Ready to ride: security and transit-related determinants of ride-hailing adoption in Latin America

Transport Division

Daniel Oviedo
Orlando Sabogal-Cardona
Lynn Scholl

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Lynn Scholl (lscholl@iadb.org)

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Acronyms

CFA	Confirmatory Factor Analysis
LAC	Latin America and the Caribbean
LATAM	Latin America
SEM	Structural Equation Model
TNC	Transportation Network Company

Contents

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Daniel Oviedo[2], Orlando Sabogal-Cardona[2], Lynn Scholl[1]

Abstract

Previous research on ride-hailing has focused on the effects that the built environment, demographic variables, and personal attitudes have on the frequency of ride-hailing use, finding that adopters are mainly young and highly educated people with increased levels of technology embracement. Despite that some scholars have shown that the convenience of ride-hailing such as their flexibility and major geographical coverage has led to users to prefer services provided by Transportation Network Companies (TNCs) over public transportation for some trips, there is a lack of research on how perceptions of public transit systems and TNCs can induce ride-hailing usage. In this article we extend the understanding of ride-hailing phenomena by proposing that structural gaps in public transit are key explanatory variables in the uptake and willingness to pay for ride-hailing trips. Building on an international survey in Mexico City, Bogotá, and Medellín, we develop a Structural Equation Model (SEM) incorporating latent variables expressing perceptions people have about features of ride-hailing and vulnerabilities in public transit. Results show that these variables are relevant. We also confirm that educational attainment and income are instrumental for ride-hailing trips, and that technology embracement is the most important variable to distinguish among levels of adoption. Findings inform public policy by focusing on the negative experiences of using public transit and how this could be generating more ride-hailing trips. TNCs are an attractive transport alternative that can fill gaps in public transit systems but that are also benefiting from structural problems in the transit systems.

JEL classifications: J16, N76, 032
Keywords: Ride-hailing, Public Transportation, Structural Equation Models, Transportation Network Companies

[1] Interamerican Development Bank, Washington, United States.
[2] Development Planning Unit, University College London.

1. Introduction

Ride-hailing has consolidated as a common transport alternative in virtually all markets where has started operation, generating debates about its sustainability implications. On the one hand, there is a concern that ride-hailing is increasing vehicle miles travelled (VMT) (Tirachini and Gomez-Lobo, 2019) and, more importantly, that could be taking passengers from public transportation (Oviedo et al., 2020). On the other hand, ride-hailing could improve sustainability by offering a mobility service similar to that offered by the private car, it could potentially reduce car ownership. Other theories proposed include the idea that ride-hailing could complement larger transport systems in the first or last mile trips (Hall et al., 2018), and that it has the potential to fulfill mobility needs in areas with gaps in public transport coverage (Barajas and Brown, 2020) or at moments when transit is not operating.

With early work focusing on North America, the mainstream of research has showed that being young, highly educated and technology savvy are often the main determinants for the adoption of ride-hailing services (Alemi et al., 2018a; Dias et al., 2017; Fu, 2020; Sabogal-Cardona et al., 2021). Recent literature on ride-hailing in the Global South reinforce these ideas (Acheampong et al., 2020; Etminani-Ghasrodashti and Hamidi, 2019), while challenging others such as if car availability has a significant effect on ride-hailing (Tirachini and del Río, 2019).

A thread of research that has not yet been explored in detail, and that is even more relevant in developing countries, is how current public transport systems have deep functional problems that can position ride-hailing as an even more appealing alternative. Problems in the operation, low levels of quality of service, recurrent mugging, and other personal security tensions in public transportation systems can set up the scenario in which people with enough financial resources see Transportation Network Companies (TNCs) as a safe and better transport option. Moreover, difficulties in travelling with bags and in travelling with kids, elders, disabled people, people with reduced mobility, or people temporary sick, can facilitate a transition towards ride-hailing trips.

In this research we focus on how perceptions of public transportation systems are related to the frequency of use of ride-hailing services and to other variables reflecting willingness to pay for ride-hailing services. We rely on an international survey gathered in the cities of Bogota, Medellin, and Mexico City. In a structural equation model (SEM), we include latent variables to capture user's perceptions related to public transit and TNCs, and attitudes regarding technology. Results show that fear of using public transportation is a relevant explanatory variable of the ride-hailing phenomena, raising issues about possible modal substitutions associated with gaps in quality and security of public transportation, particularly among those who can afford it. Results also confirm that high levels of education and technological embracement are the main determinants of the use of TNCs.

2. Literature Review

Ride-hailing services offer a set of features often not available in other transport modes and that are attractive for people. The possibilities of booking trips with a smartphone from any place, and at any time, add geographic coverage to users and more schedule alternatives. Also, having the opportunity to see the rating of the drivers and feedback from other users, knowing beforehand the type of vehicle where the service will be delivered, and having control over the details of the trip (e.g., pick up time, travel time, route) can increase perceptions of security. According to a recent literature review (Tirachini, 2020), the main reported reasons to use ride-hailing across many studies are: the affordable cost when compared to other transport modes; short travel times; reliable information about travel and waiting times; the convenience of electronic payment; and the possibility to avoid driving under the influence of alcohol. Other less frequent reasons to use TNCs are comfort, security/safety, avoiding the hassle of searching for parking, the ability for driver identification and fare transparency.

It is also important to bear in mind that some of these features might have a reverse effect on other users. For example, electronic payment can make the travelling experience easier for some people, but for other people without access to credit cards or that simply do not trust electronic transactions, it could become a barrier. Rooted in ride-hailing services is the need of access to internet, a luxury that is not available to everyone.

Specific research on the determinants of adoption have consistently shown that younger generations with high educational attainment and living in urban areas are more likely to adopt ride-hailing services (Alemi et al., 2018b, 2018a; Dias et al., 2017). Nevertheless, there are differences even within members of the same age cohort and the influence of income and built environment mediates throughout the different levels of adoption. For example, Alemi et al (2018b) focus on people born between 1981 and 1997 (generation X and millennials) and people born between 1965 and 1989 (preceding generation X) and using Latent Class Analysis find three different clusters of ride-hailing adopters (Alemi et al., 2018b). The first is characterized by higher adoption rates and is composed of established millennials not living with their parents. This cluster tends to live in areas with high-quality transit associated with more ride-hailing trips. The second cluster has members living with their parents from Generation X (high income) and Millennials (dependent on their families). With the second highest level of TNCs usage, ride-hailing trips in the second cluster are influenced by living in zones with high mix land-use. The third cluster has the lowest level of ride-hailing trips and people are characterized by living in rural areas, having low income, and being least educated that people in the other classes.

The influence of the built environment and the presence of public transit infrastructure has been highlighted in other works. For example, a recent study (Sabouri et al., 2020) considers 24 regions in the United States and using large datasets of Uber trips in multilevel models states that "…the built environment affects ride-sourcing in much the same way it affects travel by other modes." (Sabouri et al., 2020 page 9). That is to say that the "D" variables (Ewing et al., 2015; Sabouri et al., 2020) of the built environment (density, diversity, design, destination accessibility, and distance to transit) influence ride-hailing trips even after controlling for socio-demographics. A study in Chicago (Barajas and Brown, 2020) finds that there are clusters of pickups and drop-offs and a different pattern in overnight weekends ride-hailing pick-ups in cases where transit density seems to influence more night ride-hailing trips. In other words, TNCs appear to not be serving transit deserts. Instead, they are filling gaps in public transit schedules.

Assessment of how technology affinity affects ride-hailing has often been considered in ride-hailing studies (Alemi et al., 2018a; Dias et al., 2017; Lavieri and Bhat, 2019). A recent is study in China (Fu, 2020) gathered over 1,000 internet-based surveys, and after classifying respondents in heavy Information and Communication Technology (ICT) users and light users through a latent class cluster analysis LCCA, estimated an ordered logistic model. Results indicate that heavy ICT users are more likely to adopt ride-hailing. Another recent study was conducted in the United States (Kong et al., 2020) using 173,079 surveys from the 2017 U.S. National Household Travel Survey (NHTS) and a Structural Equation Model SEM. Results show that more engagement with technology explains ride-hailing adoption but after controlling for several demographics, is not useful to predict frequency of use.

Despite the demographic variables and the possible built environment effects, the characteristics (or bad quality) of other transport modes and the bad experiences using them also need to be considered when explaining ride-hailing adoption. Specifically speaking about public transit, there is a lack of knowledge on how current features in its operation and perceptions of people might influence the generation of ride-hailing trips.

3. Methods

The survey for this study was disseminated using an online panel service. Due to the COVID-19 pandemic it was not possible to conduct traditional household or intercept surveys. Information was gathered between September 2020 and November 2020 when infectious rates were still high in Colombia and Mexico, and when governments had some measurement in place to constraint people's mobility. Panel data became popular for research during the Coronavirus pandemic, yet it was already one of the main source of data used in previous ride-hailing research (Alemi et al., 2018b, 2018a; Fu, 2020; Lee et al., 2019; Moody and Zhao, 2020). The sample was designed to retrieve public transit users, private vehicle users, and ride-hailing users. Moreover, the panel data was gathered in such a way that the final sample represents main demographic characteristics in each city.

We elaborated a Structural Equation Model (SEM) that incorporates four latent variables and three main outcomes reflecting engagement with, and willingness to pay for, ride-hailing services. Before running the SEM, we tested the measurement part of the model using confirmatory factor analysis (CFA). SEM is a popular theoretical driven statistical technique where researchers have the flexibility to model complex social phenomena and to properly incorporate subjective perceptions of people. SEM has become very popular in transport studies (Golob, 2003; Oviedo and Sabogal, 2020) and has been a prime methodological approach in ride-hailing research (Acheampong et al., 2020; Etminani-Ghasrodashti and Hamidi, 2019; Kong et al., 2020; Lavieri and Bhat, 2019; Moody et al., 2019; Moody and Zhao, 2020).

3.1. Sample description

A quota sampling approach was followed ensuring that the final sample adequately represented distribution of gender, age, and income within each city. The quota also was set to include people living near transit stations. The minimum required sample size for each population was calculated as the highest value needed to obtain a 95% confidence level and a minimum accepted margin of error of 5% for each of the variables mentioned. This resulted in an estimated minimum sample size of 1,180 surveys for the city of Bogota, 1,195 for the Medellin Metropolitan Area and 1,175 for Mexico City. Nevertheless, we targeted greater sample size and ended up with 2,063 surveys for Bogotá, 2,033 for Medellín, and 2,007 surveys for Mexico City. After deleting observation with null values in key variables for our model the sample is slightly reduced to 1,959 surveys for Bogotá, 1,902 for Medellín, and 1,815 for Mexico City, that sums 5,667 total surveys. To the best of our knowledge, this is one of the largest survey sample sizes ever collected for specific ride-hailing research.

In Table 1 we present a summary of the sample. There is a balance between males and females and age distribution is similar across three cities, though Medellín has a higher value (36.383%) of people in the twenty to thirty age cohort than Bogotá (29.590%) and Mexico City (25.730%). Even though a person is often required to be above 18 years old to get an account in many ride-hailing services and even to get a credit card (needed to make electronic payment), the survey found that around 10% of people in every city is in the fifteen to nineteen category. A possible explanation for this is that some users lie when registering in the app, that they use someone else's credentials, or that an adult request the trip for the person under legal age. All respondents regardless of age are included in the analysis.

Table 1 Sample composition and demographics

	Bogotá	Medellín	Mexico City
Sample Size	1950	1902	1815
Percentage of total sample	34.410%	33.563%	32.028%
Gender			
Male	50.513%	52.629%	50.799%
Female	49.487%	47.371%	49.201%
Age			
15 to 20 years old	9.949%	11.199%	12.176%
20 to 30 years old	29.590%	36.383%	25.730%
30 to 40 years old	23.590%	24.974%	29.917%
40 to 50 years old	22.051%	17.666%	20.441%
50 to 60 years old	10.667%	7.834%	8.044%
60 to 70 years old	4.154%	1.945%	3.691%
Education level			
Low	28.718%	32.387%	43.196%
Medium	32.205%	32.334%	17.245%
High	39.077%	35.279%	39.559%
SES			
Low	49.641%	36.120%	13.884%
Medium	41.231%	52.208%	38.292%
High	9.128%	11.672%	47.824%
Internet in the phone			
No	35.333%	44.164%	36.694%
Yes	64.667%	55.836%	63.306%
Cars	0.000%	0.000%	0.000%
None	50.051%	57.098%	44.904%
One	37.538%	33.070%	39.780%
More Than One	12.410%	9.832%	15.317%
Relationship With the Head of Household (RHH)			
Head of Household	49.795%	44.848%	47.548%
Partner	20.564%	18.559%	18.292%
Child	24.667%	30.810%	29.642%
Other	4.974%	5.783%	4.518%
Kids in the Household			
None	61.487%	64.984%	62.700%
One	25.846%	24.448%	23.636%
Two	9.744%	8.675%	9.917%
More Than Two	2.923%	1.893%	3.747%
Elders in the Household			
None	61.487%	66.509%	59.945%
One	26.359%	23.449%	24.628%
More Than One	12.154%	10.042%	15.427%
Main transport mode			
Car	17.795%	12.513%	19.229%
Public transit	58.359%	62.513%	62.479%

Other	23.846%	24.974%	18.292%
Willingness to walk to nearest transit station			
No	27.744%	23.081%	32.727%
Yes	72.256%	76.919%	67.273%
Distance to nearest station			
Do not Know	1.846%	1.525%	3.912%
1 to 10 min	26.410%	29.916%	25.620%
10 to 20 min	31.026%	33.438%	25.620%
20 to 30 min	20.667%	19.085%	15.978%
more than 30 min	20.051%	16.036%	28.871%

First row has the number of surveys gathered and second row the percentage by city (out of the total 5667 surveys).
All other rows show the distribution of the variable within the city.
Education was originally asked considering the official titles in each country and then aggregated. The low category represents people with no education or with basic education, the medium category is for people with technical education, and high level is for people with undergraduate or postgraduate studies
Socioeconomic Stratum (SES) is an official measure used to categorize income level of people according to the place where they live considering facilities available and the built environment. Colombian SES range from 1 to 6 and here are grouped into low (1 and 2), medium (3 and 4), and high (5 and 6). Mexico has a different but similar scale, so we also grouped observations in Mexico into the low, medium, and high SES.

As can be seen in Table 1, Mexico has slightly more people with low education and a shorter amount with medium education. Socioeconomic Stratum (SES) is an official measure used to categorize income level of people according to the place where they live considering facilities available and the built environment. Colombian SES range from 1 to 6 and here are grouped into low (1 and 2), medium (3 and 4), and high (5 and 6). Mexico has a different but similar scale, so we also grouped observations in Mexico into the low, medium, and high SES. Mexico City sample has a large proportion of people in the high SES category (47.824%) compared to Bogotá (9.128%) and Medellín (12.672%). The percentages of people with mobile internet are similar for the three cities (64.667%, 55.836%, and 63.306%). It is important to notice that internet in the phone is expected to be an important predictor of ride-hailing trips and of willingness to pay for ride-hailing services. Nevertheless, people without internet in their phones could be users of ride-hailing services by requesting trips when having access to wi-fi connections.

Interestingly, most of the people in the sample do not own a private vehicle and a minority has more than one car. Barely half of the respondents are head of the household (HHH), and as expected, partner of the HHH is the most frequent kind of relationship with the HHH. The most usual household in the survey has no kids or elders. Public transit is the most used mode. This is reinforced by most of the people being willing to walk to the nearest transit station and most of the people below a twenty-minute distance to the nearest station.

We asked for seven levels of frequency of use of ride-hailing (Figure 1) finding that 21.8% of people have never used the service and that 19.6% use it only occasionally. The higher group of ride-hailing adopters use the service one or two times per week. Interestingly, 10.6% make between three or five trips per week and 5.9% make more than five trips per week. For this last category of highly adopters, it is possible that ride-hailing is instrumental for their daily mobility.

When intensity of ride-hailing use is analyzed according to the main mode of transport the person uses (Figure 1, bottom), some interesting differences emerge. While 14.9% of car users do not use ride-hailing, the percentage increase to 24.4% for transit commuters, suggesting that transit users are less likely than car users to adopt ride-hailing. This result is mirrored when looking at the category *Occasional ride-hailing use*, where 18.5% are car users and 20.5% are transit users. On the other hand, for the categories *Two or three trips per month* and up to *more than five trips per week*, car users are consistently more predominant.

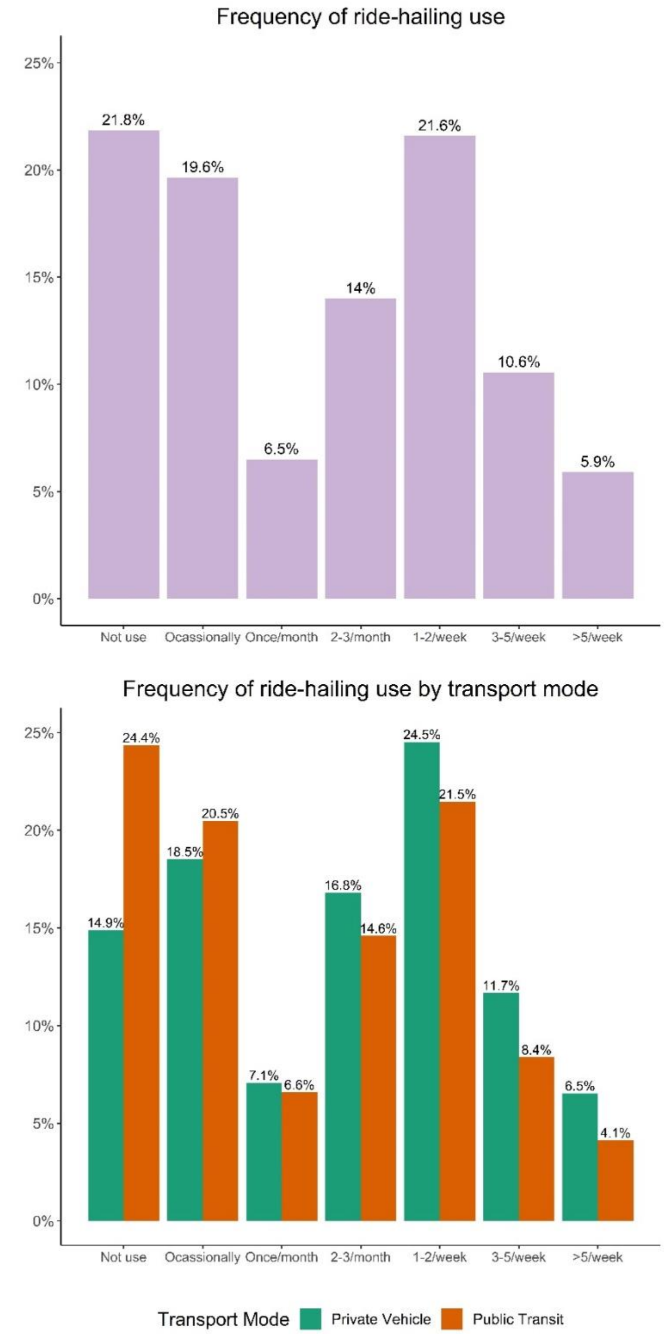

Figure 1. Frequency of use. Up: considering all modes. Bottom: considering private vehicle and public transit

Source: own elaboration

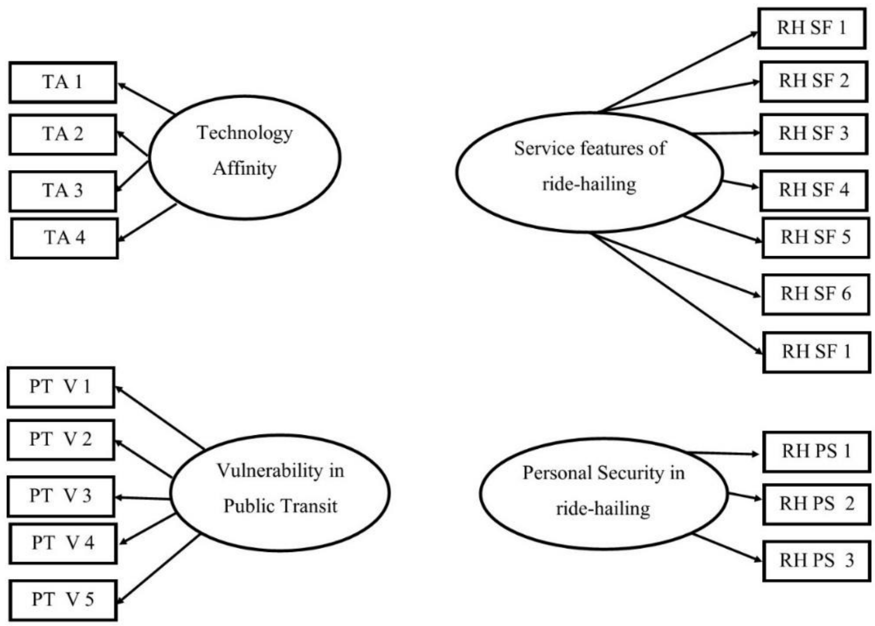

Figure 2. Path diagram of the confirmatory factor analysis CFA
Source: own elaboration

In Figure 2 we present the measurement part of the model or Confirmatory Factor Analysis CFA and in Table 2 we present mean value and standard deviation by city of all the indicator variables. The construct *Technology Affinity* is composed by variables expressing how relevant people consider technology is, as well as the use of streaming service. *Service Features of Ride-hailing* includes perceptions of key operational features, and the latent *Personal Security in Ride-hailing* includes the perception of safety from robbery, crashes, and violence and sexual abuse. *Vulnerability in Public Transit* expresses different fears people might experience when walking to a transit station or while waiting at a station. As can be seen in Table 2, the mean value and standard deviation for the indicators in T*echnology Affinity* and *Personal Security in Ride-hailing* have similar patterns across the three cities. For *Services Features of Ride-hailing* Bogotá has slightly lower values in the "easiness to transfer to other modes", "easiness to access the service", and "cost" indicators. Given that information was gathered during the Coronavirus pandemic, it is possible that feelings of risk towards getting the disease influenced some of the perceptions. For example, *Vulnerability in Public Transit* might be higher for people concerned about catching covid when travelling in public transit. An analysis of the measurement part of the model has to be conducted at the city level to make sure that latent variables mean the same and behave in a similar way for the three cities.

TABLE 2 Latent variables and indicators

Latent variables and indicators	Scale	Short Name	Bogotá		Medellin		Mexico City	
			mean	sd	mean	sd	mean	sd
Technology Affinity		TA						
Technology improved my daily life	Completely disagree (1) to completely agree (5)	TA 1	3.917	0.987	3.923	1.003	3.910	1.017
I like being updated in terms of technology		TA 2	3.883	0.990	3.857	1.038	3.757	1.043
Mobile apps are important for daily life		TA 3	3.758	1.016	3.713	1.067	3.626	1.106
I am a frequent used of electronic services (such as Spotify, Netflix, YouTube Music or Dropbox)		TA 4	3.832	1.152	3.799	1.227	3.796	1.216
Service features of ride-hailing		RH SF						
Travel time reliability	Very bad (1) to very good (5)	RH SF 1	3.833	1.046	3.964	1.016	3.887	1.044
Easiness to transfer to other modes		RH SF 2	3.578	1.328	4.006	1.146	3.974	1.182
Easiness to access the service		RH SF 3	4.081	1.091	4.237	1.008	4.151	1.102
Drivers' professionalism		RH SF 4	3.797	1.042	3.923	1.019	3.826	1.045
Comfort		RH SF 5	4.302	0.996	4.428	0.903	4.399	0.929
Cleanliness		RH SF 6	4.212	1.003	4.310	0.955	4.322	0.966
Cost		RH SF 7	3.486	1.179	3.789	1.094	3.436	1.150
Personal Security in ride-hailing		RH PS						
Safety from robbery	Very bad (1) to very good (5)	RH PS 1	3.516	1.165	3.591	1.152	3.586	1.192
Safety from accidents (crashes)		RH PS 2	3.290	1.171	3.358	1.155	3.480	1.169
Safety from violence and sexual abuse		RH PS 3	3.301	1.253	3.378	1.216	3.377	1.266
Vulnerability in Public Transit		PT V						

I do not like waiting at the public transit station for fear of being victim of robbery	Completely disagree (1) to completely agree (5)	PT V 1	3.700	1.157	2.596	1.310	3.347	1.278
I do not like waiting at the mass transit station for fear of being victim of some kind of violence or physical sexual assault (examples: physical abuse, touching or being photographed without approval)		PT V 2	3.506	1.202	2.573	1.292	3.300	1.298
I do not like waiting at the mass transit station for fear of being victim of some kind of violence and/or verbal sexual abuse (examples: slurs or obscene comments)		PT V 3	3.470	1.202	2.570	1.290	3.294	1.278
I do not walk to the nearest public transit station for fear of being robbed		PT V 4	3.273	1.276	2.707	1.290	3.139	1.332
I do not walk to the nearest public transit station for fear of being sexually abused		PT V 5	3.028	1.237	2.523	1.257	3.887	1.308
Service features of public transit		PT SF						
Cost	Very bad (1) to very good (5)	PT SF 1	2.821	1.271	4.161	0.993	3.948	1.179
Travel time reliability		PT SF 2	2.876	1.262	3.922	1.173	3.218	1.238
Easiness to transfer to other modes		PT SF 3	3.227	1.317	4.107	1.140	3.420	1.295
Easiness to access the service		PT SF 4	3.116	1.360	4.300	1.002	3.804	1.266
Other variables related to willingness to pay		RH WP						
I prefer using app-based services even if they are more expensive	Completely disagree (1) to completely agree (5)	RH WP 1	3.184	1.109	2.909	1.136	2.932	1.170
If I could pay, I would always use the app-based transport services		RH WP 2	3.870	1.091	3.594	1.216	3.813	1.204

3.2. Structural Model

In Figure 3 we present the path diagram for the Structural Equation Model and that conveys the main hypothesis in this paper. The model has three main outcome variables. The first main outcome is the frequency of use of ride-hailing services presented in section 3.1 (see Figure 1). The other two outcomes (see Table 2) are “I prefer using app-based services even if they are more expensive” and “If I could pay, I would always use the app-based transport services”, that are considered proxies to willingness to pay for ride-hailing services and shed light on how much, from a financial perspective, people have adopted ride-hailing services. While the former willingness to pay outcome shed light on how sensitive or unsensitive people is to fare increases, the latter express at what extent people is not engaging more with ride-hailing due to budget constraints.

The three outcomes are influenced by the four latent variables presented in Figure 2, and by the demographic and household composition variables (Table 1). The hypotheses behind this logic are: i) that as in standard ride-hailing adoption models presented in previous works, demographics and engagement with technology play a key role, something that we are also extending to willingness to pay; ii) that perceptions of the service features and enhanced security in ride-hailing positively affect the three main outcome variables; and iii) that experiencing higher vulnerability when using public transit systems is associated with more engagement in ride-hailing trips and with more willingness to pay for ride-hailing trips. The third hypothesis is the most relevant and its assessment is the main contribution of this paper. To the best of our knowledge, no prior study has explicitly and directly explored the connection of problems experienced in public transit with ride-hailing.

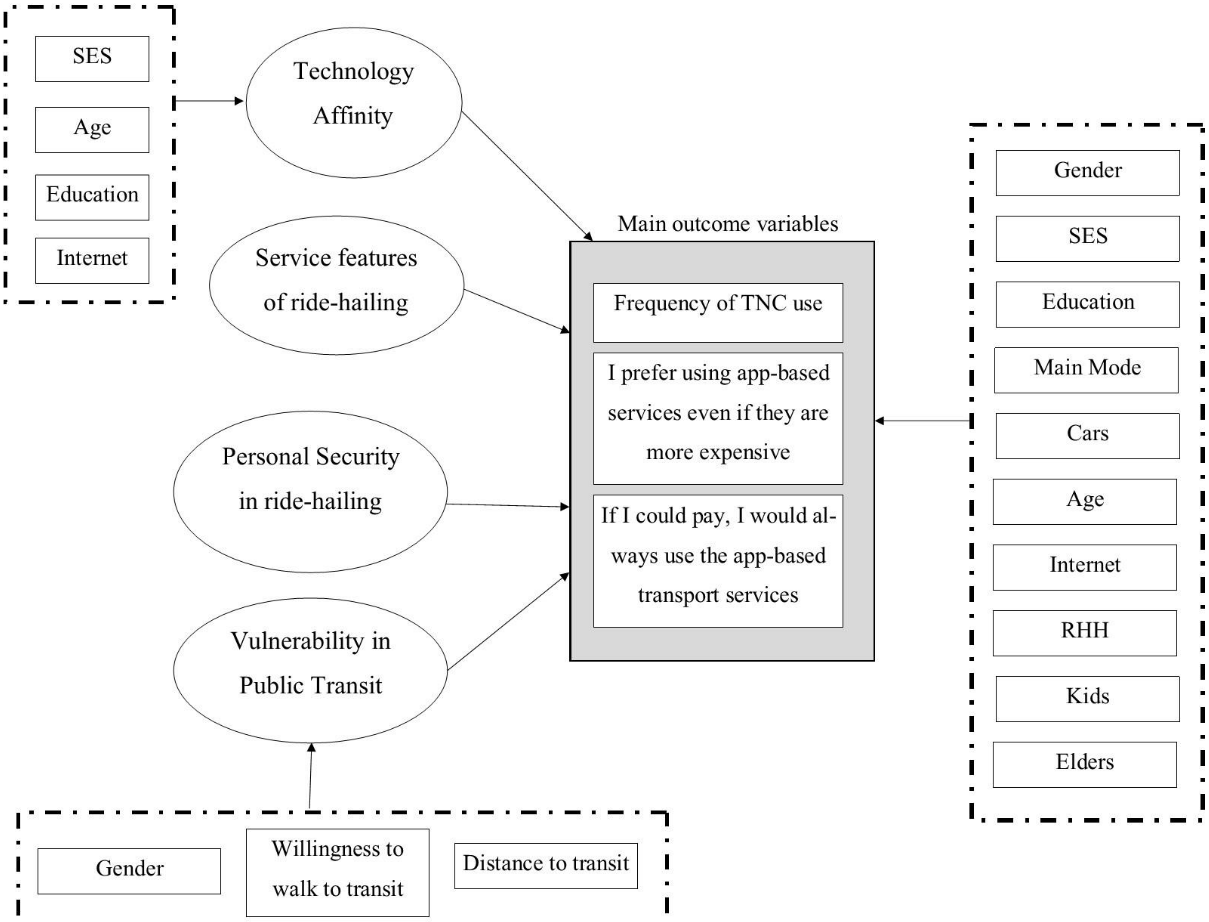

Figure 3 SEM path diagram
Source: own elaboration

Technology Affinity and *Vulnerability in Public Transit* are also dependent variables. As neither of these two latent variables is expressing anything related to ride-hailing, as is the case in the other three regressions, we do not refer to them as main outcome variables. It is important to notice, though, that the hypotheses behind how the regression for *Technology Affinity* has been formulated is that people with more income, who are younger, that are better educated, and that have regular internet in their mobiles are expected to have increased levels of engagement with technology. Ride-hailing services require internet access and are offered, delivered, and negotiated through an app installed in a smartphone. Therefore, it is essential that the app user (which sometimes may not be to passenger in the case of request rides for others, such as family members) be in the position to engage with all related details such as register and create the account, enter the origin and destination of the trip, track the trip, and rate the service. The cognitive side of using ride-hailing apps may not be a problem for many, particularly younger generations, or people that grew up with computers, tablets, and smartphones in their houses, or people with more education. Nevertheless, other population groups may struggle not only with the general use of a smartphone, but also with geolocating points in a map, as could be the case among older populations. Technology savviness also encompasses the likelihood of adopting new electronic services for its utility but also for its perceived image value. That is, high levels of technology embracement may serve to convey income, status, and competency to others.

On the other hand, for *Vulnerability in Public Transit* the rationale is that women are expected to feel more vulnerable, that willingness to walk to the nearest transit station is a predictor of vulnerability, and that people living close to transit are more familiar with the service and therefore feel least vulnerable. The overall SEM has to be also examined with an analysis of invariance.

4. Results

In Table 3 we present the output for the CFA proposed in Figure 3. We include the estimates of the loadings (Est), the respective error, the completely standardized value of the loadings (SV) to enable comparison across estimators, and the R-squared (R2) values. All loadings are significant (p value below 0.05) and load well into the latent variables. All SV are above the recommended 0.3 threshold. TA 4 is the only indicator with a not-high R-squared value (0.291), all others are above 0.4. The R-squared values for the three indicators in Personal Security in Ride-hailing are 0.784, 0.679, and 0.726. As shown at the end of Table 3, the four goodness of fit measures used to assess the model are well into the recommended margins. The SRMR and the RMSEA are below 0.05 and the TLI and CFI are above 0.95.

Higher values of the latent variables *Technology Affinity*, *Service Features of Ride-hailing*, and *Personal Security in Ride-hailing* are related to higher levels of engagement with technology and a more positive perceptions regarding ride-hailing services. On the contrary, higher values of *Vulnerability in Public Transit* are associated with more negative feelings towards public transit and with feeling more likely to be victim of a crime when using public transit.

We performed additional analysis of invariance to check if the model and the constructs are the same for both biological sex groups (men and women) and across the three cities. Results were in favor of invariance. With a strong measurement model and with the certain of having invariance constructs we can escalate the CFA to a SEM and include the key outcome variables in the research.

TABLE 3 Result of the CFA

Latent variables and indicators	Est	Error	SV	R2
Technology Affinity				
TA 1	1	---	0.689	0.474
TA 2	0.963	0.026	0.648	0.42
TA 3	1.059	0.028	0.687	0.472
TA 4	0.937	0.029	0.54	0.291
Service features of ride-hailing				
RH SF 1	1	---	0.813	0.661
RH SF 2	0.982	0.018	0.668	0.447
RH SF 3	0.932	0.015	0.734	0.539
RH SF 4	1.009	0.014	0.821	0.673
RH SF 5	0.813	0.014	0.724	0.524
RH SF 6	0.857	0.014	0.739	0.547
RH SF 7	0.917	0.017	0.671	0.45
Personal Security in ride-hailing				
RH PS 1	1	---	0.886	0.784
RH PS 2	0.929	0.012	0.824	0.679

RH PS 3	1.024	0.012	0.852	0.726
Vulnerability in Public Transit				
PT V 1	1	---	0.794	0.631
PT V 2	1.075	0.015	0.858	0.736
PT V 3	1.062	0.015	0.856	0.733
PT V 4	0.807	0.016	0.644	0.415
PT V 5	0.858	0.016	0.701	0.492

Est.: Estimate value. All estimates are significant with (p value < 0.05)

SV: Standardized solution of the estimates.
Goodness of fit measures are: srmr = 0.023; rmsea = 0.045, TLI = 0.966; CFI = 0.972

In Table 4 we present the coefficient regression estimates results for the three main outcome variables outlined in Figure 4. We will refer to “Frequency of use of ride-hailing services” as the first main outcome, to “I prefer using app-based services even if they are more expensive” as the second main outcome, and to “If I could pay, I would always use the app-based transport services” as the third main outcome. In Table 5 we put the coefficient regression estimates results for *Vulnerability in Public Transit* and *Technology Affinity*. Estimates, errors, and standardized estimates are presented in Tables 4 and 5.

TABLE 4 Result of the SEM, main outcome variables

	Frequency of use of ride-hailing services			I prefer using app-based services even if they are more expensive			If I could pay, I would always use the app-based transport services		
	Est	**Error**	**SV**	**Est**	**Error**	**SV**	**Est**	**Error**	**SV**
Technology Affinity	0.387***	0.041	0.141	0.523***	0.025	0.325	0.649***	0.027	0.391
Personal Security in ride-hailing	0.087*	0.047	0.048	0.144***	0.027	0.134	0.018	0.028	0.016
Service features of ride-hailing	0.433***	0.057	0.194	0.073**	0.034	0.055	0.273***	0.034	0.202
Vulnerability in Public Transit	0.151***	0.023	0.084	0.253***	0.014	0.241	0.251***	0.014	0.232
Gender									
Male	ref	ref	ref	ref	ref	ref	ref	ref	ref
Female	0.029	0.048	0.008	0.06**	0.028	0.027	-0.009	0.028	-0.004
SES									
Low	ref	ref	ref	ref	ref	ref	ref	ref	ref
Medium	0.262***	0.053	0.069	0.001	0.032	0	0.035	0.032	0.015
High	0.352***	0.068	0.078	-0.088**	0.04	-0.033	0.006	0.041	0.002
Education level									
Low	ref	ref	ref	ref	ref	ref	ref	ref	ref
Medium	0.213***	0.059	0.05	0.083**	0.035	0.034	0.054	0.035	0.021
High	0.442***	0.059	0.114	0.125***	0.035	0.055	0.033	0.035	0.014
Main transport mode									
Car	ref	ref	ref	ref	ref	ref	ref	ref	ref
Public transit	0.109	0.07	0.028	0.013	0.041	0.006	0.432***	0.041	0.184
Other	0.403***	0.078	0.089	0.145***	0.046	0.054	0.169***	0.047	0.062
Age									
15 to 20 years old	0.172*	0.09	0.029	-0.065	0.053	-0.018	-0.057	0.054	-0.016
20 to 30 years old	0.257***	0.063	0.063	0.006	0.037	0.002	0.05	0.038	0.02

30 to 40 years old	ref	ref	ref	ref	ref	ref	ref	ref	ref
40 to 50 years old	-0.303***	0.068	-0.064	-0.027	0.04	-0.01	0.03	0.041	0.01
50 to 60 years old	-0.639***	0.09	-0.096	0.098*	0.053	0.025	0.025	0.054	0.006
60 to 70 years old	-0.601***	0.136	-0.057	0.159**	0.08	0.026	-0.082	0.081	-0.013
Internet in the phone									
No	ref	ref	ref	ref	ref	ref	ref	ref	ref
Yes	0.472***	0.052	0.122	-0.003	0.031	-0.001	-0.072**	0.031	-0.031
Cars									
None	ref	ref	ref	ref	ref	ref	ref	ref	ref
One	0.377***	0.055	0.096	0.136***	0.032	0.059	-0.002	0.033	-0.001
More Than One	0.495***	0.078	0.087	0.166***	0.046	0.05	-0.073	0.046	-0.021
Relationship With the Head of Household (RHH)									
Head of Household	ref	ref	ref	ref	ref	ref	ref	ref	ref
Partner	-0.225***	0.064	-0.047	-0.033	0.038	-0.012	-0.007	0.038	-0.002
Child	-0.353***	0.064	-0.084	-0.057	0.037	-0.023	0.006	0.038	0.002
Other	-0.458***	0.109	-0.053	-0.053	0.064	-0.01	-0.052	0.064	-0.01
Kids in the Household									
None	ref	ref	ref	ref	ref	ref	ref	ref	ref
One	0.084	0.055	0.019	-0.017	0.033	-0.007	-0.018	0.033	-0.007
Two	0.133	0.081	0.021	-0.007	0.048	-0.002	0.036	0.048	0.009
More Than Two	0.423***	0.14	0.037	0.22***	0.082	0.033	-0.043	0.083	-0.006
Elders in the Household									
None	ref	ref	ref	ref	ref	ref	ref	ref	ref
One	0.196***	0.055	0.045	0.062*	0.032	0.024	0.06*	0.033	0.023

More Than One	0.197***	0.073	0.034	0.066	0.043	0.02	0.067	0.043	0.019

Est.: Estimate value. Significance levels: <0.1(*), <0.05(**), <0.01(***)

SV: Standardized solution of the estimates.

Goodness of fit measures are: srmr = 0.045; rmsea = 0.032, TLI = 0.925; CFI = 0.936

TABLE 5 Result of the SEM, regressors of not main outcomes

	Vulnerability in Public Transit		
	Est	**Error**	**SV**
Gender			
Male	ref	ref	ref
Female	0.377***	0.029	0.178
Willingness to walk to nearest transit station			
No	ref	ref	ref
Yes	-0.132***	0.036	-0.056
Distance to nearest station			
Do not Know	ref	ref	ref
1 to 10 min	-0.348***	0.1	-0.147
10 to 20 min	-0.236**	0.099	-0.102
20 to 30 min	-0.106	0.1	-0.039
more than 30 min	-0.085	0.099	-0.033

	Technology Affinity		
	Est	**Error**	**SV**
SES			
Low	ref	ref	ref
Medium	0.059**	0.024	0.043
High	0.172***	0.03	0.104
Age			
15 to 20 years old	-0.06	0.038	-0.027
20 to 30 years old	-0.011	0.027	-0.007
30 to 40 years old	ref	ref	ref
40 to 50 years old	-0.055*	0.03	-0.032
50 to 60 years old	-0.059	0.04	-0.024
60 to 70 years old	-0.169***	0.06	-0.043
Education level			
Low	ref	ref	ref
Medium	0.098***	0.026	0.064
High	0.2***	0.026	0.14
Internet in the phone			

No	ref	ref	ref
Yes	0.303***	0.023	0.214

Est.: Estimate value. Significance levels: <0.1(*), <0.05(**), <0.01(***)

SV: Standardized solution of the estimates.

Goodness of fit measures are: srmr = 0.045; rmsea = 0.032, TLI = 0.925; CFI = 0.936

4.1. The effect of perceptions

Technology Affinity has strong effects on the main outcomes, showing that people who are more engaged with technology are more likely to have increased levels of ride-hailing adoption, less sensitive to potential fare increases, and more willingness to make more trips should their economic capacity improve. This is an expected result consistent with prior literature (Alemi et al., 2018b; Fu, 2020; Kong et al., 2020). From Table 5 we can notice that people in medium and high-income groups have more levels of Technology Affinity. The same happens for education level, where the medium and high categories have positive effects. Interestingly, age is not an important variable, but for the group between 60 and 70 years old, for whom technology embracement is reduced by 0.169 (0.043 SV). The main variable affecting Technology Affinity is having internet in the phone (0.214 SV).

Personal Security in Ride-hailing shows a moderate effect on the frequency of use (0.048 SV). The effect is higher for the second main outcome (0.134 SV) and non-significant for the third. Service *Features of Ride-hailing* is strongly associated with frequency of use (0.194 SV) and with exclusive use of TNCs if could pay for it (0.202 SV), but a moderate effect on the second outcome. General characteristics offered by TNCs are more important for adoption than the specific features related to security. Nevertheless, those same specific features related to security are more instrumental for people to be insensitive to drop from the service if fare gets higher. In other words, results suggest that general features are having more relevance for the purpose of engagement with the service, but security associated with the service is more important for people to stay given a hypothetical fare increase.

Vulnerability in Public Transit has important effects on the three main outcomes, something that validates one of the main hypotheses in this article: that structural gaps in public transit operation are associated with ride-hailing. With SV of 0.151, 0.253, and 0.251 on the first, second, and third main outcomes, these results are evidence that the different issues people face or perceive could face when using public transit systems are pushing them to make more app-based trips. Interestingly, estimates for *Vulnerability in Public Transit* are larger than the estimates for the *Personal Security in Ride-hailing*, pointing at endemic problems and issues of fear of crime within transit systems to be more instrumental than the perceived security from TNCs. As we mentioned, the estimate of the *Personal Security in Ride-hailing* construct of the "If I could pay, I would always use the app-based transport services" outcome was not significant, yet the effect of the *Vulnerability in Public Transit* is significant with a high estimate of 0.251 (0.232 in the standardized version). If people feeling afraid of public transit improve their economic capacity, they are more likely to become exclusive ride-hailing users regardless of how safe they feel with TNCs.

Most of the variables used to explain *Vulnerability in Public Transit* are significant (see Table 5). Gender has a high estimate (see discussion below). As expected, people who are willing to walk to the nearest transit station have 0.132 lower feeling of vulnerability than those who are not willing to walk. Moreover, living to ten or twenty minutes from a transit station has important effects on feeling least vulnerable when compared to people who are not aware of their distance to transit stations.

4.2. Demographics

Gender is only significant for the second main outcome (I prefer using app-based services even if they are more expensive) but with a very low magnitude. Nevertheless, gender has a big influence on the vulnerability experienced in public transit (see Table 5). The 0.178 SV of being female shows that, even though men and women might feel insecure, women are more likely to feel insecure. The effect of gender on ride-hailing is mediated through Vulnerability in Public Transit. We decided to keep gender as a regressor in the three outcome variables to control for possible effects of gender that are independent of vulnerability in public transit.

Aligned with standard ride-hailing literature, the higher the SES the higher the ride-hailing usage. The medium and high categories have an effect of 0.262 and 0.352 on frequency. For the other two outcomes these categories are not significant or have a low value. SES is useful to explain current frequency of use but is not related to willingness to pay. Income is not as important as vulnerabilities in public transit to understand sensitivity of users. Younger people are more likely to make more ride-hailing trips and older people are less likely. Having internet on the phone has a large effect (0.122 SV).

With education level, we find a similar result to that of SES. Using the lowest level of education as reference, and looking at the frequency of use outcome, the medium category has an effect of 0.213 while the high category an effect of 0.442. Those categories have a moderate significant effect on the second outcome (0.083 and 0.125 estimates) and are not significant in the third outcome.

As with literature in the United States, the results presented so far reinforce the narrative of ride-hailing as a transport alternative being used by highly educated young people engaged in technology and with high income.

4.3. Transport Mode

From Table 4 we can see that car ownership (one and more than one car) have high estimates on frequency of use and on continuing to use the service if the fare increases. Car ownership is associated with more ride-hailing adoption. There are two non-competing possible explanations for this. One option is that car users have better economic capacity than people without cars, and therefore, can afford to use ride-hailing when their private car is not available. Also, there may be circumstances when using the car is not desirable. For example, when people want to avoid drinking and driving, driving late at night, or simply to avoid congestion or looking for parking.

Being a regular public transit user does not have any effect on frequency (using being a car user as the reference category). This result might seem counterintuitive when looking at Figure 1 where public transit users showed systematically least levels of frequency of use; nevertheless, an interpretation is that the effect of being a public transit user fades away when other control variables are included in the model. More precisely, the inclusion of SES, education level, and car ownership at some extent also explain why a person is a public transit user. Being a user of any other mode different to transit and car has a strong association of 0.403 with frequency of use. The other mode category has important effects on the last two outcomes related to willingness to pay, which could be suggesting that people outside private mobilities and public transit usage are keener towards ride-hailing service. The current paper is not providing evidence on the following, but we think that it is particularly important to understand if this share of the population, that embraces near to 20 percent of the total survey in Mexico City and almost 25%

of the total survey in the Colombian cities, are adopting a car-free lifestyle that can be complemented with the presence of ride-hailing, or if eventually will switch to car ownership.

The estimates for public transit users are non-significant for the first and second main outcomes, but there is a large estimate of 0.432 in the last main outcome variable. That is to say that being a regular user of public transit has no effect on frequency of use of ride-hailing services and on willingness to make more trips if the fare increases; nevertheless, if these same transit users somehow improve their economic capacity, they are willing to move their mobility towards ride-hailing. The main interpretation from this is that are significant share of people are not feeling comfortable in public transit, but that income is constraining them from changing transport modes. Therefore, there is a risk of increased loss in transit ridership as people improve their income, if public transit becomes more expensive, or TNCs reduce their prices.

5. Conclusions

This paper unpacks the complexities of ride-hailing adoption and willingness to pay in three Latin America cities. The paper builds on the largest dataset available to date for ride-hailing research in the region, which stems from a purpose-built survey for researching the behavior, characteristics and perceptions of ride-hailing users and non-users in the selected case studies.

The survey informing the manuscript was designed with ride-haling services in mind, seeking to reflect the unique service features and exploring in detail avenues suggested by earlier scholarship (see section 2) in relation to the role of technology affinity, individual characteristics, and service features of on-demand services as relevant factors explaining choices to use ride-hailing over other alternatives. The main innovations of the instrument and framing of the analysis in this paper are the incorporation of variables related with personal security and perceived vulnerability in public transport, as well as the analysis of subjective perceptions of willingness to pay for the use of on-demand services in contexts marked by (i) high dependency of public transit for urban mobility, (ii) high incidence of crime and insecurity in public spaces and public transport, and (iii) high levels of inequality in income and access to transport and opportunities between income groups.

The paper draws insights from the application of SEM, which has been favored in recent years in the academic literature on transport given their ability to understand latent constructs and interpret them based on conceptual models. In this case, the models enable the authors to make relevant links between previously unexplored latent constructs such as perceived vulnerability of public transit and outcome variables such as frequency of use of ride-hailing and proxies to willingness to pay for such services in cities with marked transport-related inequalities (Bautista-Hernández, 2020; Guzman et al., 2017; Levy and Dávila, 2017; Vecchio et al., 2020). The results make it clear that frequency of use of ride-hailing and willingness to pay for such services are strongly tied with factors of social and transport (dis)advantage such as affinity with technology and perceived levels of personal security both in ride-hailing and public transit. A particular contribution of this work, not previously deeply explored in literature, is the testing that different structural gaps people experience when using public transport might be contributing to the uptake of ride-hailing.

These findings are relevant for all actors involved in the provision, use, and regulation of on-demand urban transport services in Latin America. On the one hand, the high influence of technology affinity suggests a strong need for reducing the digital gaps between different groups of society, so more potential users can be included in the increasingly diverse urban mobility ecosystems in Bogota, Medellin, and Mexico. Furthermore, the findings related to personal security and public transit vulnerability suggest that more needs to be done from the public and private sectors to improve security and reduce the perceived vulnerability of public transit services if ride-hailing is not to become a substitute of public transit but an integral part of the urban transportation system of Latin American cities. The results in our paper serve as a cautionary tale for the effect of declining quality of public transit on those with the ability to pay for other alternatives like ride-hailing in cities that still depend largely on transit and the need for more action that improves perceived safety and security in such services. Findings about security also point at higher vulnerability of women in these cases. Gender influences the main outcome variables through vulnerability of public transit effects.

The analysis of the proxies for willingness to pay also suggests that some user groups are willing to devote more of their income to the use of ride-hailing for specific purposes under specific circumstances. This suggests potential avenues for policies around pricing that can increase public revenues from such willingness to pay from advantaged users that can be devoted to fund public transit.

Future work can build on the above findings and methods to explore similar issues in other cities in the region and in the global south, particularly those where ride-hailing services are only just entering the markets such as some countries in the Caribbean (e.g., Uber started operation in Jamaica in 2021). More research on the determinants of ride-hailing use and its links with the perceptions about other modes, particularly public transit, can contribute to current debates about the role of such services in an everchanging urban mobility systems and the challenges they entail for policy and regulation.

AUTHOR CONTRIBUTIONS

The authors confirm contribution to the paper as follows: study conception and design: Daniel Oviedo, Orlando Sabogal-Cardona and Lynn Scholl; data collection: Lynn Scholl; analysis and interpretation of results: Daniel Oviedo and Orlando Sabogal-Cardona; draft manuscript preparation: Daniel Oviedo, Orlando Sabogal-Cardona, and Lynn Scholl. All authors reviewed the results and approved the final version of the manuscript.

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