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Unraveling the travel patterns of ride-hailing users: A latent class cluster analysis across income groups in Yogyakarta, Indonesia

Muchlis Muchlisin [a,b,*], Jaime Soza-Parra [a], Yusak O. Susilo [c], Dick Ettema [a]

[a] Department of Human Geography and Spatial Planning, Utrecht University, 3584 CB Utrecht, Netherlands
[b] Department of Civil Engineering, Faculty of Engineering, Universitas Muhammadiyah Yogyakarta, Bantul 55183, Special Region of Yogyakarta, Indonesia
[c] Institute for Transport Studies, University of Natural Resources and Life Sciences (BOKU), Vienna, Austria

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ABSTRACT

This study provides valuable insights into ride-hailing trip patterns among various income groups, including lower-income groups and those living below the poverty line, groups often overlooked in previous research. Using latent class cluster analysis (LCCA) based on a survey in Yogyakarta Province, Indonesia, we examine how variations in trip pattern characteristics are influenced by socio-demographics, household characteristics, and travel-related attitudes toward ride-hailing usage. Our results establish that six distinct clusters representing different ride-hailing travel patterns can be identified. We found dominant clusters for short and less expensive trips using motorcycle-based ride-hailing services (RH MC). In contrast, longer and more expensive trips are associated with car-based ride-hailing (RH CAR). Moreover, ride-hailing plays an important role in essential trips such as returning home, commuting, and maintenance activities, highlighting its importance in addressing transportation challenges, particularly in regions with limited public transportation access. Lower-income individuals and those living in poverty tend to use ride-hailing primarily for shorter and cheaper trips with RH MC, while those from higher-income brackets utilize it for a broader range of purposes. These findings highlight the diverse effects of ride-hailing across income groups and suggest the potential for ride-hailing to enhance accessibility for low-income individuals in Indonesia. We propose policy recommendations to alleviate transport poverty and enhance transport equity in light of these findings.

1. Introduction

Ride-hailing, also known as ride-sourcing or e-hailing, has revolutionized the transportation industry over the past decade. The supply and use of ride-hailing have recently seen an increase year by year worldwide. Despite being affected by the impact of COVID-19, the ride-hailing industry post-pandemic continues to grow, and with a predicted annual growth rate (CAGR 2024 to 2028) of 6.83 %, the expected number of users is projected to reach 1.97 billion by 2028 in the global market (Statista, 2023). Although ride-hailing services are becoming increasingly prevalent in many urban areas, it is not yet clear whether this service brings benefits or disadvantages to urban mobility. For example, ride-hailing has the potential to eliminate the need for individuals to own a vehicle because of its ability to provide car-like services without ownership (Shaheen and Chan, 2016). However, on the other hand, ride-hailing also contributes to negative impacts by increasing vehicle miles traveled (VMT) and giving rise to traffic-related externalities such as congestion, pollution, and safety issues (Clewlow and Mishra, 2017; Tirachini, 2019). In addition, questions arise regarding the equity and accessibility of ride-hailing services, especially for vulnerable groups. This refers to extensive reports in the literature suggesting that ride-hailing services are predominantly used by high-income and highly educated individuals (Alemi et al., 2018; Gomez et al., 2021; Young and Farber, 2019), suggesting that lower-income groups profit to a lesser extent from ride-hailing services. For instance, costs and access to required technologies (smartphone, internet, online payment) may pose challenges for vulnerable groups that cannot fully benefit from these services. This holds in particular for groups living below the poverty line, for whom access to appropriate transportation is even more challenging but also critical for making a living. Theoretically, the presence of ride-hailing services could promote mobility equity by providing car-based accessibility to all, including vulnerable groups with lower car ownership levels. Thus, it is critical to explore if lower-income groups, especially those living below the poverty line, use

* Corresponding author at: Department of Human Geography and Spatial Planning, Utrecht University, Princetonlaan 8a, 3584 CB Utrecht, Netherlands.
E-mail address: m.muchlisin@uu.nl (M. Muchlisin).

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ride-hailing differently and how it may potentially facilitate their daily travels.

Different levels of access to ride-hailing may also imply that different income groups use ride-hailing in different ways. Hence, understanding ride-hailing trip characteristics is crucial for comprehending its implications for various income groups. In this respect, it is essential to note that the utilization and impacts of ride-hailing services on the transportation system vary depending on the specific local context and market conditions (Wang and Yang, 2019). In Western settings, primarily in developed countries, ride-hailing services are predominantly available as car-based (RH CAR) services. Based on trip purpose, previous studies in the West have found that social, leisure, and recreational activities are the most frequent reasons for using ride-hailing services (Clewlow and Mishra, 2017; Dias et al., 2017; Rayle et al., 2016). Additional research by (Rafiq and McNally, 2022) has found that returning home trips become the primary reasons people use ride-hailing in the United States and the District of Columbia. In line with this, Dias et al. (2019) found that returning home trips are more related to other activities, such as working, in the US. Based on factors influencing the use of ride-hailing, previous studies have found that factors such as trip cost (fare), travel time, ease of payment, the convenience of not needing to drive after drinking alcohol, and short waiting times have a positive correlation on the use of ride-hailing (Tirachini, 2019; Young and Farber, 2019).

In terms of income, previous studies have highlighted that there is a high correlation between being a frequent ride-hailing user and being of a higher income group in the West. However, trends are not uniform, and mixed results do exist. A study by Brown (2019) in Los Angeles has shown that ride-hailing is more frequently used in lower-income neighborhoods, as well as similar findings by Atkinson-Palombo et al. (2019) in New York, who found a large increase in ride-hailing use in lower-income outer suburbs. As a result, there are no universal trends in the mechanism underlying the frequency of ride-hailing and income level, as noted by (Tirachini, 2019), which may also be influenced by the quality of alternative modes, motorization rates, and residential and workplace density.

Various studies have addressed the equity effects of ride-hailing. Pan et al. (2020) found that in New York City, ride-hailing exhibited higher equity outcomes compared to traditional taxis in 2017, and both services showed improved equity compared to 2010 levels. This can be attributed to the nature of ride-hailing, which exclusively relies on smartphone apps for ride requests and facilitates real-time connections between drivers and passengers (Brown, 2019; Clewlow and Mishra, 2017). As a result, ride-hailing services have the ability to reach a broader range of areas, extending beyond high-demand locations to include low-demand and remote areas, which highlights the potential of ride-hailing to improve transportation equity and access (Fleming, 2018; Shaheen et al., 2017). Nonetheless, technological barriers pose a challenge for some groups, particularly low-income individuals, when it comes to using ride-hailing services. Wang et al. (2022) identified a group among low-income individuals in the United States who were reluctant to switch from traditional fixed-route transit to shared mobility, including ride-hailing, due to technological barriers while Brown (2019) found that low-income, Black, and Latino smartphone users may encounter challenges affording a stable data plan, which is necessary to access ride-hailing services.

In contrast to the Western context, the existence of ride-hailing in Southeast Asia is more diverse. Apart from car-based services, ride-hailing in Southeast Asia also offers various type of services, such as motorcycle-based (RH MC) services in Indonesia (Irawan et al., 2019a; Silalahi et al., 2017; Suatmadi et al., 2019) and motorized tricycle-based services in Vietnam and Cambodia (Phun et al., 2019). This trend may be due to the pre-existence of traditional paratransit options before the rise of ride-hailing, leading to their assimilation into the broader ride-hailing ecosystem (Chalermpong et al., 2022). Notably, RH MC has gained significant popularity in developing countries like those in Southeast Asia due to its lower costs (Phun et al., 2019; Silviana and Potkin, 2019; Wadud, 2020).

Given the increasing importance of ride-hailing in Southeast Asia, there has been a surge in the number of studies examining various aspects such as the adoption of ride-hailing services, usage frequency, user motivations, and policy-related regulations (Belgiawan et al., 2022; Ilahi et al., 2021; Irawan et al., 2019a; Kuswanto et al., 2019; Napalang and Regidor, 2017; Ruangkanjanases and Techapoolphol, 2018; Silalahi et al., 2017; Wadud, 2020). These scientific papers have consistently concluded that ride-hailing users in Southeast Asia tend to be young and higher educated, and vary in terms of income level, employment, and car ownership (Chalermpong et al., 2022). Additionally, female users were found to be the majority of users, such as in Kuala Lumpur (Weng et al., 2017) and Jakarta (Silalahi et al., 2017). As evidenced in the Philippines (Nistal and Regidor, 2016) and Indonesia (Irawan et al., 2019a; Suatmadi et al., 2019), most ride-hailing trips are for commuting to work and education. Ride-hailing usage in Southeast Asia has been reported to be more frequent compared to Western countries, with the most relevant reasons being price, relative safety compared to other modes of transportation, and convenience (Chalermpong et al., 2022). In addition, ride-hailing in Southeast Asia has been frequently used for short-distance trips. For example, a study by Suatmadi et al. (2019) found that the average distance of RH MC use in Jakarta, Indonesia is 6.2 km.

In the Indonesian context, different income levels have a major impact on ride-hailing services, although the effects vary across regions. Prior studies in Jakarta, Bandung and Yogyakarta showed that higher-income individuals are more likely to use RH MC services, while lower-income earners show less inclination towards ride-hailing (Belgiawan et al., 2022; Irawan et al., 2019a; Irawan et al., 2019b). This aligns with the majority of ride-hailing users in the global context, which emphasizes that ride-hailing is more correlated to higher-income than lower-income (Tirachini, 2019). However, prior studies in other Indonesian cities like Semarang, Bogor, and Bandung also found that income does not consistently determine RH MC usage (Nugroho et al., 2020). This suggests that the relationship between ride-hailing and different income levels is also complex, given the diverse cultures, behaviors, and infrastructures across various regions in Indonesia.

While a considerable body of knowledge has been developed regarding the use of ride-hailing in Southeast Asian countries, this paper aims to contribute by focusing on two particular aspects. First, while previous studies have investigated different aspects of ride-hailing usage independently (such as the travel purpose or type of ride-hailing), limited insight is available into the types of ride-hailing trips defined by purpose, timing, duration, and travel mode combined. In addition, we focus on how ride-hailing is utilized by different groups by linking these ride-hailing trip types to user types, which are defined by factors including income, gender, residential location, and other relevant characteristics. Altogether, this provides additional insight into how ride-hailing plays a role in citizens' daily travel patterns, and how this role differs between different socio-demographic groups.

A second important aspect of our study is to examine the use and significance of ride-hailing services for disadvantaged population segments, which are often overlooked in regular travel surveys. Specifically, individuals living in developing countries with very low incomes below the poverty line face specific challenges in accessing essential destinations such as workplaces, educational and medical facilities, restricting their options for inclusion and development (Ermagun and Tilahun, 2020). This is closely related to the issue of transport poverty (Lucas et al., 2016) in the Global South context, including Southeast Asia, where transportation infrastructure and services are often inadequate, inefficient, and expensive. In cities such as Jakarta, Manila, and Bangkok, the majority of the population relies on public transport, such as buses, trains, and ferries, to get around (Irawan et al., 2019b; Paronda et al., 2017; Phun et al., 2019). However, these systems are often overcrowded, unreliable, and unsafe, making it difficult for many people to access work, education, and other essential services (Jones, 1997, 2001; Van and Fujii, 2011). Low-income populations in particular face limited accessibility, since they have very limited means to take advantage of alternative travel modes. The emergence of ride-hailing services in developing countries, including Indonesia may be beneficial for disadvantaged groups, as it provides an alternative to public transportation and conventional taxis (Brown, 2019), especially in low density suburban areas (Brown, 2018). Therefore, it makes sense to identify the specific trip types made by disadvantaged populations and understand the implications for their use of the ride-hailing system. This analysis will shed light on how their use of ride-hailing differs from other users.

To do so, this paper sets out to investigate ride-hailing users across different income level groups through a survey conducted between May 2021 and January 2022 in Yogyakarta Province, Indonesia. The following research questions will be answered: (1) What are characteristic ride-hailing trips in terms of mode, purpose, timing, travel cost, journey type, and time of the week? (2) What population groups are associated with specific types of ride-hailing? and (3) How do people in low-income communities use ride-hailing services compared to middle-high income communities? To address the use of ride-hailing by disadvantaged, low-income populations, specific emphasis was put on recruiting respondents living below the poverty line. This is a unique feature of our study, providing specific insight into the use of ride-hailing by this population segment.

The paper is structured as follows: the data and methods section outline the survey design, data collection, and analytical approach. In the results section, descriptive analysis, factor analysis, and ride-hailing latent class clusters are presented. The paper concludes with a discussion and highlights key findings, study limitations, policy recommendations, avenues for further research.

2. Data and methods

In this section, we describe the research methodology, including the survey design, the variables, and the analytical approach.

2.1. Survey design

To address the research objective of this study, survey data collection was conducted with a specific focus on the last ride-hailing trip characteristics. We structured our questionnaire into five parts to address various aspects of ride-hailing usage. The first part focused on gathering general information about ride-hailing including the participants' experience with ride-hailing, usage frequency, and the impact of COVID-19 effect on ride-hailing use. In the second part, we collected data on the participants' most recent ride-hailing trip, including the type of ride-hailing service used, trip details such as origin and destination, trip purpose, travel time and cost, type of trip (one-way or a round-trip), weather conditions, activities during trip, and level of satisfaction.

The third part of the questionnaire explored out-of-home activities, modality, and vehicle ownership, aiming to understand the frequency of various activities and the use of different travel modes before and during COVID-19. Additionally, we collected data on the number of vehicles—cars, motorcycles, and bicycles—owned within the participants' household.

Socio-demographic characteristics were covered in the fourth part, which included questions related to gender, age, education, individual monthly income, employment and marital status, the total number of family members by age, housing type, and place of residence. Finally, the fifth part of the questionnaire consisted of attitudinal questions, seeking to understand the reasons respondents used ride-hailing services. Data collection took place in three sub-areas of Yogyakarta Province: Yogyakarta City, the region's heavily urbanized center, and the outlying Sleman and Bantul regions. Conditions for inclusion in the survey included a minimum age of 18 and no other household member had already participated.

We collected data from different income groups in different ways. On one side, we collected data from middle-high-income individuals who were above the poverty line group through an online survey using XM Qualtrics between May and August 2021. This method was chosen partly because of the COVID-19 situation in Indonesia at that time which restricted social interactions (The Minister of Home Affairs, 2021), including face-to-face surveys. Middle-high-income groups are more likely to have access to the internet and smartphones (Irawan et al., 2021; Jansen, 2010), which makes an online survey more appropriate for their participation. This group was approached through the snowball method, whereby respondents forwarded our survey invitation to potential new respondents (Etter and Perneger, 2000; Johnson, 2005). Initially, we recruited and trained university students as surveyors in this survey. Then we asked them to distribute survey links to their contacts, such as their relatives, friends, neighbors, and others, indicating that they were not from the poor group. After some participants had finished the questionnaires, we offered them the opportunity to become new surveyors. Their task would be to recruit new potential responders by extending our link survey invitation. At the same time, we also controlled for the representation of some key sample characteristics such as gender, employment status, and place of residence.

In addition, between November 2021 and January 2022, we collected data through a paper-and-pencil version of the questionnaire from individuals categorized as living below the poverty line. This in-person survey was deemed appropriate for this specific group, especially considering the eased COVID-19 restrictions during that period. To ensure unbiased representation, we used the following criteria for this income group: 1) Participants fell below the World Bank's 2021 poverty line standard of $3.65 per person per day (The World Bank, 2023) and were also registered as poor households by the Yogyakarta Province government; and 2) we assumed this group experienced cumulative disadvantages, including limited access to the internet and different travel modes as well as difficulties with traveling, among others. To illustrate the residential location between above and below poverty line groups in the three regions, we present it on a map in Fig. 1. It is important to highlight that not all below poverty line groups do not reside in specific locations, but they mix with non-poor groups. This could be related to the typical urban transition in Southeast Asia, taking the shape of a hybrid space between village and town (Friedmann, 2011; Leaf, 2011; McGee, 1991). In addition, Kusno (2020) called it as *kampung*, a place of interaction between the formalized area of the city and the irregular settlement in Indonesia. In our study, if people who live in poverty reside in urban areas, they typically live either in kampungs within the city or in *peri*-urban areas. Alternatively, they may reside in suburban or rural areas.

Using stratified sampling methods (Ben-Akiva and Lerman, 2018; Lerman and Manski, 1979), we ensured balanced representation across key socio-demographic characteristics such as residence, gender, and employment status. Out of 2,279 valid responses, 1,969 were from middle-high income individuals, and 310 were from those living in poverty. After data cleaning and focusing on ride-hailing users, our sample totaled 1,743 respondents, with 1,599 from the middle-high income group and 144 from below the poverty line, accounting for 12.0 % of the total sample. This proportion aligns with the reported poverty rate of 10.1 % in Yogyakarta City, Sleman, and Bantul (BPS – Statistics of Yogyakarta Province, 2022b).

2.2. Variables

In order to fulfill the aim of this study and characterize the dataset, we employed the following variables:

- **Trip characteristics**
  The study collected data on trip characteristics related to the most recent ride-hailing recent trip, as follows:

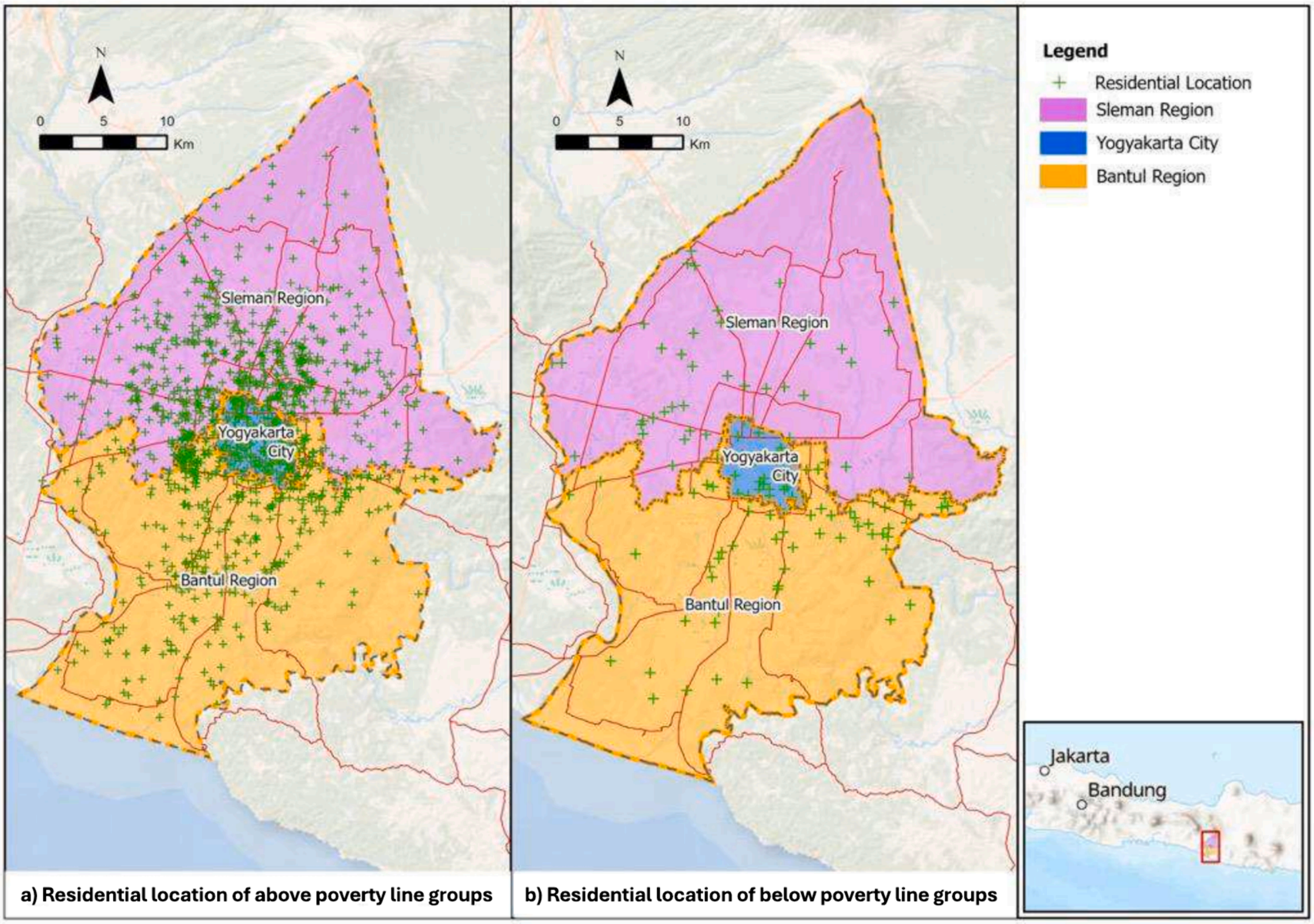

Fig. 1. Residential location for above and below poverty line groups.

(a) *Ride-hailing type* was categorized into motorcycle-based ride-hailing (RH MC) and car-based ride-hailing (RH CAR).
(b) *Travel time* was categorized into < 30 min, 30–60 min, 60–90 min, and > 90 min.
(c) *Trip fare* was categorized into < 20,000 IDR,[1] 20–40,000 IDR, and > 40,000 IDR.
(d) *Trip purpose* was based on the classification of ride-hailing trip purposes by Rafiq and McNally (2022) who categorized trip purposes into five broad activities, each consisting of several sub-categories. We combine work and education into one category however because both activities can together represent daily commuting activities. We aggregated the activities into five groups and present them in Table 1.
(e) *Trip timing* explains when a trip has been made: night (00:00–05:59), morning (06:00–11:59), afternoon (12:00–17:59), and evening (18:00–23:59).
(f) *Journey type* in this study represents the different ways that individuals use ride-hailing services for their latest trips. Round-trip refers to the use of ride-hailing services as the sole mode of transportation for the entire trip, while a one-way trip refers to the use of ride-hailing services in combination with other modes of transportation, such as private car, motorcycle, or public transportation. To gather this information, we asked participants whether their ride-hailing trip was one-way or round-trip. For those who reported a one-way trip, we inquired about the mode of transportation they used before or after the ride-hailing trip.
(g) *Time of week* is categorized into weekdays (Monday–Friday) and weekend (Saturday and Sunday).

Table 1
Ride-hailing purposes.

Activity	Sub-category
(1) Returning home	Returning home
(2) Work or education	Work/ work-related trips
	School / University
(3) Maintenance	Grocery /non-grocery shopping
	Religious activity
	Hospital/ health care
	Bank/ ATM
	Auto-care (e.g., car or motorcycle tune-up)
(4) Discretionary	Visiting family
	Eating out
	Vacation
	Leisure
	Sport
(5) Transportation hub	Station or airport
(6) Other	Not mentioned above

- **Socio-demographics**
The study collected data on socio-demographic characteristics, including age, gender, education level, employment and marital status, place of residence, and income level. Education refers to the highest level of education attained, ranging from secondary school or below to master's degree or higher. In order to examine the

[1] 100,000 IDR corresponded with 6.194 EUR in early 2022.

relationship between income level and ride-hailing use, we combined two sub-samples based on monthly individual income, dividing them into above and below poverty line groups. The categorization of dummy variables was as follows: living in poverty, 0–1 M IDR, 1–5 M IDR, 5–9 M IDR, and > 9 M IDR. This approach accounts for the fact that our sample included individuals with low income (e.g., 0–1 M IDR/month) who do not live in poverty, for example, students or housewives who rely on the income of their spouse or parents. By merging these sub-samples, we aimed to capture the effect of different income levels on ride-hailing use while also taking into consideration the nuances of income measurement.

- **Household characteristics**
  The study also gathered data on household characteristics, including:
  (a) *Household size* is based on total number of family members in the household and was treated as a continuous variable.
  (b) *Vehicle ownership* is the total number of vehicles (cars, motorcycles, and bicycles) owned by the household. This information was categorized into five groups: zero vehicles, 1 vehicle, 2 vehicles, 3 vehicles, and more than 3 vehicles.
- **Travel attitudes**
  The study assessed travel attitudes related to the reasons for adopting ride-hailing through a set of questions. These reasons include inability to drive; no need to find or pay for parking; cheaper fares; faster travel times; shorter waiting times; ease of use for ordering and payment; comfort; difficulty in accessing public transport in the area; level of safety and security of ride-hailing vehicles from accidents and crime; ease of use in adverse weather; using ride-hailing to avoid congestion; unfamiliarity with the route to the destination; and safety in terms of COVID-19 when using ride-hailing. These travel attitudes are discussed in more detail in Section 2.3.1 and Section 3.2.

2.3. Analytical approach

2.3.1. Exploratory factor analysis

In this study, we apply Exploratory Factor Analysis (EFA) (Williams et al., 2010) to investigate the attitudinal responses regarding the reasons for adopting ride-hailing services. EFA, as distinguished from principal component analysis, is a statistical method that focuses on capturing the shared variance among variables and can be performed exclusively on interval or ratio level variables (Suhr, 2005). In this study, we analyzed the reasons for ride-hailing adoption with EFA by performing maximum likelihood with Oblimin rotation for all 18 indicators while only allowing factor loading > 0.5 as cutoff points.

2.3.2. Latent class cluster analysis

In this study, we apply latent class cluster analysis (LCCA) (e.g., (Vermunt and Magidson, 2002) using Latent Gold 5.1 to identify the latent trip characteristics of the different population segments. LCCA is a model-based approach that probabilistically identifies unobserved groups (i.e., classes) with behaviors that are as homogenous as possible within each class, while being heterogenous across different classes (Lee et al., 2022; Molin et al., 2016). In this analysis technique, two models are estimated simultaneously. The first model is a measurement model, which conceptualizes indicators as outputs of unobserved class membership. It computes class-specific averages for these indicators in a way that maximizes differences in these averages across classes. The second model is the structural or membership model, which computes the probabilities of individual cases belonging to one class or another. In this study, the membership model incorporates explanatory variables, also known as active covariates, to estimate the likelihood of individuals being assigned to specific classes. Explanatory variables that are found not to have statistically significant coefficients in the model estimation are designated as inactive covariates to help identify the unique profiles of the members of each class.

Fig. 2 illustrates the relationships among the latent construct of ride-hailing trip patterns, the indicators used to measure them, and the active and inactive covariates included in the analysis. In the measurement model we selected six variables from the participants' latest ride-hailing trips: trip fare, travel time, trip timing, trip purpose, ride-hailing type, journey type, and time of week. In the structural model, we use active covariates derived from personal characteristics including socio-demographic factors, household characteristics, spatial characteristics, attitudinal variables, vehicle ownership in the household, and income level group. To mitigate potential issues of endogeneity, specifically the risk of a predictor variable being partly dependent on the variable it

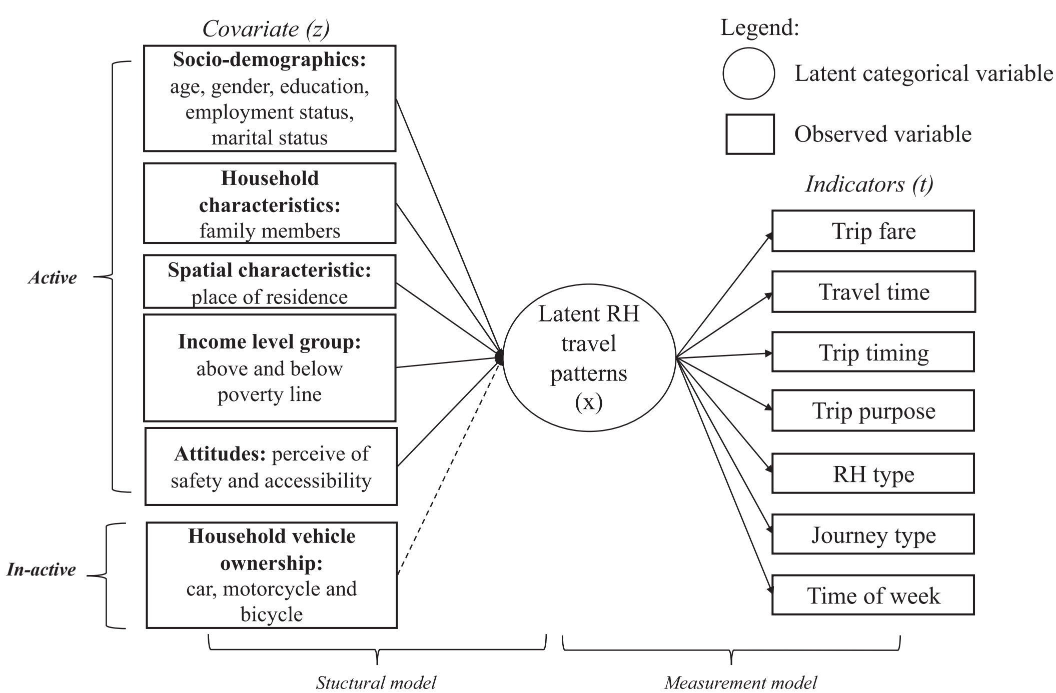

Fig. 2. Graphical representation of the latent class cluster analysis with covariates.

aims to predict, we treat the variable of vehicles ownership in the household as an inactive covariate in our model as opposed to the other covariates which are considered active. In LCCA, inactive covariates do not directly influence the cluster probabilities, although the distribution of their categories across the clusters can be calculated (Molin et al., 2016). According to the methodology of Molin et al. (2016), the availability of private vehicles may have less of an impact on travel decisions due to specific travel style preferences. Their self-selections may therefore play a role in relation to these variables.

In the mathematical formulation of the LCCA model, following the form from (Vermunt and Magidson, 2016), we have:

$$f(y_i|z_i) = \sum_{x=1}^{K} P(x|z_i) f(y_i|x,z_i) = \sum_{x=1}^{K} P(x|z_i) \bullet \prod_{t=1}^{T} f(y_{it}|x,z_{it}) \tag{1}$$

where x represents the latent variable with its K categories, z_i is the individual's characteristics of covariates and y_{it} is the individual's response to indicator t (T being the number of indicators). $\sum_{x=1}^{K} P(x|z_i)$ refers to the probability of belonging to a certain latent class given the individual's covariates, and $\prod_{t=1}^{T} f(y_{it}|x,z_{it})$ represents the probability density of y_{it} given x. The validity of this mathematical formulation holds assuming that the indicator variables are conditionally independent of each other given the latent variable x (Vermunt and Magidson, 2016). In addition, as per (Vermunt and Magidson, 2016), the indicators y_{it} may encompass one or more categorical variables (nominal or ordinal), one or more continues variables, or a single count variable. The LCCA model assumes multinomial distribution for y_{it} when the variables are categorical. For continuous variables, Latent Gold employs a multivariate normal distribution as well as censored and truncate distributions; count or binary can be modeled via Poisson or binomial distribution. Therefore, in this study we apply y_{it} with three different values, including binary, nominal, and ordinal. To determine the appropriate number of classes, Latent Gold estimated the goodness-of-fit measures and interpretability. As suggested by Vermunt and Magidson (2016), these measures tend to improve as the number of latent classes increases, with the lower BIC, AIC or AIC3 the preferred cluster model.

3. Results

3.1. Descriptive statistics

Table 2 presents the descriptive statistics of the sample. The study reveals that ride-hailing users are relatively more likely to be female (62 %), belong to the age group of 18–25 years old (67.4 %), hold a high school degree (56.1 %), and are students (47.1 %). These findings align with previous research conducted in the Indonesian context, which also indicated that ride-hailing usage is associated with females, young individuals, and those with higher levels of education (e.g., Belgiawan et al. (2022); Irawan et al., (2019a); Irawan et al., (2019b); Suatmadi et al. (2019)). Also in the Western context, including countries like the United States, Canada and various European nations, research has consistently shown that young individuals, those with higher levels of education, and individuals with higher income are more likely to adopt ride-hailing services (e.g., Alemi et al. (2018); Clewlow and Mishra (2017); Dias et al. (2019); Gomez et al. (2021); Tirachini (2019)).

In terms of trip characteristics, the study found that the majority of participants opted for RH MC (64.2 %) over car-based options. Furthermore, regarding travel costs, a significant portion of users (52.4 %) had costs under 20,000 IDR. Additionally, most ride-hailing trips were relatively short, with 65.8 % lasting less than 30 min. For trip purposes, many users (26.7 %) utilize ride-hailing to return home. Furthermore, a significant proportion of respondents (64.8 %) preferred to combine ride-hailing with other travel modes for one-way trips. In terms of timing, most trips occurred during the morning (49.6 %), and the majority of trips took place on weekdays (70.1 %).

Table 2
Descriptive statistics.

Variable	n	%	Variable	n	%
Trip characteristics			**Education**		
Trip Fare			Secondary school or under	26	1,5
<20,000 IDR	914	52.4	Highschool	977	56.1
20,000–40,000 IDR	563	32.3	Bachelor or equivalent	677	38.8
>40,000 IDR	265	15.2	Master degree or above	63	3.6
Travel Time			**Employment Status**		
<30 min	1,147	65.8	Student	821	47.1
30–60 min	513	29.4	Full-time employee	608	34.9
60–90 min	73	4.2	Part-time employee	129	7.4
>90 min	8	0.5	Unemployed	185	10.6
Trip Time			**Income Level Group**		
Night	108	6.2	Living in poverty	144	8.3
Morning	864	49.6	0–1M IDR	851	48.8
Afternoon	632	36.3	1–5M IDR	675	38.7
Evening	139	8	5–9M IDR	57	3.3
Trip Purpose			>9M IDR	16	0.9
Returning home	466	26.7	**Family Members**		
Work and school	375	21.5	Mean	4.24	
Maintenance	308	17.7	Std. Deviation	2.23	
Discretionary	348	20.0	**Place of Residence**		
Transportation hub	107	6.1	Yogyakarta city	368	21.1
Other	139	8.0	Sleman	755	43.3
RH Type			Bantul	620	35.6
RH CAR	624	35.8			
RH MC	1,119	64.2	***Household Vehicle Ownership (#)***		
Journey Type			**Motorcycle**		
Round-trip	614	35.2	0	46	2.6
One-way	1,129	64.8	1	782	44.9
Time of Week			2	443	25.4
Weekend	522	29.9	3	303	17.4
Weekday	1,221	70.1	>3	169	9.7
			Car		
Personal characteristics			0	1,150	66
Gender			1	489	28.1
Male	663	38.0	2	71	4.1
Female	1,080	62.0	3	21	1.2
Age			>3	12	0.7
18–25	1,174	67.4	**Bicycle**		
25–35	303	17.4	0	1,035	59.4
35–50	241	13.8	1	377	21.6
>50	25	1.4	2	172	9.9
Marital Status			3	112	6.4
Unmarried	1,264	72.5	>3	47	2.7
Married	479	27.5			

This study employs a survey on ride-hailing use in the Yogyakarta region (Muchlisin and Ettema, 2023), which investigated the adoption and frequency of ride-hailing usage. While it is challenging to assess the representativeness of the ride-hailing population characteristics in Yogyakarta Province or Indonesia due to the unavailability of comprehensive data, our data can be considered representative of the total

Table 3
Comparison between total sample and total population.

Variable	Total sample		Total population in the study area	
	Count	%	Count	%
Gender				
a) Female	1,361	59.72	1,240,652	50.46
b) Male	918	40.28	1,217,876	49.54
Employment				
a) Student	1,009	44.27		
b) Full-time employee	842	36.95		
c) Part-time employee	184	8.07		
d) Unemployed	244	10.71	86,197	3.51
Place of Residence				
a) Yogyakarta City	425	18.65	415,382	16.90
b) Sleman Region	991	43.48	1,087,339	44.23
c) Bantul Region	863	37.87	955,807	38.88

population based on gender, employment status, and place of residence, as shown in Table 3.

3.2. Exploratory factor analysis of ride-hailing attitudes

The survey in this study assessed factors influencing ride-hailing service usage using a 5-point Likert scale, ranging from "strongly disagree" (1) to "strongly agree" (5). After excluding variables with low factor loadings, EFA revealed two main factors: "Safety" (Factor 1) and "Accessibility" (Factor 2). The "Safety" factor relates to perceptions of safety regarding accidents and crime, while the "Accessibility" factor encompasses convenience and ease of accessing ride-hailing services. Factor loadings, means, standard deviations (STDV), and Cronbach's alpha values for each factor are presented in Table 4.

3.3. Latent class cluster analysis results

The goodness-of-fit of LCCA in terms of BIC, AIC, and AIC3 of the different models is presented in Table 5. To determine the most suitable number of classes for the analysis, we estimated models ranging from two to ten classes, considering both active and inactive covariates. For each model, we evaluated their goodness-of-fit measures and interpretability. As per Andrews and Currim (2003) AIC3 is considered a more appropriate criterion for selecting the number of latent classes in latent class and finite mixture models compared to BIC and AIC. Therefore, we select the model with six clusters. In Table 6 and Table 7, we present the estimated parameters of the final model. It should be noted that no parameters are estimated for inactive covariates, which is the reason why vehicle ownership (motorcycle, car, and bike) are not available in these two tables. We display the profile of the final LCCA model in Table 8 and Table 9 as the probability within-cluster distribution of the indicators and covariates.

3.3.1. Patterns of ride-hailing travel behavior

Based on the measurement model, and the predictions in Table 8, we present these six clusters in an ordered manner from the largest to the smallest cluster size, as follows:

- Cluster 1 (36.8 % of the sample) is labeled "*RH MC short return home trips.*" This cluster predominantly consists of returning home trips compared to other clusters. The trips within this cluster exhibit shorter travel times and lower travel costs, with 75.0 % of trips taking less than 30 min and 73.1 % of trip fares costing less than 20,000 IDR. RH MC is used for most trips, and trips typically occur on weekdays (72.6 %). Additionally, RH is usually combined with other travel modes for the outbound or return trip (84.1 %). Many trips occur in the afternoon (45.9 %), in addition to a higher likelihood of evening and night trips, making RH MC a suitable mode of transportation for trips returning home.
- Cluster 2 (20.8 %) deals with "*RH MC morning commute trips.*" This cluster is characterized by a strong preference for RH MC (94.6 %) and is strongly associated with commuting to work or for education trips. A significant majority of trips (72.3 %) occurred during the morning. However, this cluster also includes relatively large number of night trips, although with lower probability (5.7 %). This suggests that the cluster consists mainly of individuals who commute in the morning (or night) to their workplace, school, or university. This particular cluster also includes lower-cost trips, as indicated by the significant negative correlation with trip fare. However, trip durations tend to be longer than average, which can be attributed to the nature of commute trips with ride-hailing services, where they tend to be cost-effective but may involve a slightly longer travel time. Since this group includes mostly commute trips, most of them happen on weekdays (75.8 %) and use ride-hailing for one-way trips, which indicates this group prefers to use other travel modes when returning home.
- Cluster 3 (15.8 %) is labeled "*RH CAR long return home trips.*" Compared to the previous clusters, this cluster is characterized by a significant association with RH CAR and is primarily utilized for longer ride-hailing of returning home (41.4 %). These trips tend to be more expensive, as evidenced by the positive coefficients for both trip fare and travel fare. The typical trips of this group were made in the morning (38.3 %) and afternoon (37.2 %), but, also more than other clusters, also in evening and night. The majority of the trips were made during weekdays (67.1 %), and for one-way trips (79.2 %).
- Cluster 4 (11.2 %) is "*Multi-purpose RH CAR trips.*" Similar to cluster 3, this cluster also exhibits a strong preference for RH CAR (90.1 %) for different purposes including discretionary activity, maintenance activities, and travel to a transportation hub such as a station or airport. Most of the trips are longer trips and relatively high fares. Trips also typically happen in the morning (66.6 %), however, we also found a higher likelihood of night and afternoon trips. This group prefers ride-hailing for round-trip journeys (94.9 %), on weekdays (69.7 %). Therefore, this cluster represents a group of users relying on RH CAR services for various purposes, including a wide range of activities and longer trips.
- Cluster 5 (9.9 %) is termed "*RH CAR short maintenance trips.*" This cluster is primarily characterized by the use of RH CAR (55.2 %), with maintenance activities as the primary trip purpose (68.3 %). This cluster also includes shorter and less expensive trips, as evidenced by the negative coefficients for both trip fare and travel time. Most of the trips in this cluster were made in the morning (60.8 %) and on weekdays (84.3 %), and where participants use ride-hailing for round-trips (68.3 %). Therefore, this cluster can be classified as individuals who employ RH CAR for shorter trips, such as grocery shopping or engaging in religious activities, as part of their routine maintenance activities.
- Cluster 6 (5.5 %) is named "*RH MC weekend trips.*" Contrary to the previous clusters, which are predominantly characterized by weekday trips, this cluster exhibits a higher proportion of weekend trips (83.8 %). Ride-hailing users in this cluster favor the use RH MC (66.4

Table 4
Attitudinal responses toward ride-hailing service usage.

Item	Factor loading 1	Factor loading 2	Mean	STDV
I cannot drive			2.14	1.03
I don't need to find or pay for parking			3.23	1.13
The fare is inexpensive		0.62	3.42	0.88
The travel time is quick		0.82	3.31	0.83
The waiting time is short		0.80	3.37	0.82
RH is easy to use (ordering and payment)		0.57	3.96	0.72
RH is comfortable		0.58	3.75	0.72
It's difficult to reach public transport from my location			3.56	1.0
RH motorcycle is a safe mode of transportation	0.79		2.87	0.74
RH car is a safe mode of transportation	0.79		3.09	0.79
RH motorcycle is crime-safe	0.81		2.93	0.73
RH car is crime-safe	0.79		3.09	0.77
RH motorcycle remains convenient to use even in bad weather			2.57	0.82
RH car is easy remains convenient to use even in bad weather			3.96	0.74
I use RH motorcycle to avoid congestion			3.49	0.93
I use RH car to avoid congestion			2.43	0.81
I don't know the route I'm going to take, especially for new places			3.21	1.12
Cronbach's alpha	0.87	0.81		

Extraction Method: Maximum Likelihood.
Rotation Method: Oblimin with Kaiser Normalization.

Table 5
Goodness-of-fit measures of latent class cluster analysis.

Number of clusters	LL	BIC(LL)	AIC(LL)	AIC3(LL)	Npar	p-value	Cluster share (%)									
							1	2	3	4	5	6	7	8	9	10
1	−11256.45	22632.29	22544.90	22560.90	16.00		100.0									
2	−10830.08	22033.24	21760.16	21810.16	50.00	0.00	68.1	31.9								
3	−10702.51	22031.80	21573.03	21657.03	84.00	0.00	64.7	19.7	15.6							
4	−10597.99	22076.46	21431.98	21549.98	118.00	0.00	57.8	19.9	15.3	7.1						
5	−10499.08	22132.34	21302.17	21454.17	152.00	0.01	35.4	26.7	18.4	13.5	6.0					
6	−10427.89	22243.65	21227.78	**21413.78**	186.00	0.00	**36.8**	**20.8**	**15.8**	**11.2**	**9.9**	**5.6**				
7	−10381.25	22404.07	21202.51	21422.51	220.00	0.03	29.3	19.3	13.3	11.9	10.3	10.2	5.7			
8	−10332.44	22560.13	21172.87	21426.87	254.00	0.01	34.3	19.3	13.2	9.5	8.1	6.9	5.6	3.2		
9	−10286.11	22721.17	21148.22	21436.22	288.00	0.05	23.5	18.8	13.3	12.1	8.6	7.9	7.4	4.6	3.8	
10	−10239.02	22880.69	21122.04	21444.04	322.00	0.08	22.1	16.3	13.4	10.8	7.5	7.1	6.7	5.9	5.7	4.5

Table 6
Prediction of the indicators (the measurement model).

	Cluster1	Cluster2	Cluster3	Cluster4	Cluster5	Cluster6	Wald	p-value	R^2
Trip Fare	−1.149	−0.921	2.149	1.585	−0.431	−1.232	132.403	0.000	0.474
Travel Time	−0.142	0.252	1.478	0.924	−1.538	−0.974	113.310	0.000	0.175
Time of Trip									
Night	0.591	1.577	1.261	0.492	0.254	−4.175	92.527	0.000	0.065
Morning	−1.059	0.785	−1.040	0.449	−0.005	0.871			
Afternoon	−0.348	−0.010	−0.666	0.051	−0.224	1.197			
Evening	0.816	−2.352	0.446	−0.993	−0.024	2.107			
Trip Purpose									
Returning home	1.412	−2.451	1.100	−1.246	−0.286	1.472	228.187	0.000	0.232
Work or education	−0.961	2.900	−0.633	−0.113	−1.355	0.163			
Maintenance	−1.619	0.113	−1.353	0.634	1.611	0.615			
Discretionary	−0.115	0.107	−0.585	0.641	−0.308	0.260			
Transportation hub	0.642	−0.142	1.146	0.532	−1.054	−1.126			
Other	0.640	−0.526	0.326	−0.448	1.392	−1.383			
RH Type									
RH CAR	−0.864	−1.293	0.880	1.242	0.239	−0.204	218.257	0.000	0.479
RH MC	0.864	1.293	−0.880	−1.242	−0.239	0.204			
Journey Type									
Round-trip	−0.687	−0.076	−0.522	1.611	0.529	−0.856	91.594	0.000	0.311
One-way	0.687	0.076	0.522	−1.611	−0.529	0.856			
Time of Week									
Weekend	−0.179	−0.263	−0.048	−0.108	−0.532	1.130	71.331	0.000	0.092
Weekday	0.179	0.263	0.048	0.108	0.532	−1.130			

%) for short trips lasting less than 30 min (87.7 %), with lower trip fares under 20,000 IDR (74.8 %). While return home trips are the most common purpose (34 %), this cluster also displays a heightened propensity for multi-purpose trips for maintenance, work and education, and discretionary activities, as presented in Table 6. Most of the trips occur in the morning (46.6 %), but there is also a correlation with afternoon and evening trips, with a preference for using ride-hailing for one-way trips (88.1 %). Hence, this cluster can be categorized as cost-conscious, exhibiting a preference for shorter and less-expensive trips that serve multiple purposes during weekends.

3.3.2. User characteristics

This subsection delves into the socio-demographic characteristics that determine each cluster, relying on the significance of the variables found in the latent class membership (structural) model, as presented in Table 7, and the latent profile of covariates showcased in Table 9.

Cluster 1 in the study, labeled as "*RH MC short return home trips,*" primarily consists of males aged between 25 to 35 years old and individuals aged over 50 years. This group exhibits a unique characteristic as they possess a personal income ranging from 0 to 9 million IDR, reflecting the diverse economic backgrounds within the cluster, though not specifically linked to people living in poverty. Interestingly, this cluster also includes individuals who are not employed, such as housewives, retired individuals, and the unemployed. This cluster is more likely to include individuals residing in the Sleman and Bantul regions, indicating a representation of suburban RH trips. This could be attributed to the limited accessibility of public transportation options in suburban and rural areas in Indonesia, including Sleman and Bantul.

Cluster 2 or "*RH MC morning commute trips,*" exhibits a stronger affiliation with both younger and older males, who possess a personal income spanning from 0 to 9 million IDR. This cluster demonstrates a higher likelihood of including individuals residing in the suburban areas of Sleman and Bantul regions. This propensity might be attributed to the limited availability of public transportation options in these suburban locales. Moreover, employed individuals, encompassing both full-time and part-time workers, as along with students, are more likely to belong to this cluster. This association indicates that this cluster is reasonably associated with commuting trips.

Cluster 3, identified as *"RH CAR long return home trips,"* is mainly composed of adult females aged over 25 years, with low to high monthly incomes ranging from 0 to more than 9 M IDR. It is noteworthy that this cluster does not encompass individuals living in poverty. People living in Sleman and Bantul region have a higher likelihood of belonging to this group. In terms of employment status, this cluster is more associated with part-time workers and unemployed individuals, including housewives and retirees.

Cluster 4, or "*Multi-purpose RH CAR trips,"* exhibits a higher proportion of female individuals aged over 25 years. The personal incomes within this group vary significantly, with a majority earning between 1 and 5 million IDR and more than 9 million IDR. Notably, individuals residing in Sleman and Bantul regions are also more likely to belong to this cluster, highlighting the demand for longer trips. This group also

Table 7
Prediction of latent class membership (the structural model).

	Cluster1	Cluster2	Cluster3	Cluster4	Cluster5	Cluster6	Wald	p-value
Intercept	1.942	−1.054	0.894	1.441	2.030	−5.253	4.782	0.44
Covariates								
Gender								
Male	0.204	0.059	−0.080	−0.518	−0.146	0.480	33.567	0.000
Female	−0.204	−0.059	0.080	0.518	0.146	−0.480		
Age								
18–25	−0.814	0.664	−2.319	−0.753	−3.243	6.465	45.799	0.000
25–35	0.950	2.322	0.503	0.357	0.703	−4.834		
35–50	−0.217	1.302	0.464	0.208	0.233	−1.990		
>50	0.081	−4.287	1.351	0.189	2.308	0.359		
Education								
Secondary school or below	2.143	−3.744	−3.735	1.823	1.130	2.383	20.629	0.150
Highschool	−0.237	1.326	1.370	−0.058	−0.755	−1.646		
Bachelor or equivalent	−0.138	1.437	1.480	0.028	0.421	−3.228		
Master degree or higher	−1.768	0.980	0.886	−1.793	−0.795	2.490		
Employment Status								
Student	−0.346	−0.117	−0.041	−0.480	−0.273	1.257	41.640	0.000
Full-time employee	−0.074	0.119	−0.301	0.488	−1.110	0.878		
Part-time employee	−0.089	0.501	0.039	−0.443	0.107	−0.114		
Unemployed	0.508	−0.504	0.303	0.436	1.277	−2.020		
Place of Residence								
Yogyakarta city	−0.191	−0.101	−0.480	−0.437	0.628	0.582	23.028	0.011
Sleman	0.102	0.052	0.181	0.070	−0.111	−0.293		
Bantul	0.090	0.049	0.300	0.367	−0.517	−0.288		
Income level group								
Living in poverty	−1.813	−1.143	−2.317	−1.248	−2.950	9.471	32.305	0.040
0–1 M IDR	0.747	0.229	0.114	−0.086	0.288	−1.292		
1–5 M IDR	2.327	1.620	1.421	1.328	1.891	−8.587		
5–9 M IDR	0.016	0.250	0.530	−0.495	0.083	−0.383		
> 9 M IDR	−1.278	−0.956	0.253	0.502	0.688	0.791		
Family Members	0.075	0.023	0.058	−0.017	0.130	−0.270	5.784	0.330
Marital Status								
Unmarried	1.183	1.114	1.407	0.904	1.366	−5.974	11.586	0.041
Married	−1.183	−1.114	−1.407	−0.904	−1.366	5.974		
RH travel attitudes								
Safety	−0.078	0.003	0.015	−0.107	−0.204	0.371	2.991	0.700
Accessibility	−0.135	−0.119	−0.439	0.004	−0.183	0.872	8.905	0.110

includes a relatively substantial number of full-time workers and unemployed individuals.

Cluster 5, denoted as "*RH CAR short maintenance trips,*" predominantly consists of females aged over 25 years, encompassing a wide range of personal incomes ranging from 0 to over 9 M IDR. Different to the previous clusters, people living in Yogyakarta's urban area are more likely to belong to this group. This tendency suggests a need for short-distance travel for maintenance activities such as shopping for groceries among other items. Furthermore, this cluster is strongly associated with part-time employees as well as unemployed individuals. This may suggest that this group has more flexible schedules, facilitating the execution of maintenance activities during available daytime hours.

Finally, Cluster 6—labeled as "*RH MC for weekend trips*"—is comprised mostly of younger and older males between the ages of 18 and 25 and over 50, respectively. The personal income of individuals in this cluster is predominantly below the poverty line, indicating that this group may have limited financial resources. Residents of this cluster tend to live in the urban area of Yogyakarta. They probably do not have access to a private vehicle and cannot afford the cost of using public transport. Full-time workers and students are more likely to use ride-hailing services in this group. This cluster's travel behavior is characterized by a high utilization of RH MC for short trips with lower fares, suggesting that this mode of transportation is a reasonable choice for individuals living in poverty for various services.

3.3.3. *Distribution of ride-hailing trip clusters across income groups*

In this subsection, we examine the distribution of ride-hailing travel clusters among different income groups, focusing especially on the extent to which people in poverty travel differently than those with middle-to-high incomes. Fig. 3 illustrates the proportion of each income category within the total, based on the latent profile results outlined in Table 8.

As depicted in Fig. 3, Cluster 6 ("*RH MC for weekend trips*") emerges as the predominant trip type among individuals living in poverty (82 %). However, the remaining 18 % of this group is spread across other clusters, indicating their engagement in various other types of ride-hailing trips as well. However, we also find that Cluster 6 maintains popularity among the middle-high income groups, constituting 20 % in the 5–9 M IDR group and a 26 % in the more than 9 M IDR group. This implies that weekend ride-hailing trips are not solely confined to individuals living in poverty; rather, they also correlate with individuals within the middle- high income group. Furthermore, ride-hailing trips within the income group (0)–(1) M IDR are evenly distributed across Cluster 1 (21 %), Cluster 2 (21 %), and Cluster 3 (21 %). These clusters primarily pertain to the utilization of RH MC for shorter trips, especially for Clusters 1 and 2. Based on the results, we see that the lower-income population (0–1 M IDR category) and individuals living poverty are more likely associated with shorter and less expensive trips.

Furthermore, individuals with middle-high income tend to use RH CAR, engaging in longer trips that come with higher costs, and are more closely linked to work commutes. This observation is evident in individuals with incomes ranging from 1–5 M IDR, who are predominantly associated with Cluster 5 (23 %) and Cluster 4 (21 %). Furthermore, the group earning 5 and 9 M IDR comprises a higher proportion of Cluster 3 (33 %), highlighting the preference for utilizing RH CAR for extended return home trips. In the highest income category, (>9 M IDR), the most frequent type is Cluster 6 (use of RH MC for weekends trips) with 26 % of total sample, followed by Cluster 5 (24 %) and Cluster 3 (22 %). These results also suggest that higher income groups also engage in various cheaper trips. This could be attributed to the value these individuals

Table 8
Profile of the indicators.

	Cluster1 (%)	Cluster2 (%)	Cluster3 (%)	Cluster4 (%)	Cluster5 (%)	Cluster6 (%)	Overall (%)
Cluster Size	36.8	20.8	15.8	11.2	9.9	5.6	
Indicators							
Trip Fare							
<20,000 IDR	73.1	68.2	4.1	9.2	55.7	74.8	52.4
20–40,000 IDR	25.5	29.8	38.4	49.0	39.8	24.0	32.4
>40,000 IDR	1.4	2.1	57.6	41.8	4.5	1.2	15.2
Travel Time							
<30 min	75.0	66.3	32.1	48.1	92.7	87.7	65.9
30–60 min	23.6	31.0	51.0	44.0	7.2	12.0	29.5
60–90 min	1.4	2.6	14.7	7.3	0.1	0.3	4.2
>90 min	0.0	0.1	2.2	0.6	0.0	0.0	0.5
Trip Timing							
Night	6.3	5.7	13.7	2.5	2.8	0.0	6.2
Morning	33.7	72.3	38.3	66.6	60.8	46.6	49.5
Afternoon	45.9	21.8	37.2	29.9	32.6	43.1	36.3
Evening	14.1	0.2	10.8	1.0	3.8	10.3	8.0
Trip Purpose							
Returning home	47.5	0.3	41.4	2.7	4.8	34.0	26.7
Work or education	5.1	79.0	8.5	9.8	1.9	10.6	21.6
Maintenance	4.9	9.0	7.6	38.3	68.3	30.9	17.6
Discretionary	23.1	9.3	17.2	40.3	10.5	22.6	19.9
Transportation hub	7.6	1.1	15.0	5.6	0.8	0.9	6.2
Other	11.8	1.2	10.3	3.3	13.8	1.1	8.0
RH Type							
RH CAR	11.9	5.4	81.6	90.1	55.2	33.6	35.8
RH MC	88.1	94.6	18.4	9.9	44.9	66.4	64.2
Journey Type							
Round-trip	15.9	39.1	20.8	94.9	68.3	11.9	35.3
One-way	84.1	61.0	79.2	5.1	31.7	88.1	64.7
Time of Week							
Weekend	27.4	24.2	32.9	30.3	15.7	83.8	29.9
Weekday	72.6	75.8	67.1	69.7	84.3	16.2	70.1

place on speed and flexibility in their daily routines, with ride-hailing services offering a convenient solution for their transportation needs. On the other hand, individuals living in poverty are more likely to opt for cheaper ride-hailing trips on weekends, as evident in Cluster 6. This indicates that the use of ride-hailing services for cheaper and shorter trips is also correlated for both groups which are either living in poverty or earning higher incomes. However, when it comes to costly trips, this trend is only associated with the higher income group.

4. Discussion and conclusion

As ride-hailing services have gained significant popularity in Southeast Asian countries, it is important to understand typical ride-hailing trips within the Indonesian context. This study aims to fill the gap by identifying ride-hailing trip patterns across various income groups, focusing on low-income individuals, particularly those living in poverty, who have so far been largely overlooked. Using latent class cluster analysis (LCCA) in Yogyakarta, this survey-based study has successfully delineated six distinct clusters representing different ride-hailing trip patterns. Notably, this study is pioneering in applying the LCCA method to explore these clusters while considering various income groups.

4.1. Key findings

The first finding of our study is that understanding ride-hailing trip characteristics characterized by variations in travel cost, duration, timing, trip purpose, vehicle type, journey type, and time of week appears to matter. We found that approximately half of the identified clusters prefer utilizing RH MC for short and less expensive ride-hailing trips. This suggests that the substantial prevalence of motorcycles in the Indonesian context likely contributes to the widespread favoritism towards RH MC over RH CAR in our study. Moreover, the diminishing significance of public transportation in urban areas could increase the prevalence of RH MC options. In contrast, we found that RH CAR usage is more associated with longer and more expensive trips. It is important to note that RH CAR fares are typically higher per kilometer than RH MC, and RH CAR has a larger capacity that makes it more enjoyable during long trip experiences. Furthermore, this study found the dominance of ride-hailing services for returning home, commuting (work and education), and maintenance trips. In the Indonesian context, previous studies have found that the primary trip purpose of using RH MC is for working trips, with a small portion used for discretionary activities (Irawan et al., 2019a; Suatmadi et al., 2019). This highlights the important role of ride-hailing in Indonesia in reaching essential destinations such as homes, workplaces, or grocery stores. The prevalence of ride-hailing usage for essential trips underscores the significance of these services in addressing transportation challenges, particularly in regions with limited access to reliable public transportation. In the Global South, including Southeast Asia, transport poverty and transport equity remain critical issues, with many individuals facing barriers to accessing essential services due to inadequate transport infrastructure. The use of ride-hailing services can help bridge this gap by providing convenient and affordable transportation options, especially for those living in poverty or areas with limited mobility options.

The second finding is that typical ride-hailing users differ among clusters depending on the specific context (e.g., socio-demographics, household characteristics). We found that male users are associated with using RH MC, while female users are more likely to use RH CAR. Previous studies on ride-hailing in Indonesia have found that ride-hailing users are dominated by females, highly educated individuals, and wealthier people (Belgiawan et al., 2022; Irawan et al., 2019b). However, information regarding the specific characteristics of female users' travel type is limited in the previous studies. In addition, we found that older individuals prefer RH CAR, likely due to its comfort and convenience, while RH MC appeals to a wider age range that could be due to its lower cost, shorter travel times, and flexibility. We also found that RH CAR clusters are associated with employed and unemployed

Table 9
Profile of the covariates.

	Cluster 1 (%)	Cluster 2 (%)	Cluster 3 (%)	Cluster 4 (%)	Cluster 5 (%)	Cluster 6 (%)	Overall (%)
Cluster Size	36.8	20.8	15.8	11.2	9.9	5.6	
Covariates							
Gender							
Male	45.9	39.7	34.1	17.2	31.5	43.4	38.0
Female	54.1	60.3	65.9	82.8	68.5	56.6	62.0
Age							
18–25	76.6	75.9	59.8	64.7	29.1	67.8	67.3
25–35	15.2	15.2	16.8	14.3	37.3	13.1	17.4
35–50	7.9	8.8	21.9	20.4	28.0	10.8	13.9
>50	0.3	0.0	1.6	0.6	5.6	8.3	1.4
Level of Education							
Secondary school or below	1.6	0.0	0.0	1.0	1.8	11.4	1.5
Highschool	59.8	60.2	54.2	52.0	27.8	78.1	56.0
Bachelor or equivalent	37.4	35.2	38.0	44.9	65.6	5.8	38.9
Master degree or above	1.3	4.6	7.8	2.0	4.9	4.7	3.6
Employment Status							
Student	54.3	55.4	48.6	36.8	21.3	28.9	47.0
Full-time employee	30.2	32.6	37.4	48.8	34.7	40.6	34.9
Part-time employee	6.3	8.8	5.8	4.0	9.4	17.8	7.4
Unemployed	9.2	3.2	8.3	10.4	34.6	12.6	10.6
Place of Residence							
Yogyakarta	20.7	22.2	13.5	13.9	39.6	23.8	21.2
Sleman	45.0	44.4	46.4	41.1	38.6	32.8	43.3
Bantul	34.4	33.4	40.1	45.0	21.8	43.4	35.5
Income Group							
Living in poverty	2.2	5.5	2.1	7.8	1.5	87.0	8.2
0–1 M IDR	54.2	52.8	52.4	44.6	43.9	6.2	48.9
1–5 M IDR	42.2	37.7	36.2	43.6	48.9	0.0	38.8
5–9 M IDR	1.2	3.6	7.6	2.4	3.8	4.7	3.3
> 9 M IDR	0.2	0.5	1.7	1.6	1.9	2.1	0.9
Family Members (mean)	4.32	4.11	4.24	4.07	4.59	3.94	4.24
Marital Status							
Unmarried	81.1	80.6	68.7	66.6	47.8	51.3	72.5
Married	18.9	19.4	31.3	33.4	52.3	48.7	27.5
RH travel attitudes (mean)							
Safety	−0.02	0.05	−0.03	0.00	0.01	0.27	0.01
Accessibility	−0.04	0.00	−0.17	0.13	0.22	0.36	0.01
Motorcycle Ownership (# in-active)							
0	2.9	2.9	2.9	2.0	2.4	0.1	2.6
1	45.0	44.2	42.5	37.3	53.4	54.0	44.9
2	23.7	24.9	24.3	25.8	30.4	33.4	25.5
3	18.6	19.1	16.3	22.2	9.6	10.4	17.4
>3	9.9	8.9	14.0	12.8	4.3	2.1	9.7
Car Ownership (# in-active)							
0	65.9	64.6	56.1	66.3	68.7	94.4	66.0
1	26.6	30.4	38.3	28.0	26.0	3.6	28.0
2	5.1	3.5	3.3	4.6	3.7	1.9	4.1
3	1.5	1.1	1.1	1.0	1.5	0.0	1.2
>3	1.1	0.4	1.2	0.1	0.2	0.0	0.7
Bike ownership (# in-active)							
0	60.6	58.7	56.2	55.0	63.5	65.3	59.4
1	20.2	21.2	23.9	21.8	22.0	25.1	21.6
2	10.5	11.1	10.9	10.8	6.6	2.6	9.9
3	6.1	7.1	5.5	7.6	6.3	5.9	6.4
>3	2.7	2.0	3.5	4.8	1.6	1.1	2.7

individuals but not students, whereas RH MC clusters encompass a diverse range of employment statuses. RH CAR trips are pricier, attracting older users, while RH MC trips are more affordable, appealing to a broader user base. Furthermore, the utilization of ride-hailing services is not limited to urban areas only but can also extend to suburban areas. This suggests that ride-hailing could hold benefits for disadvantaged groups, compared to conventional taxis, mainly due to its capability to access poor-area or suburban areas (Brown, 2019).

Another goal of this research is to enhance our comprehension of ride-hailing's effects across diverse income levels. We found that lower-income individuals and those living in poverty show a tendency to use ride-hailing services primarily for shorter and more economical trips with RH MC. Conversely, individuals from higher-income brackets use ride-hailing for both economical and more expensive trips. This difference can be attributed to the broader range of transportation options available to individuals with higher incomes as compared to those with lower incomes. As a result, individuals from higher-income groups are more likely to choose ride-hailing services for broader travel needs, regardless of costs. This finding also suggests that ride-hailing could potentially enhance accessibility for low-income individuals, especially for people living in poverty in the Indonesian context, who often experience barriers to owning private vehicles. It should be noted, though, that our study solely captured ride-hailing trips undertaken by low-income groups and those living in poverty. Hence, it may be possible that low-income individuals using ride-hailing still have mobility needs that cannot be addressed by ride-hailing in its current form. Also, the relatively lower utilization of ride-hailing among low-income groups underscores that financial constraints might hinder the accessibility of ride-hailing services for all living in poverty.

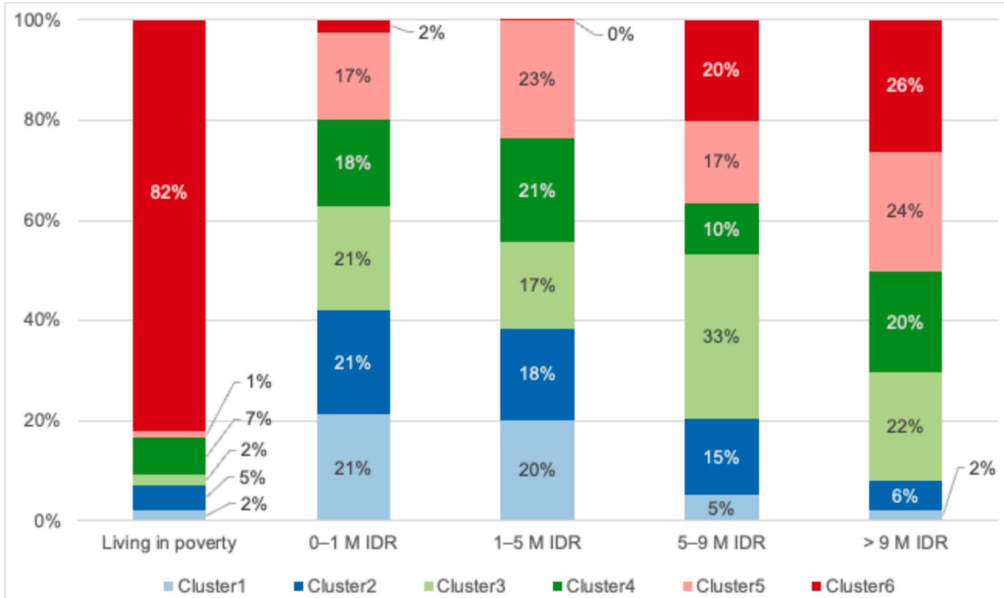

Fig. 3. Total percentage of each income group.

4.2. Policy recommendations

Based on the results of this study, the findings can inform policymakers and stakeholders on how to understand typical ride-hailing trips across various income groups aimed at alleviating transport poverty and enhancing mobility equity. *First*, given the substantial prevalence of RH MC within the identified clusters, we strongly recommend prioritizing increased safety measures for RH MC. This urgency stems from the persistently prominent safety concerns associated with motorcycle use in Indonesia, as noted by (Joewono et al., 2019; Jusuf et al., 2017; Manan and Várhelyi, 2012; Munawar, 2018; Tuffour and Appiagyei, 2014). In the Indonesian context, motorcycles often operate at high speeds, which can result in severe accidents due to the absence of protective barriers, as opposed to cars. Recommendations include implementing screening and training programs for ride-hailing drivers and enforcing vehicle safety standards to reduce traffic accidents and fatalities. Several previous studies have also suggested measures to enhance safety regarding screening and training programs for drivers. For example, Alvaro et al. (2018) propose an educational program assessment based on simulated night driving, or Zhao et al. (2019) also propose a simulator-based "perception-norm-execution" (PNE) driving training model to mitigate human errors by targeting risky driving behaviors.

Another vital policy recommendation stemming from this study pertains to the prevalence of one-way trips observed in various clusters (e.g., 1, 2, 3 and 6). In light of this trend, it is important to include ride-hailing services into cities' future planning (Conway et al., 2018). Therefore, we recommend for the integration of ride-hailing services with other modes of travel, particularly public transportation options. The rationale behind this proposal rests on the substantial expertise and infrastructure that ride-hailing services have developed in designing robust ride-hailing applications. Concurrently, public transportation systems in Indonesia stand to benefit from the technological advancements that these platforms offer. This integration aims to enhance accessibility and connectivity, which can address issues of transport poverty by providing more options for individuals with limited access to essential destinations.

5. Limitations

While our study sheds light on ride-hailing travel patterns, it is essential to acknowledge that our dataset is derived from self-reported user perspectives. This approach might not yield as precise information about ride-hailing trips as data obtained directly from ride-hailing companies, which could include details such as travel cost, time, volume, and specific origin and destination points. As highlighted by a previous study from Contreras and Paz (2018), data directly obtained from ride-hailing companies may provide more precise and comprehensive trip information. Finally, locating individuals living in poverty within our study area posed a challenge. Yogyakarta is a relatively prosperous province, boasting a robust tourism industry (Dahles, 1998) and a burgeoning economy. The complexity arises from the fact that many individuals engage in small-scale businesses, street vending, or other informal occupations, which might not officially categorize them as living below the poverty line. Additionally, assessing poverty is complicated by social stigma (The Asia Foundation, 2016), as the topic of poverty can be delicate in Indonesia. Consequently, individuals may hesitate to openly discuss their financial circumstances. Moreover, the scarcity of reliable information on poverty in certain parts of Yogyakarta further impedes our ability to precisely gauge the extent of the issue.

The authors declare that they have no known competing financial interests or personal relationships that could influence the work reported in this paper.

CRediT authorship contribution statement

Muchlis Muchlisin: Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Jaime Soza-Parra:** Writing – review & editing, Validation, Supervision, Formal analysis. **Yusak O. Susilo:** Writing – review & editing, Validation, Supervision, Methodology, Formal analysis, Data curation, Conceptualization. **Dick Ettema:** Writing – review & editing, Validation, Supervision, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

Affairs, M.o.H., 2021. Pemberlakuan Pembatasan Kegiatan Masyarakat Darurat Corona Virus Desease 2019 di Wilayah Jawa dan Bali, in: Ministry of Home Affairs, R.o.I. (Ed.), Instruction of the Minister of Home Affairs ed.

Alemi, F., Circella, G., Handy, S., Mokhtarian, P., 2018. What influences travelers to use Uber? Exploring the factors affecting the adoption of on-demand ride services in California. Travel Behav. Soc. 13, 88–104.

Alvaro, P.K., Burnett, N.M., Kennedy, G.A., Min, W.Y.X., McMahon, M., Barnes, M., Jackson, M., Howard, M.E., 2018. Driver education: Enhancing knowledge of sleep, fatigue and risky behaviour to improve decision making in young drivers. Accid. Anal. Prev. 112, 77–83.

Andrews, R.L., Currim, I.S., 2003. A comparison of segment retention criteria for finite mixture logit models. J. Mark. Res. 40 (2), 235–243.

Atkinson-Palombo, C., Varone, L., Garrick, N.W., 2019. Understanding the surprising and oversized use of ridesourcing services in poor neighborhoods in New York City. Transp. Res. Rec. 2673 (11), 185–194.

Bank, T.W., 2023. Nowcast of extreme poverty in 2015–2022. The World Bank.

Belgiawan, P.F., Joewono, T.B., Irawan, M.Z., 2022. Determinant factors of ride-sourcing usage: A case study of ride-sourcing in Bandung, Indonesia. Case Stud. Transp. Policy 10 (2), 831–840.

Ben-Akiva, M., Lerman, S.R., 2018. Discrete choice analysis: theory and application to travel demand. Transp. Stud.

Brown, A.E., 2018. Ridehail revolution: Ridehail travel and equity in Los Angeles. University of California, Los Angeles.

Brown, A., 2019. Redefining car access: Ride-hail travel and use in Los Angeles. J. Am. Plann. Assoc. 85 (2), 83–95.

Chalermpong, S., Kato, H., Thaithatkul, P., Ratanawaraha, A., Fillone, A., Hoang-Tung, N., Jittrapirom, P., 2022. Ride-hailing applications in Southeast Asia: A literature review. Int. J. Sustain. Transp. 1–21.

Clewlow, R.R., Mishra, G.S., 2017. Disruptive transportation: The adoption, utilization, and impacts of ride-hailing in the United States.

Contreras, S.D., Paz, A., 2018. The effects of ride-hailing companies on the taxicab industry in Las Vegas, Nevada. Transp. Res. A Policy Pract. 115, 63–70.

Conway, M., Salon, D., King, D., 2018. Trends in Taxi Use and the Advent of Ridehailing, 1995–2017: Evidence from the US National Household Travel Survey. Urban Sci. 2 (3).

Dahles, H., 1998. Tourism, government policy, and petty entrepreneurs in Indonesia. South East Asia Res. 6 (1), 73–98.

Dias, F.F., Lavieri, P.S., Garikapati, V.M., Astroza, S., Pendyala, R.M., Bhat, C.R., 2017. A behavioral choice model of the use of car-sharing and ride-sourcing services. Transportation 44 (6), 1307–1323.

Dias, F.F., Lavieri, P.S., Kim, T., Bhat, C.R., Pendyala, R.M., 2019. Fusing multiple sources of data to understand ride-hailing use. Transp. Res. Rec. 2673 (6), 214–224.

Ermagun, A., Tilahun, N., 2020. Equity of transit accessibility across Chicago. Transp. Res. Part D: Transp. Environ. 86, 102461.

Etter, J.-F., Perneger, T.V., 2000. Snowball sampling by application to a survey of smokers in the general population. Int. J. Epidemiol. 29 (1), 43–48.

Fleming, K.L., 2018. Social equity considerations in the new age of transportation: Electric, automated, and shared mobility. J. Sci. Policy Governance 13 (1), 20.

Foundation, A., 2016. Understanding social exclusion in Indonesia: A meta-analysis of Program Peduli's theory of change documents. The Asia Foundation.

Friedmann, J., 2011. Becoming urban: periurban dynamics in Vietnam and China—introduction. Pac. Aff. 84 (3), 425–434.

Gomez, J., Aguilera-Garcia, A., Dias, F.F., Bhat, C.R., Vassallo, J.M., 2021. Adoption and frequency of use of ride-hailing services in a European city: The case of Madrid. Transp. Res. Part C: Emerging Technol. 131, 103359.

Ilahi, A., Belgiawan, P.F., Balac, M., Axhausen, K.W., 2021. Understanding travel and mode choice with emerging modes; a pooled SP and RP model in Greater Jakarta, Indonesia. Transp. Res. A Policy Pract. 150, 398–422.

Irawan, M.Z., Belgiawan, P.F., Joewono, T.B., Simanjuntak, N.I.M., 2019a. Do motorcycle-based ride-hailing apps threaten bus ridership? A hybrid choice modeling approach with latent variables. Public Transport 12 (1), 207–231.

Irawan, M.Z., Belgiawan, P.F., Tarigan, A.K.M., Wijanarko, F., 2019b. To compete or not compete: exploring the relationships between motorcycle-based ride-sourcing, motorcycle taxis, and public transport in the Jakarta metropolitan area. Transportation.

Irawan, M.Z., Belgiawan, P.F., Joewono, T.B., Bastarianto, F.F., Rizki, M., Ilahi, A., 2021. Exploring activity-travel behavior changes during the beginning of COVID-19 pandemic in Indonesia. Transportation 1–25.

Jansen, J., 2010. Use of the internet in higher-income households. Pew Research Center Washington, DC.

Joewono, T., Legi, S., Tarigan, A., 2019. A longitudinal analysis of traffic-violation behaviours among two groups of motorcyclist in Bandung, Indonesia. J. Soc. Autom. Eng. Malaysia 3 (2).

Johnson, T.P., 2005. Snowball sampling. *Encyclopedia of biostatistics* 7.

Jones, G.W., 1997. The throughgoing urbanisation of East and Southeast Asia. Asia Pac. Viewp. 38 (3), 237–249.

Jones, G.W., 2001. Studying extended metropolitan regions in South-East Asia, *XXIV General Conference of the IUSSP. Salvador Brazil*, pp. 18-24.

Jusuf, A., Nurprasetio, I.P., Prihutama, A., 2017. Macro Data Analysis of Traffic Accidents in Indonesia. J. Eng. Technol. Sci. 49 (1).

Kusno, A., 2020. Middling urbanism: the megacity and the kampung. Urban Geogr. 41 (7), 954–970.

Kuswanto, A., Sundari, S., Harmadi, A., Hariyanti, D.A., 2019. The determinants of customer loyalty in the Indonesian ride-sharing services: offline vs online. Innov. Manage. Rev. 17 (1), 75–85.

Leaf, M., 2011. Periurban Asia: A commentary on "becoming urban". Pac. Aff. 84 (3), 525–534.

Lee, Y., Chen, G.-Y.-H., Circella, G., Mokhtarian, P.L., 2022. Substitution or complementarity? A latent-class cluster analysis of ridehailing impacts on the use of other travel modes in three southern US cities. Transp. Res. Part D: Transp. Environ. 104, 103167.

Lerman, S.R., Manski, C.F., 1979. Sample design for discrete choice analysis of travel behavior: The state of the art. Transp. Res. Part A: General 13 (1), 29–44.

Lucas, K., Mattioli, G., Verlinghieri, E., Guzman, A., 2016. Transport poverty and its adverse social consequences, *Proceedings of the institution of civil engineers-transport*. Thomas Telford Ltd, pp. 353-365.

Manan, M.M.A., Várhelyi, A., 2012. Motorcycle Fatalities in Malaysia. IATSS Res. 36 (1), 30–39.

McGee, T.G., 1991. The emergence of desakota regions in Asia: expanding a hypothesis. *The extended metropolis: Settlement transition in Asia*.

Molin, E., Mokhtarian, P., Kroesen, M., 2016. Multimodal travel groups and attitudes: A latent class cluster analysis of Dutch travelers. Transp. Res. A Policy Pract. 83, 14–29.

Muchlisin, M., Ettema, D., 2023. Motorcycle and Car-Based Ridehailing in the Different Income Group: The Adoption and Frequency in Yogyakarta, Indonesia. In: Board, T. R. (Ed.), The 102nd Annual Meeting of the Transportation Research Board. Transportation Research Board, Washington, D.C United States.

Munawar, A., 2018. Traffic accident analysis in the city of Yogyakarta, Indonesia, *Proceedings of the World congress on engineering*.

Napalang, M.S.G., Regidor, J.R.F., 2017. Innovation versus regulation: an assessment of the metro manila experience in emerging ridesourcing transport services. J. East. Asia Soc. Transp. Stud. 12, 343–355.

Nistal, P.D., Regidor, J.R.F., 2016. Comparative study of Uber and regular taxi service characteristics, *Proceedings of the 23rd Annual Conference of the Transportation Science Society of the Philippines, Quezon City, Philippines. Available from: http://ncts. upd. edu. ph/tssp/wp-content/upload/2016/08/Paronda-et-al. pdf (accessed August 13, 2017)*.

Nugroho, S.B., Zusman, E., Nakano, R., 2020. Explaining the spread of online taxi services in Semarang, Bogor and Bandung, Indonesia; a discrete choice analysis. Travel Behav. Soc. 20, 358–369.

Pan, R., Yang, H., Xie, K., Wen, Y., 2020. Exploring the equity of traditional and ride-hailing taxi services during peak hours. Transp. Res. Rec. 2674 (9), 266–278.

Paronda, A.G.A., Regidor, J.R.F., Gaabucayan-Napalang, S., 2017. An exploratory study on Uber, GrabCar, and conventional taxis in. University of the Philippines, Metro Manila.

Phun, V.K., Kato, H., Chalermpong, S., 2019. Paratransit as a connective mode for mass transit systems in Asian developing cities: Case of Bangkok in the era of ride-hailing services. Transp. Policy 75, 27–35.

Province, B.-S.o.Y., 2022b. Jumlah Penduduk Miskin Menurut Kabupaten/Kota (Ribuan), 2020-2022. Yogyakarta Province Bureau of Statistics.

Rafiq, R., McNally, M.G., 2022. An exploratory analysis of alternative travel behaviors of ride-hailing users. Transportation 1–35.

Rayle, L., Dai, D., Chan, N., Cervero, R., Shaheen, S., 2016. Just a better taxi? A survey-based comparison of taxis, transit, and ridesourcing services in San Francisco. Transp. Policy 45, 168–178.

Ruangkanjanases, A., Techapoolphol, C., 2018. Adoption of E-hailing applications: A comparative study between female and male users in Thailand. J. Telecommun., Electron. Comput. Eng. (JTEC) 10 (1–10), 43–48.

Shaheen, S., Chan, N., 2016. Mobility and the sharing economy: Potential to facilitate the first-and last-mile public transit connections. Built Environ. 42 (4), 573–588.

Shaheen, S., Bell, C., Cohen, A., Yelchuru, B., Hamilton, B.A., 2017. Travel behavior: Shared mobility and transportation equity. United States. Federal Highway Administration. Office of Policy.

Silalahi, S.L.B., Handayani, P.W., Munajat, Q., 2017. Service quality analysis for online transportation services: Case study of GO-JEK. Procedia Comput. Sci. 124, 487–495.

Silviana, C., Potkin, F., 2019. Indonesia to fix motorbike ride-hailing rates; may hurt Grab, Go-Jek, *Industrials*. Reuters.com.

Statista, 2023. Ride-hailing – Worldwide, *Shared Mobility*.

Suatmadi, A.Y., Creutzig, F., Otto, I.M., 2019. On-demand motorcycle taxis improve mobility, not sustainability. Case Stud. Transp. Policy 7 (2), 218–229.

Suhr, D.D., 2005. Principal component analysis vs. exploratory factor analysis. *SUGI 30 proceedings* 203, 230.

Tirachini, A., 2019. Ride-hailing, travel behaviour and sustainable mobility: an international review. Transportation 1–37.

Tuffour, Y.A., Appiagyei, D.K.N., 2014. Motorcycle taxis in public transportation services within the Accra metropolis. Am. J. Civil Eng. 2 (4), 117–122.

Van, H.T., Fujii, S., 2011. A cross Asian country analysis in attitudes toward car and public transport, *Proceedings of the Eastern Asia Society for Transportation Studies Vol. 8 (The 9th International Conference of Eastern Asia Society for Transportation Studies, 2011)*. Eastern Asia Society for Transportation Studies, pp. 87-87.

Vermunt, J.K., Magidson, J., 2002. Latent class cluster analysis. Appl. Latent Class Anal. 11 (89–106), 60.
Vermunt, J.K., Magidson, J., 2016. Upgrade manual for Latent GOLD 5.1. Statistical Innovations, Belmont, MA.
Wadud, Z., 2020. The effects of e-ridehailing on motorcycle ownership in an emerging-country megacity. Transp. Res. A Policy Pract. 137, 301–312.
Wang, X., Yan, X., Zhao, X., Cao, Z., 2022. Identifying latent shared mobility preference segments in low-income communities: Ride-hailing, fixed-route bus, and mobility-on-demand transit. Travel Behav. Soc. 26, 134–142.
Wang, H., Yang, H., 2019. Ridesourcing systems: A framework and review. Transp. Res. B Methodol. 129, 122–155.
Weng, G.S., Zailani, S., Iranmanesh, M., Hyun, S.S., 2017. Mobile taxi booking application service's continuance usage intention by users. Transp. Res. Part D: Transp. Environ. 57, 207–216.
Williams, B., Onsman, A., Brown, T., 2010. Exploratory factor analysis: A five-step guide for novices. Austral. J. Paramedicine 8, 1–13.
Young, M., Farber, S., 2019. The who, why, and when of Uber and other ride-hailing trips: An examination of a large sample household travel survey. Transp. Res. A Policy Pract. 119, 383–392.
Zhao, X., Xu, W., Ma, J., Gao, Y., 2019. The "PNE" driving simulator-based training model founded on the theory of planned behavior. Cogn. Tech. Work 21, 287–300.