



The influence of app function evolution on transport SuperApp use behaviour over time

Muhamad Rizki^{1,2} · Tri Basuki Joewono³ · Yusak O. Susilo¹

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Abstract

In the past few decades, there has been a significant increase in smartphone apps that are designed to help users optimise their daily activities. As a result, there has been a noticeable impact on travel demand. Some of these apps have evolved with the incorporation of additional functions in a gradual transformation into multi-function apps or SuperApps, thereby providing users with more integrated and personalised services for a wider range of activities. Focusing on Transport SuperApps (TSA) in Indonesia, this study aims to investigate how app usage behaviour interacts with the evolving functions of these apps over time. The study further examines the influence of personality traits, socio-demographic factors, and residential location on app usage patterns. In this study, longitudinal data on TSA usage from 2015–2022 was collected from users in four Indonesian cities. The Latent Markov (LMM) and Negative Binomial (NBM) Models were used to analyse the transition of behaviours, app types, and the number of apps used. The findings reveal that transport and shopping services are the most popular and consistently utilised services by users. The results suggest that the introduction of new services has a positive impact on the number of TSA services used. However, some services were found to be used only temporarily, primarily serving as alternatives to support users' daily needs and desires. Initial higher service usage was observed among educated users with sociable and disorganised personalities, while discontinuation of usage is associated with older users and affluent households. Higher transition and continuation to use more services are also observed in larger cities like Jakarta compared to smaller cities like Cianjur.

Keywords Behaviour changes · Users' personality · Apps transformation · Latent Markov model · Negative binomial model

Introduction

Ample evidence exists to suggest that the rise of information and communication technology (ICT) has influenced how individuals organise their daily activities, resulting in a shift in travel demand. ICT has alleviated time and space constraints for certain activities (Schwanen and Kwan 2008; Thulin et al. 2020), allowing individuals to participate remotely and engage in multiple activities simultaneously (Kenyon 2008; Mokhtarian

Extended author information available on the last page of the article

1990; Mokhtarian and Tal 2013). The impact of ICT on travel and activities has evolved alongside the continuous advancement of ICT itself (Aoyama and Sheppard 2003; Schwanen and Kwan 2008). One of the most widely used ICT tools, smartphone apps, has transformed from their initial function as simple utilities into platforms catering to various personal needs and desires. Various global improvements and investments in internet infrastructure have increased access to smartphone apps and improved their functionality compared to wired ICTs (e.g. fax machines and personal computers). This led to the substantial growth of their popularity over the past few decades (Anblicks 2018). As of 2020, well over 8 million apps are available (Koetsier 2020), mostly serving specific functions such as messaging, making calls and listening to music. These apps have attracted 6.6 billion smartphone users and generated more than USD40 billion in revenue as of 2022 (Flynn 2023).

Recognising the business and profit potential of the app industry, some technology companies (TCs) have developed SuperApps, which provide multiple functions within a single app (Choi and Whinston 2000). By offering a one-stop solution for various needs through a personalised and integrated ecosystem, SuperApps aim to attract a broader market and retain users. However, the development of SuperApps is not instantaneous. Instead, it is a process. TCs typically start with a single-function app, gradually introduce additional functions or services, and improve their ecosystem as they gain popularity, eventually evolving into the SuperApps we know today (Baquero 2021). Given the changing landscape of SuperApps, there is a need to understand how this evolution influences users' adoption and usage behaviour.

Generally, individuals go through a customer journey towards app adoption and usage, which can be conceptualised as a three-stage process: pre-adoption, adoption and post-adoption (Stocchi et al. 2022). Pre-adoption refers to the stage before the user decides to adopt the app; adoption occurs when the user downloads and starts using the app; post-adoption encompasses continuous app usage. Most research to date has focused on investigating the customer journey towards the initial adoption of the app rather than the way users interact with changes in the app's environment after adoption (Brand and Huizingh 2008; Horvath et al. 2022; Yousaf et al. 2021), which is similar to the adoption process of new apps. However, users do not instantly adopt new functions. Instead, there is a learning process before users decide whether to adopt the new functions. Once individuals become users of an app, they develop preferences, acceptance, attachment and habits towards the app (Chin et al. 2019; Hsiao et al. 2016), which may result in different adoption behaviours compared to new app users.

Moreover, it is incorrect to assume that users go through all stages of the customer journey. User decisions can vary across stages (Gupta et al. 2020; Xu et al. 2017). For instance, some users may choose not to adopt the app during the pre-adoption evaluation stage, while others may discontinue usage after three months. Throughout the customer journey, users interact with various firm or brand strategies that shape their customer experience and influence their decision-making (Stocchi et al. 2022). Since different users have different expectations, motivations and needs regarding app functions (C. Liu and Forsythe 2010; To et al. 2007; Zhou et al. 2022), decisions during the customer journey can vary over time. A report on global app usage found that 67% of users abandon apps after two months of use, which increases to 71% after three months (Haggerty 2019). Despite these findings, most studies investigating app adoption and usage behaviour have mostly relied on cross-sectional data (Stocchi et al. 2019; Yousaf et al. 2021), limiting their ability to predict behavioural changes throughout the customer journey.

A few studies have used panel data to investigate app usage behaviour over time, such as the three-wave survey by Horvath et al. (2022) that studied usage behaviour relating to the COVID-19 tracking system and Sarker et al.'s (2018) study on temporal mobile app usage behaviour based on smartphone usage characteristics within a single day. However, these studies mainly focused on app usage behaviour after adoption and lacked an understanding of user behaviour in the pre-adoption stage. A study by Kim (2021) on COVID-19 apps included the pre-adoption stage in a two-wave panel study. It found that wealthy and educated individuals tend to adopt apps earlier, while low-income individuals use them more frequently. However, this study mostly focused on single-function apps. The customer journey differs for SuperApps since they offer various services related to the need and desire for mobility and activity participation within one integrated and personalised ecosystem (Irawan and Belgiawan 2022; Rizki et al. 2021a, b). More importantly, since SuperApp services are constantly evolving, app usage behaviour may change over time and vary between different services. Therefore, to capture app usage behaviour in relation to evolving app services, a panel data set that captures SuperApp usage behaviour during an app's evolution is required.

Investigating SuperApp usage behaviour over time is important not only from a marketing perspective to develop strategies to attract and retain more users but also from a transport standpoint. Several SuperApps in Indonesia, such as Gojek and Grab, offer passenger transport, food and goods delivery, grocery shopping and various payment services within one app. Understanding SuperApp usage behaviour is essential since the functions offered mediate and support individuals' participation in daily activities, resulting in generational, substitutional and modification effects that considerably impact changes in travel demand, time use and mode choice (Henao and Marshall 2019; Irawan and Belgiawan 2022; Lee et al. 2022; Safira and Chikaraishi 2022). Previous research on ICT usage behaviour has been done to improve the behavioural realism of travel demand models in response to ICT advancements for participation in daily activities (Dias et al. 2017, 2020; Lavieri and Bhat 2019). Because ICT will continue to evolve in the future (Yoon 2022), understanding usage behaviour over time and response to app evolution is critical for the development and enhancement of travel demand models.

This study aims to understand the dynamics of transport SuperApp (TSA) usage behaviour that interacts with changes in the TSA environment over time with also examining the effect of users' characteristics on the usage behaviour over time. The specific research questions of this study are as follows: (1) How does TSA usage behaviour change over time? (2) How does TSA usage behaviour interact with changes in the TSA environment over time? and (3) How do socio-demographic characteristics, personality traits and residential location influence TSA usage behaviour over time? The contribution of this study is threefold. First, this study considers the evolution of SuperApp services over time. Second, it identifies the effects of introducing new functions on adoption and which services see dis/continuous usage over time. Last, this study reveals key determinants that influence SuperApp service usage over time by collecting longitudinal data on SuperApp usage behaviour. This study identifies the key determinants of app usage behaviour based on users' personality traits, residential locations and socio-demographic factors. Personality traits are represented by the Big Five Inventory (BFI) (Soto and John 2017).

This study focuses on Indonesia's TSAs, Gojek and Grab, and utilises the concept of chronology (Rownton et al. 2022) to collect longitudinal data by reconstructing past events of TSA usage from 2015 to 2022. This reconstruction aims to extend the observation of the TSA customer journey by capturing behaviours before the user enters the pre-adoption stage and when the user discontinues using certain services. Data was collected across four

different cities in Indonesia, representing medium-sized, large, metropolitan and megapolitan cities to account for the differences in the TSA adoption pattern between large and smaller metropolitan areas.

The remainder of this paper is organised as follows: The next section describes the literature about the factors that influence the adoption of apps, followed by case studies of Gojek and Grab, two TSAs in Indonesia. Next, an overview of the data collection and analysis methods will be provided. This is followed by a descriptive analysis of the respondents of this study and the results of the analysis relating to TSA usage and transition to adoption. The discussion of the results is presented in the sixth section; the conclusion of this study is presented in the final section of this paper.

Transport SuperApps (TSA) adoption and factors influencing it

Smartphones enable a new economy that generates significant revenue and creates opportunities for new businesses (Volkow 2022), while also transforming how people travel and arrange activities (Schwanen and Kwan 2008). With more than 8 million apps available for diverse purposes, the impacts of smartphones have attracted various researchers to investigate the factors that influence their adoption or usage to help the formulation of diverse strategies for both TCs and government (Frag et al. 2003; Irawan et al. 2020a, b; Koetsier 2020; Stocchi et al. 2022; Tirachini 2019). Prior studies have identified the influence of socio-demographic, built environment and psychological factors on app adoption, and this section will review the literature that investigates the role of these factors on TSA's adoption or usage with a focus on transport and shopping services as the most popular services within TSAs (Alemi et al. 2018; Irawan and Belgiawan 2022; Joewono et al. 2020).

Extensive scientific research exists regarding ride-sourcing and e-shopping, with research papers drawing certain overarching conclusions about the adoption and utilisation of these services. Younger users tend to adopt a wider array of apps for different purposes, while older individuals typically use apps more purposefully (Froehlich 2022). Within TSAs, such as those offering e-shopping or ride-hailing services, the majority of users are often found in younger and more affluent demographics (Eurostat 2022; Farag et al. 2006; Tirachini 2019); more educated users also tend to adopt ride-sourcing or e-shopping services (Aguilera-García et al. 2022; Alemi et al. 2018; Farag et al. 2007). Ride-sourcing or e-shopping apps were also found to be adopted more by full-time workers rather than non-workers (Alemi et al. 2018; Sikder 2019) and by users who live in urban areas (Alemi et al. 2018; Farag et al. 2007; Weltevreden and van Rietbergen 2009).

Furthermore, the adoption of apps is also influenced by the characteristics of the residential built environment. For example, individuals residing in mixed-use areas tend to utilise ride-hailing apps more frequently (Ghaffar et al. 2020; Yu and Peng 2020; Zheng et al. 2022), and those in areas with enhanced accessibility to public transport infrastructure and lower accessibility to offline stores exhibit higher levels of e-shopping usage (Cao et al. 2010; Shi et al. 2023). In addition, prior studies also demonstrated that app adoption is influenced by the availability and quality of ICT infrastructure since some individuals refrain from using apps because of feasibility constraints, not lack of interest (Mokhtarian 2009). The adoption and use rates of ICT services are found to be influenced not only by internet access and necessary hardware but also by the quality of the internet (Farag et al. 2007; Murphy 2007).

Previous research also emphasised the significance of personality traits in the adoption of apps, which is mostly found in the context of e-shopping apps (Stocchi et al. 2022; Wang and Yang 2008). A study conducted by Wang and Yang (2008) revealed that individuals with higher levels of openness to experience, agreeableness and conscientiousness tend to exhibit a keen interest in e-shopping activities. Additionally, personality traits influence consumption levels, particularly in shopping contexts. For instance, traits such as neuroticism, extraversion and openness, particularly among women, correlate with impulsive buying behaviours (Tarka et al. 2022).

Although the research above has provided insight into app adoption, most prior research treats the adoption as a single adoption event. In reality, users typically undergo a process (Gupta et al. 2020; Stocchi et al. 2022). Three adoption stages from Stocchi et al. (2022) have been identified as the customer journey of apps. *Pre-adoption* refers to the period before downloading the app; *adoption* occurs after downloading and utilising the app; *post-adoption* indicates fully embracing and regularly using the app on a daily basis. Existing literature on this consumer journey found that experiences in prior stages of adoption influenced the decision to further adoption, and experiences during each stage of adoption were influenced by diverse variables (Gupta et al. 2020; Liu and Forsythe 2011; Stocchi et al. 2020).

Limited studies investigate app adoption that considers the temporal aspects, especially for TSA services, such as ride-hailing services. Fauzi and Sheng (2020) and Chiu et al. (2014) investigated the factors that influence the continuation of ride-hailing and e-shopping usage, respectively. The investigations underline the influence of positive perceived hedonic and utilitarian value on the continuation of ride-hailing and e-shopping use. An app's performance and interface are among the variables that influence this longitudinal process, which is mediated by users' performance expectations (Gupta et al. 2020). Using a cross-sectional survey of ride-hailing users in Malaysia, Weng et al. (2017) found that an app's ease of use facilitated by its interface also indirectly influenced the continuation of use mediated by the app's perceived usefulness. However, there is a lack of empirical evidence on the effect of the interface on the adoption process, specifically when the interface has evolved over time.

More importantly, most prior efforts focus only on a specific part of the customer journey (pre-adoption, adoption or post-adoption) and use cross-sectional data, which limits the behavioural understanding across the customer journey process. Some studies that use panel data were done by Horvath et al. (2022) and Kim (2021), who used a multiple-wave panel survey, and Sarker et al. (2018), using single-day app usage data. In the ride-sourcing services, by utilising repeated cross-sectional data, a study by Dias et al. (2021) found that while the adoption of ride-sourcing increases into broader market segments, the propensity to use ride-hailing is softening over time. Using the seven-day shopping survey, Colaço and de Abreu e Silva (2022) found that age and income have a dominant influence on one-week e-shopping adoption; however, the effect varies between central and peripheral areas.

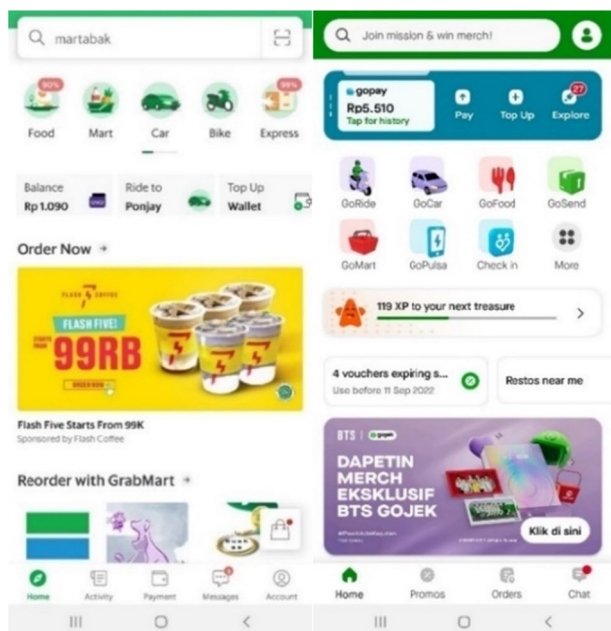
The studies above have predominantly focused on the adoption rates of single-function apps, such as e-shopping and ride-hailing, and limited studies examined the factors influencing the adoption of SuperApps. Using a single-app approach to services within SuperApps might be underestimating the influence of the complete ecosystem on the adoption process. Limited studies have investigated SuperApps, especially in terms of identifying the challenges and opportunities to establish SuperApps in Latin America and Asian countries (Baquero 2021; Steinberg 2020). These efforts underline the technical or institutional barriers. To explore the factors that influence SuperApps adoption, a study from users' perspective was done by Gelici (2022) in the Netherlands. However, the study still

treats SuperApps as a singular entity without considering the diverse range of functions they offer, and it was conducted in a country where SuperApps were not yet available. Moreover, to the author's knowledge, there exists a very limited study that investigates users' adoption behaviour that considers the change in the apps' functions. By integrating the evolution of the function within TSA, the adoption behaviour over time, and multiple variables such as socio-demographics, residential location, and personality traits, this study offers fundamental yet comprehensive insights into the longitudinal process of TSA adoption and user behaviours.

Case study: TSA in Indonesian cities and the context of study locations

There are various services provided by TSA (Fig. 1), each having a specific role in daily activities. This study uses the case study of Gojek and Grab, two of the most popular TSAs in Indonesia. Both began their businesses as an on-demand transport service in the early 2010s. In Indonesia, those TSAs utilise the informal motorbike on-demand services, known as "ojek" (Medeiros et al. 2018), providing a mobile app platform that connects potential passengers with the drivers in a motorcycle-based ride-sourcing (MRC) service. Indonesian cities are characterised by low-quality public transport services and higher gaps in the areas served by public transport services. They also suffer from heavy congestion due to high motorisation, which results in high travel time with private cars and public transport (Medeiros et al. 2018; Roberts et al. 2019). With these issues, the MRCs fill the immediate need for faster travel and shorter waiting time, door-to-door, and anytime and anywhere services (Irawan et al. 2020a, b; Rizki et al. 2021a, b).

Fig. 1 Snapshot of Grab and Gojek Apps' Interface in Indonesia (2022)



In general, individuals satisfy their needs and desire by participating in various activities at specific times and locations. However, the congestion in Indonesian cities (Johan 2012) often reduces and limits the time that individuals have to participate in physical activities. This time-space constraint for out-of-home activities has motivated TSAs to introduce shopping and delivery services (GOJEK 2018a) that eliminate the need for physical presence and trips. The platform provides food and beverages (F&B) and groceries shopping and delivery services, connecting various merchants and their products with the users. The platform does not only act as a mediator for shopping activities but also connects merchants and consumers with drivers for same-day delivery. These TSAs also provide goods (such as documents, packages, and products) delivery services by connecting users with the potential driver who will pick up the goods at the user's location and deliver it to the destination.

TSAs also offer payment services (such as electricity, donation, and stocks) and provide their own e-wallet as part of ecosystem integration, providing seamless services to retain users. E-wallet services are popular and have contributed to increasing cashless transactions in Indonesia (Mufti 2019). Since a bank account is not required, the service is popular for various payments given the high proportion of unbanked Indonesia's population (Kagda 2022). TSAs have continuously expanded their services to cover multiple needs and desires, such as health services (health consultation and medicine), entertainment (movie tickets), and traveling (hotel and apartment book), in the effort to expand their market. Compared to F&B, e-groceries, and transport services, which are regular daily needs, these services are less frequently used on a daily basis. Grab also introduces e-scooter services, expanding its mobility services. TSA services have been classified based on these characteristics as can be seen in Table 1.

The aforementioned services were developed through a process over time. Gojek commenced its business in 2010 with a call-centre system for *ojek* services in Indonesia (Gojek 2018b). On the other hand, Grab started their business in Malaysia in the early 2010s with a taxi service known as MyTaxi (Vaswani 2021). Gojek launched the mobile app-based service in early 2015 in Indonesia. In the same year, Grab expanded its services to Indonesia prior to launching their mobile app in the early 2010s in Malaysia (Gojek 2018b; Novianto 2023). This was followed by an evolution of TSA services. When they started in 2015, they began with their core business of passenger transport services (i.e., motorcycle and car ride-sourcing), F&B shopping and delivery, and goods delivery (GD). They later added an e-wallet and payment function that allows users to pay their electricity bills and mobile phone package. Over time, the payment function expanded with the addition of more payment types such as donations, stocks, and others. In 2019, SuperApps added more services such as news/education, dedicated health products and services, and traveling (i.e. hotel or apartment bookings). Grab and Gojek offer slightly different functions. For example, e-scooter and traveling functions are only available on Grab, while the news/education function is exclusive to Gojek. The timing when the services were made available also varies slightly between the two companies. F&B service was made available in 2016 by Grab and in 2015 for Gojek. The evolution of TSA services from 2015 to 2022 is described in Table 1.

Despite controversies surrounding labour practices, safety, and competition with existing transport services (Cohen and Shaheen 2018; Nangoy and Silviana 2016), the apps have gained immense popularity and steadily expanded their service areas. Both apps have experienced a substantial increase in active users over time. Gojek reached more than 15 million active users in 2017 and 29 million active users in 2019 in

Table 1 Classification and recapitulation of changes to TSA services in 2015–2022

Classification	SuperApp function	Availability of the services in each year									
		2015	2016	2017	2018	2019	2020	2021	2022		
Immediate need for daily travel	Motorcycle ride sourcing	X	X	X	X	X	X	X	X	X	X
Further steps to eliminate trips and optimise activity participation	Car ride sourcing	X	X	X	X	X	X	X	X	X	X
	Goods delivery	X	X	X	X	X	X	X	X	X	X
	Food & beverage shopping & delivery ^a	X	X	X	X	X	X	X	X	X	X
	Groceries shopping & delivery	X	X	X	X	X	X	X	X	X	X
Fulfil needs for cashless payment	Payments (i.e. e-wallet, electricity, donation, stock, etc.)	-	X	X	X	X	X	X	X	X	X
Alternative supporting system for daily needs and desire	Health services	-	-	-	-	X	X	X	X	X	X
	Entertainment ticket ^b	X	X	X	X	X	X	X	X	X	X
Alternative support system for self-actualisation	E-scooter ^c	-	-	-	-	X	X	X	X	X	X
	News or education ^d	-	-	-	-	X	X	X	X	X	X
	Travelling (i.e., hotel/apartment) ^e	-	-	-	-	X	X	X	X	X	X

^aavailable in 2016 for Grab; ^bavailable in 2019 for Grab; ^conly for Gojek; ^donly for Gojek; ^eonly for Gojek; X: available; -: unavailable; Source: interviews and various news on the launch of services

Indonesia, almost doubling in two years (Annur 2020; Kompas 2017). Grab also experienced a substantial growth, more than tripling their number of global unique users from 2017 to 2019 (Wise 2023). In terms of geographical reach, Gojek has expanded significantly from only 7 cities in 2015 to more than 165 cities in 2022 (Bibit 2023; Nistanto 2015). Jakarta and Bandung were among the first cities where the services were available, followed by other areas such as Bali, Semarang, Yogyakarta, and Balikpapan. Subsequently, the services expanded to smaller cities, such as Sukabumi and Cianjur in 2017. By 2022, the services were available in more than 160 Indonesian cities with more than 2.5 million drivers partnering with the TSA companies (Gojek 2023; Suharno 2023).

While these TSAs are available in various cities, this study only covers Jakarta, Bandung, Denpasar and Cianjur. This study selected those areas because they have varying characteristics in terms of size, population, infrastructure quality and economic activities. Therefore, different user behaviours in areas with different characteristics and the influence of various types of cities on TSA usage behaviour can be identified. Jakarta was chosen to represent the biggest megapolitan areas in Indonesia with more diverse economic and business activities and public transport infrastructure. Jakarta is the most populated city in Indonesia, with a population of more than 10 million. It serves as the nation's centre of economy and the first city where TSAs were available. Jakarta is also the core of the Greater Jakarta agglomerations area and home to more than 30 million people. Extensive rail and road transport systems are available in Jakarta, with Jakarta Mass Rapid Transit commuter lines and Trans Jakarta's bus rapid transit being the main public transport systems supported by paratransit services. Due to this intensity, various research on transportation and TSA services have been done in Jakarta (H. Burhan et al. 2021; Irawan et al. 2020a, b).

Moreover, Bandung is among the metropolitan cities in Indonesia with less intense economic activities and transport infrastructure than Jakarta. Bandung, the core of the Greater Bandung agglomerations area, is a city famous for education and small and medium industries (Tarigan et al. 2016). Home to more than 2.5 million people, Bandung is one of the metropolitan cities in Indonesia. Denpasar is one of the largest cities in Indonesia, with a population of more than 900,000. As the capital city of Bali, Denpasar is globally known for its tourism. Denpasar is also a part of the Greater Denpasar agglomerations area (Rahayu et al. 2018). Bus transit services with designated stops are available in Bandung and Denpasar, albeit at a notably lower frequency than Trans Jakarta. Moreover, Bandung operates its own railway system called the East-West Commuter Train, which serves a smaller region than Jakarta's extensive rail network (Adriana et al. 2019).

The last area is Cianjur, which is home to 160,000 people. It is the capital of the Cianjur Regency and has the smallest area (26.15 km²) compared to Jakarta (661.5 km²), Bandung (167 km²) and Denpasar (127 km²). Most of the people's activities in Cianjur are in the industrial and agriculture sectors, which differ from other areas. Compared to other cities, Cianjur has the fewest public transport services, and these are mostly in the form of paratransit. While various travel behaviour research has been done in bigger cities/areas such as Jakarta, Bandung and Denpasar (Joewono et al. 2020; Rahayu et al. 2018; Rizki et al. 2021a, b; Rizki et al. 2021b), only limited research has been done in smaller areas like Cianjur Regency despite steady economic growth and urbanisation (BAPPENAS 2023). Therefore, this study also aims to provide information about behaviour in smaller cities/areas and if this can contribute to different usage behaviours of TSA.

Methodology

Figure 2 describes this study’s flowchart, from developing the research objectives to formulating the conclusion and future work needed. Consisting of an instrument design, data collection process and data analysis framework, the methodology is designed to investigate TSA usage behaviour interactions with the changes in the TSA’s environment while examining the effect of users’ characteristics. Since this study concerns usage behaviour over time, longitudinal data collection is designed using the chronology concept. The procedure, protocol and validation of data collection are also prepared to support the chronology survey concept. This section describes the instrument formulation and data collection process, followed by the data analysis framework to answer the objectives and research questions of this study.

Instrument

This research utilised data from a 2022 one-week virtual and physical cross-dimensional survey through activity diary in Indonesian cities (Rizki et al. 2023). The survey gathered information from smartphone users in Jakarta, Bandung, Denpasar and Cianjur, focusing on virtual and physical daily activities, the impact of mobile app usage on daily travel and multitasking behaviour. A specific part of the survey gathered information on TSA usage behaviour through two self-reported questionnaires. The first questionnaire served as a diary for app usage within a one-week period, while the second questionnaire asked general questions on the respondents’ socio-demography, personality traits, chronology of usage, motivations to use and attachment to TSA and perceived residential built environments. The full explanation of the questionnaire can be found in Rizki et al. (2023), but this section will provide a general explanation of the questions relating to the chronology of

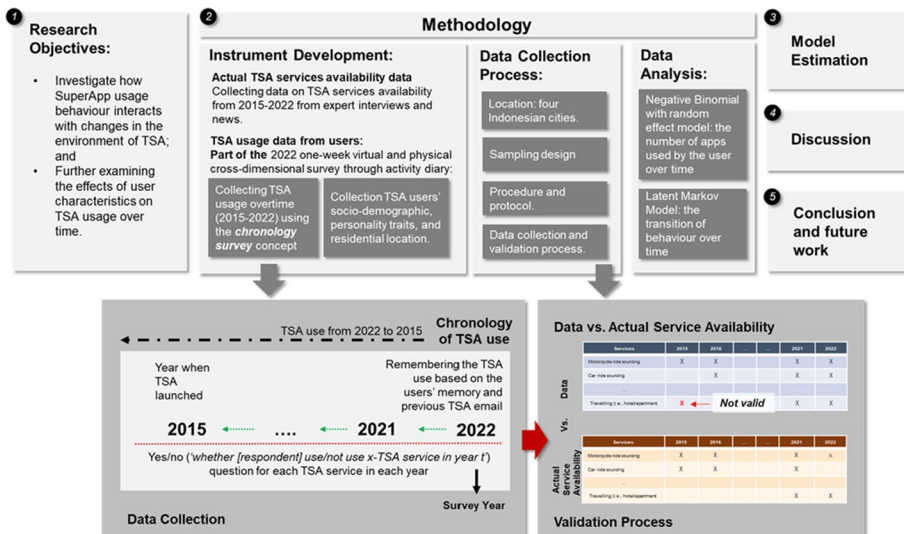


Fig. 2 Flowchart of the study

TSA usage, personality traits, residential locations and socio-demography characteristics in the first questionnaire that are relevant to this research.

The concept of chronology, defined as the “method used to order time and to place events in the sequence in which they occurred” (Rownton et al. 2022), was employed to reconstruct the sequence in which the respondent adopted TSA services. This study considers 2015 to be the first year in the chronology of the survey as it marks the launch of the Gojek and Grab mobile apps in Indonesia. The last year in the chronology of the survey is 2022, which represents the end of the survey. To reconstruct the services used each year, the questionnaire provided 11 types of services (listed in Table 1) that are currently available in the TSAs. Rather than asking about the frequency of use for each service, which could be challenging for respondents to remember, the questionnaire asked whether they used the services (1) or not (0) in each year and for each service. To capture the influence of location on service usage, the respondents were asked about their residential location for each year of the chronology survey. Moreover, questions about the respondents’ personality traits were also asked. This study utilised the BFI (Soto and John 2017) to identify users’ personality traits. The BFI divided the personality traits into five groups: *extraversion*, *agreeableness*, *conscientiousness*, *neuroticism* and *openness*. Respondents self-assessed their personality traits using a five-level Likert scale (1 represents ‘strongly disagree’ and 5 represents ‘strongly agree’). The questionnaire also asked general socio-demographic questions, such as household income, gender, age cohort, education, household size and others.

Data collection

Before the final survey, a pilot survey was conducted in April 2022. The questionnaires were finalised based on the comments gathered in the pilot survey. A combination of paper-and-pencil and digital questionnaires was utilised based on feedback from respondents during the pilot survey. Since the location of this study was in four Indonesian cities, a team of interviewers was formed in each city. The final survey commenced in mid-May 2022 in Bandung, followed by Denpasar, Cianjur and Jakarta after the mobility restrictions relating to the COVID-19 pandemic (2020–2021) were lifted in Indonesia in early 2022 (Djalante et al. 2020; Khoirunurrofik et al. 2022). However, the chronology survey also covered the period of 2021–2022 since the questions asked about the behaviour of using TSA from 2015–2022. Although the mobility restriction indirectly increased the usage of certain TSA services (F. Burhan 2021; The Jakarta Post 2021) such as food and goods delivery, this research did not capture or measure the influence of these policies on the usage of TSA services over time. This is one of the limitations of this study, which is left for future research.

Given the survey’s focus on smartphone users and the lack of information about the user population in each city, the Cochran formula (Heinisch 1965) was employed to calculate the sample size with a 96% confidence level. A minimum sample size of 245 respondents was determined for each city. This confidence level and sample size are reasonably good compared to other prior studies in travel behaviour research (Ahmad Termida et al. 2016; Larson et al. 2014; Terry and Bachmann 2023). However, to accommodate variations in city size and population, this study adjusted the number of respondents, allocating more to larger cities. Respondents were recruited using a convenience sampling method based on their residential districts. Each city set up a team of coordinators and interviewers to oversee the survey process. Interviewers were tasked with recruiting respondents from their respective districts, prioritising districts based on population size drawn from local statistics. However, since the survey also asked for information about complex one-week

time-use and app-use diaries (with many respondents predicted to withdraw during the process), the survey only aimed to cover approximately 80% of each city's districts. Before conducting the survey, coordinators obtained survey permits from relevant sub-district authorities. Taking cues from previous successful panel surveys (Axhausen et al. 2002; Dharmowijoyo et al. 2015; Hartwig et al. 2022), incentives were provided based on local wage standards to encourage participation. Several criteria were required to qualify as respondents in this study. They had to be at least 18 years old – the age at which an individual reaches legal adulthood – and could consent and make adult decisions (Vanbuskirk 2022). Respondents also had to have experience using apps and the internet.

Before the survey, the interviewer would explain the purpose of the survey, the questions to be asked, and the incentives the respondents would receive. The interviewer would then ask the respondent for consent. The survey would only continue if the respondent agreed to provide their data for the research. Understanding that recalling information on TSA service usage from eight years ago could be challenging, the survey incorporated additional steps, especially for the chronology survey, in the explanation and validation process. Before the respondent filled out the form, the interviewer would explain the chronology survey. They also encouraged the respondent to check their TSA history or the email accounts associated with the TSA to determine when they began using TSA services. During the validation process, the responses were cross-checked with the actual availability of TSA services from 2015 to 2022 and responses that did not match were excluded. The chronology survey procedure for this research is illustrated in below part of Fig. 2. The survey concluded in mid-January 2023. Out of the 3,092 respondents approached, the validation process found that 1,251 respondents were valid. Many respondents were withdrawn during the survey due to the complex one-week app-use and time-use diaries. Further, excluding individuals who did not use TSA services, only 1,051 datasets were used for this research. TSA users residing in Jakarta in 2022 constituted the highest proportion (28.9%) of respondents, followed by Bandung (27.02%), Denpasar (23.7%) and Cianjur (20.4%). The analysis in this study combines the data ($N=1051$) from all cities, therefore, despite the TSA respondents from Cianjur (which is still above 210 respondents) being lower than the minimum sample size (245), this will not be a serious problem. This approach is similar to prior studies (Irawan et al. 2022; Irawan et al. 2020a, b) that use data from respondents from multiple Indonesian cities. More explanation about the survey and validation can be found in Rizki et al. (2023).

Data analysis framework

To answer the research questions, this study examines TSA usage behaviour over time with also concerning the evolving app functions and the effects of users' characteristics under two analyses. The first analysis focuses on the number of apps used by the user over time and investigate the influence of services availability. The hypothesis for this analysis is that the number of services used increases as the number of services available in the TSA increases. As the number of services available in the TSA increases, users are enticed to employ more services since they fulfil people's daily needs and desires. Since users have different preferences and acceptance levels towards TSA services, TSA usage behaviour may vary over time and across services. Therefore, the hypothesis suggests that over time, there is a transition in behaviour across services where some users may continue to use the services, while others may decide to discontinue using certain services after a while. As found in prior studies, this transition is hypothesised to be

influenced by socio-demography, personality traits and residential location characteristics. Therefore, the second analysis further examines changes in TSA usage behaviour over time based on the type of services used.

Figure 3 illustrates the analytical framework used in this study, which employs two models for analysing longitudinal data. The negative binomial model (NBM) with random effect was utilised to assess the number of services used, and the latent Markov model (LMM) was utilised to examine behavioural transitions in TSA usage based on the type of services. The NBM was used due to its ability to handle overdispersion data in the number of services used where the mean is lower than the variance (mean = 1.61 and variance = 3.89) with high zero frequency. The specification of both models is explained in the next subsection. In addition to changes in the number of TSA services available, both models incorporated variables related to users' personality traits, socio-demographic factors and residential location to explore the determinants that influence behavioural changes over time. Since only changes in the number and type of services, as well as residential location, were captured, this study assumes that personality traits and socio-demographic variables remain static over time. Some variables, such as personality traits (Stachl et al. 2017), are, in fact, more stable over a period of time, so the assumption relating to socio-demographic variables, such as income and occupation, is one of the limitations of this study. Still, such assumptions may produce preliminary findings on how these variables influence behaviour over time, serving as a basis for further analysis that considers changes in users' socio-demographic characteristics over time.

Moreover, confirmatory factor analysis (CFA) was used to reduce the dimension of personality traits, and the Bartlett score was generated to represent the new factors (Hair et al. 2010). Kaiser-Meyer-Olkin (KMO) and Bartlett's test of Sphericity (BTS) were used to evaluate the quality of each factor (Chan and Idris 2017; Hair et al. 2010). CFA has been used for various travel behaviour research involving diverse psychological factors such as attitude, social norms, etc. Moreover, the Bartlett score serves as an alternative approach for estimating factor score coefficients. In this method, the objective is to minimise the sum of squared components related to 'error' factors (i.e. unique factors) across a set of variables. The resultant factor scores exhibit a strong correlation with their respective factors and minimal correlation with other factors (DiStefano et al. 2019).

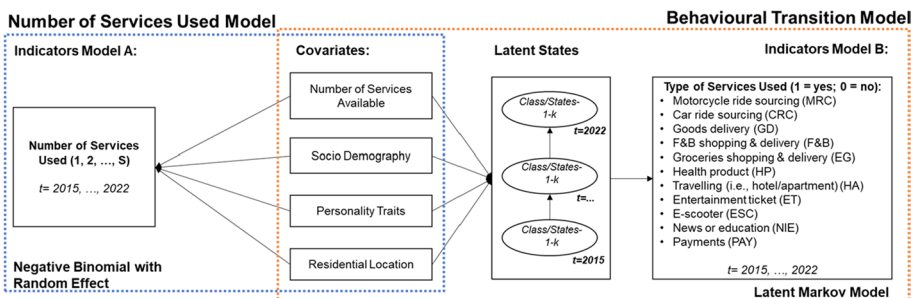


Fig. 3 Conceptual analytical framework

Negative binomial model with random effect

The Negative Binomial model (NBM) with random effect was employed to assess the number of TSA services used from 2015 to 2022. The NBM is a generalised linear model (GLM) for count data that is suitable for overdispersion count data. The overdispersion can result in underestimating standard errors if the analysis still uses standard count distribution such as Poisson regression model (Bayart et al. 2018). This study modified the responses regarding the TSA services used in the chronology survey by aggregating the services used each year to calculate the total number of TSA services used, which was then used as the dependent variable. The NBM model is a modification of the Poisson regression model (PRM). In PRM, the mean, π_i , respecified to introduce a certain kind of unobserved individual heterogeneity, so that $\log \pi_i = \log \lambda_{it} + \varepsilon_i$ and $\exp(\varepsilon_i)$, or error term, has a gamma distribution (θ) with mean 1.0 and variance α (Greene 2003). Y is the discrete random variable, and y_{it} is the observed non-negative integer count of the frequency of TSA service usage of i respondents ($i \in 1, \dots, N$) at time t . The y_{it} is assumed to be influenced by x_{it} as the covariates of respondent i at time t . The observation time t in y_{it} and x_{it} is defined as 2015–2022 ($t \in 1, 2, \dots, 8$). The basic formulation of NBM is (Greene 2003):

$$\begin{aligned}
 Prob(Y = y_{it} | x_{it}, \varepsilon_i) &= \frac{\Gamma(\theta + y_{it})}{\Gamma(y_{it} + 1)\Gamma(\theta)} u_{it}^\theta (1 - u_{it})^{y_{it}}, \\
 \lambda_{it} &= \exp(\beta'x_{it} + \varepsilon_i), \\
 u_{it} &= \theta / (\theta + \lambda_{it})
 \end{aligned}
 \tag{1}$$

In this model, $\Gamma(\cdot)$ is the gamma function, λ is both the mean and variance of y_{it} , and $\theta = 1/\alpha$. This study used the random effect in NBM to estimate the overall effect of time and predictors across multiple groups. The approach involves integrating out the random effect and estimating the parameters of the resulting distribution at maximum likelihood. The NBM random effects model is:

$$\log \lambda_{it} = \beta'x_{it} + v_i \tag{2}$$

where v_i is a random effect for the i -th group and the $\exp(v_i)$ is assumed to follow the gamma distribution with parameters $v_i \sim [\theta_i, \theta_i]$. Then, it is assumed that $\theta_i/(1 + \theta_i)$ is distributed as beta(a_n, b_n), which layers the random group effect onto the NBM. The random effect is added to the NBM by assuming that the overdispersion parameter is randomly distributed across groups. To estimate the model, the likelihood function is formed. For the i -th group, conditioned on v_i , the T_i observations are independent. The unconditional density for the observed data is formed by integrating v_i out of the joint density (Greene 2003). Thus, the log likelihood function is:

$$p(y_1, \dots, y_{T_i}) = \int_{-\infty}^{\infty} \prod_{t=1}^{T_i} \frac{\exp(-\lambda_{it}|v_i)(\lambda_{it}|v_i)^{y_{it}}}{y_{it}!} \left(\frac{1}{\sigma}\right) \varnothing\left(\frac{v_i}{\sigma}\right) dv_i \tag{3}$$

where $\lambda_{it}|v_i = \exp(\beta'x_{it} + v_i)$ is the mean of y_{it} conditioned on the group effect. The log likelihood, its derivatives with respect to β and σ , and the estimate of the Hessian are calculated and the Berndt–Hall–Hall–Hausman (BHHH) algorithm is used. The BHHH algorithm is among the practical approach for maximising the log-likelihood functions that the approximation is asymptotically equivalent to the actual Hessian when evaluated at the parameter values which maximize the function (Chong 1981; Ramachandran et al. 2024). This method extends the Newton-Raphson technique by substituting the negative of the

Hessian matrix with an approximation derived from the summation of outer products of the gradient vectors, each representing the contribution of individual observations to the objective function (Mohammed Ridha et al. 2022). The estimation of the model uses *pglm* in R Studio (Croissant 2021).

Latent Markov model

This study further assessed changes in the type of TSA services used over time using the Latent Markov Model (LMM). The LMM is an extension of the dynamic logit model for longitudinal data and shares the same model assumption. LMM is commonly used in longitudinal data analyses, while the Hidden Markov Model (HMM) is commonly used in time series data analyses (Zucchini et al. 2017). Not only for studying the evolution of behaviour over time, LMM is also useful for accounting for unobserved heterogeneity due to omitted covariates that may vary over time (Bartolucci et al. 2017).

In this research, TSA services usage (Y_{ij}^t) is considered as the response or indicator variable for each service j ($j \in \{1, 2, \dots, J\}$), respondent i ($i \in \{1, 2, \dots, n\}$), and time t ($t \in \{1, 2, \dots, T\}$). The usage of each service is categorised as r_j , where 0 = not using the app and 1 = using the app. Let x_i be the vector of covariates for respondent i at time $t = 1, 2, \dots, T$. The LLM consists of two components: the measurement model and the latent process (S. Liu et al. 2023). The latent process, denoted by U^t , affects the distribution of response variables and is assumed to follow a first-order Markov chain with state space $c \in \{1, 2, \dots, k\}$. Under the assumption of local independence (Bartolucci et al. 2017), the response vector (Y_{ij}^t) is assumed to be conditionally independent given the latent process (U^t). The measurement model determines the latent states using the parameter of conditional response probability:

$$\Phi_{j|y|cx}^t = P\left(Y_{ij}^t = y \mid U_i^t = c, X_i^t = x\right) \tag{4}$$

where c represents the latent state $c = 1, \dots, k$. The parameters of the latent process include the initial probability of (π_c) for each latent state and the transition probability ($\pi_{c|\zeta}$) between states. The initial probability is formulated as:

$$\pi_{c|x} = P(U_i^1 = c \mid X_i^1 = x) \tag{5}$$

where $c = 1, \dots, k$. Meanwhile, the transition probability is formulated as:

$$\pi_{c|\zeta x}^{(t)} = P(U_i^t = c \mid U_i^{t-1} = \zeta, X_i^t = x) \tag{6}$$

where $t = 2, \dots, T$, $\zeta, c = 1, \dots, k$, x is the realization of covariates X^t , c is the realization of U^t , and ζ is the realization of U^{t-1} . The initial probability and the transition probability (latent process) adopted multinomial logit parametrisation (Bartolucci et al. 2017). In this study, the latent model uses the following initial probability:

$$\log \frac{P(U_i^1 = c \mid X_i^1 = x)}{P(U_i^1 = 1 \mid X_i^1 = x)} = \log \frac{\pi_{c|x}}{\pi_{1|x}} = \beta_{0c} + x^T \beta_{1c}, c = 2, \dots, k \tag{7}$$

This initial probability uses the first state as reference. Meanwhile, the transition probability is as follows:

$$\log \frac{P(U_i^t = c | U_i^{t-1} = \zeta, X_i^t = x)}{P(U_i^t = \zeta | U_i^{t-1} = \zeta, X_i^t = x)} = \log \frac{\pi_{c|\zeta x}^t}{\pi_{\zeta|\zeta x}^t} = \gamma_{0\zeta c} + x^\top \gamma_{1\zeta c}, \quad (8)$$

where $t=2, \dots, T$ and $\zeta, c=1, \dots, k$, with $\zeta \neq c$. In the above formula (4, 5), $\beta_c = (\beta_{0c}, \beta_{1c}^\top)^\top$ and $\gamma_{\zeta c} = (\gamma_{0\zeta c}, \gamma_{1\zeta c}^\top)^\top$ are the parameter vectors to be estimated. For estimating all the parameters, the Expectation-Maximization (EM) algorithm is used, and the complete data log-likelihood (LL) functions to be maximised is as follows:

$$\begin{aligned} l(\theta) = & \sum_{j=1}^J \sum_{t=1}^T \sum_{c=1}^k \sum_X \sum_{y=0}^{r_j-1} a_{jy|cx}^t \log \phi_{jy|ux}^t \\ & + \sum_{c=1}^k \sum_X b_{c|x}^t \log \pi_{c|x} + \sum_{t=2}^T \sum_{\zeta=1}^k \sum_{c=1}^k \sum_X b_{c|\zeta x}^t \log \pi_{c|\zeta x}^{(t)} \end{aligned} \quad (9)$$

This LL functions consist of three parts: (1) latent process, (2) initial probability, and (3) transition probability where t represents the reference time, x represents the covariate configuration, $a_{jy|cx}^t$ represents the number of subjects in the latent state c that respond with y to variable Y_{ij}^t , $b_{c|x}^t$ represents the usage frequency of respondents in state c , and $b_{c|\zeta x}^t$ represents the number of transitions from state ζ to state c . This study does not incorporate any covariates into the latent process, since the analysis focuses on the effect of covariates on changes in the type of the TSA services used during transition between the states. Moreover, since the availability of TSA services evolves over time and across locations, as explained in the previous sections, this study treats the unavailability of TSA services at specific times and in specific locations as missing data, which is assumed to be missing at random in the estimation (Bartolucci et al. 2017). The Expectation Maximization (EM) algorithm is used to estimates the maximum likelihood of parameters in the presence of missing values in the data (Ofiaz et al. 2023). The EM algorithm serves as a versatile method for maximizing the likelihood function when the model involves both observed and unobserved (latent) components specified probabilistically. LMM or HMM fits into this framework due to its inclusion of hidden states as unobserved components, with the observed data often referred to as *emissions* in LMM terminology (Baum et al. 1970). LMest package (Bartolucci et al. 2017) in R Studio is used for estimating the LMM.

Results

Respondents' characteristics

The respondents in this study were predominantly male (56.2%), employed (70.4%) in 2022 and holders of undergraduate degrees (55%) (Table 2). A majority had a monthly household income of over IDR6 million (USD394) (39.5%) in 2022. The respondents were dominated by millennials born between 1988 and 1996 and older Gen Z born between 1997 and 2002. Compared to the actual populations in the four cities, these datasets over-sample individuals born between 1988 and 2002 and under-sample those born before 1972. This is a recurring issue in research on ICT behaviour as ICT services are primarily used by the younger generation (Eurostat 2022; Irawan et al. 2020a, b; Tirachini 2019). When

Table 2 Respondents' socio-demographic factors and residential location ($N=1051$)

Variable	Sample	Population ^b
Age cohort		
Users born in 2003 or younger	3.04%	10.69%
Users born in 1988 to 2002	60.61%	32.89%
Users born in 1973 to 1987	31.78%	31.10%
Users born in 1972 or older	4.57%	25.32%
Gender		
Male	56.23%	50.39%
Female	43.77%	49.61%
Household monthly income in 2022 ^a		
< IDR3,000,000	21.03%	-
IDR3,000,000–IDR4,500,000	16.08%	-
IDR4,500,000–IDR6,000,000	23.41%	-
IDR6,000,000–IDR8,000,000	20.27%	-
> IDR8,000,000	19.22%	-
Personal monthly spending on 2022 ^a		
< IDR1,000,000	11.23%	-
IDR1,000,000–IDR1,500,000	24.26%	-
IDR1,500,000–IDR3,000,000	38.82%	-
IDR3,000,001–IDR4,500,000	14.27%	-
> IDR4,500,000	11.42%	-
Occupation in 2022		
Civil servant	2.76%	-
Private company employee	38.25%	-
Self-employed/freelance	11.04%	-
Doctor/medical staff	1.90%	-
Teacher/lecturer	5.52%	-
Students	19.70%	-
Housewife/husband	9.90%	-
Farmer	0.29%	-
Industrial workers	4.85%	-
Entrepreneur	1.71%	-
Others	4.09%	-
Education degree in 2022		
Junior/senior high school	42.63%	-
Bachelor's degree	56.33%	-
Master's/Doctoral degree	1.05%	-
Household size in 2022		
Single	8.75%	-
Two members	20.17%	-
Three members	29.78%	-
Four members or more	41.29%	-
Residential location in 2022		
Jakarta	28.92%	-
Bandung	27.02%	-
Denpasar	23.69%	-
Cianjur	20.36%	-

Table 2 (continued)

^aUSD1 was equal to 15,270 IDR as of 30 July 2022; ^bbased on the compilation of statistics from the four cities (Bandung Statistics Bureau 2022; Cianjur Bureau of Statistics 2022; Denpasar Statistics Bureau 2021; Jakarta Bureau of Statistics 2022)

generalising the results to the population, it is important to keep this limitation in mind. Most of the respondents lived in homes with three or more people.

Table 3 presents TSA usage from 2015 to 2022. In the first three years after the launch (2016–2018) of these TSAs, the majority of respondents still did not use them. The number of services used increased significantly in 2019, with most respondents using 1–3 services. The number of services used gradually increased over the years, and by 2022, most respondents were using 3–5 services. The usage characteristics based on the types of services are described in Table 4. Among all services, MRC and F&B shopping and delivery were reported as the most utilised services. In contrast, e-scooters, news and education and travelling services were the least used services among the respondents.

The respondents' personality traits are described in Table 4. The participants in this study described themselves as *outgoing* and *sociable* (extraversion, 3.87), *respectful*

Table 3 Number and type of TSA services used per year

Number of services	Year							
	2015	2016	2017	2018	2019	2020	2021	2022
0	93%	88%	75%	53%	23%	19%	11%	0%
1	3%	5%	7%	16%	22%	25%	23%	16%
2	1%	2%	7%	8%	12%	15%	18%	14%
3	1%	2%	4%	9%	19%	17%	19%	18%
4	0%	1%	3%	8%	15%	16%	15%	28%
5	1%	2%	2%	3%	6%	5%	8%	14%
6	0%	0%	2%	3%	0%	1%	3%	6%
7	0%	0%	0%	0%	1%	1%	1%	1%
8	0%	0%	0%	0%	0%	1%	0%	1%
9	0%	0%	0%	0%	0%	0%	1%	1%
10	0%	0%	0%	0%	1%	0%	0%	0%
11	0%	0%	0%	0%	0%	1%	1%	1%
Type of services	Year							
	2015	2016	2017	2018	2019	2020	2021	2022
Motorcycle ride sourcing (MRC)	6%	8%	18%	31%	51%	44%	52%	65%
Car ride sourcing (CRC)	2%	5%	8%	14%	25%	22%	21%	33%
Goods delivery (GD)	3%	4%	10%	17%	27%	31%	41%	57%
F&B shopping & delivery (F&B)	5%	8%	18%	38%	63%	70%	77%	91%
Groceries shopping & delivery (EG)	3%	3%	3%	4%	6%	8%	10%	16%
Payments (PAY)	0%	0%	10%	16%	32%	31%	39%	52%
Health product and services (HP)	0%	0%	0%	0%	4%	5%	6%	5%
Entertainment ticket (ET)	0%	2%	2%	3%	4%	3%	8%	13%
E-scooter (ESC)	0%	0%	0%	0%	0%	3%	3%	2%
News or education (NIE)	0%	0%	0%	0%	3%	3%	4%	4%
Travelling (HA)	0%	0%	0%	0%	4%	3%	4%	4%

Table 4 Respondents' personality traits

Dimension	Questions (I am person who...)	Mean ^a	Std. dev	Loadings ^b
Extraversion (KMO: 0.746; BTS: 873.361)	tends to be quiet	2.68	0.98	-0.69
	is outgoing or sociable	3.87	0.82	0.78
	is dominant or acts as a leader	3.32	0.9	0.72
	is hoping other to be a leader	3.1	0.79	-0.51
Agreeableness (KMO: 0.644; BTS: 544.312)	is full of energy	3.76	0.73	0.74
	is compassionate or has a soft heart	3.96	0.69	0.79
	is respectful or treats others with respect	4.04	0.67	0.83
Conscientiousness (KMO: 0.751; BTS: 693.104)	assumes the best about people	3.82	0.66	0.73
	keeps things neat and tidy	3.81	0.8	-0.68
	tends to be disorganised	2.4	0.72	0.58
	is persistent or works until the task is finished	4.08	0.69	-0.67
	has difficulty getting started on tasks	2.67	0.98	0.75
Negative emotionality (KMO: 0.562; BTS: 141.44)	can be somewhat careless	3.18	0.82	0.6
	worries a lot	3.12	0.82	0.64
	tends to feel depressed or blue	2.42	0.75	0.77
Open-mindedness (KMO: 0.57; BTS: 353.928)	is temperamental or gets emotional easily	2.37	0.8	0.65
	is fascinated by art, music, or literature	3.65	0.91	0.52
	is complex or a deep thinker	3.57	0.81	0.81
	is original or comes up with new ideas	3.52	0.68	0.83

^aResponse 1 (strongly agree) to 5 (strongly disagree); ^bloadings are calculated based on the CFA of the motivation and personality trait factors. Principal component analysis is used for the CFA, and Bartlett scores were generated for each case of each factor; KMO: Kaiser-Meyer-Olkin Test; BTS: Bartlett Test of Sphericity

of others (agreeableness, 4.04) and persistent (conscientious, 4.08). CFA was used to reduce the dimensions of personality traits based on the five-group classification of BFI. The KMO findings indicate that most factors display robust partial correlations (>0.60) among variables, indicating shared information. Specifically, negative emotionality and open-mindedness show KMO values between 0.5 and 0.6, suggesting a somewhat weaker partial correlation. However, all factors for Bartlett Test of Sphericity (BTS) yield statistically significant results, rejecting the null hypothesis of orthogonality or lack of correlation among variables.

This study utilises all factors, with interpretations of the final factors based on their statement loadings (Table 4) (Hair et al. 2010). Positive *extraversion* represents individuals who are more sociable, dominant and full of energy, while positive *agreeableness* represents kind-hearted and respectful individuals. Positive loadings on *conscientiousness* were found on negative questions, meaning that positive conscientiousness represents individuals who tend to procrastinate, are disorganised and are impulsive. Positive *negative emotionality* represents individuals who worry and experience a lot of stress, while positive *open-mindedness* represents individuals who are creative and deep thinkers.

Model for the number of TSA functions used

Figure 4 illustrates changes in the number of services used based on socio-demographic characteristics (e.g. gender, age cohort, household income and residential location). Based on residential location, users from Cianjur consistently recorded the lowest average number of services used compared to users from other cities. Users from Jakarta showed the most significant increase in the number of services used from 2018 to 2019. Male and female users showed slightly different averages in the number of services used. The profile was also based on the users' household income in 2022. Users from more affluent households in 2022 reported a higher average number of services used in 2019, 2020, 2021 and 2022. Users with a monthly household income of less than IDR6 million (USD400) reported a lower average number of services used. Based on age cohort, users born between 1973 and 2022 (millennials and older Gen Z) reported a higher average number of services used between 2017 and 2021 than those from other age cohorts.

The estimation model for the number of services used is presented in Table 5. The model produced a value of 0.17 for the goodness-of-fit parameter from adjusted rho². A significant random effect estimation (*a* and *b*) was found, which suggests that incorporating the overall effect of time and predictors across multiple groups results in a meaningful improvement of the model. The estimated model demonstrates that the number of services available influences the increase in the number of services used. This suggests that the introduction of new services within the TSAs encourages users to explore the apps. The study also found a correlation between users' socio-demographic factors and the number of services used. Users who are employed tend to use a greater number of services compared

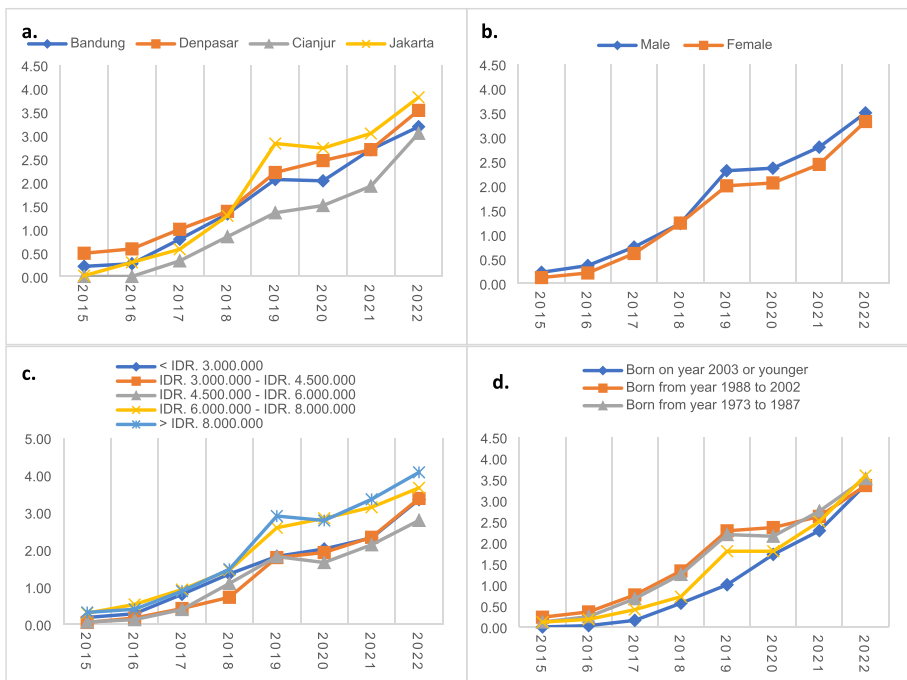


Fig. 4 Average number of TSA services used from 2015 to 2022 based on respondents' **a** residential location in 2022, **b** gender, **c** household income in 2022 and **d** age cohort

Table 5 Estimation model for the number of TSA functions used

Variables	Estimate	t-stat	p-value
Intercept	-2.85	-14.17	0.00
App functions			
Number of functions available	0.41	58.03	0.00
Socio-demography			
Worker [D] (reference: student and non-worker)	0.21	4.29	0.00
Female [D] (reference: male)	-0.06	-1.33	0.18
Age cohort (reference: born in 2003 or younger)			
Users who born from 1988 to 2002 [D]	0.23	1.72	0.08
Users who born from 1973 to 1987 [D]	0.19	1.41	0.16
Users who born in 1972 or older [D]	0.06	0.37	0.71
Household income in 2022 (reference: less than IDR3,000,000)			
IDR3,000,000–IDR4,500,000 [D]	-0.16	-2.21	0.03
IDR4,500,000–IDR6,000,000 [D]	-0.22	-3.19	0.00
IDR6,000,000–IDR8,000,000 [D]	-0.08	-1.12	0.26
> IDR8,000,000 [D]	-0.07	-0.97	0.33
Education degree in 2022 (reference: lower than senior high school)			
Senior high school [D]	0.11	0.81	0.42
Bachelor's degree [D]	0.10	0.68	0.49
Master's/Doctoral degree [D]	-0.03	-0.11	0.91
Residential location (reference: Cianjur)			
Bandung [D]	0.38	5.90	0.00
Denpasar [D]	0.35	5.53	0.00
Jakarta [D]	0.61	9.39	0.00
Personality traits			
Extraversion	0.05	2.37	0.02
Agreeableness	0.03	1.28	0.20
Open-minded	0.08	3.56	0.00
Conscientiousness	0.02	0.79	0.43
Random effect			
<i>a</i>	13.38	12.98	0.00
<i>b</i>	4.29	15.35	0.00
Final loglikelihood	-11835.7		
Adjusted rho ²	0.17		

[D]: Dummy variables; 1 if yes; 0: otherwise

to students or unemployed users. Users in the middle household income group (IDR3–6 million or USD200–400) tend to use fewer services compared to those in the low household income group (less than IDR3 million).

Another factor that influences the number of services used is residential location. Users from Jakarta tend to use a higher number of services, while users from Cianjur tend to use a lower number of services compared to those from other cities. The number of services used was also found to be influenced by users' personality traits. Extraversion (sociable and full-of-energy personality) and open-mindedness (creative and deep-thinking personality) are the traits that positively influence the number of services used.

Model for TSA usage transition

The study further examines the transition of usage behaviour based on the type of services using the LMM. This study utilised BIC, AIC, and Log-likelihood (LL) criteria to evaluate and determine the number of conditions/states, which is a crucial step in the LMM. The assessment (Table 6) found that increasing the number of states actually improved the model. However, only slight improvement was recorded in LL, AIC, and BIC scores beyond the four states. Moreover, the interpretability of the profile was more satisfactory when covering four states compared to a higher number. Therefore, this study opted to employ four classes.

The profile of each state based on TSA classification is presented in Table 7. The TSA services were classified based on their role in daily activities in Indonesia, as described in the third section.

The first state represents the condition before usage of the TSA or occasional usage of MRC (1%) or GD (1%), referred to as the pre and occasional use of the app (PO) state. This state also represents the pre-adoption phase in the customer journey. However, since this study utilises aggregate data, the pre-adoption stage represents the state where users are aware of the services and start the predisposition process, as well as when users are not aware of the services. The second state is characterised by users mostly using MRC (37%) and F&B (74%) services. In this state, users also utilise CRC (14%), GD (10%), EG (2%), and PAY (13%) services, but to a lesser extent compared to MRC and F&B. MRC is the core of TSA services, providing mobility services for daily travel, while F&B is a popular service that allows users to avoid trips and optimise daily activities. Considering the limited number of services used and the nature of the classification, this state is referred to as minimalist for daily travel and optimised activity (MI).

The third state represents the use of TSA for transport (MRC (84%), CRC (39%)), GD (68%), shopping (F&B (92%) and EG (5%)) and payment (PAY (65%) services. In this state, users more extensively utilise the apps for daily mobility to avoid trips and optimise their activities. Users in this state also extend their usage of the TSA to payment platforms and methods that promote cashless payment. Therefore, this state is referred to as the personalisation for daily travel, activity and e-payment (PI) state. The last state is characterised by users having explored the majority of TSA services. Among the services, F&B (90%), MRC (75%), EG (87%) and PAY (82%) constitute the highest proportion, while e-scooters constitute the lowest (17%). Users in this state not only fulfil their daily travel or activity optimisation needs but also address additional needs, including health services (50%) or entertainment tickets (41%), and self-actualisation needs such as news (31%) and education (31%). This state is referred to as the full personalisation of the apps (FP) state.

Table 6 Goodness-of-fit measurement of the LMM to determine the number of states

Number of states	Number of parameters	Log-likelihood	AIC	BIC
2	25	-21688.00	43425.99	43549.93
3	41	-20150.59	40383.18	40586.44
4	59	-19071.32	38260.64	38553.13
5	79	-18305.38	36768.77	37160.41
6	101	-17932.25	36066.49	36567.20

AIC, Akaike Information Criterion; BIC, Bayesian Information Criterion

Table 7 Profile of each state based on TSA services usage

Classification	States				
	Pre and occasional use of apps (PO)	Minimalist for daily travel and optimise activity (MI)	Personalisation for daily travel, activity, and e-payment (PI)	Full personalisation of apps (FP)	
Immediate need for daily travel	1%	37%	84%	75%	
Further steps to eliminate trips and optimise activity participation	0%	14%	39%	58%	
Further steps to eliminate trips and optimise activity participation	1%	10%	68%	79%	
Further steps to eliminate trips and optimise activity participation	0%	74%	92%	90%	
Further steps to eliminate trips and optimise activity participation	0%	2%	5%	87%	
Further steps to eliminate trips and optimise activity participation	0%	13%	65%	82%	
Further steps to eliminate trips and optimise activity participation	0%	0%	2%	50%	
Further steps to eliminate trips and optimise activity participation	0%	0%	8%	41%	
Further steps to eliminate trips and optimise activity participation	0%	1%	1%	17%	
Further steps to eliminate trips and optimise activity participation	0%	0%	2%	31%	
Further steps to eliminate trips and optimise activity participation	0%	0%	3%	31%	

Of these four states, three (FP, PI and MI) are classified into the adoption and post-adoption stages where users employ the apps. The profile of each stage based on the type of services for each year is presented in Appendix Table 9.

Since this study focuses on behaviour change over time, the transition between states is illustrated in Fig. 5. The PO state makes up the largest proportion in the first four years following the launch of the TSA, suggesting that most of the respondents in this study were in the pre-adoption stage from 2015 to 2018. Once users started using the apps, the MI state made up the largest proportion from 2016 to 2020, while PI made up the largest proportion between 2021 and 2022. The state where users explored the apps the most and personalised them shows relatively small changes in proportion from 2.9% to 9.9%. Figure 5 illustrates not only the proportion of each state in each year but also the users' transition between states.

To understand the behaviour transition, this study calculated the average transition probability from one state to another (Fig. 6). Surprisingly, the FP (49%) and PO (58.9%) states were found to be less stable, with the lowest probability of staying in the same state from year to year, while PI (0.88%) and MI (87%) were the more stable states. From the PO state, which represents the pre-adoption stage, most users transition to the MI state instead of the PI or FP states. In contrast, from the FP state, where users extensively use the services, most users transition to the PI state. Although these numbers indicate gradual changes, some users showed a significant shift in the type of services used, whether a significant increase that moved them from the PO state directly to the FP or PI state or a significant decrease that moved them from the FP or PI state to the MI or PO state.

The factors influencing this transition pattern were also investigated using LMM (Table 8). To account for the four states, the LMM produced four transition probability models. As illustrated in Fig. 6, there are four possible transitions: three transitions represent a shift between states, and one transition represents users staying in the same state. Since the transition probability model has been characterised as multinomial logistics

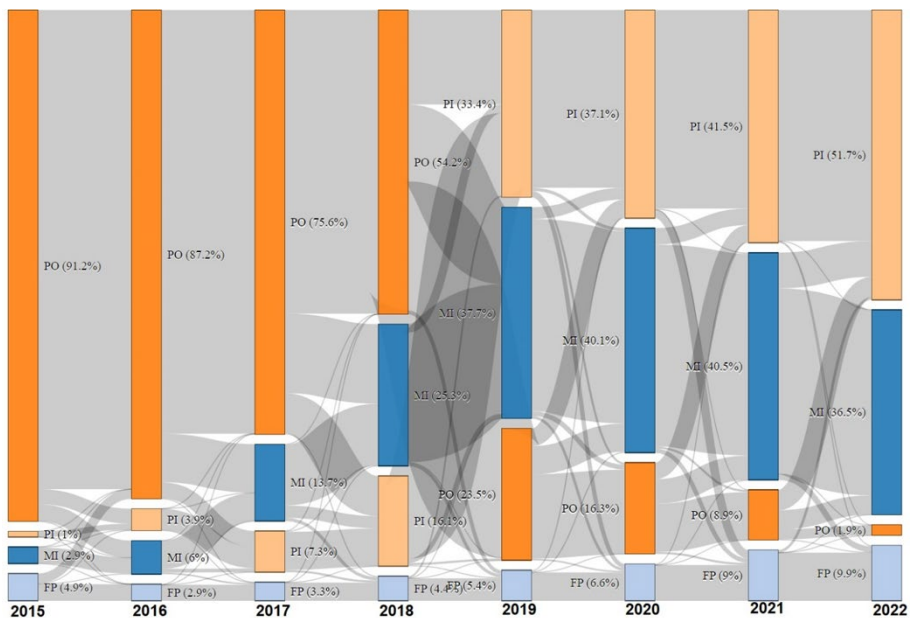


Fig. 5 Distribution of states from 2015 to 2022

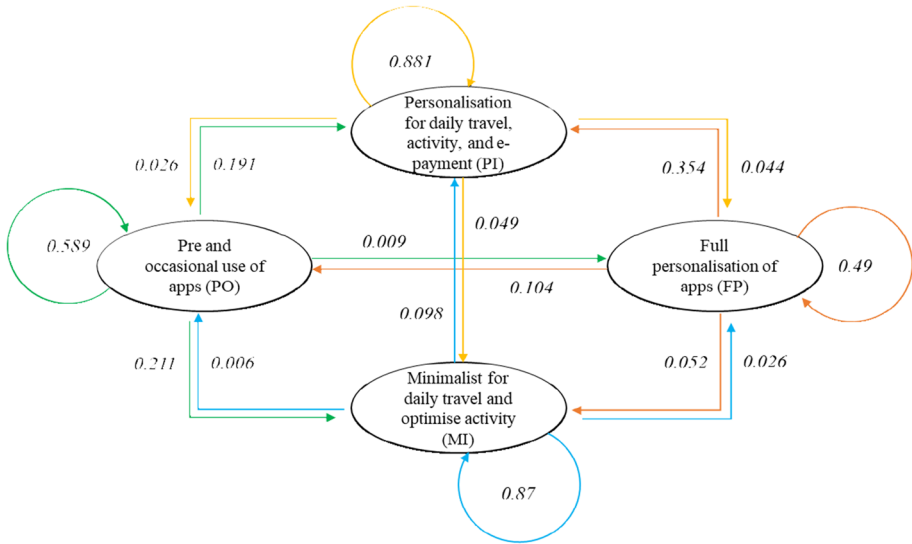


Fig. 6 Average transition probability

regression (Eq. 8), the reference category for all models is the transition where users remain in the same state (Bartolucci et al. 2017; Ofiaz et al. 2023).

In support and extension of the previous model, the number of services available was found to influence the transition between states, but only from the PO state to the MI, FP, and PI states. Interestingly, this transition from the PO state is more likely to lead to the FP and PI states than to the MI state. This suggests that users tend to explore more apps initially, but the broader exploration of TSA in the FP state might be temporary considering users in the FP state tend to record less stable usage compared to those in the PI state.

Socio-demographic variables were also found to influence transition patterns. Users who were employed in 2022 and in the MI state were more likely to transition to the FP state. However, if they are already in a higher exploration state (PI or FP), they tend to gradually reduce the types of service used, moving them from FP to PI or from PI to MI. The age cohort was also found to influence the transition from PI to MI, where the older generation tends to reduce the types of service used in the apps. In line with previous findings, users in the middle household income group (IDR3-6 million or USD200-400) tend to use minimalist services in the TSAs for travel and trip avoidance. Education was also found to shape transition in the type of TSA services used. Educated users tend to explore more and continuously use the services, especially for mobility, cashless payment, and activity optimisation through shopping services. However, users with undergraduate degrees exhibit higher acceleration in exploring and using the services, while users with postgraduate degrees show a gradual exploration and usage pattern.

Another factor that was found to influence behavioural transition was residential location. Users who live in Jakarta and Bandung tend to transition directly from the PO state to the PI state where they use multiple core TSA services for travel, activity optimisation, and cashless payment. Users from Jakarta, Bandung, and Denpasar tend to report more stable use of broader TSA services (FP). Transition patterns were also found to be shaped by users' personality traits. Individuals who are more sociable and disorganised tend to transition directly

Table 8 Estimation model for transition probabilities

Variables	Transition from PO to		Transition from MI to	
	MI	FP	FP	PO
Intercept	Estimate β -5.61 **	Estimate β -17.2 **	Estimate β -21.21 **	Estimate β -42.31 *
App functions				Estimate β -3.46 **
Number of functions available	0.48 **	0.72 **	0.54 **	
Socio-demography				
Worker [D] (reference: student and non-worker)			2.66 *	
Female [D] (reference: male)	0.32 *			0.53 *
Age cohort (reference: born in year 2003 or younger)				
Users who born from year 1988 to 2002 [D]				
Users who born from year 1973 to 1987 [D]		-9.67 **		
Users who born in year 1972 or older [D]				
Household income in year 2022 (reference: less than IDR. 3.000.000)				
IDR. 3.000.000—IDR. 4.500.000 [D]		-10.05 **	-12.83 **	
IDR. 4.500.000—IDR. 6.000.000 [D]			-5.68 **	-1.22 **
IDR. 6.000.000—IDR. 8.000.000 [D]				-2.48 **
> IDR. 8.000.000 [D]				
Degree of education in year 2022 (reference: lower than senior high school)				
Senior high-school [D]		7.07 **	5.63 **	
Bachelors' degree [D]	0.88 *	8.35 **	7.44 **	
Master/Doctorals' degree [D]	1.6 **	-1.58 **	-0.11 **	3.02 *
Residential location (reference: Cianjur)				
Bandung [D]	0.52 **	-9.21 **	6.11 **	-19.74 **
Denpasar [D]			-10.64 **	1.31 **
Jakarta [D]	-0.78 **	-8.49 **		-20.82 **

Table 8 (continued)

Residential location (reference: Cianjur)			
Bandung [D]			-30.83 **
Denpasar [D]	-29.24 **	-37.6 *	-35.88 **
Jakarta [D]	-29.7 **	-32.02 **	-24.64 **
Personality traits			
Extraversion		2.01 **	
Agreeableness			
Open-minded			-0.97 **
Conscientiousness			-1.46 **
			-7.22 **

[D]: dummy variables; *significant at 5%; **significant at 1%; MI: Minimalist for daily travel and optimise activity, FP: Full personalisation of apps; PO: Pre and occasional use of apps; PI: Personalisation for daily travel, activity, and e-payment. Only significant variables are reported in the table

from the PO state to the PI state, while users who show pro-social behaviour (agreeableness) tend to explore the apps gradually, transitioning from MI to PI or from PI to FP.

Discussion

The growing usage of TSAs in recent years has significantly influenced individuals' travel patterns (Irawan et al. 2020a, b; Safira and Chikaraishi 2022). These apps offer a wide range of services that facilitate and support participation in daily activities. As TSAs have evolved over the last seven years, questions have arisen regarding how these evolving TSA functions influence TSA usage behaviour. This study explores how TSA transformation, as well as users' personality traits, residential location and socio-demographic factors, influence TSA usage patterns over time. Longitudinal data collected from users in four Indonesian cities revealed several important findings on app usage behaviour over time. Two analyses were conducted to investigate the evolution of TSA usage behaviour over time, and this section will discuss the findings of these analyses.

The study confirms that the availability of more services in the apps leads to more services adopted by users. The highest number of services used was observed in 2019 when TSAs reached their peak number of services available on their platforms. The number of services used was found to be influenced by the users' socio-demographic characteristics, residential location and personality traits. Employed individuals tend to use a higher number of services, leveraging TSAs to optimise participation in daily activities alongside their work routine. The study also found that users based in Jakarta tend to use more services, which confirms the influence of the built environment on TSA usage. Jakarta is characterised by higher population density, economic intensity and urban sprawl that create more complex daily activity patterns (Dharmowijoyo et al. 2016). Utilising multiple TSA services allows users to optimise their daily activities and cope with heavy congestion and air pollution issues in the city (Roberts et al. 2019). The findings of this study also confirmed that personality traits influence app usage behaviour (Yeh et al. 2021). Among the five personality traits under BFI, sociable and open-minded personalities are associated with a higher number of services used, as they tend to report higher app consumption and usage (Svensden et al. 2013; Tarka et al. 2022), which can be facilitated by TSAs.

Although the availability of more services influences to higher use and some users employ a wider range of TSA services, this study found that most users utilise an average of three to four services. These findings are important for TSA companies in evaluating their apps and TCs that plan on broadening their apps' functionalities in the future. MRC and F&B services are the most popular, which might be attributed to traffic conditions in Indonesia. These services enable users to travel faster, avoid trips, and, as a result, optimise daily activities (Irawan et al. 2020a, b; Irawan and Belgiawan 2022). On the other hand, supporting services such as for entertainment, news/education, or travelling purposes have the lowest popularity.

The study identified four distinct states of the customer journey based on the type of TSA services used over time. The first state, pre and occasional use of the apps (PO), represents the pre-adoption stage, where users have very limited use of MRC and GD. The second state is minimalist for daily travel and optimise activity (MI), which is characterised by minimal use of TSA services that enable faster mobility (MRC) and optimise daily activities (F&B). The third state extends the personalisation of TSA services beyond daily travel and trip avoidance (i.e. F&B, EG and GD) to include cashless payment. The fourth state (FP) represents full personalisation of most TSA services for daily activities. In 2022,

most users were in the MI and PI states, which suggests the popularity of EG and GD services among users besides MRC and F&B services. The change in the adoption from time to time suggests that adoption has increased in recent years and reached broader market segments, similar to those studied by Dias et al. (2021) concerning ride-sourcing services. However, the study found that user transition between states varies over time, confirming that users' decisions within the TSA customer journey vary. Evaluating these states' composition, MRC and F&B services were the services that were stable in use from time to time. These findings contribute to the policymakers in designing and anticipating their urban mobility policy by considering particular TSA services that have superior popularity over time, given the significant impact of TSA on mobility and urban transformation (Irawan et al. 2020a, b; Irawan and Belgiawan 2022; Safira and Chikaraishi 2022).

In evaluating app performance, users are influenced by preference, needs and their personal characteristics (Horvath et al. 2022; Stocchi et al. 2022; Zhou et al. 2022). This leads to changes in the types of services used over time. The pre-adoption (PO) state is less stable than other states, which is not surprising as this study focused on TSA users who adopted the app at some point. However, most users in the PO state transition to MI or PI, indicating that while some users begin their TSA journey with more services (PI), others begin with minimalist services (MI). A decrease in the number of services used was prevalent among users in the FP state, suggesting that users tend to discontinue usage of certain services after trying them out. In contrast, the MI and PI states exhibit more stable usage of the services. A possible reason for this is that users in these states mostly use the core services of TSA that optimise daily activities, such as travel, activity participation and payments. Meanwhile, users in the FP state cover supporting services offered by other apps or physical activities, such as health services, education and news.

This study extends the prior cross-sectional investigation of TSA usage behaviour (Alemi et al. 2018; Irawan and Belgiawan 2022; Lavieri and Bhat 2019; Rizki et al. 2021a, b) by identifying the longitudinal adoption pattern of TSA users. The LMM identified the four usage transition stages over time: high acceleration, progressive adoption, continuous use and discontinuation. This finding not only reveals that there is no uniform pattern (increase, decrease, and stay the same) of TSA adoption over time but also demonstrates that the increase of the adoption can be gradually or instantly higher. More importantly, despite the net increase of adoption throughout diverse segments, some users also discontinued the use of some apps (particularly for supporting services), extending what Dias et al. (2021) found for ride-sourcing services. These transition patterns were found to be influenced by users' personality traits, socio-demographic characteristics and residential location. By revealing these patterns and the factors that affect them, this paper makes a theoretical contribution by extending the knowledge of temporal apps' adoption process that considers the evolution of the apps' functions.

High acceleration mostly occurs in the pre-adoption (PO) stage when users immediately personalise most TSA services (PI or FP). Rather than gradually adopting the services, users explore a wide range of services upon adoption as more apps are introduced within the TSA. Users based in Jakarta tend to use more services upon pre-adoption compared to those from other cities. This finding further confirms the influence of the built environment on app services usage (Lee et al. 2017; Wali and Khattak 2022), suggesting a more immediate effect on adopting a broader range of services from the beginning in more economic-intensive cities. The rate of increase in the number of services used in the transition from the PO state is also influenced by users' socio-demographic characteristics. Employed and educated users tend to use a wider range of services from the beginning, supporting previous findings that employed and educated users tend to be driven by daily obligations and higher knowledge in app adoption (Lake 2021; Mokhtarian 2004). Confirming previous

findings on the role of personality traits (Svendson et al. 2013; Tarka et al. 2022), this study also found that users with sociable and disorganised personalities tend to use more services initially since sociable individuals tend to be socially active, while disorganised individuals tend to be impulsive (Bosnjak et al. 2007). Since TSAs offer services that can be accessed anywhere at any time, users can use them for broader and incidental purposes.

Progressive adoption characterises a gradual exploration of the functions of the apps, such as from PO to MI, MI to PI and PI to FP. This transition pattern is mostly found in highly educated users who tend to be more selective with the services they utilise. Initially, they used minimalist services (MI) for travel and activity participation (MRC and F&B) before expanding to broader services (PI), such as cashless payment. The progressive adoption pattern is also prevalent in users who show positive agreeableness or pro-social behaviour.

Continuous use refers to situations where users consistently utilise the same combination of services without transitioning between states. In the post-adoption stage of the customer journey, this can be defined as continuity of use (Stocchi et al. 2022). Despite being one of the less stable states, some users in the FP state exhibit more stable usage of TSA services, influenced by the built environment. Users from Jakarta, Bandung and Denpasar who are in the FP state tend to show continuous use of various services compared to users from Cianjur. This could be attributed to the characteristics of Cianjur city, which offers fewer economic activities and experiences less congestion than other cities. This makes most TSA services, especially supporting services designed for daily activity optimisation, less attractive. Millennials and older Gen Z also tend to exhibit more stability when they reach the FP state. This might relate to the characteristics of millennials or newer generations that are more open and adapt to new ICT services than the older generations (Circella et al. 2016; Lee and Circella 2019).

The final transition stage is *discontinue*, where users stop using certain services. Higher-income individuals were found to discontinue using some TSA services, especially supporting services such as health, e-scooters, news and education and travelling. Discontinuation of use is also observed among older generations. There are various reasons for this finding that might be related to the quality of the apps or the different daily activity patterns of older individuals. On one hand, it is possibly due to less complex and less frequent daily activities and obligations compared to younger users. The older generation is known to use apps purposefully (Froehlich 2022), meaning they more carefully evaluate and select the most important services for their daily activities. On the other hand, the TSA might not provide the interface or the services that are more friendly for older people, which might result in them discontinuing the use of the services. This knowledge about the factors that influence these patterns contributes to TSA companies in evaluating their services and formulating marketing or improvement strategies.

Conclusion

The popularity of Transport-SuperApps (TSAs) has significantly increased from the prior decade along with the evolution of the functions they provided, beginning with urban mobility and shopping and integrating payment and entertainment in more recent years. This broadening scope of services has significantly altered individual travel habits. With the evolution of TSAs over the last seven years, there's a growing interest in understanding how these changing functionalities impact TSA usage behaviour. This study, which centred

on TSAs in Indonesia, sought to explore the dynamic relationship between app usage behaviour and the changing features of these applications. Additionally, it investigated how personality traits, socio-demographic factors and residential location affect patterns of app usage. The study collected data using a chronology concept in four Indonesian cities, capturing the longitudinal TSA usage pattern.

The study confirms that more services available in the apps influenced the number of services adopted by the users. The change in the number of services used is more visible in 2019, four years after its establishment, when the TSA had a peak number of services available on its platform. Car and motorcycle transport and e-shopping services were the most popular in the TSA, while e-scooters, entertainment, travelling and health services were the least popular.

The Latent Markov Model (LMM) reveals four states of adoptions. The first state, pre and occasional use of the apps (PO), represents the pre-adoption stage. The second state is minimalist for daily travel and optimise activity (MI), characterised by minimal use of TSA services that enable faster mobility and optimise daily activities. The third state extends the personalisation (PI) of TSA services beyond daily travel and trip avoidance to include cashless payment. The fourth state (FP) represents the full personalisation of most TSA services for daily activities.

In 2022, most users were in the MI and PI states, which suggests the popularity of transport and e-shopping services. The study also found the longitudinal transformation of behaviour denoted by user transition between states, which varies over time and is identified in four transition patterns. The high acceleration pattern (HA) represents behaviour when users immediately personalise most TSA services; the progressive pattern (PRO) is characterised as a gradual exploration of the functions of the apps; the continuous pattern (CON) represents when users consistently utilise the same combination of services; and the discontinue pattern (DIS) is when users stop using certain services. These patterns were found to be influenced by users' characteristics, where the HA pattern is more visible for TSA users who are workers, educated and live in Jakarta. The DIS pattern is more prevalent for older TSA users, indicating their temporary use of various TSA services. In addition, continuous usage of the same services tends to be observed in bigger cities than smaller cities when they already use various services (FP state). This might indicate the reliance on TSA services is higher in bigger cities with more significant congestion and air pollution.

The findings of this study provide important nuances from prior studies on the relationship between ICT and travel behaviour, particularly shaping the knowledge about the dynamic behaviour of app usage. From the perspective of transport modelling, the findings could improve a travel demand model that incorporates TSA services used for future projection by treating app use differently over time between one service and another. While it is safe to assume continuous use for some services, such as ride-sourcing and fast-food delivery services, supporting services tend to be used temporarily. Such a distinction can also be made based on other factors that influence app usage over time, such as socio-demographic factors, personality traits and residential location of users.

In addition, there has been a consistent rise in global smartphone usage over the past decade, driven by efforts to enhance ICT infrastructure and the myriad opportunities smartphones offer for business, economic and social interactions. Indonesia emerges as one of the largest markets for smartphones worldwide, boasting a user base exceeding 68.1% of its population and hosting numerous TSAs (Newzoo 2020). Forecasts suggest a further

increase in smartphone and TSA usage, propelled by advancements in the digital economy and the suitability of apps tailored to Indonesia's distinct societal, economic and infrastructural context (Rodenbaugh 2020; Switzerland Global Enterprise 2023; Team 2023). Consequently, it becomes imperative to anticipate adverse impacts while maximising the positive outcomes of TSAs for transitioning towards more sustainable urban environments. This study also offers insights into enhancing future infrastructure and urban planning, particularly concerning the perspectives of government bodies and technological companies (TCs).

First, despite the positive influence of the number of services available, usage of these services may be temporary or remain stagnant over time. Comprehensive and long-term implementation policies should be established for services that will continuously be used in daily activities (i.e. MRC and F&B), especially when such services have the potential to contribute to congestion and emissions by stimulating new travel and activities. This indicates the urgency to integrate this service into governments' urban mobility policy not only for the short-term but also the long-term. The policymakers should carefully plan to integrate MRC services into the urban public transport system and F&B delivery services on urban freight transport. In doing so, the government can also cooperate with TCs in integrating their services into the urban transport system by empowering them to use more sustainable modes such as e-vehicles and designing the supporting infrastructure to support the services.

Second, our findings suggest that interventions to reduce the negative impact and enhance the positive impact of TSAs in urban areas are more crucial in larger cities (e.g. metropolitan and megapolitan cities). These cities are associated with more complex daily activities and congestion, which means that TSA users tend to explore more functions upon adoption and exhibit more stable behaviour over time compared to users in smaller cities. Prioritisation to take various measures to ensure the sustainable transition of the sectors influenced by TSA should be taken and emphasised in these larger cities by both local and central governments to accelerate the progress.

Finally, while it is evident that most users evaluate services over time to reach the optimal number of TSA services used, some users engage in app exploration. The number and types of services used vary across socio-demographic characteristics and personality traits, with more educated, sociable and less disorganised individuals exhibiting a tendency to explore more. If TCs plan to expand their market beyond the core services, they can focus their marketing strategy on these demographic and personality groups. Moreover, TCs can evaluate the quality of their services, particularly by investigating the needs of older users since the pattern of discontinuation is prevalent in this socio-demographic segment. Improvement of the services for this segment of users will benefit by retaining the users of TSAs.

Despite the findings, this study has limitations that offer opportunities for further research. This study assumes static variables for certain socio-demographic factors in the longitudinal data. Further studies that capture and explore the dynamic effects of socio-demographic factors can improve this study's findings. Moreover, since this study used aggregated data to understand TSA usage behaviour, future studies that accommodate changes in usage frequency over time can provide deeper insights into TSA usage behaviour over time. This information can significantly improve travel demand models. Furthermore, this study did not investigate the temporal impact of TSA usage on travel and activity participation. Integrating the temporal effect of the impact of TSA services can enrich our understanding of how app usage impacts travel and activity participation over time.

Appendix 1

Table 9 States' characteristics per year based on the TSA's services usage

	Use of										
	MRC	CRC	GD	F&B	EG	ET	ESC	NIE	HP	HA	PAY
States	2015										
MI	61%	19%	13%	45%	0%	0%	0%	0%	0%	0%	0%
FP	45%	31%	37%	55%	51%	0%	0%	0%	0%	0%	0%
PO	1%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
PI	100%	27%	27%	64%	0%	0%	0%	0%	0%	0%	0%
States	2016										
MI	43%	21%	6%	41%	10%	0%	0%	0%	0%	0%	0%
FP	74%	45%	68%	84%	77%	26%	0%	0%	0%	0%	0%
PO	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
PI	90%	54%	51%	76%	0%	22%	0%	0%	0%	0%	0%
States	2017										
MI	57%	19%	11%	63%	1%	0%	0%	0%	0%	0%	20%
FP	91%	57%	74%	91%	94%	26%	0%	0%	0%	0%	77%
PO	0%	0%	1%	0%	0%	0%	0%	0%	0%	0%	0%
PI	91%	53%	73%	84%	1%	10%	0%	0%	0%	0%	62%
States	2018										
MI	43%	17%	8%	80%	1%	0%	0%	0%	0%	0%	9%
FP	80%	72%	74%	93%	93%	24%	0%	0%	0%	0%	80%
PO	1%	0%	1%	0%	0%	0%	0%	0%	0%	0%	0%
PI	96%	43%	69%	88%	0%	10%	0%	0%	0%	0%	64%
States	2019										
MI	44%	16%	6%	75%	2%	0%	0%	1%	1%	0%	13%
FP	70%	60%	67%	75%	84%	51%	2%	40%	61%	37%	81%
PO	5%	0%	2%	0%	0%	0%	0%	0%	0%	0%	1%
PI	87%	46%	62%	93%	1%	2%	0%	2%	2%	5%	66%
States	2020										
MI	29%	9%	9%	74%	1%	0%	2%	0%	1%	0%	11%
FP	65%	57%	75%	88%	88%	42%	19%	39%	55%	28%	83%
PO	0%	0%	1%	0%	0%	0%	0%	0%	0%	0%	0%
PI	76%	38%	61%	93%	4%	2%	3%	1%	3%	4%	57%
States	2021										
MI	32%	8%	11%	74%	2%	0%	0%	0%	0%	0%	13%
FP	71%	54%	92%	92%	88%	52%	26%	23%	49%	28%	80%
PO	0%	0%	3%	0%	0%	0%	0%	0%	0%	0%	0%
PI	80%	31%	67%	92%	4%	9%	0%	3%	3%	4%	63%
States	2022										
MI	37%	18%	17%	87%	5%	0%	0%	0%	0%	0%	14%
FP	76%	61%	86%	95%	87%	55%	15%	26%	41%	33%	88%
PO	0%	0%	10%	0%	0%	0%	0%	0%	0%	0%	0%
PI	86%	39%	82%	97%	11%	14%	0%	3%	3%	1%	74%

MRC, motorcycle ride-sourcing; *CRC*, car ride-sourcing; *GD*, goods delivery; *F&B*, food and beverage delivery; *EG*, e-groceries; *ET*, entertainment ticket; *ESC*, e-scooter; *NIE*, news, information, and education; *HP*, health product; *HA*, hotel/apartment book; *PAY*, e-payments; *MI*, Minimalist for daily travel and optimise activity, *FP*, Full personalisation of apps; *PO*, Pre and occasional use of apps; *PI*, Personalisation for daily travel, activity, and e-payment

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Declarations

Competing interests The authors declare no competing interests.

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Muhamad Rizki is a Ph.D. student at the Institute for Transport Studies, University of Natural Resources and Life Sciences (BOKU), Vienna, Austria. He is also an assistant professor at the civil engineering department at Institut Teknologi Nasional Bandung, Indonesia. He received his B.S. degree in civil engineering from Parahyangan University and his M.S. degree in civil engineering from Institut Teknologi Bandung. His research interests include travel behaviour, the impact of information and communication technology on travel and activity participation, transport and climate change, and behaviour around the adoption of new technology.

Tri Basuki Joewono is a professor of transportation in the Department of Civil Engineering, Faculty of Engineering at Universitas Katolik Parahyangan (UNPAR), Bandung, Indonesia. He holds bachelor's and master's degrees in civil engineering from UNPAR and a master's degree in transportation from Bandung Institute of Technology. His doctoral degree is from Saitama University, Japan. He teaches and conducts research in the areas of transportation engineering, infrastructure management, built environment, public transportation, travel behaviour, and urban transportation.

Yusak Susilo is the Chair and BMK (Austrian Federal Ministry) Endowed Professor in Digitalisation and Automation in Transport and Mobility System at the University of Natural Resources and Life Sciences, Vienna, Austria, and is also the head of Austrian Federal Ministry's endowed research group, DAVeMoS. His research interest lies in the intersection between transport and urban planning, transport policy, decision-making processes, and travellers' well-being and health. In particular, he is interested in the complexity of decision-making process and one's activity-travel patterns and the interaction of such decisions and patterns with temporal changes in one's well-being, activity locations, urban form, policy, environment, and technology characteristics.

Authors and Affiliations

Muhamad Rizki^{1,2} · Tri Basuki Joewono³ · Yusak O. Susilo¹

✉ Muhamad Rizki
muhamad.rizki@boku.ac.at

Tri Basuki Joewono
vftribas@unpar.ac.id

Yusak O. Susilo
yusak.susilo@boku.ac.at

¹ Institute for Transport Studies, University of Natural Resources and Life Sciences (BOKU), Gregor-Mendel-Straße 33, 1180 Vienna, Austria

² Department of Civil Engineering, Institut Teknologi Nasional Bandung, Phh. Mustofa 23, 40124 Bandung, Indonesia

³ Department of Civil Engineering, Universitas Katolik Parahyangan, Ciumbuleuit 94, 40141 Bandung, Indonesia