Exploring the Effect of Apps Evolution and Users' Personality on Mobile Apps Adoption and Post-Adoption Pattern Over Time: Evidence from Super-Apps Users in Indonesian Cities

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SHORT SUMMARY

This study aims to investigate the effect of users' personality as well as apps' transformation to the adoption and post-adoption patterns of multi-functional apps/Super-Apps over time. A questionnaire was distributed to Super-Apps users in four Indonesian cities. Latent Markov model (LMM) was used to investigate the users' Super-Apps usage from 2015 to 2022. Four distinctive states were recognized: the Super User (SU) state; the Transport, Consumption, and Finance (TCF) state; the Food and Beverage (F&B) and Transport (FT) state; and the Less Explored (LE) state. The analysis found that LE users have a higher probability of changing into another state of users, while TCF users tend to be more stable than other groups. A higher number of functions available does not necessarily lead to highest exploration, but it contributes to making the users evolve from LE to other states. Users who more sociable tend to explore the apps more.

Keywords: behaviour changes, users' personality, apps' transformation, latent markov model, Super-Apps

1. INTRODUCTION

Mobile apps (apps) have developed from their beginnings as simple utilities into platforms that fulfill variety of personal needs and desires. The substantial number of apps and the opportunities that they provide have attracted research on apps' adoption in various disciplines (Mehra et al., 2021; Stocchi et al., 2022). However, people's decision process to adopt apps is complex in their consumer journey phases. The phases identified as pre-adoption, which refers to the predisposition of customers before app adoption; adoption, which refers to the result of a positive predisposition towards the app and therefore, downloading and using the app; and post-adoption, which is defined as the continuation of using the app (Stocchi et al., 2022). The customer experience within the customer journey also evolves over time in response to users' characteristics, such as attitude, personality, and demography, as well as changes in the app environment, such as the level of service quality, features, or design (Kim et al., 2016). The latter has been of interest to various technological companies seeking to improve their app environment to increase the level of engagement, including the current evolution of mobile apps that provide multiple functions called Super-Apps.

Most of previous research has separated the investigation of pre-adoption (Stocchi et al., 2019), adoption (Mehra et al., 2021), and post-adoption (Kim et al., 2016). However, research has also shown that the continuation of app use is influenced by users' past behaviour (Kang et al., 2015), suggesting a pattern in mobile app usage. Attempts to integrate adoption and post-adoption by capturing behaviour over time have been done by Horvath et al. (2022) with a three-wave panel survey. Despite the study integrating the attitude of the respondents towards the apps, the study did not accommodate the effect of personality (Stocchi et al., 2022). The importance of personality has been underlined because it also drives people's motivations (Yeh et al., 2021) and consumption characteristics (such as stickiness, willingness to pay, etc.) (Dinsmore et al., 2017). Moreover, the relationship between personality and app adoption is might even more complicated in Super-Apps due to their evolution from single to multiple functions, leading to different usage patterns.

The investigation of Super-Apps use evolution is important from various perspectives. From marketing, investigating the adoption and post-adoption stages can offer strategic recommendations for apps developers aiming to optimize user engagement within apps (Kim et al., 2016; Stocchi et al., 2022). The importance of this inquiry also lies in the transportation sector, specifically urban mobility. The advancement of apps has been recognized to have a substitution, generation, modification, or neutral impact on travel demand (Mokhtarian, 2009). Some of Super-Apps functions have found related to change the travel behaviour such as ride-sourcing, food and beverage delivery, or e-shopping. Therefore, this examination is relevant to reducing negative externalities resulting from Super-Apps usage.

This study aims to explore how the evolution of apps and users' personalities contribute to the users' behaviour of using Super-Apps over time. Specifically, we focus on the adoption and post-adoption concepts of the customer journey (Stocchi et al., 2022) and extend it with temporal investigation in response to the changes in the number of functions available on the apps. Additionally, we integrate the effect of users' personalities, residential location, and socio-demography, which prior studies only considered as a factor in a specific phase (Yeh et al., 2021). Consequently, this research aims not only to comprehend the pattern of adoption and post-adoption of Super-Apps but also how this pattern evolves over time and is influenced by the apps' transformation and users' characteristics.

2. METHODOLOGY

Data Analysis

For examining the effect of the users' personality and apps' evolution to the use of Super-Apps over time, this study uses LMM. The LMM is commonly known as extension of the dynamic logit model for longitudinal data (Bartolucci et al., 2017).

For this research, we observed the use of Super-Apps services (Y_{ij}^{t}) as the response/indicator variable, for each service j ($j \in \{1, 2, ..., J\}$), respondent i ($i \in \{1, 2, ..., n\}$), and time t ($t \in \{1, 2, ..., T\}$), by the category of 0 = not using the app and 1 = using the app. Let also x_{it} be the vector of respondents' (i) covariates for $t = 1, 2, ..., T$. The general LMM formulation assumes the existence of latent process, denoted by U_c^{t}, which affects the distribution of response variables, and the process is assumed to follow a first-order Markov chain with state space ($c \in \{1, 2, ..., k\}$). Under local independence assumption (Bartolucci et al., 2017), the response vector (Y_{ij}^{t}) are assumed to be conditionally independent given the latent process (U_c^{t}). The parameter of measurement model to determine the latent states are the conditional response probabilities:

$$\Phi^{t}_{y|ux} = P\left(Y^{t}_{ij} = y \left| U^{t}_{i} = c \right.\right) \ (1)$$

The parameters of the latent process include the initial probabilities of (π_c) of each latent state and the transition probability ($\pi_{c|\acute{\varsigma}}$) between states:

$$\pi_{c|x} = P(U^{1}_{i} = c \ | X^{1}_{i} = x\ ) \ (2)$$

As the initial probability, where the c = 1, …, k, and the transition probability:

$$\pi^{(t)}_{c|\acute{\varsigma}x} = P(U^{t}_{i} = c \ |U^{t-1}_{i} = \acute{\varsigma}\ , X^{t}_{i} = x\ ) \ (3)$$

Where t = 2, …, T, $\acute{\varsigma}, c = 1, \ldots, k$, x denotes a realization of the covariates X^t, c a realization of U^t, and $\acute{\varsigma}$ a realization of U^{t-1}. The initial and transition probability (latent model) are adopting multinomial logit parametrization (Bartolucci et al., 2017). In this study the latent model:

$$log\frac{P(U^{1}_{i} = c \ |X^{t}_{i} = x\ )}{P(U^{1}_{i} = 1 \ |X^{t}_{i} = x\ )} = \log\frac{\pi_{c|x}}{\pi_{1|x}} = \beta_{0c} + x^{\top}\beta_{1c}\ , c = 2, \ldots, k \ \ (4)$$

As the initial probability with having first state as reference, and for transition probability:

$$log\frac{P(U^{t}_{i} = c \ |U^{t-1}_{i} = \acute{\varsigma}\ , X^{t}_{i} = x\ )}{P(U^{t}_{i} = c \ |U^{t-1}_{i} = \acute{\varsigma}\ , X^{t}_{i} = x\ )} = \log\frac{\pi_{c|\acute{\varsigma}x}}{\pi_{\acute{\varsigma}|\acute{\varsigma}x}} = \gamma_{0\acute{\varsigma}c} + x^{\top}\gamma_{1\acute{\varsigma}c}\ , (5)$$

where t = 2, …, T and $\acute{\varsigma}$, c = 1, …, k, with $\acute{\varsigma} \neq$ c. In above expression (4, 5), $\beta_c = (\beta_{0c}, \beta^{\top}_{1c})^{\top}$ and $\gamma_{\acute{\varsigma}c}=(\gamma_{0\acute{\varsigma}c}, \gamma^{\top}_{1\acute{\varsigma}c})^{\top}$ are parameter vectors to be estimated. The illustrative framework of the LMM of Super-App use, indicators and covariates is described in Figure 1.

Data Collection

Data used in this research is part of a 2022 one-week virtual and physical activity diary survey in Indonesian cities that also specifically investigates Super-App use behaviour. Grab and Gojek, launched in 2015, are the representation of transportation-based Super-apps in this study. We used the data of the respondents' socio-demography, personality traits with the Big Five Inventory (BFI), and chronology of Super-Apps use from the survey. The chronology of use section asks about the monthly frequency of each use of Super-App service (e.g., transport, goods, food transport, etc.) from 2015 to 2022 and we transformed this number into the code of whether they use it or not use it for the analysis.

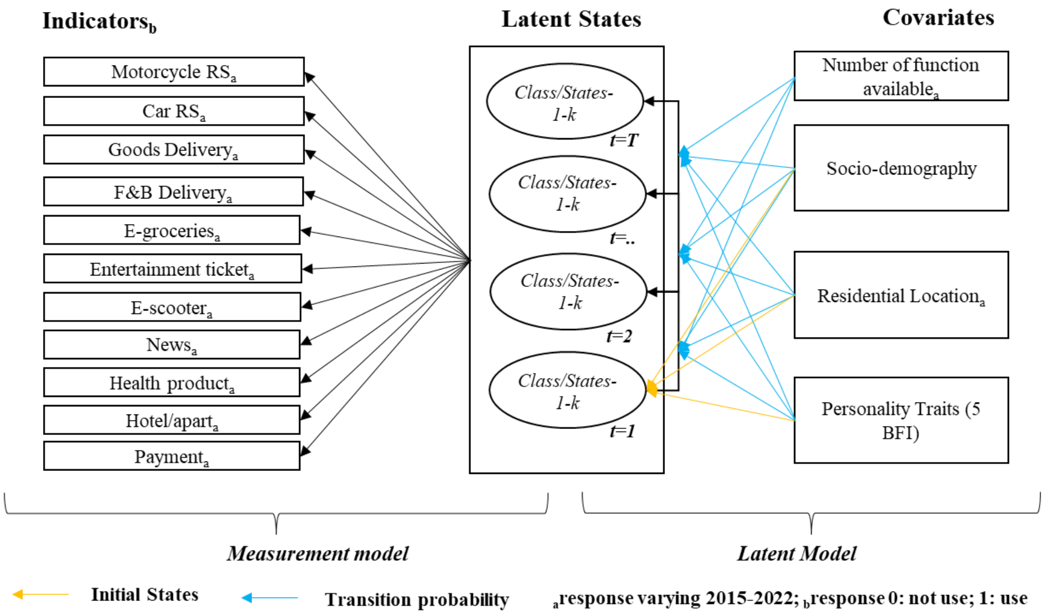


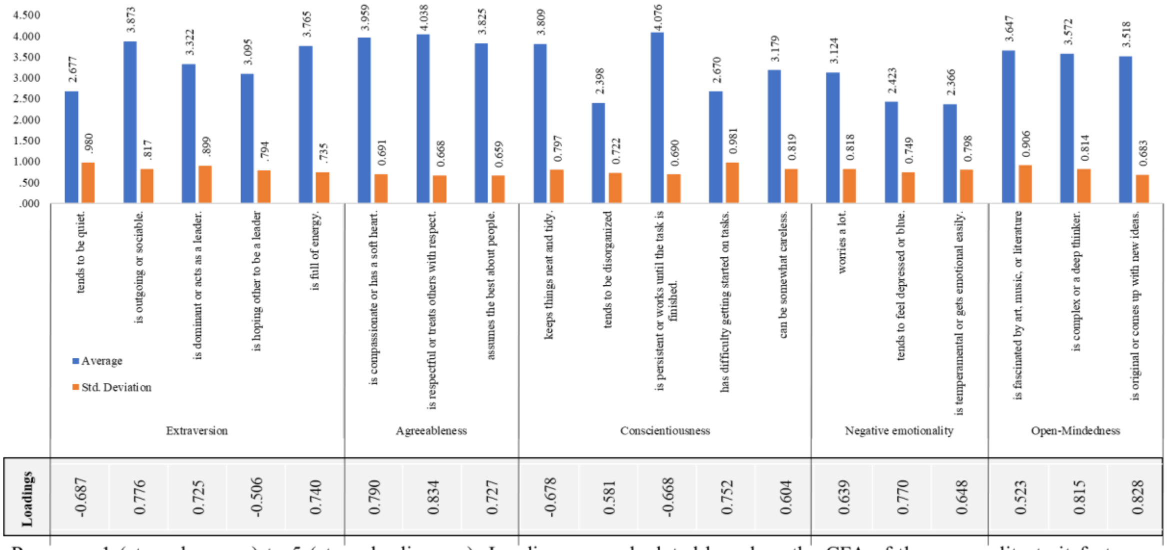
Figure 1. Conceptual Framework of Analysis

Convenience sampling method was used for data collection with surveyors distributed the questionnaire based on the small district within the city. The study location is on four Indonesian Cities that are differ in terms of population size, namely Jakarta, a megapolitan city, Bandung, a metropolitan city, Denpasar, a big city, and Cianjur, a medium city. The survey was conducted between May 2022 and January 2023. 1251 data were valid for the analysis and this study only use on 1051 datasets of Super-Apps users, excluding the respondents that not the users.

3. RESULTS AND DISCUSSION

In this study (N=1051), most of the respondents were male (56.2%), employed (70.4%), and possessed undergraduate degrees (55%). Additionally, most of them had a monthly household income of more than 6 million IDR (394 USD) (39.5%). The respondents were nearly evenly distributed across four locations based on their residential status, with Jakarta having the highest percentage (28.9%), followed by Bandung, Denpasar, and Cianjur. The study also uses secondary data about Super-Apps transformation. In 2015, only five functions were available: motorcycle and car ride-sourcing (RC), goods delivery, food and beverage (F&B) delivery, and e-groceries. In 2016, the function that offered buying entertainment tickets became available, followed by various payments (i.e., electricity, bills, stocks, donation, mobile package) in 2017. E-scooters, news/information/education, health services and products, and hotel booking became available in 2019 until now.

The respondents' personality characteristics are described in Figure 2. The variable that has the highest score is persistency in the conscientiousness dimension, while the lowest one is temperamental in negative emotionality. We used Confirmatory Factor Analysis (CFA) to reduce the personality dimension based on the five-group classification of BFI. The loading factors of each group are shown in Figure 2.



Response 1 (strongly agree) to 5 (strongly disagree); Loadings are calculated based on the CFA of the personality trait factors with Principal component analysis, and Bartlett scores for generated for each case of each factor.

Figure 2. Respondents Personality Characteristics (Question: I am person who…)

Determining the appropriate number of states is a crucial factor in LMM. Based on the recommendations of a prior research, we utilize BIC and AIC criteria to assess the states. The assessment, which is presented in Figure 3, indicates that there is no considerable improvement in AIC and BIC scores beyond four states. Additionally, the interpretability of the profile for four states is satisfactory and therefore, we decide that using four states.

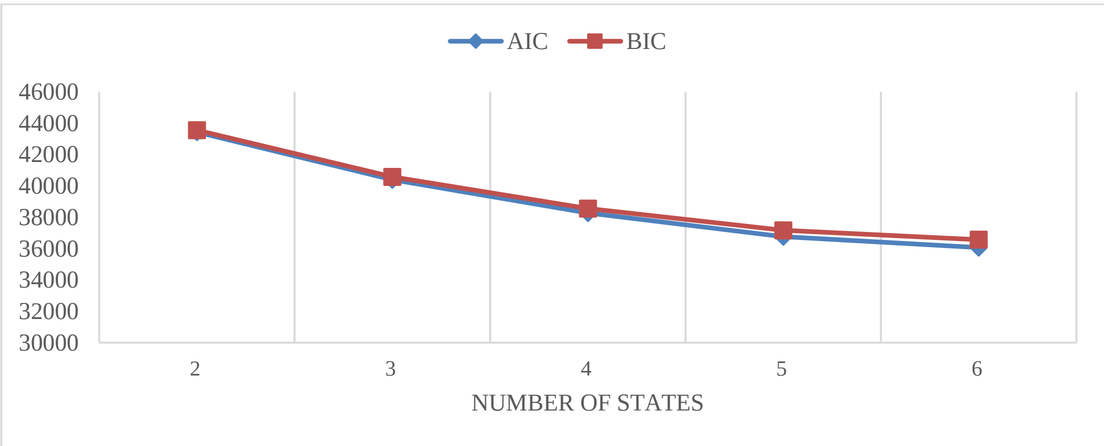


Figure 3. Determine Number of States

The profile of states based on Super-Apps function usage is described in Figure 4. The first state represents the use of motorcycle and car RC, goods delivery, F&B delivery, and payments, which we named the Transport, Consumption, and Finance (TCF) state. The second state is the Super User (SU) state, where users explore most of the Super-Apps functions. The third state represents situations where users only use a limited function, named the Low Exploration (LE) state. The last state represents the use of Super-Apps for motorcycle and car RC, goods delivery, and F&B delivery, or the F&B and Transport (FT) state.

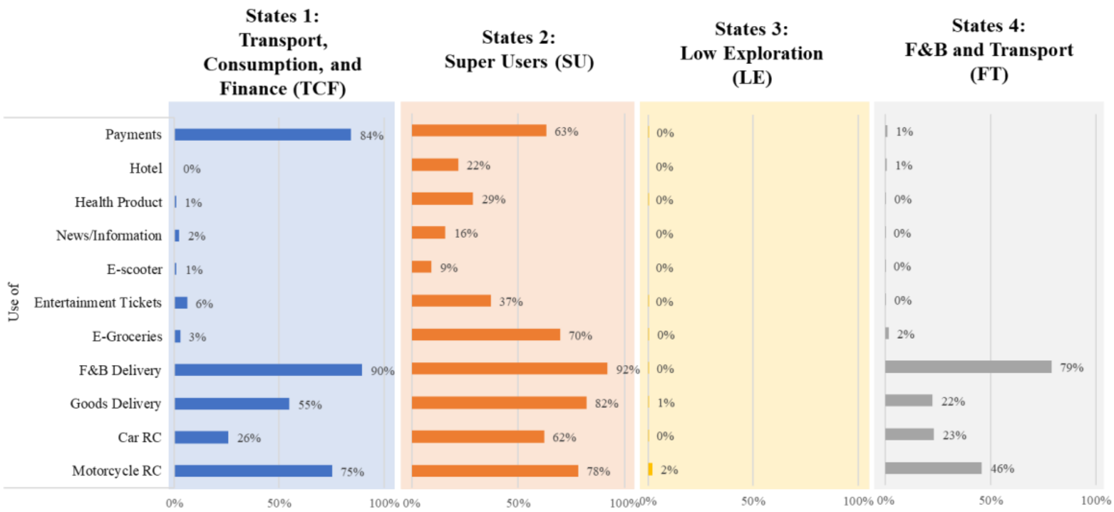


Figure 4. States Profile Based on the Functions Use

Since we are interested in patterns over time, in this study, we focus on estimating the transition probabilities (Table 1). Socio-demographic characteristics were found to influence the transition. It was found that older users are less likely to change from the LE state to another state compared to younger users. Female users are less likely to change from the TCF state to the LE or FT state, but they tend to change from LE states to FT compared to men. Workers tend to change from TCF to SU state compared to non-workers or students. Users with higher education tend to change from SU to TCF state. Differences in city characteristics were also found to shape the transition. All cities have the same negative tendency for transition from TCF to LE states. However, users from Bandung, Jakarta, and Denpasar tend to change from TCF to FT state compared to Cianjur users. Compared to Denpasar, Bandung users tend to change from TCF to SU states. Jakarta users also tend to change to FT from SU state.

The availability of more functions in the apps was found to influence the changes of states when users are in the LE state. Personality was also found to influence the behaviour of use over time. Users who are sociable, respectful, but disorganized tend to change from LE to TCF state. Users who are open-minded are less likely to lower their function use from TCF to FT or LE state. People who are respectful/kind-hearted tend to be less stable but have a positive influence on the transition. While users who are sociable tend to change from TCF to SU or FT state, they are less likely to change from SU to TCF state.

The average transition probability (Figure 4-a) reported that TCF is the most stable state, while the LE/3rd state is the least stable compared to others. Significant changes in LE states (Figure 4-b) were found from 2018 to 2019, five years after Super-Apps launched. Currently, users' states are mostly in TCF and FT.

Table 1. Estimation of Parameter Logit for Transition Probabilities

Transition from	**TCF to**			**SU to**			**LE to**			**FT to**		
	SU	**LE**	**FT**	**TCF**	**LE**	**FT**	**TCF**	**SU**	**FT**	**TCF**	**SU**	**LE**
Variables												
Intercept	-12.2 **	-83.8 **	10.82 **	-46.72 **	-34.87 **	-8.42 *	-10 **	-15.64 **	-7.03 **		-8.29 **	-23.66 **
Age							-0.02 *	-0.07 *	-0.03 **	0.03 *		0.11 *
Female [D]		-10.39 **	-2.4 **		11.05 *	4.11 **			0.38 **			
Household Income	-0.68 **	4.53 *								-0.14 *		
Workers [D]	15.49 **	7.42 **	1.32 **	-11.2 **			0.71 **				0.99 *	
Education		12.47 **	-5.9 **	24.17 **				1.1 *	0.62 **	-0.48 *		-2.77 **
Bandung [D]	3.15 **	-22.99 **	4.97 **	-50.63 **	-74.15 **				1.5 **		3.24 **	-8.54 *
Denpasar [D]	-15.78 **	-25.56 **	10.61 **	-49.15 **	-64.14 **			4.9 **	0.93 *		2.74 **	-9.4 *
Jakarta [D]		-36.45 **	6.24 **	-28 **	-59.62 **	5.59 **		-7.15 **	0.88 *		4.23 **	-17.82 **
Cianjur [D]		-12.93 **	-4.65 **	-31.11 **	-60.17 **			4.58 **	0.88 *		2.13 **	-9.7 *
Number of Functions Available	-0.49 **		-1.27 **		6.44 **		0.69 **	0.75 **	0.43 **	-0.31 **		
Extraversion	0.62 *		0.52 **	-14.72 **			0.46 **				0.38 *	
Agreeableness		5.57 **	1.11 **	6.03 *			0.31 **				0.76 **	
Open-mindedness		-6.53 **	-1.28 **							0.30 *		
Conscientiousness							0.26 **		-0.12 *	0.57 **		

[D]: dummy variables; *significant at 5%; **significant at 1%

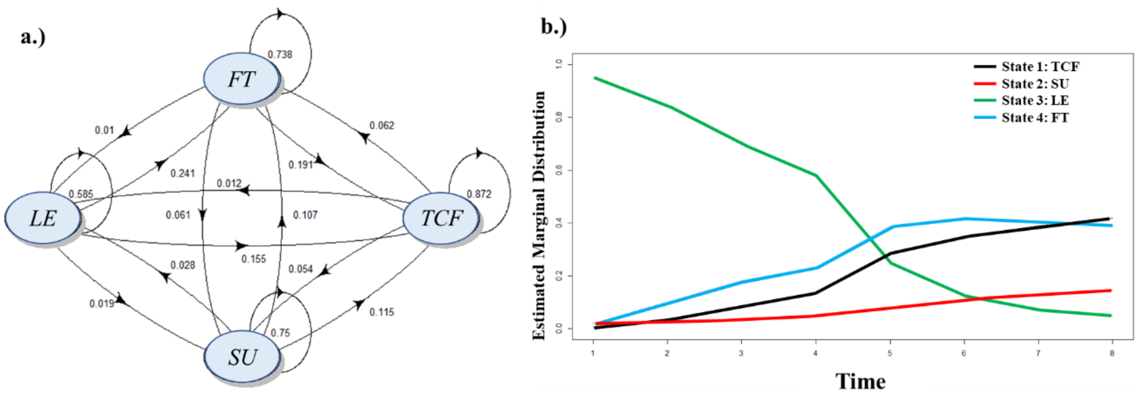


Figure 4. a.) Average Transition Probability, b.) Marginal Distribution Over Time

4. CONCLUSIONS

This study explores the effects of the transformation of apps and users' personality, residential location, and personal characteristics on the pattern of Super-Apps use over time. The study found four states that represent specific use of Super-Apps' functions: the Transport, Consumption, and Finance (TCF) state, Super users (SU) state, Low exploration (LE) state, and F&B and Transport (FT) state. The study also found that adding more functions to the apps influences the adoption of Super-Apps, leading to a transition from LE to other states but not necessarily to the highest exploration (SU state). Personality also influences the transition, with sociable users tending to explore the apps more, suggesting that Super-Apps might facilitate their outgoing personality needs. The economic intensity of a city does not influence greater use exploration, as every city has its own transition into the SU state. However, Jakarta stands out from other cities in its tendency to change from the SU to the FT state.

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