraging of outdoor activities during lockdown periods.

The comparison between mode choice before and during COVID-19 was conducted with the McNemar statistical test. The test results were (Chi-square = 12.706, p = 0.122). Since the p-value is greater than the common significance level of 0.05, we fail to reject the null hypothesis, suggesting that the differences in mode choice before and during COVID-19 are not statistically significant. We could conclude from the MCNemar test that temporary shifts occurred however, on the long term the behavior of changing the travel mode significantly may require policy and infrastructure developments.

These insights emphasize the need for policies that support active travel infrastructure and safer public transit to meet evolving traveler preferences.

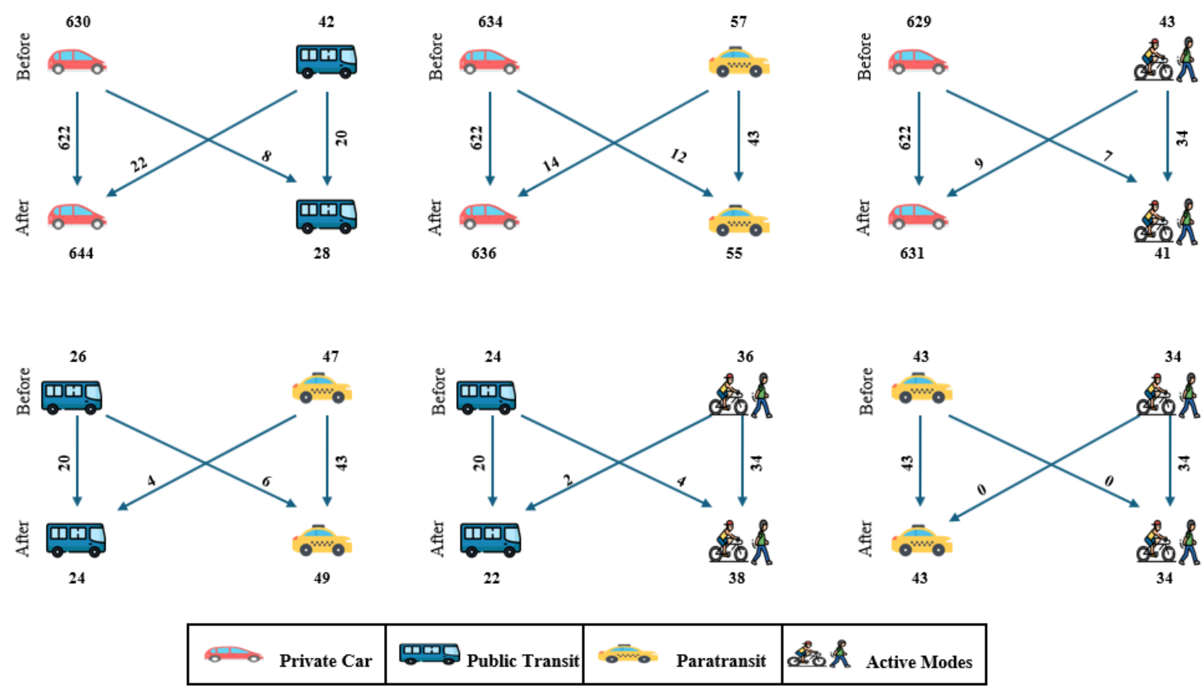


Figure 4-4. Travel mode shifts caused by COVID-19

4.3. Modeling the Mode Choice Before and During COVID-19

4.3.1. Relationship between the Socio-Demographic data and the Potential of Mode Change due to COVID-19

To explore the relationship between demographic factors and mode choice changes during the COVID-19 pandemic, a binary logistic regression model was developed. The dependent variable was the reported change in mode choice due to the pandemic (Yes/No), and predictors included demographic characteristics such as gender, age, education level, income, and mode choice before the pandemic. The analysis provided valuable insights into the likelihood of individuals changing their mode of travel due to the pandemic.

The results shown in Table 4.2 reveal significant relationships between some predictors and mode choice changes. Respondents aged 26–35 years were significantly less likely to change their mode of travel compared to those aged 65 or older (Odds Ratio = 0.367, $p = 0.018$). Similarly, individuals with advanced degrees were much less likely to alter their travel mode than those with post-secondary (non-advanced) education (Odds Ratio = 0.152, $p < 0.001$). Additionally, mode choice before the pandemic played a crucial role. For instance, respondents who primarily used private cars were significantly more likely to maintain their travel mode compared to those who primarily walked (Odds Ratio = 8.773, $p = 0.006$). On the other hand, individuals who relied on bicycles were less likely to maintain their mode choice during the pandemic (Odds Ratio = 0.187, $p = 0.027$).

The model demonstrated a reasonable fit to the data, as indicated by a Cox & Snell R^2 Square of 0.20 and a Nagelkerke R^2 of 0.40. These values suggest that the model accounts for a significant portion of the variation in mode choice changes. Furthermore, the Hosmer and Lemeshow Test yielded a significant value of 0.237, which reflects good model fit.

The classification performance of the model was assessed using a classification table. The model exhibited high specificity, correctly classifying 97.6% of respondents who did not change their travel mode. However, its sensitivity, or ability to correctly classify those who did change their mode, was lower at 41.8%. The overall accuracy of the model was 91.3%, demonstrating strong performance in classifying most cases. These results highlight the model’s strengths in identifying individuals who maintained their mode of travel but also suggest the need for further refinement to improve sensitivity.

In summary, the logistic regression analysis revealed that demographic characteristics and pre-pandemic mode choices were significant predictors of mode choice changes during the pandemic. While the model performed well overall, improving its sensitivity through additional variables or alternative modeling approaches could enhance its ability to predict changes in travel behavior.

Table 4-2. Parameter Estimates for Mode Change Due to COVID-19

Category	Variable	Regression Coefficient	S.E.	df	Sig.	Odd Ratio	95% C.I. (Lower, Upper)
Intercept	-	0.143	0.910	1	0.875	1.154	-
Gender	Female	-0.125	0.316	1	0.691	0.882	(0.475, 1.638)
	Male	0.641	0.858	1	0.455	1.899	(0.353, 10.207)
	Other	0b	-	-	-	-	-
Age	18-25 years old	-0.135	0.414	1	0.745	0.874	(0.388, 1.967)
	26-35 years old	-1.003	0.422	1	0.018	0.367	(0.160, 0.839)
	36-49 years old	-0.591	0.515	1	0.251	0.554	(0.202, 1.518)
	50-64 years old	-0.890	0.789	1	0.260	0.411	(0.087, 1.930)
	65 years or older	0[b]	-	-	-	-	-
Education Level	Advanced degree	-1.883	0.510	1	0.000	0.152	(0.056, 0.413)
	High school or below	-0.740	0.401	1	0.065	0.477	(0.217, 1.046)
	Post-Secondary (Non advanced degree)	0[b]	-	-	-	-	-
Annual Income	$100,000 - $149,000	0.265	0.539	1	0.623	1.304	(0.453, 3.749)
	$150,000 or higher	-1.013	0.534	1	0.058	0.363	(0.127, 1.034)
	$50,000 - $74,999	0.135	0.529	1	0.798	1.145	(0.406, 3.229)
	$75,000 - $99,999	-0.169	0.443	1	0.702	0.844	(0.354, 2.013)
	Less than $50,000	-0.785	0.958	1	0.413	0.456	(0.070, 2.982)
	Prefer not to say	0[b]	-	-	-	-	-
Mode Choice	Bicycle	-1.677	0.757	1	0.027	0.187	(0.042, 0.824)
	Private Car	2.172	0.793	1	0.006	8.773	(1.854, 41.508)
	Public Transit	0.894	0.792	1	0.259	2.444	(0.518, 11.530)
	Taxi/Shared	1.073	0.842	1	0.202	2.926	(0.562, 15.233)
	Walking	0[b]	-	-	-	-	-

[a] The reference category is: Yes.
[b] This parameter is set to zero because it is redundant.

4.3.2. Modeling the Mode Choice Before COVID-19

A multinomial logistic regression model was employed to analyze the travel mode choice for primary trips before and during the COVID-19 pandemic. The outcome variable was the mode of travel, which was categorized into three groups: private car, public/paratransit, and active modes. Public transport and paratransit services were grouped under "public/paratransit", and walking and bicycling were categorized as "active modes". "Private Car" was set as the reference category. Respondents who did not disclose gender, annual income, or employment details were excluded from the analysis. The final models for the mode choice before and during the COVID-19 pandemic were developed based on data from 807 respondents and have estimated parameters, as well as model fitting information as shown in Table 4.3, Table 4.4, Table 4.5, and Table 4.6, respectively. The predictors included gender, age group, education level, and employment status. Variables found to be insignificant or those with very few responses in certain categories were excluded from the final model. A forward stepwise method was employed to select significant predictors, ensuring the models were robust and efficient.

The likelihood ratio test indicated that the developed models were a significant improvement over the intercept-only models. The goodness-of-fit test, based on the deviance chi-square, was non-significant for both the pre-pandemic ($\chi2 = 252.114$, $p = 0.995$) and pandemic periods ($\chi2 = 243.018$, $p = 0.999$). Moreover, Pearson's chi-square test was insignificant for both periods. The Cox & Snell R^2 and Nagelkerke R^2 values were 0.098 and 0.14, respectively, for the pre-pandemic model, and 0.12 and 0.179 during the pandemic. The models correctly classified 80.7% and 83.2% of the cases for the pre-pandemic and pandemic periods, respectively.

Table 4-3. Model Fitting Information Before COVID-19

Model	**Model Fitting Criteria**	**Likelihood Ratio Tests**		
	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	500.809	-	-	-
Final	469.465	79.345	24	<0.001

Table 4-4. Model Fitting Information After COVID-19

Model	**Model Fitting Criteria**	**Likelihood Ratio Tests**		
	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	483.283	-	-	-
Final	433.010	98.273	24	<0.001

Table 4-5. Parameter Estimates for Mode choice Before COVID-19

Travel Mode	Category	Variable	Regression Coefficient	S.E.	df	Sig.	Odd Ratio	95% C.I. (Lower, Upper)
Active Modes	Intercept	-	-3.386	1.021	1	< 0.001	-	-
	Gender	Female	-1.128	0.329	1	< 0.001	0.324	(0.17, 0.616)
		Male	0[b]	-	-	-	-	-
	Age	18-25 years old	2.404	1.083	1	0.026	11.067	(1.324, 92.495)
		26-35 years old	1.883	1.049	1	0.073	6.571	(0.841, 51.323)
		36-49 years old	1.152	1.051	1	0.273	3.165	(0.403, 24.834)
		50-64 years old	1.530	1.087	1	0.159	4.619	(0.548, 38.919)
		65 years or older	0[b]	-	-	-	-	-
	Education Level	Advanced degree	0.342	0.590	1	0.562	1.408	(0.443, 4.473)
		High school or below	0.851	0.348	1	0.014	2.341	(1.185, 4.626)
		Post-Secondary (Non advanced degree)	0[b]	-	-	-	-	-
	Annual Income	$150,000 or higher	0.330	0.586	1	0.574	1.39	(0.441, 4.385)
		$100,000 - $149,000	-0.616	0.588	1	0.295	0.540	(0.170, 1.712)
		$75,000 - $99,999	-2.026	1.017	1	0.046	0.132	(0.018, 0.967)
		$50,000 - $74,999	-0.82	0.398	1	0.837	0.921	(0.422, 2.011)
		Less than $50,000	0[b]	-	-	-	-	-
	Employment Status	Employed	-0.372	0.357	1	0.297	0.689	(0.343, 1.388)
		Unemployed	0[b]	-	-	-	-	-
Public / Paratransit	Intercept		-2.841	0.730	1	<0.001	-	-
	Gender	Female	-0.383	0.241	1	0.112	0.682	(0.425, 1.094)
		Male	0[b]	-	-	-	-	-
	Age	18-25 years old	2.480	0.772	1	0.001	11.938	(2.630, 54.189)
		26-35 years old	1.783	0.749	1	0.017	5.949	(1.370, 25.837)
		36-49 years old	1.758	0.736	1	0.017	5.798	(1.370, 24.545)
		50-64 years old	1.136	0.794	1	0.153	3.116	(0.657, 14.779)
		65 years or older	0[b]	-	-	-	-	-
	Education Level	Advanced degree	0.659	0.359	1	0.067	1.932	(0.955, 3.909)
		High school or below	0.546	0.239	1	0.023	1.726	(1.079, 2.759)
		Post-Secondary (Non advanced degree)	0[b]	-	-	-	-	-
	Annual Income	$150,000 or higher	0.203	0.407	1	0.618	1.225	(0.552, 2.722)
		$100,000 to $149,999	-0.728	0.383	1	0.057	0.483	(0.228, 1.022)
		$75,000 to $99,999	-0.619	0.371	1	0.095	0.538	(0.260, 1.114)
		$50,000 to $74,999	-0.709	0.314	1	0.024	0.492	(0.266, 0.911)
		Less than $50,000	0[b]	-	-	-	-	-
	Employment Status	Employed	-0.584	0.239	1	0.015	0.558	(0.349, 0.891)
		Unemployed	0[b]	-	-	-	-	-

[a] The reference category is: Private Car.
[b] This parameter is set to zero because it is redundant.

Table 4-6. Parameter Estimates for Mode Choice After COVID-19

Travel Mode	Category	Variable	Regression Coefficient	S.E.	df	Sig.	Odd Ratio	95% C.I. (Lower, Upper)
Active Modes	Intercept	-	-3.552	1.069	1	< 0.001	-	-
	Gender	Female	-1.118	0.347	1	< 0.001	0.327	(0.166, 0.646)
		Male	0[b]	-	-	-	-	-
	Age	18-25 years old	2.401	1.116	1	0.031	11.035	(1.239, 98.270)
		26-35 years old	1.651	1.090	1	0.104	5.212	(0.615, 44.153)
		36-49 years old	1.112	1.091	1	0.308	3.040	(0.361, 25.815)
		50-64 years old	1.129	1.165	1	0.339	3.092	(0.345, 27.708)
		65 years or older	0[b]	-	-	-	-	-
	Education Level	Advanced degree	0.836	0.631	1	0.184	2.307	(0.671, 7.944)
		High school or below	1.230	0.371	1	< 0.001	3.420	(1.653, 7.075)
		Post-Secondary (Non advanced degree)	0[b]	-	-	-	-	-
	Annual Income	$150,000 or higher	-0.425	0.725	1	0.554	0.654	(0.158, 2.710)
		$100,000 - $149,000	-1.318	0.798	1	0.099	0.268	(0.056, 1.279)
		$75,000 - $99,999	-1.333	0.778	1	0.087	0.264	(0.057, 1.212)
		$50,000 - $74,999	-1.074	0.375	1	0.006	0.342	(0.164, 0.712)
		Less than $50,000	0[b]	-	-	-	-	-
	Employment Status	Employed	-0.321	0.375	1	0.392	0.725	(0.348, 1.514)
		Unemployed	0[b]	-	-	-		
Public / Paratransit	Intercept		-1.675	0.523	1	< 0.001	-	-
	Gender	Female	-0.426	0.275	1	0.121	0.653	(0.381, 1.119)
		Male	0[b]	-	-	-	-	-
	Age	18-25 years old	1.223	0.611	1	0.045	3.398	(1.026, 11.249)
		26-35 years old	0.733	0.561	1	0.194	2.081	(0.693, 6.249)
		36-49 years old	0.872	0.533	1	0.101	2.392	(0.826, 6.974)
		50-64 years old	0.417	0.613	1	0.464	1.518	(0.457, 5.048)
		65 years or older	0[b]	-	-	-	-	-
	Education Level	Advanced degree	0.883	0.435	1	0.043	2.417	(1.030, 5.672)
		High school or below	0.387	0.268	1	0.148	1.473	(0.871, 2.490)
		Post-Secondary (Non advanced degree)	0[b]	-	-	-	-	-
	Annual Income	$150,000 or higher	-0.898	0.420	1	0.032	0.407	(0.179, 0.928)
		$100,000 to $149,999	-2.460	1.055	1	0.045	0.085	(0.011, 0.690)
		$75,000 to $99,999	-1.074	0.375	1	0.006	0.342	(0.164, 0.712)
		$50,000 to $74,999	-1.333	0.778	1	0.087	0.264	(0.057, 1.212)
		Less than $50,000	0[b]	-	-	-		
	Employment Status	Employed	-0.951	0.270	1	< 0.001	0.386	(0.228, 0.652)
		Unemployed	0[b]	-	-	-	-	-

[a] The reference category is: Private Car.
[b] This parameter is set to zero because it is redundant.

4.4. Latent Class analysis for the Sample Grouping

Latent Class Analysis (LCA) was performed on the dataset to identify underlying subgroups, or "latent classes," within the population. Six variables were used in defining the model: respondent state of living, gender, age group, annual income, travel mode before COVID-19, and incidence of change mode of transportation. Table 4.7 and Figure 4.5 present the results for the model's key evaluation metrics with different numbers of latent classes, ranging from 2 to 7 classes. Evaluation metrics such as the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), likelihood ratio statistic (G2), and the chi-square goodness of fit were used to assess the model fit. A lower AIC indicates a better model fit relative to others. In this case, the AIC decreases from the 2-class model (9123.7) to the 6-class model (9037.4), suggesting improvement in model fit as more classes are added. However, the AIC increases slightly for the 7-class model (9063.1), indicating that the 6-class model may be optimal. Like AIC, the BIC starts at 9325.54 for the 2-class model and then increases as the number of classes increases, reaching 9781.2 for the 7-class model. This increase in BIC indicates that the more complex models (with more latent classes) do not necessarily provide a better fit when penalizing model complexity. In summary, while the AIC suggests that the 6-class model might be optimal, the increasing BIC values indicate that simpler models with fewer latent classes might be preferred since BIC penalizes more heavily for added complexity. This suggests a trade-off between model fit and complexity, and a model with fewer latent classes might be a better choice based on BIC. Figure 4-7 shows the relation between AIC and BIC.

A model with 3 classes seems to be convenient in representing the population data. The 3-class model balances the fit and complexity of the model, with a lower AIC (9040.7) than the 2-class model and a reasonable BIC (9345.7), avoiding overfitting. It also improves G^2 (840.6) and χ^2 goodness-of-fit (3085.3), making it a practical choice for representing population data. Class 1 accounts for 32.1% of the population and displays distinct response patterns across the variables, with higher probabilities observed for some variables (e.g., changing of travel mode due to COVID-19) and lower for others (Living State). While in class 2, it represents the largest share of the population, at 56.5%, and shows relatively higher and more consistent probabilities across a range of variables, indicating more uniform responses in comparison to Class 1. Class 3, with a population share of 11.4%, exhibits lower overall probabilities for several manifest variables compared to the other two classes, but certain variables (e.g., travel mode before COVID-19, Changing of travel mode due to COVID-19) show a higher probability distribution.

Table 4-7. Key evaluation metrics for different latent class numbers

No. classes	2	3	4	5	6	7
AIC	9123.7	9040.7	9041.3	9041	9037.4	9063.1
BIC	9325.54	9345.7	9449.6	9552.6	9652.216	9781.2
G^2	967.631	840.6	797.21	752.9	705.27	687
X^2 goodness of fit	7225.262	3085.3	23945.7	2098.4	1915.7	1866.33

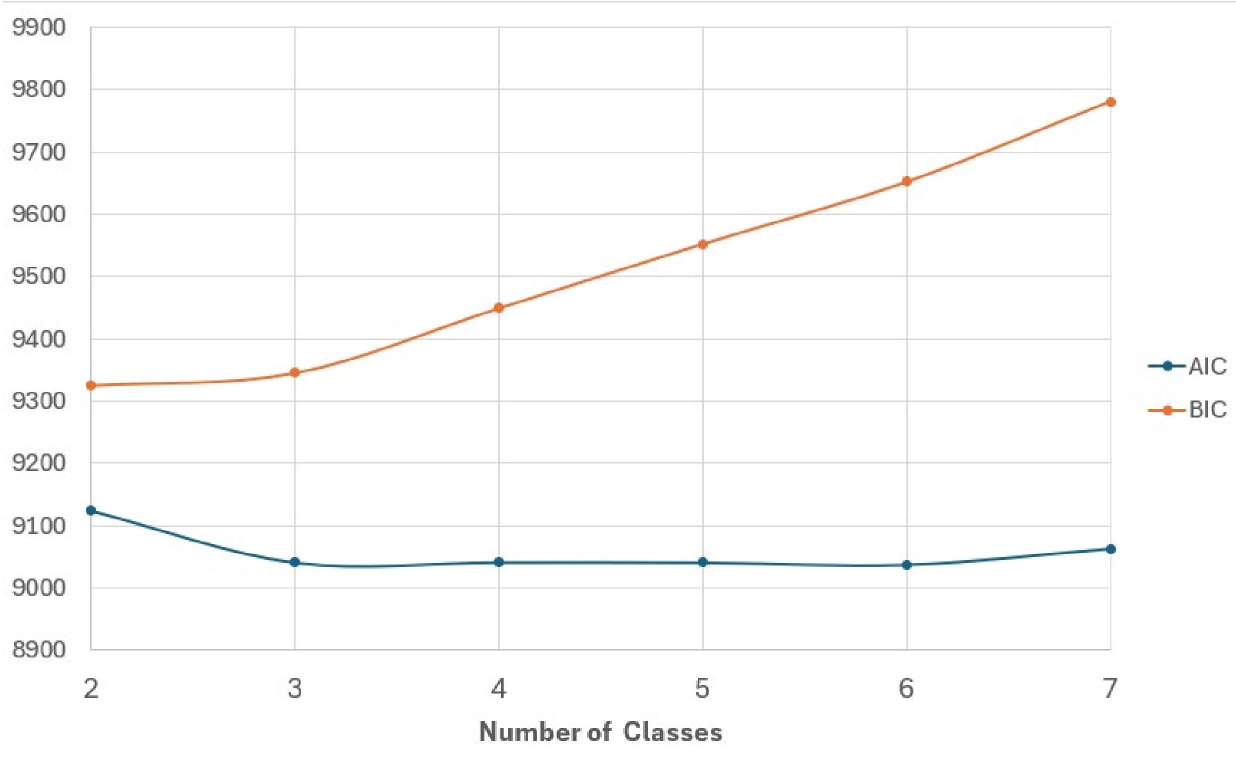
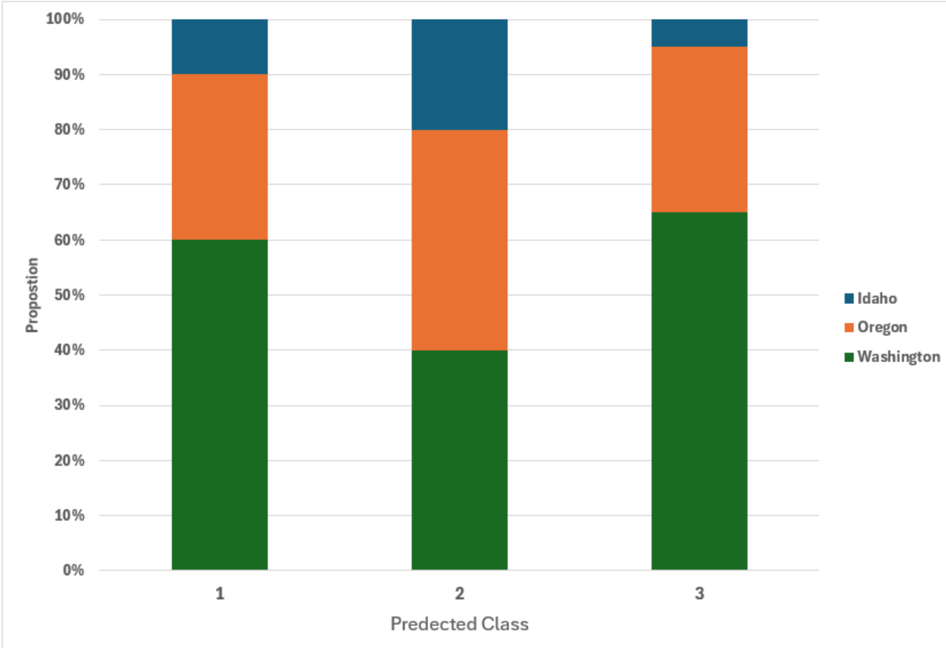


Figure 4-5. AIC and BIC values for different LCA models

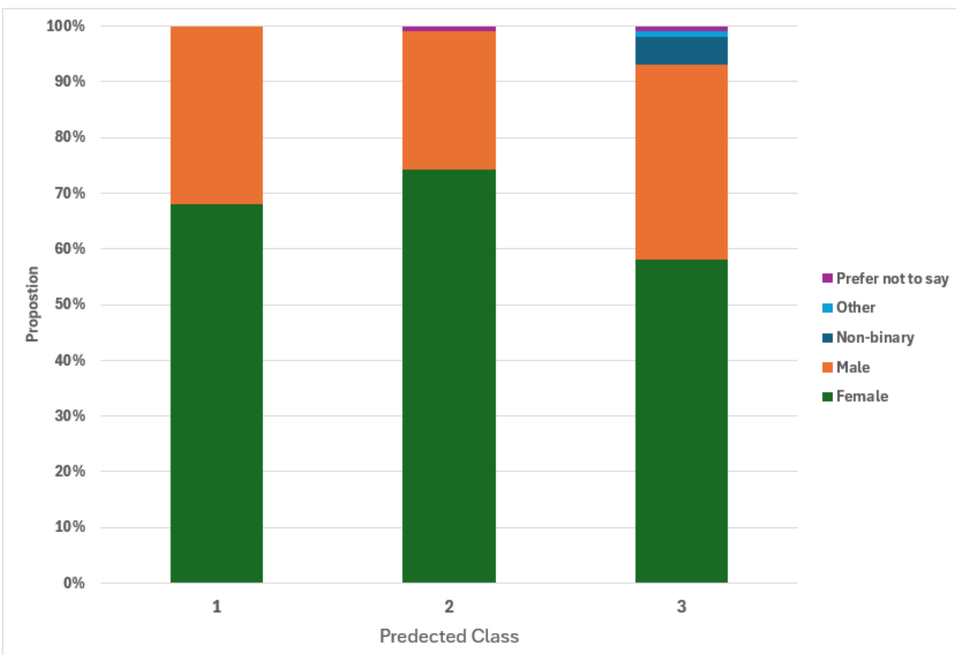
Figure 4-6a shows the predicted classes (1, 2, and 3) compared to different living states: Idaho, Oregon, and Washington. The proportions of people from these states vary across the three classes, with a significant proportion of Washington residents in each class, followed by Oregon, then Idaho. Across all classes, Washington has the largest share, while Idaho contributes the smallest proportion.

For gender, Figure 4-6b illustrates the distribution of predicted classes based on gender categories. Female dominates across all predicted classes. Males constitute a substantial portion in all classes, but especially in class non-binary, and other categories such as" Prefer not to say" make up smaller portions, particularly in class 3, where these groups have more visibility. The bar chart in Figure 4-7a shows the predicted class distributions for different age groups. There is a clear trend where older age groups 36-49 and 50-64 are relatively more prominent in class 3, while younger age groups dominate in class 1. Class 2 has a more evenly distributed age group representation. Concerning annual income for households, Figure 4-7b illustrates the predicted class distribution across different income levels. Higher-income groups (e.g., $150,000 or higher) have larger proportions in class 1, while lower-income groups like less than $50,000 are most prominent in class 3. The income group $100,000-$149,999 appears in all classes but dominates in class 1.

Figure 4-8a further breaks down the transportation modes for the predicted classes before the pandemic. “I drove” is dominant across all classes, especially in class 1. Public transportation and walking become more visible in class 3. Other categories like Uber/Lyft are relatively small across all classes. Bars in Figure 4-8b compare the mode of transportation change (Yes or No) to the predicted classes. Class 3 is dominated by those who changed transportation mode, while classes 1 and 2 are mostly comprised of individuals who do not change transportation mode.

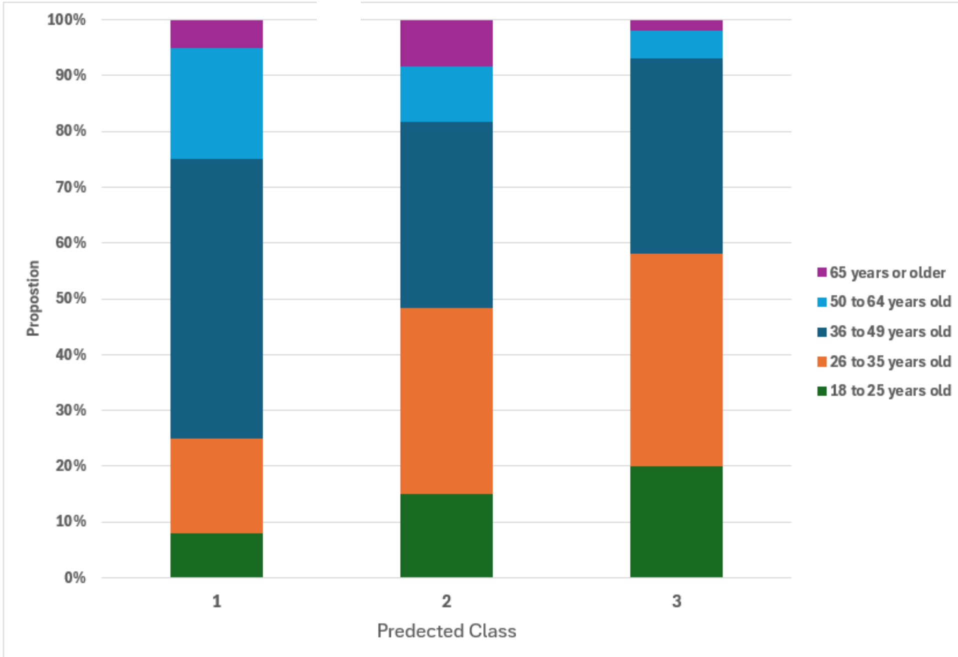


(a) Proportions of Living State for the three latent classes

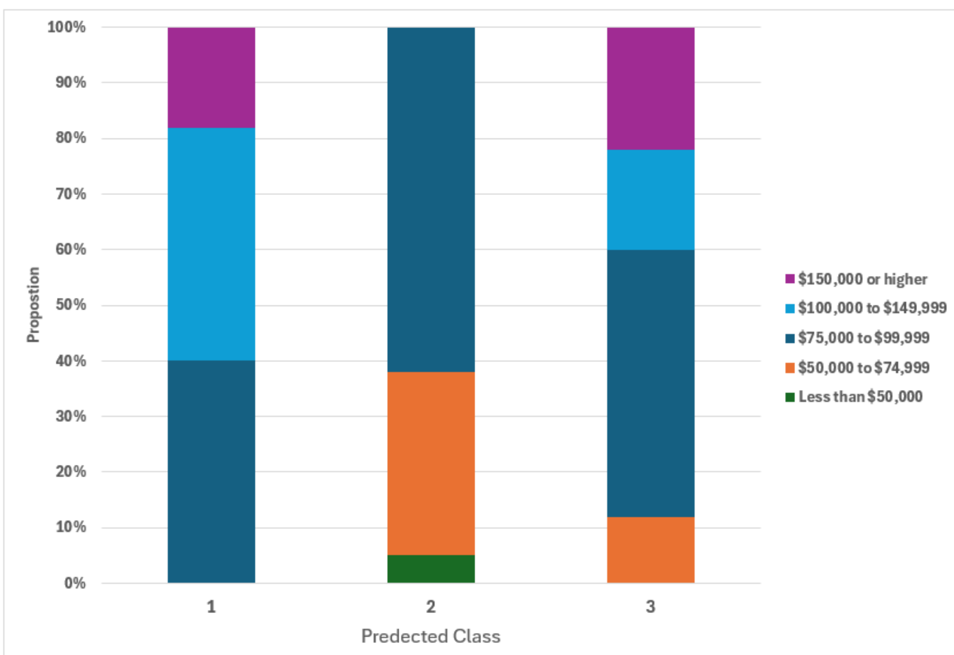


(b) Gender distribution for different latent classes

Figure 4-6. Living states and gender distribution for latent classes

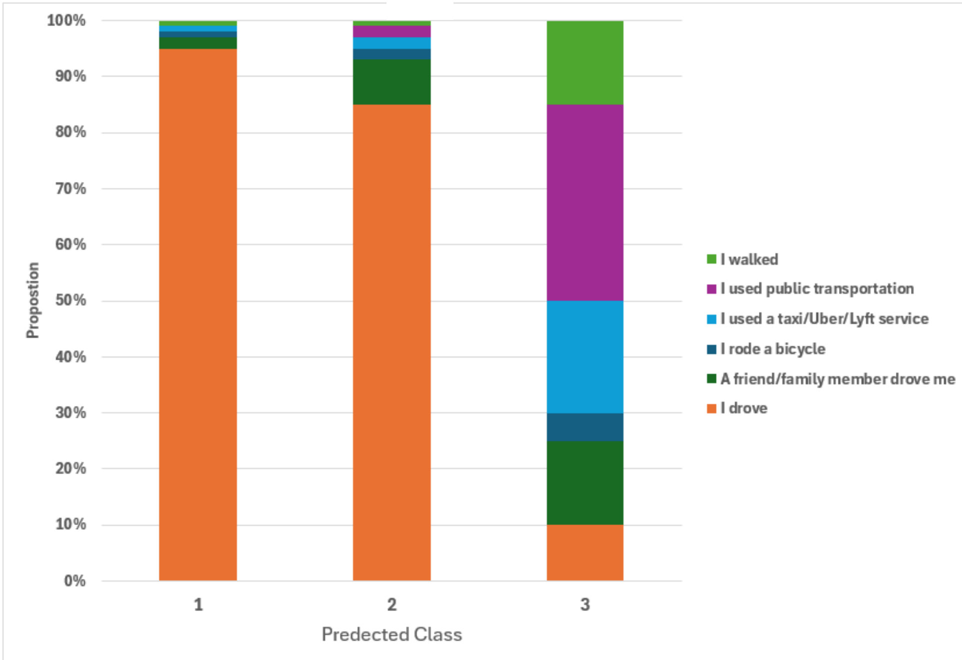


(a) Age groups distribution for the three latent classes

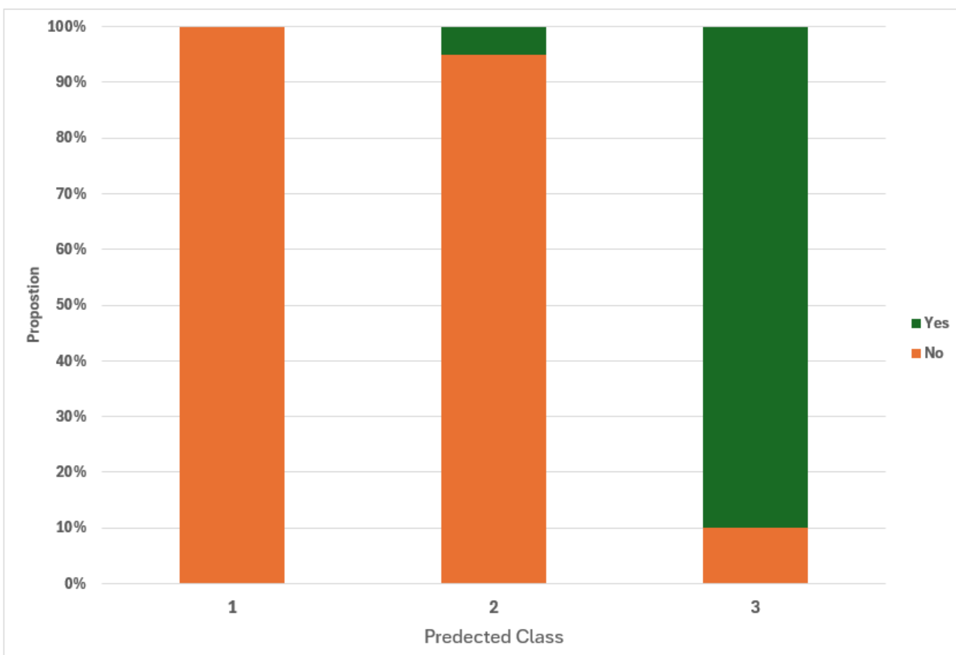


(b) Annual income for households for different latent classes

Figure 4-7. Age groups and annual income distribution for latent classes



(a) Transportation mode shares before pandemic



(b) Probability of transportation mode change due to pandemic

Figure 4-8. Transportation mode shares and mode change probability for latent classes

4.5. The effect of COVID-19 on traffic safety

The COVID-19 pandemic significantly impacted traffic safety, influencing the frequency, severity, and nature of road traffic crashes. Lockdowns, reduced mobility, and changes in travel behavior played a crucial role in shaping traffic patterns during and after the pandemic. To examine the effect of the COVID-19 pandemic on traffic safety, the State of Idaho's 2019 – 2023 crash data was analyzed. The crash data was obtained from the Idaho Transportation Department (ITD) Office of Highway Safety (OHS) WebCars's Crash Analysis Reporting System (ITD-OHS, 2023-A) and from the Idaho's Crash Reports published by ITD OSH annually (ITD-OHS, 2023-B). The crash data along with vehicle exposure data was used to investigate crash frequency and crash rate before and after the pandemic factoring different crash injury types, contributing circumstances for both urban and rural areas in the state of Idaho. The results of these analyses are presented in the following sections.

4.5.1. Changes in Traffic Crashes and Vehicle Miles Traveled (VMT)

One of the most noticeable effects of the pandemic was the reduction in total traffic crashes in 2020, as shown in Table 4-8. The total number of crashes declined from 27,015 in 2019 to 22,528 in 2020, reflecting the reduced travel activity during lockdowns. However, this number rebounded in subsequent years as restrictions eased, reaching 27,679 crashes in 2023, indicating a return to pre-pandemic crash levels. This trend is further demonstrated in Figure 4-9, which shows a dip in total crashes in 2020 followed by a steady increase.

Table 4-8. Descriptive statistics of crash data.

Years	2019		2020		2021		2022		2023	
Crash Location										
Urban	18478	68%	14653	65%	17877	65%	17770	64%	18195	66%
Rural	8537	32%	7875	35%	9672	35%	9891	36%	9484	34%
Vehicle Miles Traveled (VMT)										
Urban VMT (millions)	7949	44%	7369	42%	8084	42%	8089	42%	8262	42%
Rural VMT (millions)	10109	56%	9990	58%	11224	58%	11066	58%	11419	58%
Type of Road										
Local Roads/VMT (millions)	16083	60%	12632	56%	15414	56%	15422	56%	15702	57%
U.S. and State Highways VMT (millions)	7813	29%	7216	32%	8697	32%	8769	32%	8669	31%
Interstate Highways	3119	11%	2680	12%	3436	12%	3470	12%	3308	12%
Type of Crash Injury										
Suspected Serious Injury	1154	2%	1102	2%	1367	2%	1336	2%	1228	2%
Suspected Minor Injury	3889	6%	3637	7%	4393	7%	4604	7%	4611	7%
Possible Injuries	8288	12%	6716	12%	6856	10%	6215	9%	6020	9%
No Injuries	53251	79%	42205	78%	53591	80%	53667	81%	54218	81%
Unknown / Missing	600	1%	546	1%	712	1%	835	1%	848	1%
Contributing circumstances										
Impaired Driving Crashes	1501	7%	1513	9%	1729	8%	1799	9%	1708	8%
Aggressive Dri vi ng Crashes	13638	67%	10742	65%	13633	67%	14036	68%	13948	68%
Distracted Dri vi ng Crashes	5066	26%	4253	26%	5003	25%	4736	23%	4757	24%

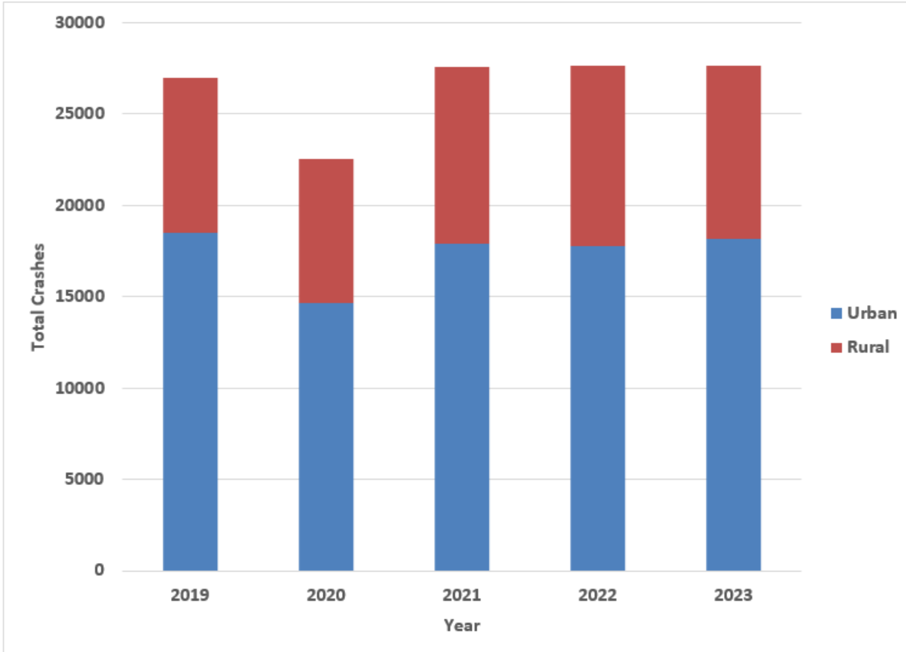


Figure 4-9. Total number of crashes during and after COVID-19

The changes in crash locations were also evident. Urban crashes accounted for 68% of total crashes in 2019, decreasing to 65% in 2020, before gradually increasing again to 66% in 2023. Meanwhile, rural crashes followed the opposite trend, peaking at 36% in 2022 before slightly declining. This variation can be attributed to changing travel patterns, with essential travel and localized movements predominating during lockdowns.

Furthermore, vehicle miles traveled (VMT) and crashes per VMT saw a similar trend, as illustrated in Figure 4-10 and 4-11. Both urban and rural VMT declined in 2020 due to movement restrictions but increased gradually in later years. Rural areas experienced a slightly higher proportion of VMT than urban areas, suggesting that essential and long-distance travel continued even during lockdown periods.

In addition to changes in travel volume, the type of roads on which crashes occurred varied significantly during the pandemic. Figure 4-12 highlights the fluctuations in crashes per VMT across different road types. In 2020, local roads saw the most significant reduction in crashes per VMT, as non-essential travel declined during lockdowns. However, from 2021 onwards, crash rates began increasing again, particularly on highways, suggesting a return to normal traffic conditions and potential congestion-related risks. State highways and interstate highways exhibited a smaller reduction in crash rates during 2020, likely due to the continued movement of freight and essential travel.

These findings suggest that the pandemic affected not only the volume of crashes but also their distribution across different road types, with local roads experiencing the most significant temporary reductions. The post-pandemic trends indicate a gradual return to normal traffic conditions, with crash rates increasing across all road types, particularly in urban settings.

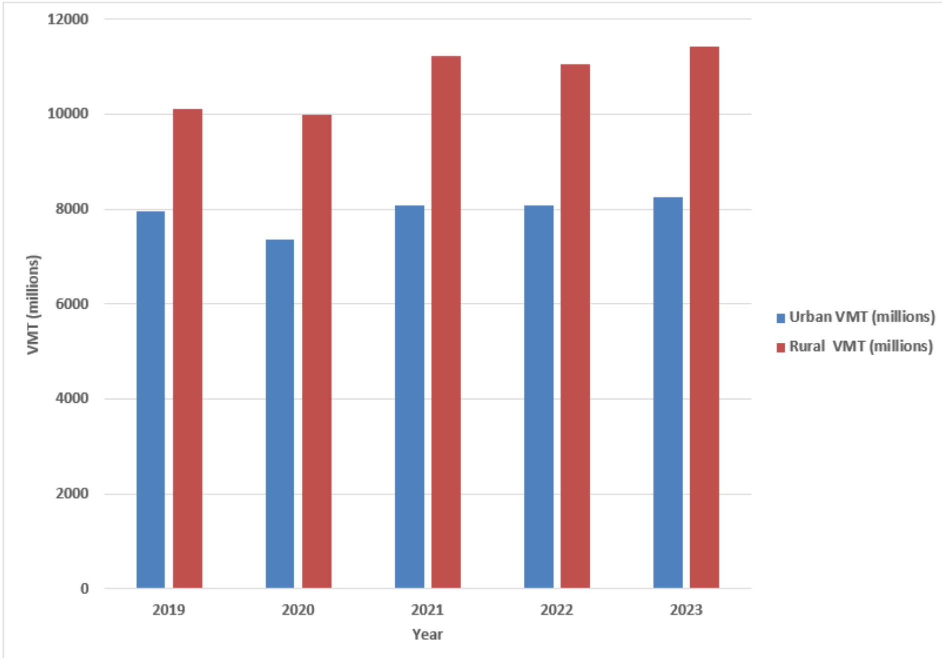


Figure 4-10. Vehicle miles traveled in rural and urban areas during and after COVID-19

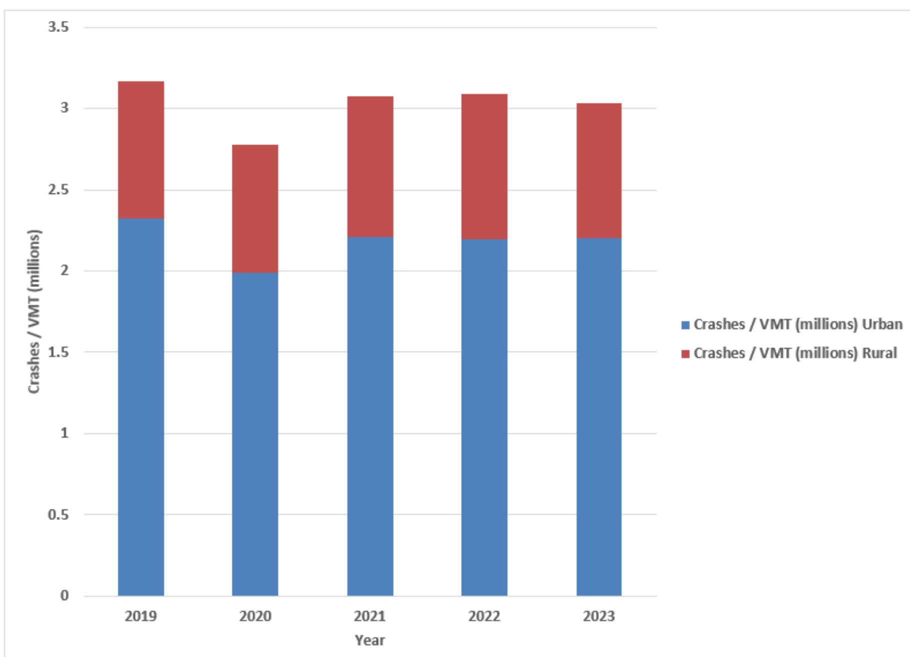


Figure 4-11. Total crashes per VMT in rural and urban areas

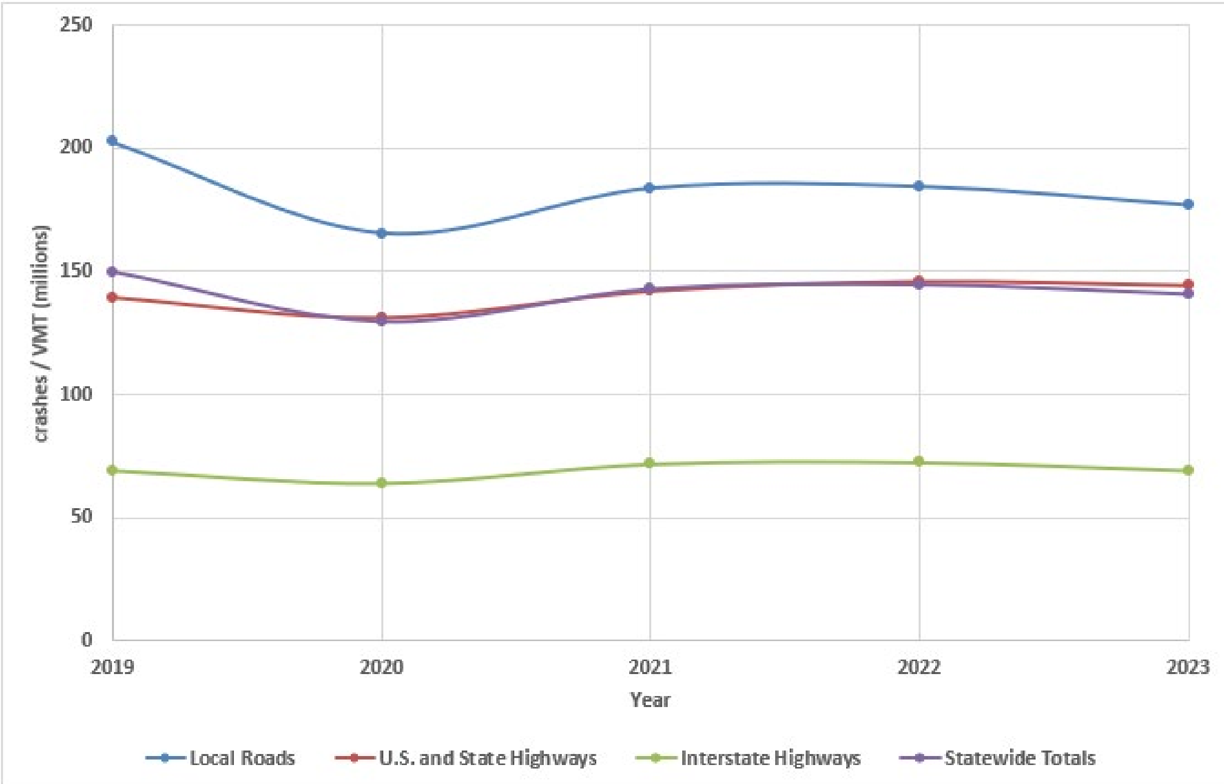


Figure 4-12. Number of crashes per VMT for different types of roads

4.5.2. Crash Severity and Injury Types

Despite the reduction in overall crashes during the pandemic, the severity of injuries varied across different crash categories. Table 4-8 reveals that while suspected serious injuries and minor injuries remained relatively stable, the number of "possible injuries" decreased significantly from 8,288 in 2019 to 6,716 in 2020, reflecting lower crash occurrences. However, crashes involving no injuries remained dominant, with 78% of all crashes in 2020 resulting in no recorded injuries. Fatal crashes also exhibited notable fluctuations. Figure 4-13 illustrates an initial decrease in crash fatalities in 2020, followed by a sharp increase in 2021 and 2023. This pattern aligns with findings from other studies that observed riskier driving behaviors, such as increased speeding on roads, leading to more severe crashes despite lower traffic volumes, (ITD OHS, 2023-B).

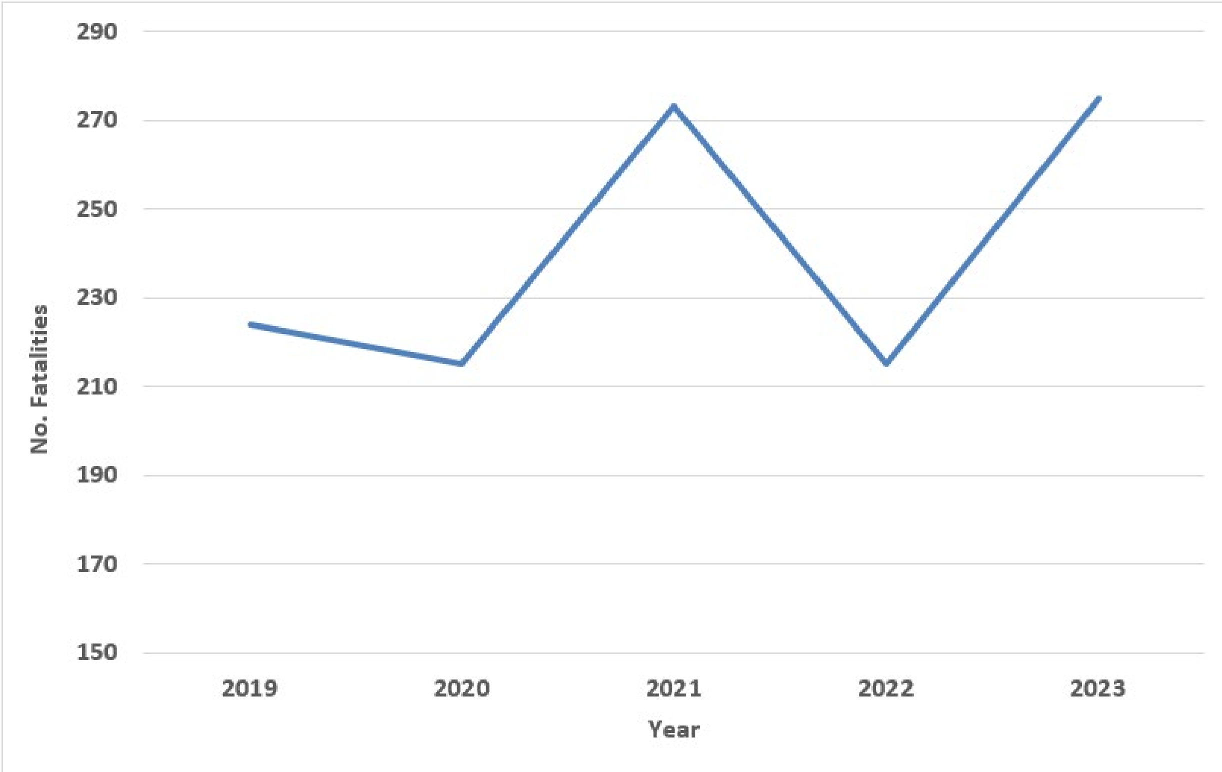


Figure 4-13. Crash fatalities during and after COVID-19

4.5.3. Contributing Factors to Crashes

The pandemic also influenced the causes of crashes, as indicated in Table 4-8 and Figure 4-14. Distracted driving crashes saw a decline in 2020 but increased in the following years, reaching 4,757 crashes in 2023, accounting for 24% of total crashes. Similarly, aggressive driving crashes decreased in 2020 but rebounded, highlighting the potential influence of changing road conditions and driver behavior post-pandemic. Interestingly, impaired driving crashes remained relatively stable, suggesting that alcohol and substance-related incidents were not significantly affected by pandemic restrictions. However, aggressive driving behavior appeared to increase after 2020, possibly due to frustration, stress, or increased speeding on less congested roads (ITD OHS, 2023-B).

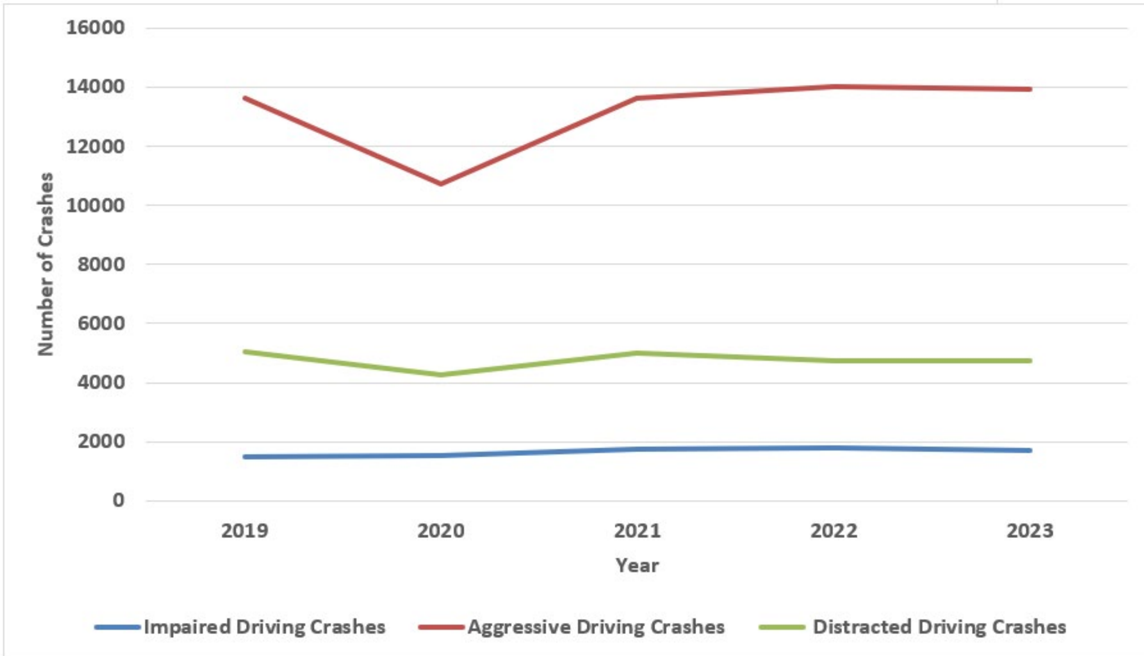


Figure 4-14. Number of crashes depending on contributing factor of crash during and after COVID-19

CHAPTER 5. CONCLUSIONS

The COVID-19 pandemic significantly changed travel behavior and mode choices across the Pacific Northwestern United States. This study highlights notable shifts, including a substantial decline in public transportation usage (from 30% before the pandemic to 22% during the pandemic), as individuals relied on safer and more socially distanced alternatives. Simultaneously, private car usage slightly decreased from 55% to 51%, while active transportation modes, such as cycling and walking, increased from 6% to 10% and 5% to 7%, respectively. These trends reflect an increasing preference for isolated and health-conscious travel modes during the pandemic.

Demographic characteristics played a crucial role in affecting these changes. For example, a logistic regression model showed that younger individuals (e.g., aged 18–25) were more likely to shift to active travel modes, while older respondents and those with advanced degrees showed lower probabilities of changing their travel mode. Latent Class Analysis further investigated distinct population subgroups, emphasizing the variance in responses to the pandemic. For instance, Class 3 exhibited a higher likelihood of switching modes, particularly toward cycling and walking, while Classes 1 and 2 remained predominantly reliant on private cars.

These findings emphasize the pandemic's broad effect on mobility mode of travel, highlighting the need for adaptive and resilient transportation policies. Investments in active travel infrastructure and policy-level measures to restore confidence in public transportation are critical for meeting evolving traveler preferences. Additionally, targeted strategies that address the needs of vulnerable demographic groups, such as lower-income individuals, are essential for fostering equitable and sustainable mobility.

By providing insights into the pandemic-induced mobility shifts, this study contributes to a deeper understanding of how future disruptions due to emergency situations can be controlled to support transportation demand and improve transportation planning. The observed changes underscore the importance of designing flexible transportation systems capable of adapting to both public health crises and the long-term pursuit of sustainable urban mobility.

The analysis of traffic safety during and after COVID-19 highlights several key trends. While overall crashes and VMT declined during lockdowns in 2020, they returned to pre-pandemic levels in later years. However, fluctuations in crash severity and fatalities suggest that changes in driver behavior played a role in shaping these trends. The increase in fatalities in 2021 and 2023, despite reduced travel in 2020, supports the hypothesis that riskier driving behaviors, such as speeding and distracted driving, became more prevalent. Additionally, variations in crash contributions from different road types and behaviors indicate that post-pandemic mobility patterns continue to evolve.

Understanding these impacts is essential for traffic safety planning and policymaking. Future efforts should focus on addressing the increase in risky driving behaviors, improving road infrastructure to accommodate changing mobility trends, and strengthening enforcement measures to mitigate crash risks in both urban and rural areas.

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APPENDIX

Transportation Survey - University of Idaho

Researchers from the University of Idaho's Department of Civil and Environmental Engineering are conducting a study that examines public perceptions related to travel and the pandemic. Your participation will involve answering an online survey that should take about five to eight minutes to complete. Your involvement in the study is voluntary, and you may choose not to participate. You can refuse to answer any of the questions at any time. No names will be associated with your confidential responses. The findings from this project will provide information on various travel behaviors and perceptions. If published, results will be presented in summary form only with no personal identifiers. All data will be stored for a minimum of three years. If you have any questions about this research project, please feel free to call Kevin Chang at (208) 885-4028. If you have questions regarding your rights as a research subject, or if you want to obtain information or offer input you may call the Office of Research Assurances at (208) 885-6340 or irb@uidaho.edu. The terms of service and privacy policy for Qualtrics can be found online at [www.qualtrics.com/terms-of-service/] and [www.qualtrics.com/privacy-statement/]. By clicking the arrow, you certify that you are at least 18 years of age and agree to participate in the above-described research study. Thank you in advance.

Q1 Rural areas can be defined as settlements with less than 5,000 people or open-countryside. Based on this definition, do you live in a rural area?

o Yes
o No
o Maybe

Q2 Which state do you live in?

o Idaho
o Oregon
o Washington
o [Other]
o I do not reside in the United States

Q3 What is your home zip code?

____

Q4 What is your gender?

o Male
o Female
o Non-binary
o Other
o Prefer not to say

Q5 How old are you?

o 18 to 25 years old
o 26 to 35 years old
o 36 to 49 years old
o 50 to 64 years old
o 65 years or older

Q6 What is your marital status?
- o Single
- o In a long-term committed partnership
- o Married/Legally paired
- o Seperated
- o Divorced
- o Widowed

Q7 How many school-aged children (under 18) live with you in your household?
- o None
- o 1
- o 2
- o 3 or more

Q8 What racial category do you most identify with?
- o White/Caucasian
- o American Indian/Alaskan Native
- o Asian
- o Native Hawaiian/Pacific Islander
- o Black/African American
- o Hispanic/Latino
- o Other

Q9 What is the highest level of formal education you have completed?
- o Did not graduate high school
- o High school diploma or equivalent (GED)
- o Some college, no degree
- o Trade / Vocational Training / Technical Degree
- o Associate Degree
- o Bachelor's Degree
- o Master's Degree
- o Professional Degree
- o Doctorate Degree

Q10 What is the expected annual income for your household?
- o Less than $50,000
- o $50,000 to $74,999
- o $75,000 to $99,999
- o $100,000 to $149,999
- o $150,000 or higher
- o Prefer not to answer

Q11 What political ideology do you mostly affiliate with?
- o Liberal
- o Moderately Liberal
- o Moderate
- o Moderately Conservative
- o Conservative

Q12 How many adults in your household are currently employed including yourself?
o None
o 1
o 2
o 3 or more

Q13 Which of the following best describes your current employment status?
o Employed, full-time
o Employed, part-time
o Student
o Unemployed
o Retired
o Other

Q14 What type of industry do you work in?
o Private Sector
o Public Sector
o Self Employed
o Other

The next series of questions focus on school transportation. While answering these questions consider only ONE of your school-aged children.

Q15 What age is this child?
o 5 years old or under
o 6 to 9 years old
o 10 to 13 years old
o 14 to 17 years old
o 18 years or older

Q16 What is the grade level of this child?
o Pre-K or Kindergarten
o Grade 1 to Grade 5
o Grade 6 to Grade 8
o Grade 9 to Grade 12

Q17 Is this child home-schooled?
o Yes
o No

Q18 In what place in the birth order does this child fall?
o Youngest
o Somewhere in the middle
o Oldest
o Only Child

Q19 What is the child's gender?
o Male
o Female

o Non-binary
o Other
o Prefer not to answer

Q20 Is the child physically disabled?
o No
o Yes
o Prefer not to answer

For these questions please continue considering the same child for which you answered questions on the previous section.

Q22 What is the approximate distance in miles from your home to your child's school?
o 1/4 mile or less
o 1/2 mile
o 3/4 mile
o 1 mile
o More than 1 mile

Q23 Is it geographically possible for your child to walk to school?
o Yes
o No

Q24 Before the pandemic, what was your child's primary method of travel to school?
o They walked or biked to school on their own
o They walked or biked to school with adult supervision
o They were given a (car) ride
o They rode the bus
o They drove themselves
o Other

Q25 Since the start of the pandemic, has your child's primary method of travel changed?
o Yes
o No

Q26 What is the current method by which your child is transported to school?
o They walk or bike to school on their own
o They walk or bike to school with adult supervision
o They are given a (car) ride
o They ride the bus
o They drive themselves
o Other

Q27 Why did it change? (Select all that apply.)
o Personal preference
o Attending different school due to older age (i.e., was elementary and now middle, was middle and now high)
o Attending different school due to personal preference (i.e., enrolled in different school)
o Attending different school due to different home (i.e., moved or relocated)

- Now/was home-schooled

Q28 Did you change the way your child traveled to school at any time during the pandemic because of health concerns (i.e., increased social distancing)?
- Yes
- No

Q29 Are there sidewalks along your child's current route to school?
- Yes
- Some Sidewalks/Partial Coverage
- No

Q30 Are there crossing guards present at intersections along the route to school?
- Yes
- Some Crossing Guards/Partial Coverage
- No

Q31 To what extent does high traffic areas or busy intersections influence your decision to allow your child to walk or bike to school?
- Not at all
- To a little extent
- To some extent
- To a moderate extent
- To a large extent

Q33 Approximately how long is your child's bus ride to school?
- Less than 30 minutes
- Between 30 minutes and 1 hour
- 1 hour to 2 hours
- More than 2 hours

The last series of questions focus on your own travel patterns as a result of the pandemic.

Before the pandemic, how did you usually travel to where you needed to go within the community for work, shopping, errands, or medical appointments?
- I drove
- I walked
- I rode a bicycle
- I used public transportation
- I used a taxi/Uber/Lyft service
- A friend/family member drove me

Q40 Has this mode of transportation changed as a result of the pandemic?
- Yes
- No

Q41 As a result of the pandemic, how do you usually travel to where you need to go within the community for work, shopping, errands, or medical appointments?
- I drive

- I walk
- I ride a bicycle
- I use public transportation
- I use a taxi/Uber/Lyft service
- A friend/family member drives me

Q42 Do you own a vehicle?
- Yes
- No

Q43 What kind of vehicle is your primary vehicle?
- Passenger car
- Sport utility vehicle (SUV)
- Van
- Pickup truck
- Semi-truck
- Motorcycle
- Other

Q44 How many vehicles do you own?
- 1
- 2
- 3 or more

Q45 How many years of driving experience do you have?
- 1 year or less
- 2 to 5 years
- 6 to 10 years
- 11 to 15 years
- 16 years or more

Q46 Do you have a driver's license?
- Yes
- No

Q47 Do you have any health issues or disabilities that affect your ability to drive?
- Yes
- No
- Prefer not to answer

Q48 How long have you lived in your current community/neighborhood?
- Less than 1 year
- 1 to 3 years
- 4 to 6 years
- 7 to 10 years
- Longer than 10 years