Keywords: ride-hailing services, higher education area, transport supply and demand

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RIDE-HAILING SERVICE USERS AND PROVIDERS IN THE HIGHER EDUCATION AREA: A SPATIAL AND NON-SPATIAL PERSPECTIVE

Summary. This article describes supply and demand through the spatial and non-spatial dimensions of the users and providers of ride-hailing services in the higher education area. The structural equation modeling method determines the relationship between variables based on a perception survey of 200 users and 200 ride-hailing service providers in the Tembalang higher education area, Semarang, conducted from 2020–2021. The modeling results show that there is an insignificant spatial and non-spatial relationship. The non-spatial dimension in both users and ride-hailing providers influences the moderating of both spatial dimensions. The development of higher education institutions in peri-urban areas creates new growth poles in line with the evolution of digital platforms that dictate physical geographies due to the fusion of non-spatial conditions. Reconciling the public transportation system with campus-based operational adjustments, appropriate fares, and fees will provide more equal opportunities for campus residents to engage and succeed in higher education.

1. INTRODUCTION

The density of students in higher education zones could significantly impact traffic congestion, primarily due to these institutions' high volume of trips. This congestion is exacerbated by the concentration of educational facilities and the associated transportation infrastructure. The presence of universities and colleges in urban areas increases vehicular and pedestrian traffic, particularly during peak hours, which can result in severe congestion and related issues, such as traffic accidents and environmental pollution. Some researchers have pointed out that higher education zones generate substantial traffic, with studies indicating peak vehicle entries at specific times [1]. Thus, the trip rate is notably higher than standard rates, necessitating traffic management strategies.

While some researchers have highlighted the impact of higher education zones on urban traffic, their research has focused on urban complexes and their influence on traffic generation, trip modes, peak hours, and parking demand within urban planning. Research also suggests mitigating strategies such as rescheduling courses, increasing public transport use, and implementing pricing strategies for parking to alleviate congestion in these areas. Some areas of higher education zones significantly contribute to urban traffic, accounting for up to 10% of city journeys [2]. Universities significantly impact urban traffic by generating a high volume of daily trips due to their concentrated campuses, which house thousands of students and employees. This creates challenges for neighboring areas and the overall transport systems in cities.

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In Indonesia, the higher education zone is becoming a symbol of cities, showing heightened importance in terms of its physical scope and prestige. In many large cities in Indonesia, the density of higher education zones, defined as the number of students per unit area, varies among Indonesia's prominent universities. Depok City, West Java, is inhabited by the University of Indonesia and other universities, with a total educational area of about 359 hectares and 47,357 students. The city of Bandung, West Java, has the Bandung Institute of Technology and other universities, and it has a total campus area of around 77 hectares, with 34,296 students. Another higher education area with renowned universities is located in Bogor City, West Java, which has Institut Pertanian Bogor and other universities with a total area of 250 hectares and 36,746 students. In Central Java Province, Semarang City's higher education area is geographically located in Tembalang. It is populated by universities such as Diponegoro University, with a total area of 213 hectares and approximately 60,000 students. This makes higher education zones in Indonesia the largest in significant cities in Asian countries.

Universities in major urban centers, such as the University of Tokyo in Japan or the National University of Singapore, often have higher student densities due to limited land availability and higher enrollment numbers. In contrast, rural or suburban institutions may have more expansive campuses with lower student densities. While specific numerical comparisons are limited, student density in higher education zones across Asia, notably in Indonesia, is influenced by a combination of geographic location, campus design, and enrollment sizes. Urban institutions tend to have higher densities due to space constraints and higher demand.

Over the last five years, the transportation sector in major Indonesian cities has been heavily affected by the rise of online transport and ride-hailing platforms. This trend has particularly impacted areas around higher education institutions. After the global expansion of Uber in Europe and America, Indonesia also developed its online transport massively in terms of car- and bike ride-hailing platforms.

A previous study showed that the higher education zone is one of the profitable markets for online transport, and up to 2024, the number of online transport drivers has reached 3.5 million. Moreover, in terms of mobility behavior perspectives, ride-hailing services have changed travel behavior in the urban transportation sector over the past decade. Due to the evolution of the sharing economy, ride-hailing has become increasingly prominent due to its flexibility and ease of use. Ride-hailing services can provide differentiated services with a more flexible pricing mechanism in the market, while traditional public transport pricing is controlled and regulated by the government. Despite its evident significance over the past five years, the transportation sector in major Indonesian cities has significantly been affected by the rise of online transportation services.

While the significant impact of ride-hailing on urban practices is evident, it is crucial to recognize that its effects on urban structures and patterns are complex and multifaceted. These impacts vary significantly depending on technology adoption, policy interventions, and societal behaviors. Higher education zones are key mobility hubs characterized by high student density, diverse travel needs, and dynamic commuting patterns. College communities require flexible transportation options due to irregular schedules, diverse destinations, and a mix of on- and off-campus activities. The convenience and accessibility of ride-hailing services have made them an attractive alternative to traditional public transportation in these areas, affecting travel behavior in ways that may not be immediately apparent.

The Indonesian government's efforts to improve its human resources in achieving the "Indonesia Emas 2045" target should start by criticizing the pattern of activities that occur in its superior HR factory, the higher education area. Higher education's effectiveness is critical to a nation's development and modernization. High education success significantly correlates with students' time on campus-oriented activities [3].

The phenomenon also includes the trend of higher education development in suburban areas, where there are issues related to the mode of transport for their movement. The presence of private vehicle ownership as a mode that is considered easier in the existence of higher education areas located in the suburbs is allegedly causing chaos and disruption of movement on road space along with the position of this area as a spatial growth point that develops economic activities sporadically [4]. Failure to intervene in these transport issues will slow efforts to produce effective human resources. While ride-hailing services can complement public transportation by improving first-mile and last-mile connectivity, their increasing adoption raises concerns about their long-term impact on the same patterns caused by private vehicles. Well-established public transport networks serve many higher education areas, but shifting from buses and other modes of transportation to ride-hailing decreases ridership.

A vital aspect of policies related to ride-hailing or urban digital mobility is understanding how it affects other modes of transportation in urban areas, especially in higher education areas. This research focuses on the Tembalang higher education area in Semarang City and raises concerns about the lack of attention given to the higher education area as a New Growth Pole, especially concerning the Tembalang higher education area, which is home to more than 60,000 students and has the potential to become a prosperous economic area that can generate unprecedented impacts on the surrounding environment.

Traffic disruption will be a limiting factor for students' attendance on campuses [3]. The movement needs in higher education areas organically create demand for time-efficient transport services, especially for those who would prefer to drive due to congestion or not owning a private vehicle. The popularity of ride-hailing among people in higher education areas can indirectly disrupt the stability of existing transportation, especially the pattern of movement with short distances being considered so that integration between public transportation and ride-hailing at the last mile is considered ineffective.

Understanding how ride-hailing and shared mobility, in general, are changing travel behaviors today and how autonomous shared-mobility services will change them in the future is not easy. Recent studies in Indonesia have examined the presence of ride-hailing services, from general topics related to the differences between online and conventional transport of mobility patterns [5, 6], social media marketing effects [7], and customer satisfaction [8, 9]. However, such research partially focuses on the existence of ride-hailing services, and no previous research has concentrated on the causal relationship between ride-hailing providers or the supply and demand of ride-hailing services. Some global research has explored ride-hailing services both from the demand side [10, 11] and the supply side [12, 13], but few studies have specifically examined the higher education area.

This study aims to determine the characteristics of supply and demand seen from the relationship between users and providers of ride-hailing services in Tembalang higher education areas in Semarang City from a spatial and non-spatial perspective. The results are expected to contribute to considering the direction of transport management policies in the higher education area. The objectives derived from the aims of this research are as follows:

- To identify the impact of users' spatial factors on users' non-spatial factors and ride-hailing service providers' non-spatial factors separately.
- To identify the relationship between non-spatial factors of service providers and non-spatial factors of ride-hailing users to spatial factors of ride-hailing service providers.
- To identify the relationship between users' and ride-hailing service providers' spatial factors.

2. LITERATURE REVIEW

The rise of ride-hailing services represents a paradigm shift in urban transportation, redefining how people move within cities. One of the key drivers behind the surge of ride-hailing services is the increased accessibility and affordability they offer compared to traditional transport services [14]. The relevance of ride-hailing services to higher education areas is a multifaceted phenomenon that intertwines with the unique dynamics and demands of university campuses [15]. Ride-hailing services offer a flexible and on-demand mode of transportation that aligns with students' dynamic and often unpredictable schedules. University students frequently move between the campus and their homes during breaks or holidays. Ride-hailing services cater to the transitory nature of the student population, providing an easily accessible and familiar mode of transportation.

2.1. Ride-Hailing Supply Related to Drivers

The evolution of digital geography and ride-hailing services has revolutionized urban transport and changed the paradigm of mobility and travel patterns [16, 17]. From a spatial perspective, previous research on the geographical distribution of ride-hailing drivers [18, 19] has found concentrations associated with passenger pickup and drop hotspots [12]. Other explored dimensions address the spatial coverage of ride-hailing services, emphasizing the factors of distance traveled, trip frequency, and travel time. On the non-spatial side, some research has investigated the influences of driver income [5, 14] and incentive structure on driver participation [13]. In recent years, safety and risk factors have impacted the presence and decision-making considerations for drivers of ride-hailing services. At the same time, the non-spatial factor of ride-hailing providers also relates to the driver's mastery of the field, which is related to matching bookings with the service features [5]. Meanwhile, several studies have explored market dynamics and competition patterns that shed light on the direct benefits [13, 14] that ride-hailing service providers can derive.

2.2. Ride-Hailing Demand Related to Users

Recent studies on ride-hailing mostly consider the demand side of ride-hailing users, including user behavioral intentions [8], socioeconomic characteristics [11], and characteristics of trips made by users [20]. From a spatial perspective, the study by Belgiawan [9] and Silalahi [10] explored the distribution of origin and destination of ride-hailing demand and variations in user preferences regarding travel intent and frequency of trips made. In addition, several studies have assessed the spatial consequences of public transport coverage on the demand for ride-hailing services [6]. On the non-spatial side, several studies have investigated user preferences and satisfaction [15, 20], examining factors influencing overall demand, such as service quality, waiting time, and compatibility with activity goals [21]. Previous studies have also contributed insights into the economic aspects of car ownership [11], affordability compared to pricing [8], and its impact on users' reasons for using ride-hailing. In addition, the dimensions of users' product knowledge [10] of the technology features presented and their influence on user behavior.

Knowing the pattern of demand and supply for ride-hailing, both spatially and non-spatially, can help ensure the proper implementation of the policy for structuring public transportation in the higher education area.

3. RESEARCH METHODS

This study critically examines ride-hailing supply and demand in Tembalang higher education. The selected area consists of four campuses located close together and concentrated in a radius of 3 km^2.

3.1. Research Design

This paper aims to develop and validate a model of the relationship between spatial and non-spatial factors of users and spatial and non-spatial factors of ride-hailing service providers. As presented in Table 1, the measurement model consisted of four latent variables with 22 manifest indicators generated based on the literature. This model uses 5-point Likert scale questionnaire data from 200 users and 200 ride-hailing providers (drivers) in the Tembalang higher education area. The data were analyzed through the PLS-SEM method using STATA. We applied a package of tools and guidelines developed by Venturini and Mehmetoglu [22].

3.2. Conceptual Model

The non-spatial variables in both the user (UNS) and provider (SPNS) dimensions, along with the spatial variables in the provider (SPS) dimension, are endogenous. In contrast, the user spatial (US) variables are the only exogenous variables. Based on literature reviews, the proposed variables that reflect each of their manifest indicators are then visualized in the conceptual model in Fig. 1.

3.3. Construct Validity and Reliability (Outer Model)

Outer model measurement for reflexive indicators was carried out by assessing the validity of each manifest indicator against its latent variable. Validity measurement was based on convergence validity, consisting of factor loading values and average variance extracted (AVE). The measurement results show that the factor loading values of all manifest indicators are higher than 0.708 (Fig. 2), which indicates a good validity scale [23]. A good validity value is also indicated by the AVE value, as all indicators are higher than 0.50 [23].

Table 1

Variables and indicators used in the model

Dimensions	Latent Variable	Manifest Indicators	Code
User/ Customer	Users's Spatial (US)	Origin-destination distance after using ride-hailing	US1
		Trip frequency	US2
		Travel time preferences suitability	US3
		Public transportation proximity	US4
		Ride-hailing service usage spatial clustering	US5
	Users' Non-Spatial (UNS)	Car ownership shifts	UNS1
		Income reach to service purchase	UNS2
		Duration of ride-hailing service subscription	UNS3
		Reasons for using ride-hailing services	UNS4
		Suitability with the type of activity	UNS5
		Level of product knowledge	UNS6
Provider/ Driver	Service Providers's Spatial (SPS)	Daily service mileage	SPS1
		Frequency of serving customers	SPS2
		Total service travel time	SPS3
		Hotspots for pickups and drop-offs	SPS4
	Service Providers's Non-Spatial (SPNS)	Level of safety in road space	SPNS1
		Risk factors encountered	SPNS2
		Direct costs incurred for services	SPNS3
		Level of conformity of service requests	SPNS4
		Direct benefits perceived	SPNS5

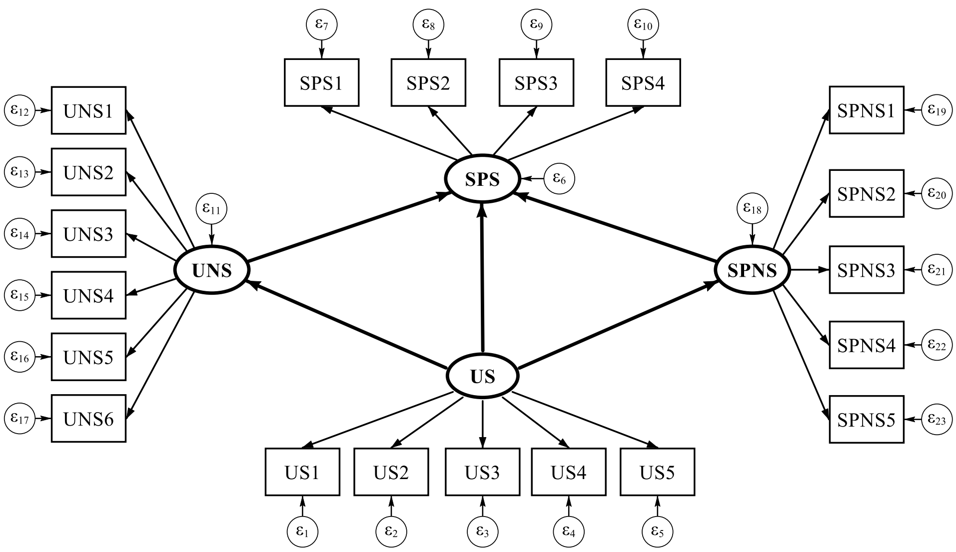

Fig. 1. Conceptual Model

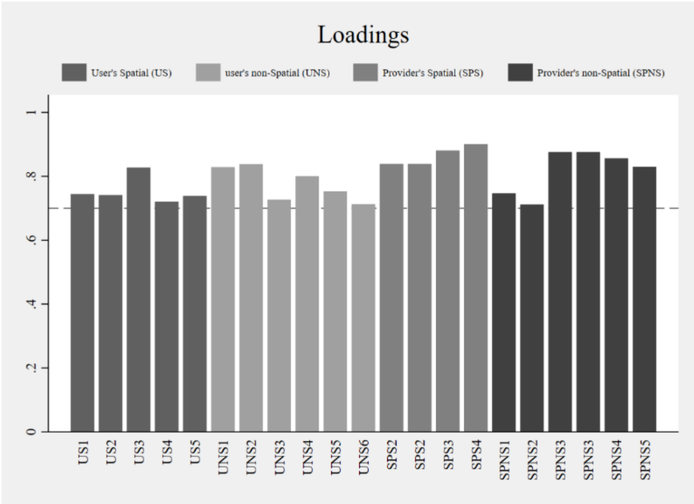

Fig. 2. Outer Loadings Value

Discriminant validity was also used to measure the validity of the outer model. This kind of validity indicator consists of crossloadings and the Fornell-Larcker criterion. As shown in Fig. 3, the cross-loading test results show that all outer loadings of indicators on the related constructs are more significant than the correlation between latent variables, meaning all constructs have good discriminant validity [23]. This construct value is also considered valid because it has fulfilled the Fornell-Larcker criterion [24], as the AVE is higher than 0.5.

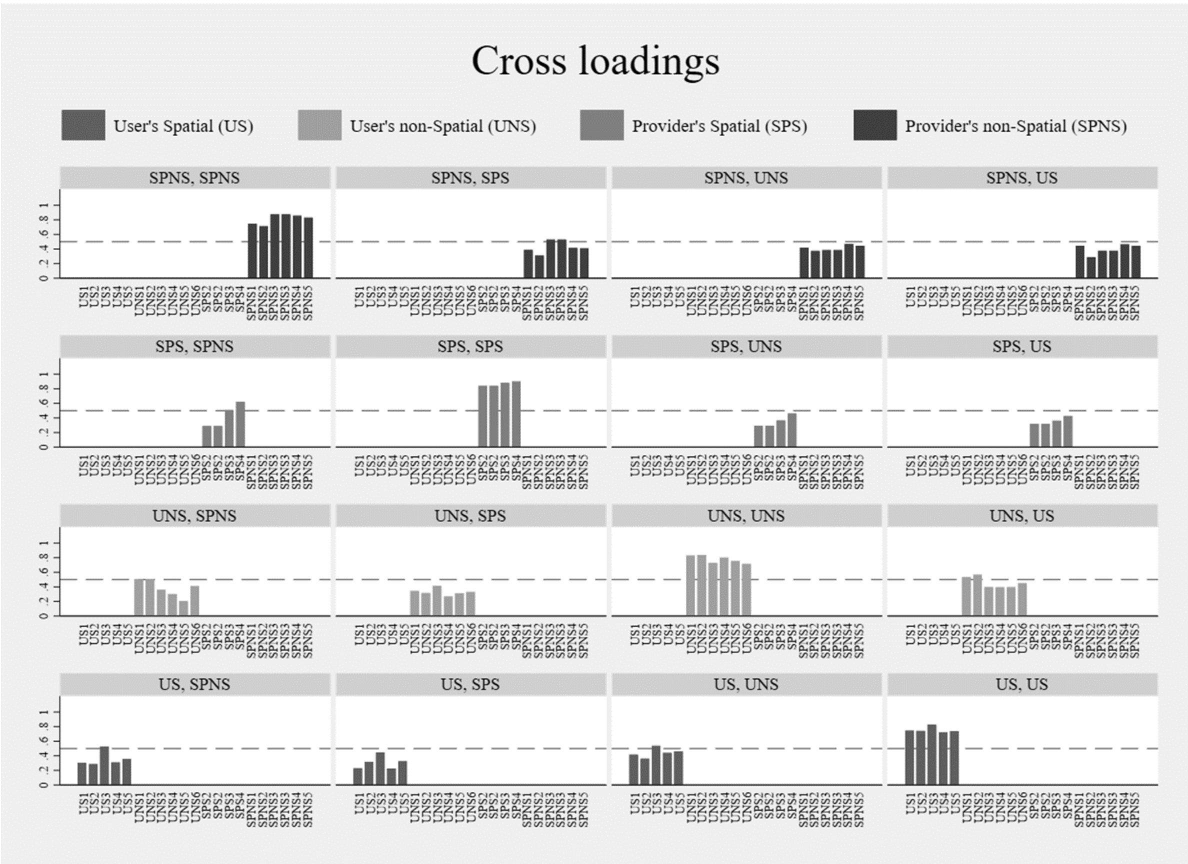

Fig. 3. Cross Loadings Value

Reliability testing was carried out to prove accuracy and precision in measuring constructs. Construct reliability can be seen from the composite reliability (DG) and Cronbach alpha indicators higher than 0.7 [23]. The calculation results in Table 2 show that all constructs are reliable and that the model has internal consistency reliability. Based on the test results of the validity and reliability of the construct (outer model), the results of the convergent validity, discriminant validity, composite reliability, and Cronbach alpha tests are adequate and have been accepted. As such, the model is feasible and can be used for the structural model evaluation.

Table 2

Construct reliability and validity

	US	UNS	SPS	SPNS
Cronbach	0.813	0.869	0.895	0.900
DG	0.869	0.902	0.922	0.924
rho_A	0.837	0.876	0.949	0.909
AVE	0.570	0.606	0.748	0.670

3.4. Structural Model Evaluation (Inner Model)

Inner model measurement is interpreted to test the causality between latent variables. In the initial stage of checking the structural model, the absence of multicollinearity between latent variables was checked, as shown in Table 3. The results show no multicollinearity problem in the latent variables, as the values are between -0.9 and 0.9 [23].

Table 3

Correlation of latent variables

	US	UNS	SPS	SPNS
US	1.000			
UNS	0.526	1.000		
SPS	0.515	0.444	1.000	
SPNS	0.501	0.415	0.595	1.000

4. RESULTS

Following the multicollinearity check, the stability of the estimates was tested using the t-statistical test through 500 bootstrap resampling [25]. As shown in Fig. 4, there was an insignificant effect on the relationship between **US** and **SPS** due to the t-value, which is below 1.96 with a 95% confidence degree. However, a significant effect was found for other latent variable relationships, as the t-value was higher than 1.96. The figure illustrates the relative relationship depicted by the thickness of the dashes.

These results suggest that spatial factors do not significantly determine the relationship between users and ride-hailing service providers in higher education areas. This could be due to users' more flexible mobility characteristics and demand patterns that are not necessarily influenced by spatial factors. In other words, geographical proximity between users and providers does not necessarily increase their likelihood of interaction. This could be due to the vehicle allocation mechanism in ride-hailing apps, which prioritizes other factors, such as the availability of drivers within a certain radius, optimal travel time, and current traffic conditions. Meanwhile, significant relationships between other latent variables suggest that factors other than spatial are crucial in determining the dynamics of ride-hailing services. Ride fares, drivers' incentives, and time-based demand patterns are likely to affect the balance between users and service providers.

The results of the structural model evaluation shown in Table 4 outline the path coefficient value, p-value, and effect size (f^2). Concerning the first (H1) to fourth (H4) hypotheses, the relationship is positive (based on the β value) and significant ($p < 0.05$). The f^2 value is above 0.025 [23], indicating that these four hypotheses are accepted. However, for H5, the coefficient is positive, p > 0.05, showing an insignificant relationship [23], and f^2 is moderate, as it is higher than 0.01 and lower than 0.025 [23]. Hence, the hypothesis is rejected.

The insignificant relationship between the user's spatial and the provider's spatial needs to be further described regarding the indirect relationship formed from the moderation function of non-spatial dimensions.

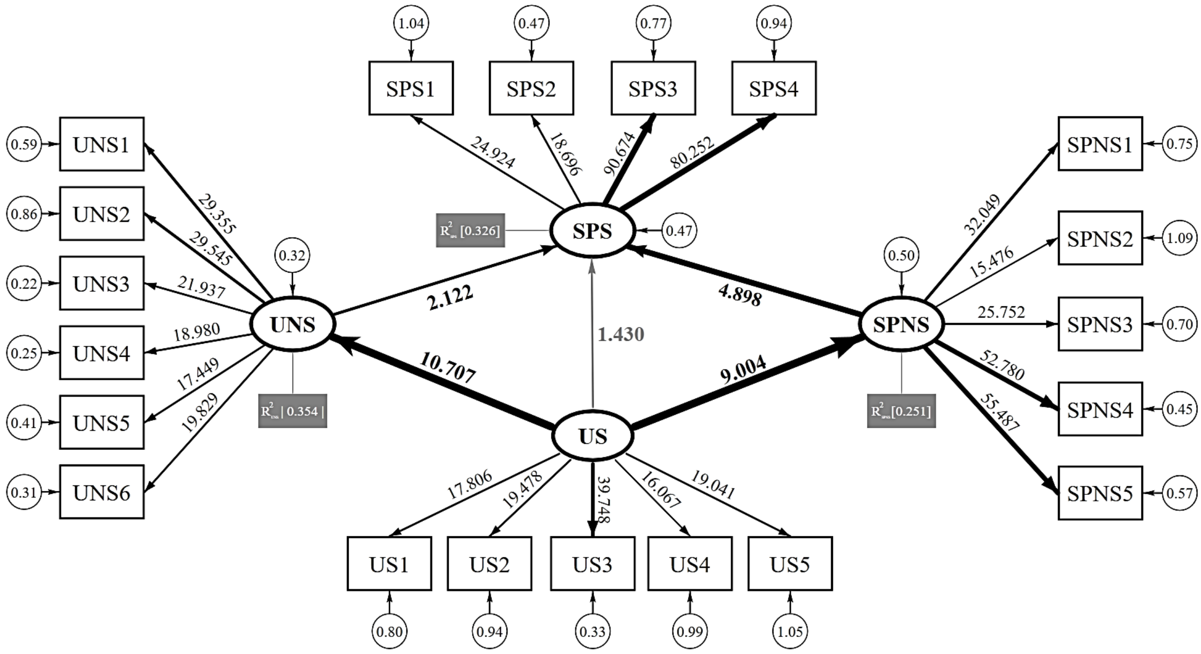

Fig. 4. Bootstrapping test results (t-value)

Table 4

Result of model evaluation

	Relationship	β	p-value	STDEV	t-value	Lower limit 2.5%	Upper limit 95%	f^2
H1	US ⇒ UNS	0.595	0.000	0.056	10.707	0.476	0.695	0.547
H2	US ⇒ SPNS	0.501	0.000	0.056	9.004	0.389	0.605	0.335
H3	SPNS ⇒ SPS	0.373	0.034	0.076	4.898	0.236	0.513	0.140
H4	UNS ⇒ SPS	0.180	0.000	0.085	2.122	0.008	0.342	0.028
H5	US ⇒ SPS	0.121	0.153	0.084	1.430	-0.050	0.273	0.013

The results of user-side measurements in this research show that the user's spatial dimension significantly affects the user's non-spatial dimension. In line with previous studies, accessibility plays a vital role in users' decisions to use online transportation services because they will always choose services that are quick, easy to access, and cost-effective [9, 15]. The consumptive mindset of most user behavior in Indonesia also influences the intention to use ride-hailing services [4, 8]. These behaviors can confirm the results that show a positive and significant relationship between user's non spatial and service provider spatial dimension.

The spatial dimension of users is also positively and significantly related to the non-spatial dimension of service providers. This relationship is represented by the level of conformity of service requests and direct benefits perceived [14]. Previous research found variations in drivers' time, location, and strategy for attracting customers [18], with drivers varying between minimizing congestion, driving to places with high demand, or circling until they receive a ride request [12].

The specific value of the indirect effect, as shown in Table 5, shows a significant relationship since the p-value is lower than 0.05 [23]. The f^2 value of the specific indirect effect of the non-spatial dimension of the provider is higher than 0.025, indicating that it has a moderating influence at a high level [26]. Meanwhile, non-spatial users have a moderate moderating influence, as the value is not much higher than 0.15 [26].

The results of structural calculations show that the user's spatial relationship with the provider's spatial dimension is insignificant. This was confirmed by a calculation of the specific indirect effect showing that the moderating factor of non-spatial variables has a significant impact. From the demand side, non-spatial users have a moderate influence in moderating spatial users with spatial providers. Socio-demographic factors are vital in individual mode preference behavior [12, 15]. From the supply side, non-spatial providers strongly influence moderating spatial users with spatial providers. This is related to the driver's travel costs because they impact the income received from operations. Indirectly, benefits become a factor that affects the spatial location of ride-hailing providers, as shown by the positive and significant relationship between service providers' non-spatial and spatial dimension in the calculation model. However, conflicts with conventional taxis sometimes affect the location of ride-hailing providers [12, 27].

Table 5

Spesific indirect effect

	US ⇒ SPNS ⇒ SPS	US ⇒ UNS ⇒ SPS
Indirect Effect (υ)	0.187	0.107
f^2 (υ^2)	0.034	0.015
Sample mean	0.190	0.105
t-statistic	4.357	2.005
STDEV	0.043	0.053
Bias	0.003	-0.002
Lower limit confidence	0.108	0.017
Upper limit confidence	0.276	0.229
p-value	0.000	0.046

Although user spatial factors do not directly affect service providers' spatial patterns, research shows that the indirect relationship through non-spatial factors is highly significant. Safety, occupational risk, operational costs, and financial benefits heavily influence drivers' decisions on where to operate.

5. DISCUSSION

This paper differs from previous research in that it centers on the causal relationship in ride-hailing services, with providers representing supply and users representing demand. This research systematically explored the supply-demand relationship of ride-hailing in the higher education area, assessing it from both spatial and non-spatial perspectives.

On the demand side, students and educators are the leading ride-hailing users in higher education areas, with travel patterns often covering dormitory-campus, campus-dormitory, or campus-nearest commercial area routes.

On the supply side, ride-hailing providers do not consistently distribute drivers according to the spatial pattern of users due to the more dynamic demand-based system and the use of driver incentives, dynamic pricing, and driver travel preferences. Factors such as fare policies, incentive schemes, and ride-hailing business strategies significantly determine where and when drivers are available in a zone.

5.1. Impact of Users' Spatial Factors on Ride-Hailing Decisions

This paper's findings show a unique phenomenon in the causality of ride-hailing supply and demand in this area. The trend of locating higher education areas in peri-urban areas [28] periodically increases the indicators of spatial development. From an empirical point of view, massive and organic changes in building functions have occurred in the Tembalang higher education area and several other higher education areas in Indonesia. Geographically, a new growth pole with diverse activity derivatives is created in this area. The growth of the activity system is simultaneous with the digital revolution, which has become a massive enabler for changes in mobility patterns [17, 19], including the effect of digital instruments that form virtual geographic patterns between users and ride-hailing drivers. The phenomenon is filled by ride-hailing, which offers a service system that can answer rapid changes in demand patterns.

Users' spatial factors strongly impact their non-spatial factors due to travel distance, frequency of use, proximity to public transportation, and travel time preference, among other factors. Such spatial indicators determine how users make non-spatial decisions regarding personal vehicle ownership, ability to pay for ride-hailing services, reasons and motivations for using ride-hailing, and awareness of ride-hailing products and services. Accessibility is vital in users' decision-making when using online transportation services; they choose services that are quick, accessible, and affordable.

Higher education areas tend to create fluctuating demand patterns, encouraging service providers to implement dynamic pricing strategies (surge pricing). Users' spatial characteristics determine how service providers design their operational strategies, including strategies to minimize service capital costs, which leads to operational cost efficiency.

5.2. Digital Platforms and Spatial Adaptation in Ride-Hailing Services

The variety of activities also formed by elaborating digital transportation application platforms with non-spatial conditions places digital platforms into physical geographic dictation [16]. Mobility patterns and a diversity of activities allow students and academics to fill time other than campus-based activities that impact their participation rate on campus. A linear response to this phenomenon puts the transportation sector and the use of time as a barrier for campus residents to attend [3]. The position of public transportation that cannot reach the first and last mile is a complementary factor that seems obsolete due to the representation of the efficiency of the value of time created by digital platforms and decision-making patterns by the ride-hailing ecosystem moderated by non-spatial factors.

The relationship between users non-spatial and service providers spatial shows that ride-hailing users' patterns and preferences strongly influence how service providers distribute their fleets spatially. More specifically, fare preferences determine the distribution of drivers in a particular area. At the same time, users' trip types and destinations determine the spatial flexibility of ride-hailing operations.

5.3. Ride-hailing Distribution and Demand Dynamics in Higher Education Areas

Although students frequently use ride-hailing services in campus areas, the distribution of drivers still depends on a demand algorithm rather than a fixed spatial pattern of users. Service providers are considering trip profitability and incentives for drivers rather than following users' spatial patterns. If the spatial pattern of users is too dispersed or inconsistent, the service provider cannot directly match the driver distribution to the pattern. Ride-hailing platforms use an automatic matching system between drivers and users based on real-time demand. Service providers adjust the distribution of drivers based on the level of demand rather than the spatial pattern of users.

The findings show that drivers in higher education areas mostly choose locations with minimal expenditure costs when considering the distance to potential pickup locations. Although the initial purpose of ride-hailing drivers is flexibility (part-time), scholars found that the platform is gradually moving towards de-flexibility (full-time), which impacts the existence of ride-hailing drivers widely spread in the Tembalang higher education zone.

5.4. The Impact of Ride-Hailing in Higher Education Areas and Policy Implications

Olayode's systematic review [27] found that public transportation use decreased in areas where ride-hailing services were offered. In urban contexts with cumulative commuter movements and larger agglomeration areas, ride-hailing is considered a public transit feeder in reconciling the first and last mile [6]. However, the application differs in higher education areas, where ride-hailing disrupts public transport due to relatively short travel distances. Concerning this context, the absence of public transport in higher education areas can broaden the perspective that private transportation modes are necessary due to non-spatial factors influencing it.

Therefore, policies should focus on reducing obstacles to public transportation and emphasize improving scheduling to accommodate student timetables and campus-specific routes, implementing more cost-effective public transit fees, promoting active forms of transportation, and decreasing the expense of on-campus accommodation. The intervention aims to reduce transportation accessibility inequality and provide more opportunities for students to participate in and succeed in higher education. The policy can also serve as a win-win solution to the market mechanism that favors private companies to monopolize due to greater financial readiness.

6. CONCLUSIONS

The non-spatial dimension is significantly related to both user and provider spatial dimensions in higher education, while the user's and provider's spatial dimensions are insignificant. The evolution of digital platforms, which enable the formation of virtual geographical supply and demand relationships, is likely to change mobility and activity patterns.

More broadly, regarding the results of this study, the framing of ride-hailing as one of the modes that fill the gap in the movement needs of academics in higher education areas can be interpreted as one of the tasks of stakeholders to address the fact that the effects of creating physical growth poles cannot be allowed organically. Understanding and intervening in developing digital platforms that can indirectly shape physical geographies is necessary due to their relationship with non-spatial ones identical to movement patterns and time value-based decision-making patterns.

7. LIMITATIONS AND FUTURE RESEARCH

The pattern of activity creation to encourage non-spatiality is one topic that needs to be researched because of its dimension, which can affect the spatial dimension. The current model has some shortcomings that should be addressed by future studies. For one, a larger sample size may provide more robust results. Moreover, as the analysis was limited to a specific geographical context, the results may not fully capture variations in ride-hailing adoption and public transport usage across different cities or countries. Local policies, infrastructure development, and cultural differences in transportation preferences may have also influenced the findings. Finally, future studies could explore potential policy interventions and regulatory frameworks that improve the integration between ride-hailing services and public transportation. Investigating strategies related to factors such as fare integration, multimodal mobility platforms, and transit-oriented development could offer practical recommendations for enhancing the sustainability of urban transport ecosystems in higher education areas.

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