Post-Adoption Behavior of Taxi Drivers Toward Ride-Hailing Apps: Postprint

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Abstract

[Purpose/Significance] This study selects traditional taxi drivers as its research sample, grounded in post-adoption behavior of ride-hailing apps, to explore behavioral patterns and their attributions, which holds theoretical significance for refining the post-adoption behavior domain and offers practical value for user retention in the new economic paradigm of the Internet era. [Method/Process] With Beijing taxi drivers as research subjects, this study employs field research methods to collect case data, including in-depth interviews and participant observation, and utilizes grounded theory for analysis to construct a model of taxi drivers' post-adoption behavior of ride-hailing apps, exploring the underlying mechanism of post-adoption behavior. [Results/Conclusions] This study systematically explores the theoretical framework of user post-adoption behavior. After adopting ride-hailing apps, taxi drivers' emotions are influenced by personal, cognitive, social, and technical factors, thereby triggering subsequent continuous usage, discretionary usage, and discontinuous usage behaviors. The model also reveals the interaction paths among these factors.

Full Text

Preamble

Study on Taxi Drivers'Post-Adoption Behavior of Online Ride-Hailing Apps

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Abstract: [Purpose/Significance] This study examines traditional taxi drivers as its research sample, grounded in the post-adoption behavior of ride-hailing apps to explore behavioral patterns and their attributions. The research holds theoretical significance for enriching the post-adoption behavior domain and practical value for user retention in new economic forms of the internet era. [Method/Process] Beijing taxi drivers were selected as research subjects through fieldwork methods, including in-depth interviews and participant observation. Grounded theory was employed to analyze the data and construct a behavioral model of taxi drivers' post-adoption of ride-hailing apps, investigating the mechanisms underlying post-adoption behavior. [Result/Conclusion] The study systematically explores the theoretical framework of user post-adoption behavior. After adopting ride-hailing apps, taxi drivers' emotions are influenced by personal, cognitive, social, and technical factors, leading to subsequent continuous use, flexible use, or discontinuous use behaviors. The model also demonstrates interrelationships among these factors.

Keywords: post-adoption behavior; online ride-hailing; mobile application; taxi driver
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1 Research Background and Significance

Ride-hailing refers to a new business model based on mobile internet that uses smartphone apps as the primary service platform to facilitate communication and secure connections between passengers with travel needs and qualified drivers. Ride-hailing includes not only dedicated cars, express cars, and carpooling services but also traditional cruising taxis (hereinafter referred to as "traditional taxis" or simply "taxis") that have integrated into ride-hailing platforms.

While the United States saw early platforms integrating supply and demand information via the internet as early as 1999, true ride-hailing services emerged with Uber in California in 2009 [?]. China' s ride-hailing market began with Yidao Yongche in 2010. In July 2016, China became the world' s first country to formally legalize ride-hailing services through the "Interim Measures for the Administration of Online Ride-Hailing Services." By June 2019, ride-hailing taxi user scale reached 337 million, accounting for 39.4% of all internet users, while dedicated and express car users reached 339 million, representing 39.7% of internet users.

Most existing research on ride-hailing app adoption focuses on passenger-side user behavior, yet the platform connects both drivers (suppliers) and passengers (demanders)—both indispensable to its operation. If either party abandons the platform, the other' s experience suffers, affecting effective platform operation. Passenger and driver usage differs fundamentally in motivation, making passenger-focused factors inapplicable to drivers. Therefore, drivers warrant dedicated study, offering important practical significance for user retention in internet-era economic models. Theoretically, this research contributes by identifying new explanatory variables and constructing a theoretical framework that comprehensively articulates emotional and behavioral changes, thereby enriching information systems post-adoption behavior research.

2 Literature Review

Taxi drivers' use of ride-hailing apps essentially represents adoption and use behavior of mobile information systems. Preliminary research reveals that drivers' post-adoption patterns can be broadly categorized into continuous use and discontinuous (negative) use behaviors. This section reviews relevant theories and models.

2.1 Continuous Use Behavior Research

2.1.1 Theoretical Foundations Continuous use behavior represents an extension of initial adoption. Researchers commonly employ several behavioral theories when studying continuous use, as summarized in Table 1 .

Table 1. Theoretical Models of Continuous Use Behavior

Theory	Representative Studies
Technology Acceptance Model	Chen et al. (2014) [?]; Dai & Xu (2011) [?]; Dai et al. (2016) [?]
Information Systems Continuance Model	A. Bhattacherjee (2001) [?]; Wang (2017) [?]; Chen et al. (2014) [?]; Liu et al. (2011) [?]; M. Limayem & C.M.K. Cheung (2008) [?]; M. Limayem & C.M.K. Cheung (2007) [?]; J.Y.L. Thong et al. (2006) [?]
Information Systems Success Model	Hu (2013) [?]; Zeng & Cong (2014) [?]
Self-Determination Theory	Yang (2016) [?]

2.1.2 Influencing Factors Dai' s research on WeChat adoption and continuous use categorized influencing factors into internal and external factors [?], which this study extends. Internal factors include cognitive, attitudinal/experiential, and psychological factors; external factors include social and technical factors.

(1) Cognitive Factors. Common cognitive factors include perceived usefulness [?, ?], perceived ease of use [?, ?], expectation confirmation [?, ?, ?], and perceived enjoyment/interest [?, ?, ?]. Other factors like context awareness [?] and perceived mobile value [?] appear less frequently.

(2) Attitudinal/Experiential Factors. Satisfaction is a crucial antecedent of continuous use intention in the Information Systems Continuance Model, validated across numerous empirical studies [?, ?].

(3) Psychological Factors. D. Gefen distinguished habit from continuous use intention, suggesting habit may better predict actual continuous use [?]. Many scholars incorporate habit [?, ?, ?] and motivation [?] as influencing factors.

(4) Social Factors. Primary social influences include network externality, subjective norms, social influence, and facilitating conditions [?, ?].

(5) Technical Factors. System design and attributes affect adoption and use intentions. System quality, information quality, and service quality from the Information Systems Success Model (ISSM) directly influence continuous use intention [?, ?, ?]. Mobility [?] and interactivity [?, ?] are also considered technical factors.

2.2 Negative Use Behavior Research

2.2.1 Theoretical Foundations Domestic research on negative use behavior remains limited, primarily focusing on social platforms. Table 2 summarizes relevant theories.

Table 2. Main Theoretical Foundations for Social Media Users' Negative Use Behavior

Theory	Representative Studies
Stressor-Strain-Outcome Theory	Lu (2018) [?]; Guo & Cao (2018) [?]; A.R. Lee et al. (2016) [?] Liu et al. (2017) [?]; L.F. Bright et al. (2015) [?]; S. Zhang et al. (2016) [?] C. Maier et al. (2015) [?] Zhang et al. (2017) [?]

2.2.2 Influencing Factors **(1) Cognitive Factors.** Negative use behavior factors include perceived overload (information overload [?, ?, ?], system feature overload [?, ?], and social overload [?, ?]), privacy concerns [?, ?, ?], and self-efficacy [?, ?]. Less frequently mentioned factors include platform value perception [?], cost perception [?], and perceived usefulness [?].

(2) Technical Factors. Information quality [?, ?] receives the most attention. Lu et al. described low-quality information across four dimensions—inherent, contextual, representational, and accessibility—to measure its impact on social media fatigue [?].

(3) Attitudinal/Experiential Factors. Factors influencing social media users' discontinuous intention include fatigue [?, ?], satisfaction [?, ?], flow experience [?], and social media attitude [?].

(4) Other Factors. These include personality factors [?] (personality traits, self-control) and psychological factors (motivation) [?].

2.3 Ride-Hailing App Research

Current research on ride-hailing app behavior remains scarce. Some studies [?] integrate Technology Acceptance Model (TAM), Innovation Diffusion Theory (IDT), and Theory of Reasoned Action (TRA) to model passenger behavior. Others [?] examine drivers using customer perceived value theory, introducing perceived cost and risk to model continuous use. Additional research includes user switching intention based on the Push-Pull-Mooring (PPM) model [?], passenger satisfaction using structural equation modeling [?], and urban residents' taxi vs. ride-hailing choices using binomial logit models [?].

Existing studies insufficiently explore post-adoption behavior depth, typically dividing it into two crude categories and rarely considering behavioral diversity. Most adopt quantitative methods capturing static time-point data without examining behavioral dynamics and continuity.

3 Research Questions and Methods

This study addresses two core questions: (1) What behaviors do taxi drivers exhibit when using smartphones during work hours after adopting ride-hailing apps? (2) What factors influence these behavioral choices? Preliminary investigation identified Didi, Dida, and Taxi Alliance as the most popular apps among Beijing taxi drivers.

Data collection employed field research methods, primarily through in-depth (semi-structured) interviews supplemented by participant observation during taxi rides. Grounded theory was used to analyze qualitative data and construct a theoretical model.

4 Grounded Theory Analysis

Through grounded theory analysis involving deconstruction, comparison, induction, and coding of interview transcripts, this study developed a behavioral model of taxi drivers' post-adoption of ride-hailing apps based on conceptual logic relationships. From 41 samples, 38 were randomly selected for three-stage coding; the remaining 3 underwent theoretical saturation testing, revealing no new concepts or categories.

Open coding generated categories including: reduced empty cruising, less counterfeit money, order selectivity, convenient payment, enriched work forms, navigation, occasional tips, backup preparation, reluctance to cruise, system intuitiveness, operational ease, upgrade difficulties, learning confidence, attention distraction, etc. Axial coding grouped these into perceived usefulness, information quality, habit, motivation, external influence, loss emotions [?], achievement emotions [?], challenge emotions [?], forced use, active use, wait-and-see behavior, balanced use, basic exit, and complete exit behaviors. Selective coding identified core categories: cognitive factors, technical factors, personal factors, social factors, negative emotions, positive emotions, continuous use behavior, flexible behavior, and discontinuous use behavior. Due to space constraints, partial coding processes are omitted but available online (https://docs.qq.com/sheet/DV3hNcVdycmNNWWJN).

4.1 Types of Taxi Drivers' Post-Adoption Behavior

Macroscopically, drivers' mobile app usage divides into three categories: continuous use behavior, flexible behavior, and discontinuous use behavior.

4.1.1 Continuous Use Behavior Continuous use behavior occurs when drivers receive more passengers via ride-hailing apps than through cruising. It subdivides into active use, forced use, and wait-and-see behavior.

Active use describes sustained app use driven by positive emotions. These users show high satisfaction and strong continuous intention, with some deliberately avoiding traditional cruising.

Forced use occurs when external factors compel high-frequency system use, creating a facade of active use. Despite initial motivations, these users currently use the app out of necessity, as one driver (A02) noted: "Except for elderly drivers who can' t use smartphones, everyone else orders rides through apps before even leaving home, so you can't pick up passengers on the street anymore."

Wait-and-see behavior maintains continuous use without emotional bias. While showing negative emotional orientation, these drivers still express varying satisfaction and confidence in the app' s future. Driver A27 exemplified this: "Now I mainly use Didi—there' s no choice. But the apps are gradually improving. I hope they' ll benefit both passengers and drivers in the future."

4.1.2 Flexible Behavior Flexible behavior occurs when drivers receive roughly equal numbers of passengers through apps and cruising. This behavior isn' t directly influenced by emotions but by personal traits and passenger habits. A typical response: "It' s about the same. Street hailing is freer, but when the platform assigns an order, I prioritize that" (A23).

4.1.3 Discontinuous Use Behavior Discontinuous use behavior involves receiving more passengers through cruising than via apps, subdivided into basic exit and complete exit behaviors.

Basic exit means minimal, near-zero app usage persists. **Complete exit** describes former users who have abandoned apps entirely for cruising. Typical examples: "I use Taxi Alliance, but it never has orders and I' m not good at it. I only grab them incidentally—sometimes one every three days, sometimes one every two days" (A28, basic exit). "I used it for half a month and then quit completely" (A40, complete exit).

4.2 Attribution of Taxi Drivers' Post-Adoption Behavior

4.2.1 Self-Attribution Self-attribution divides into cognitive factors, personal factors, negative emotions, and positive emotions.

Cognitive factors refer to subjective perceptions during app use, including perceived usefulness, perceived ease of use, privacy, self-efficacy, negative perceptions, and cost perception. Due to the research context, risk perception is assigned special meaning under negative perceptions, including concerns about distracted driving (A01, A11, A15) and serious safety hazards (A26).

Personal factors encompass user characteristics, habits, dependency, and motivation—particularly initial adoption motivation, which affects subsequent use. Drivers who adopted apps due to cruising difficulties or conformity show more negative attitudes later, while those motivated by subsidies or work convenience maintain positive attitudes. Personality traits also matter: conservative drivers who avoid smartphones exhibit spontaneous resistance and negative emotions toward ride-hailing apps.

Emotions influence beliefs and attitudes, guiding thoughts, decisions, and actions [**?**]. This study treats emotions as antecedents to more stable post-adoption behaviors. A. Beaudry [**?**] categorized emotions into four types based on opportunity/threat and controllability dimensions: achievement, challenge, loss, and deterrence emotions—where achievement and challenge are positive, while loss and deterrence are negative.

4.2.2 External Attribution External attribution divides into technical and social factors.

Technical factors include system quality, information quality, and service quality. Ride-hailing platforms face criticism for poor order quality (A05, A20, A21) and low order assignment rates (A09, A16, A17).

Social factors comprise subjective norms, social support, external influence, and social conflicts. External influence—passengers' app usage habits critically affecting drivers' habits—emerged as a key factor. As driver A27 noted: "Now there' s no choice. Passengers have developed habits. You can' t pick up rides on the road." While passenger convenience drives this shift, it pressures drivers to improve digital skills. **Social conflicts** refer to interpersonal tensions during app use, such as communication issues (disagreements on pickup location/time) or trust problems (passenger cancellations or fare evasion), significantly impacting negative emotions.

4.3 Model Construction

4.3.1 Interrelationships Among Influencing Factors Individual emotions affect behavioral choices. Synthesizing behavior types and influencing factors reveals their interrelationships:

(1) Cognitive factors' impact on emotions. Strong perceived utility (e.g., new orders, selective choice, passenger autonomy) generates positive emotions. Conversely, strong negative perceptions (e.g., information security risks, property safety concerns) produce negative emotions.

(2) Technical factors' impact on emotions. Technical factors affect both positive and negative emotions. Low-quality orders (short distances, low income) or time-consuming pickups—resulting from poor information quality—are primary sources of negative emotions and subsequent exit behaviors. Information quality impacts drivers more than system or service quality.

(3) Personal factors' impact on emotions. Psychological factors (habit, dependency, motivation) and personality traits primarily affect emotions. Different initial motivations produce varying emotional responses, both indirectly leading to continuous use. Conservative drivers show spontaneous resistance and negative emotions.

(4) Social factors'impact on emotions. Subjective norms and social support showed minimal emotional impact due to low frequency. However, **social conflicts** emerged as a novel influencing factor. Communication problems (pickup disagreements) and trust issues (fare evasion) create social pressure, generating negative emotions and exit behaviors.

(5) Interaction between personal and social factors. Drivers and passengers form a two-sided market where behavioral changes on either side inevitably affect the other.

(6) Personal factors' impact on cognition. Beijing taxi drivers are predominantly male, aged 40-60, with varying smartphone acceptance levels determined by age, education, and personality traits.

(7) Combined impacts on post-adoption behavior. Consistent with prior research, satisfaction directly influences active use. Negative emotions (reluctance, dissatisfaction, annoyance) lead to basic or complete exit. Several novel behavior types were identified:

- **Forced use from negative emotions/personal factors:** Despite negative emotions from social/technical factors, profit-driven pressure forces high-frequency use, representing passive rather than active behavior.
- **Forced use from external influence:** When passengers predominantly use apps, drivers must adopt them regardless of emotions or habits to secure customers.
- **Wait-and-see behavior from mixed emotions:** Unlike forced use, this involves drivers with dual emotional orientations who remain unstable and susceptible to future change.
- **Flexible behavior from personal/social factors:** This behavior is determined more by personality traits and passenger habits than emotions, showing no clear preference for either method.

4.3.2 Post-Adoption Behavior Model The core storyline reveals: cognitive, personal, and technical factors affect both positive and negative emotions; social factors affect only negative emotions; emotions subsequently trigger different usage behaviors; habits and dependency directly influence behavior; personal factors also affect cognition and interact with social factors. Based on this, the study constructed the taxi driver ride-hailing app post-adoption behavior model shown in Figure 1 [Figure 1: see original paper].

5 Conclusion and Outlook

This study examined Beijing taxi drivers with ride-hailing app experience to construct a post-adoption behavior model. The model describes behavior types, identifies influencing factors, and reveals their interrelationships, systematically exploring the theoretical framework of user behavior.

Findings show that drivers' post-adoption behavior is influenced by both external environments and user-specific factors. While some factors have been previously validated, this study identified **external influence** and **social conflicts** as mobile system-specific phenomena previously overlooked. The research also refined post-adoption behavior typology, comprehensively depicting driver behaviors. Users exhibiting wait-and-see or flexible behaviors remain unstable and likely to change; forced use behavior—where negative emotions paradoxically drive continuous use—represents a novel mechanism rarely examined previously.

Based on these findings, recommendations include:

1. **Strengthen platform development** by improving services, attending to driver needs, providing regular online training for new features, and creating opportunities for practice and mindset shifts to enhance positive experiences.
2. **Regulate passenger behavior** by curbing fare evasion, educating passengers on traffic safety laws and the negative impacts of illegal parking on drivers, enhancing passenger credit and communication awareness to reduce drivers' negative perceptions.
3. **Provide psychological support** to help drivers overcome negative emotions toward ride-hailing apps, enabling more enjoyable and effective work engagement.

Limitations include the Beijing-focused sample, predominantly male drivers aged 40-60, which may limit generalizability due to sample size and regional differences. Future research should quantify and operationalize the conceptual model.

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Zhang Yuhao: Responsible for initial topic selection, research design and execution, and manuscript drafting.
Yan Hui: Responsible for research design and manuscript revision, overall guidance on adoption behavior segmentation and research process.

Note: Figure translations are in progress. See original paper for figures.