Civil Engineering and Applied Solutions

Research Article

journal homepage: ceas.journals.umz.ac.ir

CEAS Civil Engineering and Applied Solutions

Determinants of Ride-Hailing Adoption in Developing Urban Contexts: Evidence from Western Districts of Mashhad, Iran

Mahdi Nosrati [a], Amir Abbas Rassafi [a*], Hossein Rahimi Farahani [a]

[a] *Department of Transportation Planning, Faculty of Engineering, Imam Khomeini International University, Qazvin, Iran*

A R T I C L E I N F O

Article history:

Received 25 May 2026

Revised 24 June 2026

Accepted 01 August 2026

Available online 01 April 2027

Keywords:

Ride-hailing adoption

Travel behavior

Mode choice

Pandemic-related impacts

Discrete choice modeling

Public transportation

A B S T R A C T

Ride-Hailing (RH) services have emerged as a preferred non-shared mobility option, contributing to a notable increase in their volume and modal share within urban transportation systems in Iranian cities. Despite this trend, limited empirical research exists on RH adoption in Iran and other developing countries. This study investigates the factors influencing RH usage in Iran, focusing on Mashhad, the nation's second-largest metropolis. Data were collected in 2022 through 619 valid questionnaires encompassing four categories of variables: demographic, travel-related, environmental, and latent psychological factors. Exploratory factor analysis was first used to derive factor scores, followed by the development of an ordered probit discrete choice model. Findings reveal that variables such as marital status, employment, physical disability, household size, and social media use showed no significant effect. However, travel purpose, limited public transit access, proximity to traffic-restricted area, and trip characteristics such as duration and time of day significantly influenced usage. Among latent variables, privacy concerns and dissatisfaction with public transportation positively affected RH preference. Whereas pandemic-related apprehensions and economic constraints diminished it. The study offers insights into urban mobility behavior in developing contexts and highlights the multifaceted factors shaping RH demand.

How to cite this article: Nosrati, M., Rassafi, Amir A., Rahimi Farahani, H. Determinants of Ride-Hailing Adoption in Developing Urban Contexts: Evidence from Western Districts of Mashhad, Iran. Civil Engineering and Applied Solutions. 2027; 3(2): 69–86. doi:10.22080/ceas.2026.31910.1103.

1. Introduction

The rise of platform businesses has sparked a clash between traditional economic players and new, innovative actors [1]. App-based mobility encompasses a range of transportation services facilitated via smartphone applications. Among these, ride-hailing remains the most prevalent service. Despite being introduced over a decade ago, ride-hailing continues to generate considerable debate regarding its effects on urban transportation systems [2]. RH has altered traffic patterns, potentially affecting related externalities such as congestion, traffic accidents, and environmental impacts [3]. Transportation Network Companies (TNCs) such as Uber, Lyft, and Didi have fundamentally transformed the conventional taxi industry on a global scale. For instance, Uber's entry into New York in 2011 reduced hourly traditional taxi usage by 25% [4], similarly Shenzhen, China, saw a 20% decline in taxi revenues [5]. Such shifts highlight ride-hailing's dual role as both a complement to and a substitute for public transit, leading to substantial changes in urban mobility patterns [6, 7]. In Iran, the 2014 launch of RH services like Snapp facilitated by Information and Communication Technology (ICT) advancements and internet penetration revolutionized transportation. Snapp enables users to book rides, view driver profiles, estimate fares, and choose payment methods via smartphones, amassing over 40 million users and 2 million daily trips by 2020 [8].

Focusing on Mashhad, Iran's second-largest city, this research combines Exploratory Factor Analysis (EFA) and ordered probit

* Corresponding author.
E-mail addresses: rasafi@eng.ikiu.ac.ir (A. A. Rassafi).

https://doi.org/10.22080/ceas.2026.31910.1103
ISSN: 3092-7749/© 2027 The Author(s). Published by University of Mazandaran.
This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC-BY) license (https://creativecommons.org/licenses/by/4.0/deed.en)

modeling to analyze 619 survey responses in 2022. It identifies key demographic, travel-related, environmental, and latent psychological predictors of RH usage while highlighting the pandemic's unique impact [9]. The findings offer policymakers and urban planner insights into sustainable mobility solutions tailored to developing economies.

This study contributes to the existing literature in several ways. First, it investigates ride-hailing adoption in Mashhad, one of the largest metropolitan areas in Iran, where empirical evidence on ride-hailing behavior remains limited. Second, the study jointly examines demographic, travel-related, environmental, and latent psychological factors affecting ride-hailing usage. Third, it explicitly incorporates pandemic-related perceptions and concerns, as well as privacy concerns associated with public transportation, factors that have received limited attention in previous studies conducted in developing countries. Finally, by combining exploratory factor analysis with an ordered probit model, the study provides a comprehensive framework for analyzing both latent attitudes and observed travel behavior.

2. Research background

2.1. Analysis approaches

Recent advancements integrate machine learning with macro-level data (e.g., land use, urban density) and micro-level variables (e.g., demographics, real-time weather, traffic congestion) to model RH demand [10]. RH platforms operate as two-sided markets, where supply (drivers) and demand (passengers) interact dynamically [11, 12]. This framework emphasizes the interdependence of driver incentives (e.g., wage structures, surge pricing) and passenger demand in shaping service accessibility, pricing, and transaction volumes. For instance, driver availability directly affects wait times and user satisfaction, while demand surges influence pricing algorithms. Balancing these dynamics is essential for platform sustainability, as mismatches between supply and demand can lead to service inefficiencies or driver attrition [13].

Mode choice modeling, examines the behavioral and contextual factors influencing individuals' preferences for RH over alternatives like public transit or private vehicles. By accounting for the interconnected factors on mode choice (service attributes, passenger characteristics, and external conditions), the framework ensures a holistic analysis of transportation systems, balancing user needs, operational efficiency, and environmental variables [14]. Structural Equation Models empower the analysis by considering interactions between latent factors such as passenger attitudes and perceptions and observable variables like socioeconomic traits [4]. For instance, multigroup MIMIC models have been used to investigate the pandemic-driven shifts in RH intentions [9]. This study employs an ordered probit model to assess both observed variables and latent constructs. In ordered probit, a normal distribution of the error term is assumed, which can be more appropriate for modeling processes [15, 16].

2.2. SH demand determinants

RH services have revolutionized urban transportation, yet their demand dynamics remain context-dependent, particularly in understudied developing economies [3, 17]. This review synthesizes global evidence on socio-demographic, attitudinal, and environmental determinants of RH adoption, highlighting critical research gaps in Iran and similar contexts. By integrating latent variables and the pandemic-era behavioral shifts, this study advances methodological and empirical insights for sustainable mobility planning. The rapid proliferation of RH platforms like Uber, Lyft, and Snapp has redefined urban mobility, offering flexible alternatives to private vehicles and public transit [7, 8, 17, 18]. This review examines the determinants of RH demand, critiques methodological approaches, and identifies gaps in Iran's mobility literature.

2.2.1. Socio-demographics

Demographic factors such as age, income, and educational attainment serve as reliable indicators of RH adoption, with younger, affluent, and highly educated groups typically exhibiting higher usage rates [9, 19, 20]. However, regional variations challenge this trend; For instance, in China, users frequently lack higher education qualifications [21]. A counterintuitive pattern also emerges in low-income New York communities, which show unexpectedly high RH demand [22]. Gender remains a subject of debate in adoption research; while some studies in underdeveloped nations suggest higher female adoption rates of ride-hailing services [23, 24], recent evidence from countries such as Pakistan indicates lower female usage due to stronger safety concerns and contextual constraints. However, other findings suggest no significant gender or racial influences [25, 26]. Similarly, car ownership is generally linked to reduced demand in most studies [7, 23, 27], though this trend does not hold in Chile, where research shows no such relationship [18].

2.2.2. Travel and built environment

Environmental factors demonstrate a stronger association with usage frequency compared to socio-demographic characteristics [28]. Neighborhood walkability, urban compactness, pedestrian-oriented design, transit accessibility, educational institutions, and accessibility to town centers are associated with individuals' use of ride-hailing services [29, 30]. Demand patterns are notably shaped by trip purposes (such as work, education, leisure, or business) and urban density [17, 31]. Additionally, individuals residing near metro systems, commercial centers, or in densely populated urban areas show a higher likelihood of adopting ride-sourcing services [19, 32]. Similarly, limited parking availability and traffic congestion further drive reliance on RH platforms [33].

2.2.3. Latent factors

Psychological factors, including perceived safety, service quality, travel time efficiency, reliability, cost-effectiveness, flexibility, and environmental citizenship serve as primary motivators for adopting RH services [25, 31, 34-37]. Features like real-time tracking and driver verification significantly increase usage in regions with high crime rates [38], whereas dissatisfaction with public transportation drives transitions to RH platforms [39].

2.3. Iran's RH landscape

In Iran, RH services constitute a vital component of the urban mobility economy [40], distinguished by high public trust, perceived utility, and service convenience [41]. Iranian users prioritize flexibility and distrust in public transit [41]. Women, students, and formal-sector employees constitute primary adopters, while vehicle ownership reduces usage [24, 42]. Despite its societal embeddedness, empirical studies on Iran's RH ecosystem remain scarce, reflecting a broader neglect of developing contexts.

2.4. Research gaps and contributions

This study addresses three critical gaps. First, while latent variables (e.g., attitudes, perceptions) are recognized predictors of transportation demand, their role in RH adoption remains rarely understudied. We integrate attitudinal questions with observed variables in a Discrete Choice Model (DCM) to capture these nuances. Second, by examining the pandemic-era data, we reveal how health and economic shocks reshape mobility preferences. Third, although technology-enabled services such as ride-hailing comprise a substantial portion of the modal split in many developing countries, including Iran, scholarly research on this topic remains limited [3]. In particular, there is a notable gap in studies exploring the factors that influence the frequency of ride-hailing usage. Iran, as a developing country with a population of more than 90 million and large usage of RH services, is a worthy case study and opens up new insights on travelers' attitudes in developing countries.

3. Methodology

This study employs EFA and DCM to analyze factors influencing RH demand. Fig. 1 summarizes the overall research framework adopted in this study. The process begins with questionnaire design and data collection, followed by data preprocessing and exploratory factor analysis (EFA) to identify latent constructs. The extracted factor scores are then combined with demographic, travel-related, and environmental variables and incorporated into an ordered probit model to estimate the determinants of ride-hailing usage. Finally, marginal effects are calculated to facilitate the interpretation of the model results.

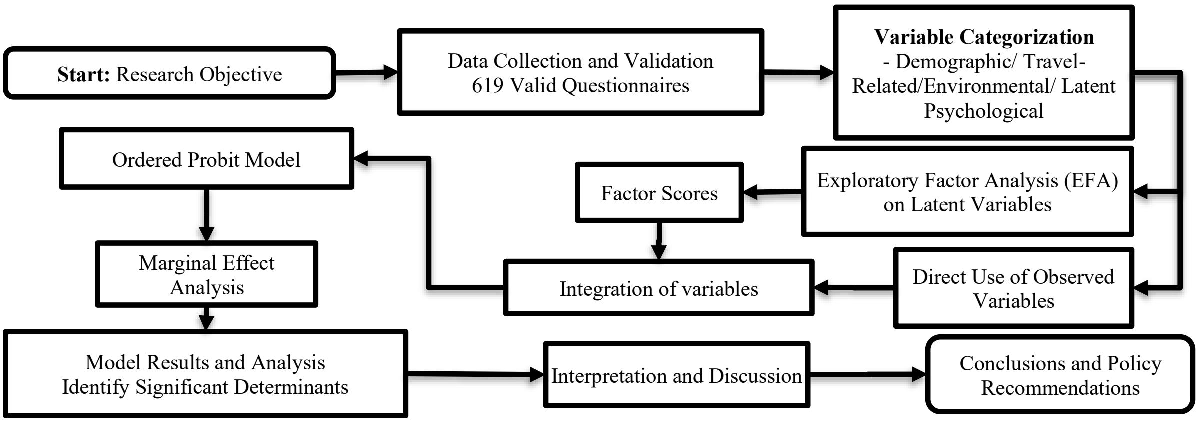

Fig. 1. Framework for estimating RH demand.

3.1. DCM framework and ordered probit model

DCMs analyze decisions among mutually exclusive alternatives, assuming individuals choose the alternative maximizing their utility [16]. The utility function U_{in} for individual i choosing alternative n is expressed as Eq. 1 [43].

$$U_{in} = V_{in} + \varepsilon_{in} \quad (1)$$

where:

U_{in}: The utility of alternative n for the decision maker i (i denotes the individual respondent and n denotes the alternative)

V_{in}: The observable or measurable component in the utility that the analyst calculates or estimates

ε_{in}: The portion of utility that is unobservable or error remains unknown to the analyst

The Ordered Probit Model is particularly suited for analyzing ordinal survey data (e.g., Likert-scale responses), where categories have inherent order but lack numerical meaning. The model preserves the ordinal nature of responses while accommodating unequal spacing between categories, making it a statistically rigorous method for interpreting ordered categorical variables [44].

Let i denote a respondent ($i = 1, \dots, N$), where N represents the sample size. The observed ordinal response of individual i to a survey question is denoted y_i, which can take integer values $(1, 2, 3, \dots, J)$. The model posits a latent variable y^*_i, representing the unobserved propensity of respondent i to agree with a statement, bounded between $(-\infty < y^*_i < +\infty)$. This latent variable y^*_i is linked linearly to a vector of explanatory features x_i by Eq. 2.

$$y^*_i = x_i\beta + u_i \qquad i = 1, \dots, n \tag{2}$$

Here, β parameter analogously to slope parameters in linear regression. While y^*_i is unobserved, its relationship to the observed y is defined as Eq. 3.

$$\begin{aligned} &y = 1 \;\; if \;\; -\infty < y^* < \kappa_1 \\ &y = 2 \;\; if \;\; \kappa_1 < y^* < \kappa_2 \\ &y = J \;\; if \;\; \kappa_{J-1} < y^* < \infty \end{aligned} \tag{3}$$

The parameters $\kappa_j (j = 1, \dots, J-1)$ are referred to as cut points or threshold parameters. For example, the probability density function of y^*_i for $J = 4$ is illustrated in Fig. 2 [44].

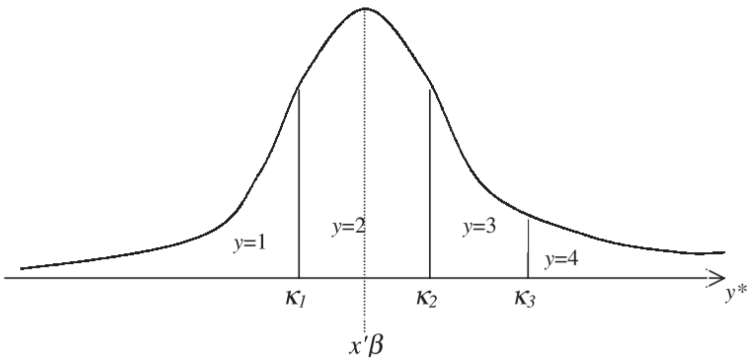

Fig. 2. Density function of y^*_i.

Let $P_i(y)$ represent the probability that respondent *i* chooses category *y*. This probability is expressed as Eq. 4.

$$P_i(y) = P(\kappa_{y-1} < y^* < \kappa_y) = \Phi(\kappa_y - x_i\beta) - \Phi(\kappa_{y-1} - x_i\beta) \;\; y = 1, \dots, J \tag{4}$$

where Φ is the standard normal cumulative distribution function. The log-likelihood for the sample is expressed as Eq. 5.

$$LogL = \sum_i ln[P_i(y_i)] = \sum_i ln[\Phi(\kappa_{yi} - x_i\beta) - \Phi(\kappa_{yi-1} - x_i\beta)] \tag{5}$$

DCMs, such as logit and probit models, require systematic validation to evaluate their accuracy. Common statistical methods used for this purpose include hypothesis testing, diagnostic assessments, and goodness-of-fit measures such as McFadden's pseudo-R^2 and the Akaike/Bayesian Information Criteria (AIC/BIC).

3.2. Exploratory factor analysis

Factor analysis is a versatile multivariate method extensively utilized in psychology, education, health, and social sciences to refine and validate measurement tools and theoretical concepts. EFA is a statistical method used to identify latent structures within a set of observed variables. Basically, it includes 5 steps, namely: Data suitability, extraction criteria, factor extraction, rotation, and interpretation [45]. In the current study, principal component analysis and varimax were used for factor extraction and rotation approaches, respectively [45, 46].

To validate the factor analysis framework, three statistical criteria were applied. First, the correlation matrix was examined to ensure moderate-to-strong correlations (≥ 0.3) among variables within proposed factors, a prerequisite for justifying shared latent constructs [46]. Second, the Kaiser-Meyer-Olkin (KMO) test assessed sampling adequacy, with values ≥ 0.6 confirming the data's suitability for EFA [45]. Finally, Bartlett's test of sphericity; ($p < 0.05$) rejected the null hypothesis of random noise, thereby supporting the use of EFA [46, 47]. Together, these tests ensure methodological rigor in identifying latent structures within the dataset.

4. Case study and data

The empirical survey underlying this research was conducted between January and March 2022, when the COVID-19 pandemic continued to affect everyday urban mobility patterns in Mashhad. During this phase, several public health measures and mobility restrictions were still enforced, shaping individuals' travel decisions and their reliance on ride-hailing services. Therefore, this study employing an online survey, investigated the determinants influencing the adoption of RH services by incorporating an analysis of both latent attitudinal and observed variables. Given the well-established presence and widespread utilization of RH services in

Mashhad, it was presumed that the respondents had substantial familiarity with this mode of transportation. Additionally, precautionary measures were implemented at the survey's outset, and comprehensive explanations were provided to participants to ensure clarity and accuracy in their responses. The internal consistency of the questionnaire was assessed using Cronbach's alpha, which yielded an acceptable level of reliability.

Participants were recruited through an online survey using a convenience sampling method, as the pandemic-related restrictions prevented in-person data collection. The questionnaire link was distributed via social media platforms and local digital communities of ride-hailing users in Mashhad. The study focused on residents of recently developed neighborhoods in the city's western districts, representing a more modern urban population. Eligible participants had completed at least secondary school education, resided in the selected areas, and were familiar with ride-hailing services. Individuals not meeting these criteria or providing incomplete responses were excluded from the analysis.

Mashhad, spanning an area of over 300 square kilometers, is situated in Khorasan Razavi Province in northeastern Iran, with a population of approximately 3.5 million and over 30 million visitors annually [48, 49]. Mashhad serves as Iran's leading tourist hub, drawing international visitors from countries such as Iraq, Bahrain, Kuwait, Lebanon, Pakistan, Afghanistan, Azerbaijan, and Qatar. The city is structured into 13 districts, with the Samen district being of particular religious and governmental importance (Fig. 3). Like many other major metropolitan areas, Mashhad grapples with substantial challenges associated with the widespread use of motor vehicles.

Before administering the full-scale survey, a pilot study was conducted. The pilot sample consisted of 45 transportation experts and students, each of whom provided individualized feedback on survey questions to ensure clarity and eliminate ambiguity. Following the pilot phase, and preliminary modeling, unclear or irrelevant questions were modified to enhance response accuracy and participation rates. The final data collection took place between January and March 2022. Traditional communities are primarily concentrated in the eastern districts of Mashhad. In contrast, the current study centers on more modern populations and neighborhoods characterized by recent urban development. The survey was distributed among individuals in Mashhad's Districts 9, 10, and 11, resulting in 619 completed questionnaires (District 12 is a developing area that currently lacks a significant residential population). The RH Questionnaire was systematically structured into two sections, comprising 46 questions in total. The first section focused on observed variables, employing multiple-choice and fill-in-the-blank formats, while the second section assessed latent variables using a five-point Likert scale.

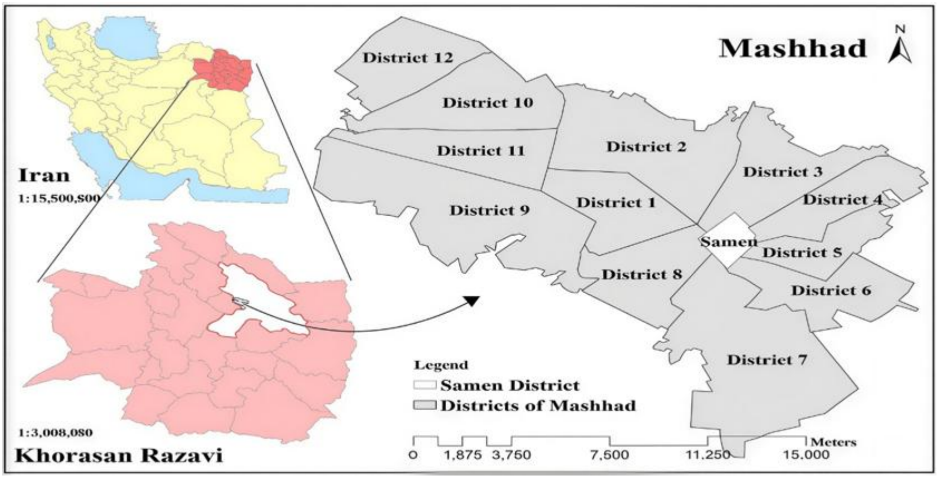

Fig. 3. The location and urban zoning of Mashhad [50].

5. Results

5.1. Demographic, travel-related and environmental characteristics

Table 1 summarizes the key demographic characteristics of the study sample. According to the table, more than 50% of the respondents are under 25 years old, possess educational qualifications below a postgraduate degree, and are predominantly single. This trend suggests that a significant portion of the respondents are students or pupils from universities and schools. Women comprise approximately 53% of the respondents, while men account for 47%. This gender disparity may be attributed to higher response rates among women, despite the survey being distributed nearly equally among both genders. Approximately 60% of the respondents are either students or part-time employed, aligning with the prevalence of lower income levels below 30 million Rials (MR) and between 30 and 80 MR. Additionally, the most common household structure consists of four family members with two licensed drivers.

The data reveals that 53% of the respondents reside within a five-minute distance from public transit stations, while 30.4% are between five and ten minutes away, indicating widespread accessibility to transit options. Additionally, the data suggests that most individuals have access to both private and public transportation options. Approximately half of the respondents prefer to delegate parcel deliveries to RH drivers, rather than making trips themselves.

Regarding RH travel behavior, 39.7% of the respondents did not specify a particular trip purpose. Among those who did, the most frequently cited trip purposes were returning home, work, and personal errands. Notably, the afternoon emerged as the most preferred time for RH usage, followed by morning trips and travel during the pandemic restrictions.

Table 1. Studied variables and their specifications.

Variable	Unit	Type*	Category	Freq. (%)
Age	Year	O	Under 18	19.4
			18 to 24	32.5
			24 to 30	6.8
			30 to 40	16.2
			40 to 50	15.3
			Over 50	9.9
Educational attainment	-	O	Less than high school diploma	23.6
			High school diploma or associate degree	31.2
			Bachelor's degree	28.9
			Postgraduate degree	16.3
Marital status	-	N	Single	57.4
			Married	42.6
Gender	-	N	Female	52.5
			Male	47.5
Use of RH for parcel delivery	-	N	Yes	51.2
			No	48.6
Walking time to the nearest public transit station	min	O	0 to 5	53
			5 to 10	30.4
			10 to 15	8.7
			>15	7.9
Trip purpose	-	N	Work	16.3
			Education	4.4
			Returning home	18.4
			Leisure	4.2
			Personal errands	16.2
			Various destinations	39.7
Preferred trip duration for RH use	min	N	>20	14.2
			≤20	24.7
			No preference	60.4
Daily social media usage	h	O	≤1	9.4
			1 to 2	27.3
			>2	63.2
Monthly income	MR	N	≤30	27.1
			30-80	27.1
			80-120	11.6
			>120	2.4
			Prefer not to answer	31.5
Employment status	-	N	Full-time	29.6
			Part-time	12.9
			Student	46
			Retired	2.7
			Housekeeper	3.9
			Unemployed	4.8
Household size	Persons	O	1	1
			2	7.3
			3	19.2
			4 or more	72.5

Number of licensed drivers in household	Persons	O	0 or 1	16.6
			2	48
			3 or more	35.2
Physical or intellectual disability	-	N	Yes	2.9
			No	96.8
Type of vehicle accessible to the respondent	-	N	Motorcycle	3.9
			Car	66.7
			both	5
			No vehicle	24.4
Preferred time of day for RH usage	-	N	During the morning period	12.1
			During the afternoon period	34.9
			During the pandemic restrictions	4.8
			At different times throughout the day	47.5
Frequency of RH usage in the past month	Times/month	O	0	25.4
			1 to 8	51.9
			> 8	22.8
RH usage before the pandemic	Times/month	O	0	17.1
			0 to 8	59.1
			> 8	23.4
Workplace/study location in CBD	-	N	Yes	25.5
			No	74.5
Residence in CBD zone	-	N	Yes	16.6
			No	83.4

* Type = Measurement type (O: Ordinal / N: Nominal)

The study also found high engagement with social media, as about two-thirds of the respondents reported spending more than two hours per day on social networking platforms. This aligns with the high participation rate in the online questionnaire, underscoring the respondents' familiarity with mobile technology and digital platforms.

In terms of geographical distribution, 74.5% of the respondents' workplaces or educational institutions and 83.4% of their residences were located outside the Mashhad traffic-restricted area. This finding is consistent with the urban layout, where the traffic-restricted area primarily accommodates administrative, commercial, and religious centers, as well as hotels, with few permanent residents. Given that this study primarily focuses on Mashhad's developed residential population, only a small proportion of the respondents resided within the traffic-restricted area.

The willingness to use RH services has declined in the aftermath of the COVID-19 pandemic and is shown in Fig. 4. Before the pandemic, 17.1% of the respondents reported not using RH services at all during the month, whereas this number increased to 25.4% during the pandemic. Notably, the overall 8.3% decline in RH usage primarily stemmed from a reduction among moderate users, while the proportion of frequent users remained relatively stable throughout the same period.

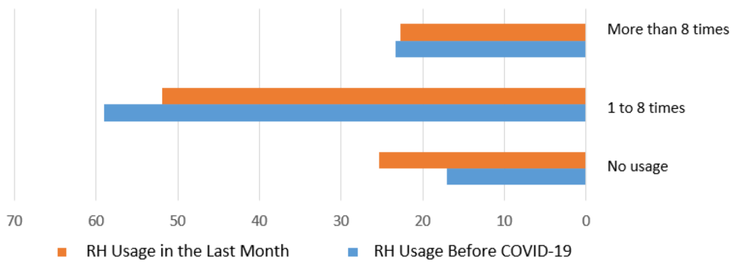

Fig. 4. Frequency of internet taxi usage.

5.2. Psychological variables

Fig. 5 portrays a summary of the level-of-importance questions made by the respondents. A substantial proportion of the respondents expressed significant concerns regarding parking availability during urban travel, highlighting the urgent need for adequate parking infrastructure across all districts of Mashhad. Furthermore, over 50% of the respondents agreed with statements emphasizing the importance of general safety during travel, additionally, more than 75% highlighted the necessity of always being aware of their location throughout a trip. Also, the majority of respondents reported difficulty in trusting strangers, reflecting security concerns. Additionally, the majority of participants are technologically proficient and remain informed about modern advancements. Knowing the cost of travel beforehand is a priority for most respondents. However, within this group, only 35.9% strongly agreed, and 26.7% agreed that they always opt for the most economical mode of transportation.

Most of the respondents preferred using pedestrian bridges when available, and 70% considered motorcycles to be a hazardous mode of transportation. The majority of the respondents are reluctant to share rides with other passengers, even if it would reduce travel costs, emphasizing the importance placed on privacy during travel. Less than half of the respondents perceived the facilities at stations and the fleets' conditions as inadequate. Additionally, 78.1% found buses and subways to be overcrowded and unpleasant.

Data collection for this study occurred during the COVID-19 pandemic and the cold seasons of 2021–2022. As expected, a significant proportion of the respondents avoided crowded places, gatherings, and similar activities to minimize the risk of contracting the virus. Most of the respondents exhibited environmentally conscious attitudes. Specifically, 72.2% believed that environmental protection efforts should persist; similarly, 69.9% expressed a willingness to pay more for environmentally friendly products. 75% of the respondents identified traffic congestion as a major cause of inconvenience. Congestion and pollution in central urban districts are significant concerns, as the majority of the respondents rely more on private vehicles than on public transportation.

Fig. 5. Aggregate shares of responses to the level-of-importance questions from the respondents.

5.3. EFA

The inclusion of numerous correlated attitudinal variables in behavioral models introduces complexity. To address this, exploratory factor analysis is employed to reduce observed variables into fewer uncorrelated latent constructs (factors). This section applies principal components analysis to distill the respondents' attitudes into interpretable dimensions, generating factor scores for integration into DCMs. Table 2 presents the factors identified by loadings exceeding 0.4. After pruning variables with weak loadings (<0.4), six factors were explored, namely (1) Parking and congestion concerns, (2) Safety and security concerns, (3) Concerns about the pandemic, (4) Privacy concerns regarding public transit, (5) Economic concerns, and (6) Variety-seeking perceptions.

Table 2. Results of the EFA.

Component items	Mean	Standard deviation	Communality	1	2	3	4	5	6
I often worry about finding a parking spot during urban trips.	3.85	1.064	0.560	0.704					
Constructing parking lots in city centers should be a priority.	4.43	0.834	0.543	0.601					
Traffic congestion is a major problem for me, and it bothers me.	4.09	1.001	0.489	0.570					
Time spent on daily commutes is wasted time.	3.68	1.204	0.485	0.559					
If a pedestrian bridge exists, I usually use it to cross the street.	4.24	1.060	0.446		0.595				
Being able to track my location at any moment during a trip is important to me.	4.25	0.947	0.462		0.569				
I find it hard to trust strangers.	4.16	0.915	0.447		0.555				
I always choose the shortest route, even if it is only two or three minutes shorter.	3.90	1.062	0.498		0.444				
I believe motorcycles are dangerous vehicles.	3.93	1.225	0.426		0.433				
Due to not contracting the pandemic, I have almost completely stopped visiting relatives, going to cafés, restaurants, etc.	3.77	1.201	0.653			0.795			
Avoiding the pandemic due to sensitivity, weakness, or illness of my relatives is very important to me.	4.40	0.809	0.626			0.746			
Buses and subways are usually crowded, and this is bothersome.	4.15	0.994	0.369			0.407			
Using public transportation with a friend, spouse, or children is difficult.	3.30	1.407	0.569				0.654		
I prefer living in a large house, even if it is far from public transportation and places I frequently visit.	3.26	1.344	0.456				0.636		
I am not interested in sharing travel with other passengers, even if it reduces travel costs.	3.58	1.298	0.542				0.622		
I try to choose the cheapest mode of transportation.	3.73	1.249	0.700					0.827	
Knowing the cost of travel before starting a trip is important to me.	4.51	0.747	0.584					0.688	
I believe having new experiences is important, and I am always trying new things.	3.79	1.009	0.560						0.740
I am so busy that I do not get to complete many of my daily tasks.	3.18	1.208	0.516						0.647

Table 3 presents the eigenvalues for the factors. As observed, in the final EFA, a total of six latent factors with eigenvalues greater than 1 have been identified. Additionally, the percentage of variance explained by each factor and the total variance explained for each category are provided. The explained variance represents the proportion of total variance accounted for by each extracted factor, indicating its relative contribution to explaining the observed data. Factors with higher explained variance capture a greater share of the information contained in the original variables. The cumulative explained variance reflects the overall proportion of total variance explained by all retained factors and provides an indication of how well the extracted factor structure represents the underlying data.

5.4. Model estimation

The modeling process was conducted in Stata software, evaluating a range of model specifications. Ultimately, the Ordered Probit Model with the highest content validity and statistical significance was selected. Additionally, the average marginal effects quantify the percentage change in the probability of choosing RH associated with each variable. This section introduces the variables used in the modeling process and outlines the steps taken to construct the model in Stata software. Following this, the results of the modeling are presented, along with a detailed discussion of their implications.

The dependent variable in the RH modeling is the frequency of using RH after the pandemic. Since the dependent variable in choice models must be discrete, it was grouped into intervals. The grouping was determined by evaluating the statistical and content significance of the model. The three ordered groups of the dependent variable demonstrated the highest significance in the ordered probit model. The classification thresholds were determined based on an iterative modeling process and the observed distribution of the data, ensuring meaningful behavioral segmentation of users. The independent variables encompass observed variables, including demographic attributes (e.g., age, gender, income), travel-related variables (e.g., access to personal vehicles, trip purpose), and environmental conditions (e.g., proximity to public transit, traffic congestion), as well as factors for attitudinal factors. A detailed description of the estimated coefficients is provided in Table 4.

The pseudo R^2 indicates an acceptable level of explanatory power for behavioral modeling; however, it also suggests that additional relevant factors may further improve the model's performance in future research. A diagnostic assessment showed that all Variance Inflation Factor (VIF) values were below 2.75, confirming the absence of significant collinearity among the predictors.

Table 3. Eigenvalues for the factors.

Component	Without factor rotation			With orthogonal factor rotation		
	Eigenvalue	Variance percentage	Cumulative variance percentage	Eigenvalue	Variance percentage	Cumulative variance percentage
1	3.646	19.188%	19.188%	2.108	11.094%	11.094%
2	1.443	7.594%	26.782%	1.743	9.171%	20.266%
3	1.385	7.289%	34.070%	1.666	8.767%	29.032%
4	1.205	6.344%	40.414%	1.533	8.066%	37.098%
5	1.145	6.027%	46.441%	1.487	7.824%	44.923%
6	1.108	5.834%	52.275%	1.397	7.353%	52.275%

Table 4. Ordered probit results.

Variable	Coefficient	T-statistic	P-value
AGE (reference group: above 50 years)			
Below 18 years	0.241	0.86	0.390
18–24 years	0.442	2.09	0.037**
24–30 years	0.766	2.91	0.004***
30–40 years	0.648	3.12	0.002***
40–50 years	0.226	1.11	0.266
Gender (reference group: female)			
Male	-0.641	-6.28	0.000***
Educational attainment (reference group: postgraduate degree)			
Less than high school diploma	0.099	0.36	0.723
High school diploma or associate degree	0.386	1.94	0.052*
Bachelor's degree	0.246	1.59	0.111
Monthly income (reference group: less than 30 MR)			
30-80 MR	0.005	0.03	0.974
80-120 MR	-0.124	-0.61	0.545
More than 120 MR	-0.010	-0.03	0.978
Prefer not to answer	-0.271	-2.05	0.041**
Type of vehicle (reference group: car)			
Motorcycle	-0.153	-0.59	0.556
Motorcycle and car	0.336	1.48	0.139
No vehicle	0.565	4.61	0.000***
Trip purpose (reference group: leisure)			
Work	0.893	3.28	0.001***
Education	0.697	2.08	0.037**
Returning home	0.528	2.01	0.045**
Personal errands	0.365	1.36	0.174
Multiple purposes	0.615	2.44	0.015**
Workplace/study location in traffic-restricted zone	0.379	3.25	0.001***
Preferred time of RH use (reference group: during COVID restrictions)			
Morning	0.505	1.89	0.059*
Afternoon	0.634	2.67	0.008***
Various times	0.525	2.24	0.025**
Using RH for package delivery	0.359	3.51	0.000***

Preferred trip duration (reference group: trips longer than 20 minutes)			
Trips shorter than 20 minutes	0.305	1.88	0.060*
No preference	0.358	2.44	0.015**
Walking distance to nearest public transit (reference group: less than 5 minutes)			
5–10 minutes	0.352	3.10	0.002***
10–15 minutes	0.349	1.95	0.051*
More than 15 minutes	0.049	0.26	0.796
Concerns & perceptions			
Parking and congestion concerns	0.083	1.54	0.123
Safety and security concerns	-0.036	-0.74	0.462
Concern about the pandemic	-0.126	-2.47	0.013**
Privacy concerns regarding public transit	0.092	1.84	0.066*
Economic concerns	-0.075	-1.50	0.134
Variety-seeking perceptions	-0.034	-0.68	0.497

Model fit statistics: Pseudo R^2: 0.167; Log likelihood: -515.507; Chi^2 (37): 206.35; p-value (prob > chi^2): 0.000; $p < 0.01$ (highly significant), $p < 0.05$ (statistically significant), $p < 0.10$ (marginally significant)

5.4.1. Marginal effects

The marginal effects were calculated for three groups of the dependent variable, including (1) No use of RH, (2) Moderate use of RH and (3) High use of RH. However, the average marginal effects for the moderate use group were not statistically significant, unlike those for the no use and high use groups. As a result, the marginal effects for the moderate use group are not discussed further in this section. The marginal effects for the no use and high use groups are presented in Table 5. These results provide insights into the factors influencing the likelihood of individuals either not using RH at all or using them frequently, offering valuable information for policymakers and service providers. Table 5 presents the average marginal effects of variables for groups with no usage and high usage of RH services. It shows how different factors (such as age, gender, education, income, vehicle ownership, trip purpose, and travel preferences) influence the likelihood of using RH services either very frequently or not at all.

5.4.2. Attitudinal factors

In the model, two attitudinal factors, namely concern about the pandemic and privacy regarding public transportation, demonstrated strong statistical significance, and at a lower level of confidence, parking and economic concerns were significant. Individuals who are more concerned about the pandemic and prioritize cost-effectiveness are less inclined to use RH. Additionally, individuals who value privacy and have a negative perception of public transportation are more likely to use RH. Two factors, diversity seeking and security, did not significantly influence the frequency of RH usage.

5.4.3. Demographic variables

According to Table 5, individuals aged 18-24, 24-30, and 30-40 are 9.6%, 18.5%, and 15.1% more likely, respectively, to use RH frequently. Gender also influenced RH usage; Being male reduces the probability of frequent RH use by 15.5%. Educational attainment impacted usage as well; Individuals with a high school diploma or associate degree are more inclined (9.2%) to use RH compared to those with a postgraduate degree. Contrary to expectations, monthly income and employment status did not significantly affect RH demand. The only significant coefficient related to income was the unwillingness to report monthly income, which negatively impacted the likelihood of using RH. Vehicle ownership was another significant factor; Not having access to a vehicle increases the probability of frequent RH use by 14.8. Social media usage did not show statistical significance in the model.

5.4.4. Travel-related variables

Trip purpose significantly influenced RH usage. According to Table 5, work, education, and returning home trips increase the likelihood of using RH by 19.6%, 14.3%, and 10.2%, respectively. Time of travel also played a role; Traveling in the afternoon increases the likelihood of using RH by 13.1%, while morning travel increases it by 9.9%. Additionally, trips lasting less than 20 minutes increase the likelihood of RH use by 6.7%. Using RH for transporting goods also increases the likelihood of usage by 8.6%.

5.4.5. Environmental variables

The location of the workplace or educational institution within the traffic-restricted area increases the likelihood of RH usage by 9.6%. However, residing within the traffic-restricted area did not show statistical significance. Regarding proximity to public transportation, walking distances of up to 10 minutes increased the likelihood of using RH, but walking distances exceeding 10 minutes had no significant effect.

Table 5. Average marginal effects of variables on high and no usage of RH services.

Variable	High usage group			No usage group		
	dy/dx	T-statistic	Significance level	dy/dx	T-statistic	Significance level
Age (reference group: above 50)						
Below 18	0.049	0.84	0.401	-0.071	-0.87	0.383
18–24	0.096	2.18	0.029**	-0.124	-2.02	0.043**
24–30	0.185	2.74	0.006***	-0.196	-3.03	0.002***
30–40	0.151	3.18	0.001***	-0.172	-3.02	0.003***
40–50	0.045	1.12	0.262	-0.066	-1.10	0.269
Gender (reference group: female)						
Male	-0.155	-6.36	0.000***	0.168	6.31	0.000***
Educational attainment (reference group: postgraduate degree)						
Less than high school diploma	0.021	0.35	0.724	-0.028	-0.36	0.721
High school diploma or associate degree	0.092	1.99	0.047**	-0.100	-1.90	0.057*
Bachelor’s degree	0.056	1.63	0.103	-0.067	-1.55	0.120
Monthly income (reference group: less than 30 MR)						
30-80 MR	0.001	0.03	0.974	-0.001	-0.03	0.974
80-120 MR	-0.031	-0.61	0.539	0.031	0.60	0.552
More than 120 MR	-0.002	-0.03	0.978	0.002	0.03	0.978
Prefer not to answer	-0.064	-2.05	0.040**	0.071	2.04	0.041**
Vehicle type (reference group: car)						
Motorcycle	-0.032	-0.62	0.533	0.044	0.57	0.566
Motorcycle + Car	0.083	1.36	0.173	-0.086	-1.62	0.105
No vehicle	0.148	4.33	0.000***	-0.134	-5.06	0.000***
Trip purpose (reference group: leisure)						
Work	0.196	3.82	0.000***	-0.241	-3.02	0.003***
Education	0.143	2.03	0.043**	-0.197	-2.11	0.035**
Returning home	0.102	2.28	0.023**	-0.155	-1.93	0.054*
Personal errands	0.066	1.48	0.139	-0.110	-1.33	0.184
Multiple purposes	0.123	2.98	0.003***	-0.177	-2.28	0.022**
Preferred time for RH (reference group: during COVID restrictions)						
Morning	0.099	2.01	0.044**	-0.146	-1.84	0.066*
Afternoon	0.131	3.20	0.001***	-0.178	-2.48	0.013**
Various times	0.104	2.65	0.008***	-0.151	-2.10	0.036**
Trip duration for RH (reference group: trips longer than 20 minutes)						
Trips shorter than 20 minutes	0.067	1.93	0.053*	-0.084	-1.85	0.064*
No preference	0.080	2.64	0.008***	-0.097	-2.33	0.020**
Work/study location in traffic-restricted area	0.096	3.10	0.002***	-0.092	-3.46	0.001***
Use of RH for cargo/packages	0.086	3.52	0.000***	-0.093	-3.50	0.000***
Walking distance to nearest public transit stop (reference group: less than 5 minutes)						
5–10 minutes	0.086	3.02	0.003***	-0.088	-3.20	0.001***
10–15 minutes	0.086	1.82	0.069*	-0.088	-2.10	0.036**
More than 15 minutes	0.011	0.26	0.798	-0.013	-0.26	0.794

Significance levels: $p < 0.10$ */ $p < 0.05$ **/ $p < 0.01$ ***
Interpretation:
Positive coefficients → Increase in probability of using RH frequently – Negative coefficients → Increase in probability of not using RH

6. Discussion

Given that the factors influencing the choice of RH services in developing countries have rarely been analyzed, this study aims to fill this research gap. This section provides a detailed discussion of the results of demand modeling and discusses explanatory variables.

6.1. Latent attitudinal factors

Previous studies have reported that attitudinal variables such as being technology-friendly, environmentally friendly, variety-seeking, concerns about security, cost-effectiveness, and privacy significantly impact the willingness to use RH services [4, 31, 33, 51, 52].

Among previously introduced attitudinal factors, variety-seeking, security, economic concerns, and parking and traffic congestion were statistically insignificant at the 90% confidence level. The insignificance of some psychological factors may reflect contextual and socio-spatial differences compared to previous studies.

Our findings, similar to Baghestani et al. [53] reveal that concerns about the pandemic reduce the likelihood of using RH services. Given the pandemic, it was expected that individuals would prefer to use more RH services. However, since most survey participants were from affluent urban districts of Mashhad (districts 9, 10 and 11) where car ownership is high, they preferred using their private vehicles instead of RH during the pandemic. Car ownership and its negative effects on RH usage have been reported in numerous studies [23, 42, 54].

The consideration of RH for travel is influenced by total costs [55]. In a study conducted before the pandemic, cost-effectiveness was reported as a significant positive factor in the adoption of RH in Tehran, Iran [4]. According to our results, economic concerns reduce the tendency to use RH; This may be due to the economic crises caused by the pandemic and economic instability in Iran, leading cost-conscious respondents to maximize savings across all expenses. Similarly, Azimi et al. stated that individuals concerned about affordability are less likely to use such services [39].

Contrary to the past studies, variety-seeking and safety and security did not significantly impact RH usage in this study [14, 17, 33, 34, 51]. RH services have been available in Iran for a decade, making them a common mode of urban transportation, and the lack of an effect from variety-seeking may stem from the diminished novelty of these services.

In Iran, users of RH services typically rely on public, semi-public, or non-private transportation and do not own personal vehicles [4, 24]. Despite competition between RH and public transportation due to short commute times and most respondents' proximity to public transit hubs like bus stations, concerns about safety and security do not significantly influence the frequency of RH usage. This contrasts with findings from other regions which attitudinal factors such as reliability, safety, and convenience have been shown to reduce frequent use of RH services [56]. In Mexico City, social issues like perceived crime rates and risks of sexual harassment in public transportation strongly shape the adoption of RH platforms [57].

Previous studies indicate that parking unavailability, high parking costs, and privacy concerns increase the likelihood of using RH [4, 17, 33]. Contrary to expectations, concerns about parking and traffic congestion had no effect on RH usage in our study. Given the limited parking spaces, traffic issues in most urban districts, and the stressful nature of driving in congestion, these factors were expected to influence demand.

However, privacy concerns and negative attitudes toward public transportation significantly increased the likelihood of using RH. This may be due to factors such as overcrowding, inadequate facilities, the pandemic [58], and the lack of cleanliness in public transit and traditional taxis.

6.2. Demographic variables

Findings indicate that RH services in Mashhad are predominantly used by young women without private vehicles, holding high school diplomas or bachelor's degrees. However, due to the online data collection method, despite validity checks, potential biases may exist.

Model estimations show that household size, number of licensed family members, marital status, monthly income, employment status, and social media usage were statistically insignificant at the 90% confidence level. About half of the demographic variables were statistically insignificant in the demand model for RH in Mashhad. This represents that, compared to attitudinal, travel-related, and environmental variables, demographic variables have less influence on RH adoption. Similarly, other studies reported that environmental and Attitudinal factors had a greater effect on the frequency of RH use than demographic variables [28, 56].

Contrary to previous studies, income and employment status had no significant impact on RH usage. These differences may reflect contextual variations across countries in terms of socioeconomic conditions, technology adoption, and the maturity of ride-hailing services. In the Iranian context, ride-hailing services have become widely accessible across different social groups, which may reduce the explanatory power of income and employment characteristics. Similarly, the widespread use of smartphones and mobile applications may limit the influence of social media usage as a distinguishing factor. These findings highlight the importance of local context when interpreting ride-hailing adoption behavior. However, employment status was a significant factor in Tehran's RH usage, possibly due to higher service costs in Tehran, leading students, unemployed individuals, or retirees to prefer traditional taxis [42].

Previous studies have shown that mobile phone usage and interest in technology directly influence the adoption of RH services [4, 24, 31]. However, contrary to expectations, the current study found no significant relationship between social media usage and RH adoption. This discrepancy may stem from methodological limitations, such as insufficient demographic categorization in the questionnaire design.

As expected, young individuals (18-40 years old) were more inclined to frequently use RH. This is likely due to their familiarity with mobile applications and RH services, as well as their vehicle ownership rates. Additionally, results indicate that gender is a significant determinant of ride-hailing usage, with women exhibiting a higher likelihood of using these services compared to men. This finding is consistent with previous studies highlighting gender-based differences in urban mobility patterns [58]. In particular, it may reflect the role of contextual factors in shaping women's driving experiences and in contributing to variations in perceived stress levels [23, 24].

Individuals with high school diplomas or associate degrees were more likely to use RH compared to highly educated individuals. This may be due to lower car ownership rates among students and self-employed individuals. Some studies found that educational attainment had no impact on travel mode choice [21, 42], while others reported that highly educated individuals were major users of RH in the US [19, 20, 31].

As expected, the absence of private vehicles significantly increased the likelihood of using RH due to mobility challenges, public transportation limitations, and security concerns, aligning with previous research [7, 23, 35, 42].

6.3. Travel-related variables

Findings indicate that all travel-related variables significantly influence the demand for RH services. Among these, work trips exert the greatest impact on increasing the likelihood of RH usage. In addition to work trips, educational trips and home-returning trips similarly contribute to a higher tendency to use RH services. This outcome may be attributed to the fact that RH services offer significant time savings compared to other transportation modes (such as traditional taxis and public transit), enabling passengers to reach their workplace or educational institution without delay. Moreover, since most administrative, commercial, educational, and healthcare centers were established in the central districts of Mashhad, these areas now experience traffic congestion, parking shortages, and are subject to traffic restrictions, all of which contribute to the high utilization of RH services. Additionally, due to exhaustion from work or study, travelers tend to prioritize getting home as quickly as possible, opting for the fastest and most convenient mode of transportation after private vehicles. However, for leisure trips, passengers often prefer private vehicles. The finding regarding the strong influence of work trips on increased RH usage aligns with previous studies [4, 17, 42, 59].

Contrary to expectations, findings indicate that during the pandemic restriction hours (10 PM to 4 AM), RH usage was at its lowest. This outcome may stem from the fact that individuals engaging in late-night activities such as social gatherings, dining out, or entertainment are generally from wealthier demographics and prefer to use their own comfortable vehicles. During other times of the day, the highest likelihood of RH usage occurs in the afternoons and mornings, respectively. This result may be explained by the tendency of citizens to schedule shopping, social events (e.g., dining out, visiting coffee shops, or seeing relatives), and medical appointments for the afternoon. Factors such as limited parking, traffic-related stress, safety concerns when waiting for transportation at night [7], and overcrowded public transit contribute to the preference for RH during these times. Similarly, other studies have reported that RH is frequently used for social-related travel, such as trips to bars, restaurants, and concerts [7]. Acheampong et al. also found that the majority of RH trips occur in the evening, with 31% between 12 PM and 5 PM and 29% between 5 PM and 11 PM [17].

Prior research reported that RH is often used for short-duration trips (10 to 30 minutes) [17]. Similarly, in the present study, trips lasting shorter than 20 minutes were associated with an increased likelihood of RH usage. This preference may arise from the time-consuming and cumbersome process of retrieving a private vehicle from a parking space, navigating traffic, and searching for parking at the destination. Other studies have also cited time savings and stress reduction as key reasons for choosing RH [7, 25]. Additionally, longer trips increase their costs and may lead to discomfort from prolonged sitting in low-quality vehicles (as RH fleets in Iran typically consist of older, less-maintained cars). In such cases, individuals may prefer public or private transportation.

Results from Table 5 indicate that using RH services for freight and package delivery significantly increases the likelihood of frequent RH usage. This suggests that individuals without access to a private vehicle prefer RH for its convenience. Additionally, RH services allow for package delivery without requiring the sender's presence during the trip, offering time savings and better tracking capabilities compared to alternative methods.

6.4. Environmental variables

Previous studies have identified several environmental factors that influence RH usage, including land use type, private car accessibility, public transportation availability, urban versus suburban residence, and population and employment density [4, 19, 31, 32, 54]. Circella et al. even reported that environmental factors have a greater impact than demographic variables on RH usage [28].

As expected, working or studying in districts subject to traffic restrictions is one of the most influential variables increasing RH usage. In these central urban districts, parking prohibitions, congestion, and travel restrictions make private vehicle use highly impractical for employees and students, leading them to opt for alternative modes. Compared to traditional public transportation, RH services offer greater comfort, shorter travel times, cost-effectiveness, privacy, technology-driven convenience, and enhanced security for these individuals [4, 42].

Some studies have reported that high accessibility to public transit (buses and metro) negatively affects RH usage [21, 23]. Conversely, other studies suggest that proximity to metro stations correlates with increased RH adoption [4, 32]. Findings from the present study indicate that when walking distance to a public transit station exceeds five minutes, passengers are more likely to use RH services. Notably, when walking time exceeds ten minutes, no significant impact on RH adoption is observed. Furthermore, given the high population density in restricted-traffic areas, it was expected that residents in these districts would have a higher tendency to use RH services [54]. However, the model does not indicate a significant relationship between living in a traffic-restricted area and RH usage.

7. Conclusions

RH have become a primary mode of transportation in Iran and developing countries. Despite their growing importance, there is a lack of sufficient research on RH usage in Iran. This study aimed to estimate the demand for RH in Iran (Mashhad) and provide a deeper understanding of the travel behavior of RH users. The findings reveal that urban transportation users are more likely to rely on RH when they do not have access to a personal vehicle. Therefore, identifying and analyzing the factors influencing RH usage is crucial for urban planning and transportation policy. As in previous studies, these factors were categorized into four groups, including demographic, travel-related, environmental characteristics, and latent factors. In this study, a stated preference online questionnaire was designed to gather comprehensive data on Mashhad citizens, covering these factors. A total of 619 questionnaires were collected. Due to pandemic-related restrictions and the online nature of data collection, the sample was mainly concentrated in the western and relatively more affluent districts of Mashhad (9, 10, and 11).

Results highlight the significance of both observed variables and latent factors of RH demand. Among the observed variables, demographic characteristics were found to be less influential compared to travel-related and environmental characteristics. More than half of the demographic variables, such as marital status, employment status, physical disability or illness, social media usage, family size, and the number of licensed drivers in the household, showed no significant impact on RH usage. Additionally, the demographic variables of education and income were statistically significant only at specific levels. Variables such as age, gender, and vehicle ownership were significant, and young women without access to a vehicle showed a high tendency to use RH frequently. Travel-related variables, including trip purpose, preferred travel time, and use of RH for transporting goods, were all significant and influential.

The findings indicate that travel-related characteristics are more important than other factors in determining RH usage. Business trips, educational trips, and returning home increased the probability of using RH, respectively. In contrast to other studies, leisure trips had a negative effect on RH usage. Regarding preferred travel times, traveling in the afternoon and morning increased the probability of using RH, respectively. Surprisingly, the pandemic restriction times (10 PM to 4 AM) had a negative effect on RH usage. Additionally, trips lasting shorter than 20 minutes and the use of RH for transporting goods were significant factors, though they have received less attention in prior literature. Among environmental variables, residing within the Mashhad traffic-restricted area did not significantly affect RH usage. However, being within the traffic-restricted area for work or school and increasing the walking distance to public transportation from 5 to 10 minutes increased the probability of using RH, respectively.

This study identified six latent factors through EFA, including concerns about (1) the pandemic, (2) parking and congestion, (3) safety and security, (4) privacy of public transit, (5) cost-effectiveness, and (6) variety seeking. Among these, concerns about the pandemic and privacy were the most significant ones. The factors of the pandemic and economic concerns had negative effects on RH demand. Conversely, concerns about public transportation, privacy and parking, and congestion increased the likelihood of using RH.

Overall, it should be noted that the study is based on an online, non-probability sample collected during the COVID-19 pandemic and concentrated in the western districts of Mashhad, which are generally characterized by relatively higher socioeconomic status. Consequently, younger, more educated, and technology-oriented individuals may be overrepresented in the sample. In addition, the data were collected during a unique phase of the COVID-19 pandemic, which may have influenced travel behavior and ride-hailing usage patterns. Therefore, the findings should be interpreted in light of both spatial and temporal contexts and may not be fully generalizable to the entire population of Mashhad, other Iranian cities, or different urban environments. Nevertheless, several of the identified behavioral relationships are expected to remain relevant under normal conditions, although their magnitude may vary over time.

Statements & declarations

Author contributions

Mahdi Nosrati: Data curation, Formal analysis, Investigation, Software, Visualization, Writing - Original Draft.

Amir Abbas Rassafi: Conceptualization, Investigation, Methodology, Supervision, Validation, Writing - Review & Editing.

Hossein Rahimi Farahani: Formal analysis, Investigation, Methodology, Validation, Writing - Review & Editing.

Funding

Funding information is not available.

Data availability

The data supporting the findings of this study are available from the corresponding author upon reasonable request. Due to privacy and ethical considerations, individual-level responses are not publicly shared.

Declarations

The authors declare no conflict of interest.

References

[1] Soltanzadeh, J., Blind, K., Elyasi, M. Exploring how regulators face platform business issues in the lifecycle stages: Evidence of Iranian ride-hailing platform business. Telecommunications Policy, 2023; 47: 102582. doi:10.1016/j.telpol.2023.102582.

[2] Oviedo, D., Sabogal-Cardona, O., Scholl, L. Transport and social (dis)advantage in ride-hailing. Area Development and Policy, 2025; 10: 295–325. doi:10.1080/23792949.2024.2404024.

[3] Martins, D. L., Meira, L. H., Costa, C. S., Pitombo, C. S. An overview of the impacts of ridesourcing in developing countries: Main topics and questions for future research. Latin American Transport Studies, 2024; 2: 100017. doi:10.1016/j.latran.2024.100017.

[4] Etminani-Ghasrodashti, R., Hamidi, S. Individuals' Demand for Ride-hailing Services: Investigating the Combined Effects of Attitudinal Factors, Land Use, and Travel Attributes on Demand for App-based Taxis in Tehran, Iran. Sustainability, 2019; 11: 5755. doi:10.3390/su11205755.

[5] Nie, Y. How can the taxi industry survive the tide of ridesourcing? Evidence from Shenzhen, China. Transportation Research Part C: Emerging Technologies, 2017; 79: 242–256. doi:10.1016/j.trc.2017.03.017.

[6] Tirachini, A. Ride-hailing, travel behaviour and sustainable mobility: an international review. Transportation, 2020; 47: 2011–2047. doi:10.1007/s11116-019-10070-2.

[7] Rayle, L., Dai, D., Chan, N., Cervero, R., Shaheen, S. Just a better taxi? A survey-based comparison of taxis, transit, and ridesourcing services in San Francisco. Transport Policy, 2016; 45: 168–178. doi:10.1016/j.tranpol.2015.10.004.

[8] Snapp. Snapp group annual report. Tehran (IR): Snapp; 2020. Report No.: 2.

[9] Said, M., Soria, J., Stathopoulos, A. Shifting Mobility Behaviors in Unprecedented Times: A Multigroup MIMIC Model Investigating Intentions to Use On-Demand Ride Services During the COVID-19 Pandemic. Transportation Research Record, 2023; 2677: 704–722. doi:10.1177/03611981221147520.

[10] Ke, J., Yang, H., Zheng, H., Chen, X., Jia, Y., Gong, P., Ye, J. Hexagon-Based Convolutional Neural Network for Supply-Demand Forecasting of Ride-Sourcing Services. IEEE Transactions on Intelligent Transportation Systems, 2019; 20: 4160–4173. doi:10.1109/TITS.2018.2882861.

[11] Weyl, E. G. A Price Theory of Multi-sided Platforms. American Economic Review, 2010; 100: 1642–72. doi:10.1257/aer.100.4.1642.

[12] Armstrong, M. Competition in Two-Sided Markets. RAND Journal of Economics, 2006; 37: 668–691. doi:10.1111/j.1756-2171.2006.tb00037.x.

[13] Wang, H., Yang, H. Ridesourcing systems: A framework and review. Transportation Research Part B: Methodological, 2019; 129: 122–155. doi:10.1016/j.trb.2019.07.009.

[14] Alemi, F., Circella, G., Mokhtarian, P., Handy, S. What drives the use of ride-hailing in California? Ordered probit models of the usage frequency of Uber and Lyft. Transportation Research Part C: Emerging Technologies, 2019; 102: 233–248. doi:10.1016/j.trc.2018.12.016.

[15] Greene, W. H. Econometric Analysis. 7th ed. Boston (MA): Pearson; 2012.

[16] Train, K. Discrete choice methods with simulation. 2nd ed. Cambridge (UK): Cambridge University Press; 2009.

[17] Acheampong, R. A., Siiba, A., Okyere, D. K., Tuffour, J. P. Mobility-on-demand: An empirical study of internet-based ride-hailing adoption factors, travel characteristics and mode substitution effects. Transportation Research Part C: Emerging Technologies, 2020; 115: 102638. doi:10.1016/j.trc.2020.102638.

[18] Tirachini, A., del Río, M. Ride-hailing in Santiago de Chile: Users' characterisation and effects on travel behaviour. Transport Policy, 2019; 82: 46–57. doi:10.1016/j.tranpol.2019.07.008.

[19] Dias, F. F., Lavieri, P. S., Garikapati, V. M., Astroza, S., Pendyala, R. M., Bhat, C. R. A behavioral choice model of the use of car-sharing and ride-sourcing services. Transportation, 2017; 44: 1307–1323. doi:10.1007/s11116-017-9797-8.

[20] Vinayak, P., Dias, F. F., Astroza, S., Bhat, C. R., Pendyala, R. M., Garikapati, V. M. Accounting for multi-dimensional dependencies among decision-makers within a generalized model framework: An application to understanding shared mobility service usage levels. Transport Policy, 2018; 72: 129–137. doi:10.1016/j.tranpol.2018.09.013.

[21] Tang, B.-J., Li, X.-Y., Yu, B., Wei, Y.-M. How app-based ride-hailing services influence travel behavior: An empirical study from China. International Journal of Sustainable Transportation, 2020; 14: 554–568. doi:10.1080/15568318.2019.1584932.

[22] Atkinson-Palombo, C., Varone, L., Garrick, N. W. Understanding the Surprising and Oversized Use of Ridesourcing Services in Poor Neighborhoods in New York City. Transportation Research Record, 2019; 2673: 185–194. doi:10.1177/0361198119835809.

[23] Nugroho, S. B., Zusman, E., Nakano, R. Explaining the spread of online taxi services in Semarang, Bogor and Bandung, Indonesia; a discrete choice analysis. Travel Behaviour and Society, 2020; 20: 358–369. doi:10.1016/j.tbs.2020.04.008.

[24] Lesteven, G., Samadzad, M. Ride-hailing, a new mode to commute? Evidence from Tehran, Iran. Travel Behaviour and Society, 2021; 22: 175–185. doi:10.1016/j.tbs.2020.09.006.

[25] Smith, A. Shared, Collaborative and On Demand: The New Digital Economy. Washington, D.C. (US): Pew Research Center; 2016. Report No.: 02.

[26] Hussain, I., Hussain, Q., Dias, C., Bargi, W. A., Ali, N., Abdullah, M., Cheng, L. Exploring Commuter's Preferences and Future Intentions to Use Ride-Sharing: A Case Study From a Developing Country. Journal of Advanced Transportation, 2025; 2025: 5516034. doi:10.1155/atr/5516034.

[27] Sabouri, S., Brewer, S., Ewing, R. Exploring the relationship between ride-sourcing services and vehicle ownership, using both inferential and machine learning approaches. Landscape and Urban Planning, 2020; 198: 103797. doi:10.1016/j.landurbplan.2020.103797.

[28] Circella, G., Alemi, F., Tiedeman, K., Handy, S., Mokhtarian, P. L. The Adoption of Shared Mobility in California and Its Relationship with Other Components of Travel Behavior. Davis (CA): National Center for Sustainable Transportation; 2018. Report No.: 03.

[29] Wali, B., Santi, P., Ratti, C. Modeling ride-hailing and carsharing adoption & use patterns: deciphering the substitutive and complementary impacts of built environment, transit accessibility, & active travel. Sustainable Cities and Society, 2025; 120: 105931. doi:10.1016/j.scs.2024.105931.

[30] Li, W., Ma, J., Cai, H., Chen, F., Qin, W. The role of built environment in shaping reserved ride-hailing services: Insights from interpretable machine learning approach. Research in Transportation Business & Management, 2024; 56: 101173. doi:10.1016/j.rtbm.2024.101173.

[31] Alemi, F., Circella, G., Mokhtarian, P., Handy, S. Exploring the latent constructs behind the use of ride-hailing in California. Journal of Choice Modelling, 2018; 29: 47–62. doi:10.1016/j.jocm.2018.08.003.

[32] Wang, S., Noland, R. B. Variation in ride-hailing trips in Chengdu, China. Transportation Research Part D: Transport and Environment, 2021; 90: 102596. doi:10.1016/j.trd.2020.102596.

[33] Sarjana, S., Ramadan, O., Sisiopiku, V. Analysis of Transportation Users' Preferences and Attitudes for Identifying Micro-Level Determinants of Transportation Network Companies' (TNCs) Growth. Journal of Transportation Technologies, 2020; 10: 251–264. doi:10.4236/jtts.2020.103016.

[34] Bhaduri, E., Pal, S., Goswami, A. K. Analysing heterogeneity in factors affecting adoption of ride-hailing services: a stepwise LCCA-MCDM modelling approach. Transportation, 2024; doi:10.1007/s11116-024-10563-9.

[35] Sikder, S. Who Uses Ride-Hailing Services in the United States? Transportation Research Record, 2019; 2673: 40–54. doi:10.1177/0361198119859302.

[36] Nguyen-Phuoc, D. Q., Su, D. N., Tran, P. T. K., Le, D.-T. T., Johnson, L. W. Factors influencing customer's loyalty towards ride-hailing taxi services – A case study of Vietnam. Transportation Research Part A: Policy and Practice, 2020; 134: 96–112. doi:10.1016/j.tra.2020.02.008.

[37] Anser, M., Ahmed, F., Ali, A. Investigating Factors Impacting the Use of Ride-Hailing Service Applications. International Journal of Management Research and Emerging Sciences, 2024; 14: doi:10.56536/ijmres.v14i3.637.

[38] Ghaffar, A., Mitra, S., Hyland, M. Modeling determinants of ridesourcing usage: A census tract-level analysis of Chicago. Transportation Research Part C: Emerging Technologies, 2020; 119: 102769. doi:10.1016/j.trc.2020.102769.

[39] Azimi, G., Rahimi, A., Asgari, H., Jin, X. Role of Attitudes in Transit and Auto Users' Mode Choice of Ridesourcing. Transportation Research Record, 2020; 2674: 1–16. doi:10.1177/0361198120941841.

[40] Tohidimehr, H., Bakhtiarizadeh, H. Money on the Way: Analyzing the Impact of Ride-Sharing on Labor, Income, and Expenditure in Iran. Income, and Expenditure in Iran (October 22, 2024), 2024; doi:10.2139/ssrn.5166284.

[41] Akbari, M., Amiri, N. S., Zúñiga, M. Á., Padash, H., Shakiba, H. Evidence for Acceptance of Ride-Hailing Services in Iran. Transportation Research Record, 2020; 2674: 289–303. doi:10.1177/0361198120942224.

[42] Edrisi, A., Rezaei, H. Assessment of how Ride-Hailing services affect individuals' travel mode choice in urban transportation. International Journal of Human Capital in Urban Management, 2021; 6: 81–96. doi:10.22034/IJHCUM.2021.01.07.

[43] Koppelman, F., Bhat, C. A Self-Instructing Course in Mode Choice Modelling: Multinomial and Nested Logit Models. Washington, D.C. (US): US Federal Transit Administration - Department of Transportation; 2006. Report No.: 04.

[44] Daykin, A. R., Moffatt, P. G. Analyzing Ordered Responses: A Review of the Ordered Probit Model. Understanding Statistics, 2002; 1: 157–166. doi:10.1207/S15328031US0103_02.

[45] Tabachnick, B. G., Fidell, L. S. Using Multivariate Statistics. 6th ed. Boston (MA): Pearson; 2013.

[46] Williams, B., Onsman, A., Brown, T. Exploratory Factor Analysis: A Five-Step Guide for Novices. Australasian Journal of Paramedicine, 2010; 8: 1–13. doi:10.33151/ajp.8.3.93.

[47] Hair, J. F., Black, W. C., Babin, B. J., Anderson, R. E. Multivariate data analysis. 8th ed. Boston (MA): CENGATE; 2019.

[48] Mirkatouli, J., Samadi, R., Hosseini, A. Evaluating and analysis of socio-economic variables on land and housing prices in Mashhad, Iran. Sustainable Cities and Society, 2018; 41: 695–705. doi:10.1016/j.scs.2018.06.022.

[49] Talebian, K., Riza, M. Mashhad, City of Light. Cities, 2020; 101: 102674. doi:10.1016/j.cities.2020.102674.

[50] Soltanifard, H., Roshandel, T., Ghodrati, S. Assessment and ranking of influencing factors in the relationship between spatial patterns of urban green spaces and socioeconomic indices in Mashhad urban districts, Iran. Modeling Earth Systems and Environment, 2020; 6: 1589–1605. doi:10.1007/s40808-020-00776-z.

[51] Jing, P., Chen, Y., Wang, X., Pan, K., Yuan, D. Evaluating the effectiveness of Didi ride-hailing security measures: An integration model. Transportation Research Part F: Traffic Psychology and Behaviour, 2021; 76: 139–166. doi:10.1016/j.trf.2020.11.004.

[52] Sedighi, M., Parsaeiyan, H., Araghi, Y. An Empirical Study of Intention to Continue Using of Digital Ride-hailing Platforms. The Review of Socionetwork Strategies, 2021; 15: 489–515. doi:10.1007/s12626-021-00098-1.

[53] Baghestani, A., Heshami, S., Mahpour, A. The impact of pandemic experiences on future similar situations: analysis of latent variables and trip purposes in ride-hailing choice. Transportation Planning and Technology, 2026; 49: 691–710. doi:10.1080/03081060.2025.2458606.

[54] Conway, M. W., Salon, D., King, D. A. Trends in Taxi Use and the Advent of Ridehailing, 1995–2017: Evidence from the US National Household Travel Survey. Urban Science, 2018; 2: 79. doi:10.3390/urbansci2030079.

[55] Habib, K. N. Mode choice modelling for hailable rides: An investigation of the competition of Uber with other modes by using an integrated non-compensatory choice model with probabilistic choice set formation. Transportation Research Part A: Policy and Practice, 2019; 129: 205–216. doi:10.1016/j.tra.2019.08.014.

[56] Loa, P., Nurul Habib, K. Examining the influence of attitudinal factors on the use of ride-hailing services in Toronto. Transportation Research Part A: Policy and Practice, 2021; 146: 13–28. doi:10.1016/j.tra.2021.02.002.

[57] Sabogal-Cardona, O., Oviedo, D., Scholl, L., Crotte, A., Bedoya-Maya, F. Not my usual trip: Ride-hailing characterization in Mexico City. Travel Behaviour and Society, 2021; 25: 233–245. doi:10.1016/j.tbs.2021.07.010.

[58] Firoozi Yeganeh, S., Khademi, N., Farahani, H., Besharat, M. A. A qualitative exploration of factors influencing women's intention to use shared taxis: A study on the characteristics of urban commuting behavior in Iran. Transport Policy, 2022; 129: 90–104. doi:10.1016/j.tranpol.2022.10.001.

[59] Zhen, C. Impact of ride-sourcing services on travel habits and transportation planning [Master's Thesis]. Pittsburgh (PA): University of Pittsburgh; 2015.