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Pengcheng Wang
Kennesaw State University, pwang17@kennesaw.edu

Zefeng Bai
Washington and Lee University, zbai@wlu.edu

Kambiz Saffarizadeh
University of Texas at Arlington, kambiz.saffari@uta.edu

Chuang Wang
South China University of Technology, bmchwang@scut.edu.cn

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Pengcheng Wang
Department of Information Systems and Security
Michael J. Coles College of Business
Kennesaw State University
pwang17@kennesaw.edu
0000-0002-1850-1538

Zefeng Bai
Department of Business Administration
The Williams School of Commerce, Economics and Politics
Washington and Lee University
zbai@wlu.edu
0000-0002-9159-0784

Kambiz Saffarizadeh
Department of Information Systems and Operations Management
College of Business Administration
University of Texas at Arlington
kambiz.saffari@uta.edu
0000-0001-9490-2897

Chuang Wang
Department of Marketing
South China University of Technology
bmchwang@scut.edu.cn

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Pengcheng Wang
Department of Information Systems and Security
Michael J. Coles College of Business
Kennesaw State University
pwang17@kennesaw.edu
0000-0002-1850-1538

Zefeng Bai
Department of Business Administration
The Williams School of Commerce, Economics and Politics
Washington and Lee University
zbai@wlu.edu
0000-0002-9159-0784

Kambiz Saffarizadeh
Department of Information Systems and Operations Management
College of Business Administration
University of Texas at Arlington
kambiz.saffari@uta.edu
0000-0001-9490-2897

Chuang Wang
Department of Marketing
South China University of Technology
bmchwang@scut.edu.cn

Abstract:

This study investigates the causal effect of mobile app updates on user engagement, specifically examining how feature introductions versus bug fixes differentially impact usage frequency and duration across app categories. Using a difference-in-differences approach with propensity score matching on a proprietary dataset of individual-level app usage behavior, we analyze user responses to updates in socially-oriented apps (e.g., WeChat, QQ) and self-oriented apps (e.g., Weibo, Zhihu). Our findings reveal that app updates increase both opening frequency and usage time per session across all apps. However, we identify a critical distinction: relative to bug fixes, introducing new features significantly reduces engagement for socially-oriented apps, while no discernible negative effect occurs for self-oriented apps. These results challenge the prevailing assumption that frequent feature updates universally enhance app success. Theoretically, we contextualize IS Success by establishing app-orientation boundary conditions and isolating the distinct behavioral effects of feature introductions versus bug fixes at the individual level. Practically, our findings provide insights into tailoring update strategies to app orientation. For socially oriented apps, developers should prioritize bug fixes or pair feature launches with progressive rollout and in-app onboarding to mitigate short-run engagement losses, whereas self-oriented apps can leverage feature updates more flexibly.

Keywords: App Updates, App Success, App Actual Usages, App Markets.

[Department statements, if appropriate, will be added by the editors. Teaching cases and panel reports will have a statement, which is also added by the editors.]

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1 Introduction

The rapid evolution of app markets, characterized by over 257 billion downloads (Statista, 2024a) and generating $467 billion in global revenue in 2023 (Statista, 2024b), has revolutionized our interaction with technology. While there is a prevailing belief that frequent updates lead to app success due to enhanced user engagement and competitiveness (Agarwal & Tiwana, 2015; Tiwana, 2015a), such a view may overlook potential misalignments with user expectations and failure in enhancing user experience. This study challenges the assumption that frequent updates inevitably lead to better alignment with user needs (Simon, 2002) and enhance competitiveness in the hyper-competitive app market (Agarwal & Tiwana, 2015) and proposes a more nuanced understanding of the complex dynamics between app updates and user behavior.

The existing literature reveals contradictory findings about app updates' effectiveness, suggesting a more complex relationship than previously understood. On the one hand, app updates serve as a strategic mechanism for developers to attract new users by generating buzz around the app (Comino et al., 2016), signaling ongoing active development (Siegfried et al., 2015), and introducing new features that may appeal to prospective users (Malgaonkar et al., 2022). Updates involving core innovations, such as the introduction of new features, tend to enhance app ratings and review sentiments, thereby improving the app's overall market position (Tian et al., 2020). App updates delivered on a predictable schedule and accompanied by major improvements generally receive positive user feedback (Nayebi et al., 2016). On the other hand, app updates can disrupt existing user routines or fail to deliver added value, particularly in certain app categories (Mathur & Chetty, 2017; Saidani et al., 2022). Also, app updates may unintentionally reduce accessibility, causing user frustration when features are removed or interfaces become harder to use (Santos et al., 2024). Radical interface may also impose cognitive and usability burdens, resulting in temporary declines in user (Aydin Gokgoz et al., 2025). Significant app changes may negatively affect performance unless the apps have strong brand loyalty or an established user base (Chen et al., 2022; Fazelpour et al., 2025). These conflicting findings suggest that the effectiveness of an update often depends on its content, frequency, and the nature of the app itself. Yet literature lacks a systematic understanding of how different types of updates influence actual user behavior at the individual level.

This contradictory evidence also reflects fundamental gaps in how app updates are studied. Prior work predominantly relies on market-level metrics such as download numbers, app store rankings, and user reviews (Carare, 2012; Ghose et al., 2012; Liu et al., 2014; Picoto et al., 2019), which cannot fully explain why updates yield such varied outcomes. These metrics suffer from well-documented review biases, including self-selection bias where only users with extreme experiences provide feedback, and acquisition bias where reviews come from a non-representative subset of users (Hu et al., 2017). More importantly, downloads and rankings capture market perception rather than actual user engagement. An app may rank highly yet experience minimal user engagement post-download. These macro-level metrics cannot capture the nuanced behavioral responses of individual users to different types of updates. For instance, while an update might generate positive reviews from new users discovering novel features, it could simultaneously disrupt the routines of existing users, leading to decreased engagement, a pattern invisible in aggregate data. Also, few studies have systematically examined whether update effects vary across types of changes (feature introductions vs. bug fixes) at the individual level. This shortcoming is particularly problematic given that app developers invest substantial resources in update strategies (Singh, 2025) without clear evidence of how different update types influence the actual usage patterns that drive long-term app success.

Therefore, our research addresses these gaps by examining the impact of app updates on actual individual user engagement and behavior using granular, individual-level usage data. Specifically, we investigate the following research questions: *What is the effect of app updates on user engagement and how do feature introductions compare to bug fixes in affecting the usage frequency and duration of different apps?* This focus is particularly relevant given current update practices: As of April 2025, 36% of mobile apps on Google Play are updated by their developers weekly, while 73% receive updates monthly (Ceci, 2025). Among those frequently update apps, the top social media platforms (e.g., Facebook, Instagram, TikTok) even update their mobile apps twice a week. As such, we choose social media apps as the representatives to investigate the effect of app updates on user engagement.

To answer the above mentioned questions, we draw on two complementary theoretical perspectives. The Information Systems (IS) Success model (DeLone & McLean, 1992, 2003) provides a framework for understanding how system quality changes affect user satisfaction and usage, suggesting that updates act as quality interventions that can shift subsequent behavior. Complementing this, the Needs-Affordances-Features (NAF) framework (Karahanna et al., 2018) helps explain how different apps satisfy distinct psychological needs through their affordances. By integrating these perspectives, we conceptualize app updates as system-quality changes whose behavioral impacts are contextual, depending on both the type of update (bug fix vs. new feature) and the app's affordance orientation (socially-oriented vs. self-oriented). This theoretical integration allows us to move beyond assuming uniform update effects and instead examine how the same quality intervention may produce different outcomes based on the app's fundamental design orientation and the nature of the change introduced.

Our analysis employs a unique dataset detailing mobile app usage, including the duration of use, opening times, time spent on each app, and dates of installation, updates, and deletion. A causal analysis using a difference-in-differences (DID) design reveals significant variations in the frequency and duration of app use post-update, contingent on these app categories. Specifically, our analysis shows a notable increase in opening frequency and a substantial rise in usage time per session following updates for both self-oriented and socially-oriented apps. Interestingly, for socially-oriented apps, the effect of updating on app usage is less salient when new features are introduced, whereas such moderating effect is not observed for self-oriented apps.

These findings advance the literature by showing that update impacts are not uniform but depend on both update type and app orientation. We contribute to IS research by contextualizing the IS Success model through the NAF framework, demonstrating how system-quality changes intermingle with app affordances to shape user behavior. Practically, we show that developers and marketers should offer customized app update strategies based on app types and update types. For example, updates introducing new features may reduce user engagement for socially-oriented apps, while such effects are not observed for self-oriented apps. They also highlight the importance of enhancing the depth and value of updates to sustain user engagement. For example, while updates may attract users back to the app, they may not provide sufficient value to maintain prolonged engagement when new features are added, especially for socially-oriented apps.

2 Literature Review and Theoretical Background

2.1 App Updates and Information Systems Success Theory

The Information Systems (IS) Success model (DeLone & McLean, 1992, 2003) offers a foundational framework for understanding how information systems create value and achieve success. Central to this framework is the understanding that system quality influences both system use and user satisfaction, which in turn affect the overall information system effectiveness (DeLone & McLean, 1992, 2003). In the mobile app context, the IS Success Model suggests that app quality attributes fundamentally shape user engagement patterns (Lin et al., 2021). System quality manifests through app performance, stability, feature sets, and user interface design (Zhou et al., 2023).

App updates play a critical role in shaping user experience by enhancing system quality, such as improving reliability, speed, or usability, which in turn influences whether users continue engaging with the app over time (Lee & Raghu, 2014). When developers release updates, they are essentially attempting to enhance these quality dimensions, with the expectation that improved quality will lead to increased usage and satisfaction(Saffarizadeh et al., 2018). This stream of research has received much scholarly attention, as system updates are seen as a key mechanism through which developers can sustain or improve user engagement and app success (Al-Shamaileh & Sutcliffe, 2023; Situmorang et al., 2025; Wixom & Todd, 2005). As mobile apps evolve, updates become the main form through which developers introduce new features, fix bugs, or improve existing features. These changes can directly influence how users perceive the app's quality, which in turn affects their willingness to keep using it and their overall satisfaction.

While prior research examining the effect of app updates on market-level performance has yielded fruitful insights, such as increased downloads or improved rankings, it often relies on aggregate metrics that may be subject to review bias (Chowdhury & Raje, 2018; Martens & Maalej, 2019). These biases are not unique to mobile apps, and similar concerns have been raised in the broader literature on online product reviews. For example, Hu et al. (2017) identify two prevalent self-selection biases: acquisition bias, where mostly predisposed users download and review apps, and underreporting bias, where only users with extreme experiences tend to leave feedback. These biases distort review distributions, often resulting in a skewed, J-shaped curve that misrepresents the broader user experience.

In parallel, several studies have used demand-based or sales-based indicators to evaluate app success, showing that factors such as app descriptions, screenshots, and review volume significantly affect app downloads and revenues (Garg & Telang, 2013; Ghose & Han, 2014; Lee & Raghu, 2014; Oyekunle et al., 2023). Others have found that app pricing models (e.g., free vs paid), app visibility, and even ad presence can influence perceived market success (Carare, 2012; Liu et al., 2014). While informative, these metrics primarily capture market reactions rather than actual user engagement with the app.

Given these limitations, relying solely on subjective reviews or market indicators may not provide a complete picture of app performance. There is a need to examine how app updates influence actual user app use behavior as a more reliable and direct measure of success. This study addresses that gap by focusing on individual-level usage patterns, offering a more grounded understanding of how app features changes or improvement shape user engagement.

2.2 Different Types of App Updates and Their Effects

Mobile app updates are a direct means of improving an app's quality and functionality over time. However, recent studies suggest that different types of updates can have differential impacts on app performance. For instance, Tian et al. (2020) found that the impact of app updates on user evaluation depends on the type of update introduced. Specifically, updates that introduce core functional innovations, which will enhance the app's essential purpose, affect user ratings and review sentiments, as users perceive them as value-adding. However, updates offering only peripheral improvements, such as bug fix and minor feature improvement, can lead to decreased user satisfaction, since they may not meet user expectations or justify the disruption caused by the update. Similarly, Nayebi et al. (2016) examine the effects of app updates through of the perspective of app developer release strategies. After surveying both app users and developers, Nayebi et al. (2016) found that calendar-driven "rhythms" (e.g., weekly or bi-weekly pushes) of app update are welcomed only when each update delivers visible benefits, such as introducing new feature and improving app performance. In contrast, when frequent updates only contain minor improvement or bug fix, users become frustrated, complaining storage costs and possible app crashes after updates. In other words, both articles show the importance of app update on app uses, which meaningful functional updates improve app performance, while superficial changes may backfire.

Indeed, app updates could be a double-edged sword. While app updates aim to improve the user experience, they can also disrupt users' established routines and spark dissatisfaction if perceived as excessive or unwelcome (Fazelpour et al., 2025). Chen et al. (2022) have highlighted a "dark side" of continuous app updates that customers often become attached to the current version, so radical changes may alienate them by imposing new learning costs that undermine satisfaction. In fact, they found that introducing a new generational product version often hurt performance because users resisted the changes, whereas market-leading apps were less affected as they enjoy stronger brand and community spillovers that offset app update disruption. Similarly, after analyzing a large-scale analysis of mobile app reviews, Aydin Gokgoz et al. (2025) found that if an update introduces an unexpected interface overhaul or features that users never requested, it can break users' usage patterns and initially lower their satisfaction due to the added learning cost. In contrast, updates that incorporate user-demanded features or fix known bugs tend to improve satisfaction and boost app ratings.

2.3 App-Type Categorization and Needs–Affordances–Features Framework

The Needs-Affordances-Features (NAF) framework (Karahanna et al., 2018) explains how digital technologies satisfy distinct psychological needs through the affordances they make available. Karahanna et al. (2018) conceptualize these needs as egocentric and allocentric as follows:

Egocentric-oriented affordances enable activities that users can do alone, such as self-presentation, content sharing, and interactivity. These affordances are manifested through allowing users to engage in activities independently, without or with little influence from others. For example, content sharing can be an egocentric activity where users express themselves or share information without the presence of others. Prominent examples include Quora, Facebook Messenger and Twitter (X), where users can share the content independently.

Allocentric-oriented affordances are social in nature and likely require the presence of others. These affordances facilitate social interactions and require the involvement of others. They aim for presence signaling, relationship formation, group management, and browsing others' content. The typical manifested activities include interacting with known others, forming relationships, and managing groups. Prominent examples include WhatsApp and Facebook Messenger, where users primarily engage through direct communication and social interaction with others rather than just content sharing.

In the context of mobile social media apps, we focus on two broad orientations that map to these needs. *Socially-oriented* (allocentric) apps prioritize affordances that require or are enhanced by the presence of others, such as presence signaling, dyadic and group communication, relationship formation, and group management. These affordances support users' needs for belonging and coordination with known others. *Self-oriented* (egocentric) apps emphasize affordances that individuals can enact largely on their own, including self-presentation, unilateral content broadcast, and personal curation. These affordances support users' needs for expression, identity signaling, and consumption without extensive coordination.

Table 1. Social Media Apps Categorization and Key Affordances

App Category	Needs-Affordances-Features*	App Affordances Features	Representative Apps
Socially-Oriented	Allocentric Affordances	Presence signaling, relationship formation, group management, communication.	Study apps: WeChat & QQ Comparable examples: WhatsApp & Facebook Messenger
Self-Oriented	*Egocentric Affordances*	Self-presentation, unilateral content broadcast, personal curation.	Study apps: Weibo & Zhihu Comparable examples: Instagram & Twitter (X)
*Note: Source: Karahanna et al. (2018)			

Complementing the IS Success Model, the NAF framework helps explain how different apps satisfy distinct psychological needs through their affordances. This theoretical lens allows us to distinguish apps based on the dominant psychological needs they fulfill, thereby offering a structured basis to investigate whether similar updates generate different behavioral responses depending on the app's design orientation. Through an integration of these two perspectives, we conceptualize app updates as system-quality changes whose behavioral impacts are contextual, depending on both the type of update (bug fix vs. new feature) and the app's affordance orientation (socially-oriented vs. self-oriented). This theoretical integration allows us to move beyond assuming uniform update effects and instead examine how the same quality intervention may produce different outcomes based on the app's fundamental design orientation and the nature of the change introduced.

3 Hypothesis Development

The role of app updates on user behavior is significant yet complex. Regular updates, especially those introducing new features or expanding existing content, can stimulate user curiosity and engagement (Nayebi et al., 2016). Such updates not only improve the user experience and increased time spent on the app but also create opportunities for increased revenue through ads and in-app purchases (Zhang et al., 2023). Regular app updates are crucial for increasing app usage and leading to more successful apps. To achieve or retain their app success, developers strive to improve their apps through continual updates. In fact, about fourteen percent of apps are updated at least bi-weekly (McIlroy et al., 2016). This constitutes a high percentage of active apps, given that a large percentage (up to seventy percent) of apps on app markets are deserted by their developers (Tiwana, 2015b).

The existing research underscores the value of app updates. For instance, app updates can improve performance when developers prioritize user concerns from app reviews, as automated techniques for ranking requests for new features, enhancements, and bug fixes have been shown to significantly increase accuracy and efficiency in guiding update decisions (Malgaonkar et al., 2022). Also, McIlroy et al. (2016) found that apps updated regularly tend to garner better ratings from users. Their study analyzed the update frequency of 10,713 top free apps in the Google Play store at the start of 2014 and found that a small portion (about 1%) updated more than once a week, while 14% updated bi-weekly or more frequently. Interestingly, 45% of the frequently updated apps did not provide users with any explanation for the updates, and the updates showed a median size growth of 6%. Despite some negative consequences of app updates on user engagement (Chen et al., 2022; Fazelpour et al., 2025; Santos et al., 2024), most studies suggest that frequent updates typically imply that developers are actively fixing bugs, improving app performance, and responding to user feedback, leading to better user experience. In turn, these high-quality user experiences often translate into better app reviews and ratings. Moreover, some scholars have shown that the frequency of app updates increases the likelihood of entering and/or remaining on the top charts (Lee & Raghu, 2014; Yin et al., 2014), given that users are more attracted to updated apps (Lee & Raghu, 2014), and updates can contribute to app success by stimulating buzz around the app (Comino et al., 2016).

In summary, app updates can play a vital role in shaping user experience. While their effectiveness often depends on the nature of the update, such as bug fixes or adding new features based on user demands, it is evident that app updates often affect follow-up app usage. This is especially true for social media apps, which aim at providing users with a customized experience in social interaction and self-expression. Given these insights, we propose the following hypothesis:

Hypothesis 1: App updates positively affect user engagement (i.e., usage time and frequency).

Nevertheless, the specific impact of app updates likely varies depending on the type of update and the type of social media app involved. When developers introduce updates to their apps, they typically do so for two main reasons: to fix bugs or to introduce new features. Bug fix updates often address technical debt, resolving issues that may not be immediately noticeable to users but are crucial for the app's long-term functionality and performance (Ramasubbu & Kemerer, 2014; Wilder et al., 2023). In contrast, updates that introduce new features are designed to directly address users' needs, incorporating user-observable changes that enhance the app's functionality and user experience. This dual approach ensures that apps remain technically sound while continually evolving to meet user expectations.

Users' reactions to updates can vary based on their familiarity with the changes introduced. When users encounter a new interface or new features, the old ways of using the app may not work anymore. This leads to a state of stress and anxiety that makes users resist changes (Oreg, 2003). Radical and novel changes often meet with caution and resistance, as users are generally reluctant to adopt unfamiliar innovations or new app interface (Aydin Gokgoz et al., 2025; Greve, 1998) or such new update may unintentionally introduce accessibility barriers (Santos et al., 2024). However, prior related knowledge enables users to recognize the value of feature improvement and helps users in assimilating and using them (Ko et al., 2005; Massey & Montoya-Weiss, 2006).Thus, when updates involve changes or improvements that are similar to existing features, users are more likely to accept them. Accordingly, we propose the following hypothesis:

Hypothesis 2: The positive effect of app updates on user engagement (i.e., usage time and frequency) is weaker for new feature than bug fix.

Building on H1 and H2, we consider boundary conditions implied by the Needs–Affordances–Features (NAF) perspective (Karahanna et al., 2018). Socially oriented apps surface allocentric affordances (e.g., dyadic/group communication, relationship management), embedding interdependent routines and shared conventions. For example, social networking platforms (e.g., Facebook, WeChat) and communication apps (e.g., WhatsApp and QQ) offer features such as profile sharing, social feeds, messaging, groups, and other interaction tools with known individuals. Such affordances satisfy users' desires for belonging, friendship, and the expression of identity in a social context. WhatsApp, WeChat, and Facebook Messenger exemplify this category.[1] When updates introduce new features, users face short-term learning costs (relearning flows, remapping interfaces), coordination costs (re-synchronizing behaviors and norms with alters), accessibility issues (incompatibility with screen readers or poor interface design), or established usage patterns disruption, those are known to dampen adoption and satisfaction when change is nontrivial (Fazelpour et al., 2025; Greve, 1998; Oreg, 2003; Santos et al., 2024). Because these apps rely on coordinated interaction, these frictions make the post-update engagement increase more likely to be weaker when the update introduces new features rather than bug fixes.

By contrast, self-oriented apps focus on self-presentation rather than social interaction. They offer affordances that satisfy what Karahanna et al. (2018) describe as *egocentric affordances*. Self-oriented apps often include content-creation tools (e.g., Twitter, Instagram, Weibo) that allow individuals to customize and control their usage experience without the need for shared or communal participation. In

[1] In our empirical context, WeChat and QQ represent this category.

other words, a self-oriented app is personal use focused, providing features for individual goal achievement, self-management, or personal enjoyment, thereby fulfilling psychological needs centered on the self. Platforms such as Twitter (X), Weibo, and Instagram exemplify this category.[2] As such, self-oriented apps emphasize individual creation/consumption and personal curation; exploration of new functionality is more self-paced and optional, which facilitates easier assimilation (Ko et al., 2005; Massey & Montoya-Weiss, 2006). Consequently, the "weaker boost" from new features (versus bug fixes) toward self-oriented apps should be less noticeable where coordination needs are low.

Socially-oriented apps depend on coordinated interaction. By definition, individuals mainly use socially-oriented apps to maintain relationships with known contacts. Such use is driven by the communication utility of the app, where bug fix can help socially-oriented app users have a reliable communication channel for friends and families. Thus, it is reasonable to assume that bug fixes enhance the existing communication utility value of the current app, so the bug fix will have a greater impact. In addition, new features in socially-oriented apps often require that many contacts learn and use them at the same time. When message flows, buttons, or notification rules change, there can be version mismatch and norm mismatch across the known network. Users need to relearn the flow and re-synchronize with others, which raises effort and can reduce sustained use. In contrast, bug fixes improve reliability without changing routines, so group conversations run more smoothly.

In comparison, self-oriented apps (e.g., Instagram, Weibo, and Twitter) have a higher need to use the innovative features introduced in the new release to create attractive content. They mainly use the apps to broadcast content to mostly unknown individuals. The utility value of new features should be greater for self-oriented apps. Because use is individual and does not require coordination, users can explore new tools at their own pace or ignore them. Therefore, we posit that the negative moderation identified in H2 is stronger when allocentric coordination demands are high: the weaker effect of new feature updates (relative to bug fix updates) on user engagement is more pronounced for socially oriented apps than for self-oriented apps.

Hypothesis 3: The negative moderating effect of update type (new feature vs. bug fix) on post-update user engagement is stronger for socially oriented apps than for self-oriented apps.

4 Methodology

4.1 Data and Measurement Model

Our primary analysis utilizes a proprietary data set sourced from a mobile usage statistics application developed by a software company in China. This application tracks daily phone usage time, the number of phone unlocks, and the frequency and duration of individual app usage. It presents this information through a visual interface, such as a timeline, to help users objectively understand their phone usage habits. The data set was collected from the backend database of the software development firm. To ensure user privacy, the data does not include any personally identifiable information; instead, users are marked with anonymized codes.

The raw data consists of three tables: packages, event, and app. The packages table logs user actions related to app installation and uninstallation, including user IDs, the names of app packages, specific dates and times, and the type of action (e.g., install, replace, and uninstall). The event table records each instance of the phone screen turning on and off, as well as power-off events, with precise timestamps. The app table documents the dates and durations of individual app usage. We aggregated these behavior-level records by user ID to a daily level, extracting relevant features such as the number of installed apps, the number of apps used each day, total daily phone usage, and usage during working hours (9 am-5 pm) and leisure hours (5 pm-9 am). From the event table, we extracted daily screen unlock counts, unlock counts during different times of the day, and the average usage time per unlock. These features were then merged across the three tables using user IDs.

For our empirical analysis, we collected the dates of version updates for popular apps like WeChat, Weibo, and Zhihu from the Wandoujia platform, treating these update dates as exogenous shocks. Users who updated their apps were classified into the treatment group, while those who did not update were

[2] In our empirical context, Weibo and Zhihu represent this category.

classified into the control group. Given that 99.5% of the data falls between September 2015 and May 2016, we excluded samples outside this period. Additionally, to ensure comparability, only users with activity records both before and after the updates were retained. We handled outliers by applying Winsorization, capping values at the 97.5th percentile. This excluded around 3.01% of the observations from the sample. To mitigate the self-selection bias inherent in users' update behaviors, we employed Propensity Score Matching (PSM). Historical usage data, including the number of days and average frequency and duration of use across various app categories (e.g., tools, social, finance), were used as covariates. Due to the high dimensionality of this historical data, we first applied Principal Component Analysis (PCA) to extract 18 principal components, which were then used as covariates in the PSM to match treated users with appropriate control group users. In the manuscript, we provide a summary of definition for the 18 covariates used in the PSM in Appendix A. Additionally, we categorized updates into new feature introductions and app improvements by manually coding the app release notes. Three Chinese authors downloaded the app update release notes from their official websites and manually coded each update to determine whether the update primarily focused on introducing new features or fixing existing bugs. As each release note often contained multiple updates, we disaggregated them into individual items, with each item representing a single discrete change. Three fluent Chinese speaking authors independently coded every item as either introducing a new feature coded as one or addressing bugs or performance improvements coded as zero, using a shared codebook and examples. A release was considered a new feature introduction when the majority of its items were coded as new features. When a rare tie occurred, the coders met to discuss the items and resolved the label by consensus before analysis.

To ensure the reliability of this coding process, we assessed the internal consistency and inter-rater reliability. The consistency among the three coders was excellent, as indicated by a Cronbach's alpha of 0.927. We further evaluated reliability using a two-way mixed-effects Intraclass Correlation Coefficient (ICC). The results showed a high degree of agreement: the single measures ICC was 0.808 (95% confident interval is between 0.761 and 0.849, $p < .001$), indicating good reliability for an individual coder, and the average measures ICC was 0.927 (95% confident interval is between 0.905 and 0.944, $p < .001$), indicating excellent reliability for the aggregated ratings of the three coders. Therefore, given the strong reliability scores, the coding was deemed robust. Also, we measured the number of users who used at least one of the four apps examined in our sample: WeChat ($n = 7708$), QQ ($n = 8456$), Zhihu ($n = 4504$), and Weibo ($n = 6836$). While the distribution of users is not uniform, each app retains a sufficiently large sample to permit robust statistical comparisons between the two app-orientation types.

4.2 Empirical Analyses (Econometric Modeling)

To account for potential endogeneity concerns, we followed the literature and applied the difference-in-differences (DiD) technique in combination with propensity score matching (PSM) (Carmi et al., 2017; Rishika et al., 2013; Xu et al., 2022). Specifically, we divided users into a treated group (the users who updated the app after an update was released) and a control group (the users who did not update the app after the update was released) and used PSM to match each treated user with a similar control user. In addition, we aggregated each treated user's app usage behavior into two periods: behaviors before this user's app updating and those after. Similarly, we aggregated each control user's behaviors into before and after periods based on the time of the matched treated user's app updating time. This approach allowed us to observe behavioral changes by comparing each user's behavior before and after treatment. We describe the details of PSM below.

To study app users' potential behavior change resulting from app updating, we followed a DID+PSM empirical approach (Burtch et al., 2018; Carmi et al., 2017; Rishika et al., 2013; Xu et al., 2022), which helps alleviate potential endogeneity concerns. In PSM, we matched each treated user (with app updating) with a control user who is similar in terms of observed characteristics but has never updated the app. The basic idea is that a comparable user would be selected into the control group if they have a similar propensity for being treated. Calculating propensity scores relies on covariates reflecting users' characteristics, such as the phone usage time, the number of times of unlocking the phone, the time spent on social network apps, the number of times of opening social network apps etc. Specifically, we applied PSM to construct a "control group" that consists of users who do not install the update but exhibited very similar smart phone using patterns to the "treatment group", users who did update the app. The PSM procedure involves matching a given treatment user with a similar control user based on observable covariates. It is important to note that the conditional independence assumption (CIA) has to be satisfied for the treatment effect estimation to be valid (Rosenbaum & Rubin, 1983). This assumption states that the potential outcome of the treatment is independent of the treatment assignment, conditional on observable covariates. Rosenbaum and Rubin (1983) showed that, if CIA holds, then matching based on propensity score – the likelihood of receiving treatment – is sufficient. In our case, we modelled the propensity of receiving treatment – namely, updating – as a function of variables that reflect the user's app using characteristics prior to the updating of the app.

Technically, we performed Nearest Neighbor matching (NN matching), which pairs each user who updated the app (treatment) with the closest user who did not install the update (control) in terms of their propensity scores. We specified a logistic regression to model each user's probability of updating. Note the variables used in the logistic regression are phone usage time, the number of times of opening the phone, the time spent on social network apps, the number of times of opening social network apps. We also included measures such as users' phone usage pattern during work time and leisure time, the number of apps they use etc. Using these variables, we employed a stepwise estimation (Rosenbaum & Rubin, 1984) to specify the final propensity score formula. It is important that the treatment and control groups share a common support in terms of the propensity score, and therefore we discarded observations that lie outside of the common support region based on the Minima and Maxima comparison suggested by Caliendo and Kopeinig (Caliendo & Kopeinig, 2008). As a result, we dropped 9 observations in total (2 from the treatment group and 7 from the control group). Finally, we conducted the PSM procedure using the NN matching method with replacement.

One necessary assumption for PSM analysis is that the treatment and control groups are balanced after matching. To examine this assumption, we conducted a quality matching check by performing t-tests on the mean scores of the variables used to generate the propensity scores between the treatment and control groups. As summarized in Appendix A, there are no significant differences in the mean scores of these variables at the 0.05 significance level, suggesting that balanced matching has been achieved for the PSM analysis.

5 Results

Table 2 shows the difference-in-difference (DID) model examining the causal relationship between app updates and combined app usage. Columns 1 through 3 include results regarding app usage time, and columns 4 to 5 report app usage frequency.

Table 2. Regression Analysis, Combined App Usage Time and Frequency

	(1)	(2)	(3)	(4)	(5)	(6)
	App usage time			App usage frequency		
Controlled for new feature	No	No	Yes	No	No	Yes
Individual fixed effect	No	Yes	Yes	No	Yes	Yes
Update	1.398**			1.890***		
	(0.690)			(0.535)		
After	1.324**	2.895***	2.934***	0.498	2.392***	1.601***
	(0.605)	(0.245)	(0.325)	(0.442)	(0.160)	(0.213)
After*update	3.202***	2.540***	3.310***	1.755***	1.185***	1.588***
	(0.701)	(0.283)	(0.378)	(0.516)	(0.186)	(0.247)
After*new feature			-0.091			1.835***
			(0.495)			(0.324)
After*new feature*update			-1.676***			-0.990***
			(0.571)			(0.374)
Constant	29.897***	30.451***	30.455***	19.530***	20.273***	20.269***
	(0.580)	(0.077)	(0.077)	(0.444)	(0.050)	(0.050)
Observations	352,842	352,842	352,842	352,842	352,842	352,842
R-squared	0.002	0.626	0.626	0.002	0.707	0.707

Note: Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

As reported in Table 2, Column 1, app updates are associated with a 3.202-minute increase in app usage time when not accounting for individual fixed effects. After including user fixed effects in Column 2, the effect remains statistically significant but the magnitude of the influence decreases to a 2.540-minute increase in app usage time related to app updates. This reduction suggests that a portion of the variation in usage time may be attributed to unobservable user characteristics or confounding factors that may affect how users react to app updates. Nevertheless, the persistence of a significant coefficient indicates that app updates are still related to increased time of app usage, supporting our first hypothesis.

Column 3 adds an interaction term between app updates and new features, which studies whether introducing new features in app updates may affect app usage. While the baseline effect of an update remains positive, the coefficient on the interaction between update and new feature is negative and statistically significant. This suggests that the overall increase in app usage time associated with app updates is smaller when the update introduces new features. In other words, although updates are generally followed by extended usage times, this effect diminishes when those updates involve new features. This finding supports our second hypothesis that the types of app updates moderate the influence of app updates on app use.

A similar pattern is observed in Columns (4 to 6), which examine how app updates and new features in app updates affect app user usage frequency. Overall, as indicated in Column 4, app updates are associated with a 1.755-time increase in app use frequency. This effect, as reported on Column 5, reduces to a 1.185-time increase after controlling individual characteristics by incorporating user fixed effects. Similar to the findings about how new features affect app use time, in Column 6, we find that incorporating new features in app updates negatively moderate the linkage between app updates and app use frequency in post-update period.

Overall, our first DID model suggests that app updates relate to an increase in app usage, as indicated by extended app usage time and increased frequency of opening the app. This empirical evidence supports the ***h1*** that app updates positively affect user engagement (i.e., usage time and frequency). On the contrary, introducing new features in app updates reduces both user engagement measures (i.e., app use time and app use frequency). This result supports the ***h2*** that the positive effect of app updates on user engagement (i.e., usage time and frequency) is weaker for new feature than bug fix.

In the next step of our analyses, we conducted separate DID regression analyses on socially-oriented apps (i.e., WeChat and QQ) and self-oriented apps (i.e., Weibo and Zhihu). Table 3 presents the results for app usage of socially-oriented apps on app updates and new features.

Table 3. Regression Analysis, App Usage Time and Frequency (WeChat and QQ)

	(1)	(2)	(3)	(4)	(5)	(6)
	App usage time			App usage frequency		
Controlled for new feature	No	No	Yes	No	No	Yes
Individual fixed effect	No	Yes	Yes	No	Yes	Yes
Update	-0.802			0.487		
	(1.207)			(0.992)		
After	5.715***	6.605***	4.209***	3.484***	5.399***	2.682***
	(1.166)	(0.470)	(0.655)	(0.914)	(0.355)	(0.494)
After*update	3.041**	2.489***	4.323***	1.932*	1.436***	2.745***
	(1.325)	(0.535)	(0.749)	(1.043)	(0.404)	(0.565)
After*new feature			4.928***			5.590***
			(0.939)			(0.709)
After*new feature*update			-3.811***			-2.790***
			(1.070)			(0.808)
Constant	43.543***	42.755***	42.758***	36.763***	36.490***	36.499***
	(1.034)	(0.138)	(0.138)	(0.843)	(0.104)	(0.104)
Observations	165,381	165,381	165,381	165,381	165,381	165,381
R-squared	0.004	0.612	0.612	0.003	0.647	0.647

Note: Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In Table 3, Column 1, which does not include user fixed effects, we find that app updates are associated with an increase of 3.041 minutes in app usage time, on average. When user fixed effects are included in Column 2, this effect reduces to a 2.489-minute increase but remains statistically significant. These results suggest that app updates are positively associated with increased time spent on socially-oriented apps, even after accounting for individual fixed effects.

Likewise, we added the interaction of new features in Column 3 to examine whether introducing new features in app updates would affect app usage time in socially-orientated apps. We find that introducing new features negatively moderate the identified connection between app updates and increased app usage time in socially-orientated apps. Specifically, the coefficient is -3.81. Given that the average usage time per day is approximately 42.76 minutes based on the constant term of Column 3, this effect size translates to a reduction of approximately $3.81/42.76 = 8.9\%$ in daily usage time. In other words, while app updates extend app usage time, this effect becomes significantly smaller when the update includes introducing new features.

In Columns 4 to 6, the DID model examining how app updates and new features affect usage frequency for socially-oriented apps reveals a consistent pattern. As shown in Column 4, app updates are associated with an average increase of 4.323 in usage frequency. After accounting for individual fixed effects in Column 5, this effect decreases to 1.436. It is also important to note the change in statistical significance. Specifically, in Column 4, the coefficient of app updates is significant at a significance level of 0.10, whereas in Column 5, it is significant at 0.01. This further supports that unobservable individual characteristics may affect app usage and incorporating individual fixed effects is needed in analysis. Finally, in Column 6, we find that the increased app use frequency from app updates is smaller when new features are introduced among socially-orientated apps, as indicated by a negative interaction term of -2.790, with a baseline average of 36.5 app opens per day based on the constant term. This suggests a decrease of about $2.79/36.5 = 7.6\%$ in usage frequency following feature-based updates. In general, results from Table 3 also support both hypotheses 1 and 2, which posit that app updates related to higher app usages while introducing new features moderates this connection.

Finally, we repeat our DID analysis on self-orientated apps (i.e., Weibo and Zhihu) and Table 4 the results. In Column 1, which excludes individual fixed effects, we find that app updates correspond to a 2.089-minute increase in app usage time. After accounting for user-level fixed effects in Column 2, the coefficient remains statistically significant and slightly declines to 1.919 minutes. Overall, app updates remain related to an increased app usage time for self-orientated apps.

Table 4. Regression Analysis, App Usage Time and Frequency (Weibo and Zhihu)

	(1)	(2)	(3)	(4)	(5)	(6)
	App usage time			App usage frequency		
Controlled for new feature	No	No	Yes	No	No	Yes
Individual fixed effect	No	Yes	Yes	No	Yes	Yes
Update	1.357**			0.518**		
	(0.667)			(0.203)		
After	-0.601	0.273	2.174***	-0.106	0.266***	0.957***
	(0.534)	(0.235)	(0.301)	(0.157)	(0.065)	(0.083)
After*update	2.089***	1.919***	2.341***	0.561***	0.421***	0.542***
	(0.620)	(0.275)	(0.354)	(0.184)	(0.076)	(0.098)
After*new feature			-4.853***			-1.763***
			(0.480)			(0.133)
After*new feature*update			-0.708			-0.179
			(0.561)			(0.155)
Constant	18.953***	19.584***	19.637***	5.708***	5.956***	5.975***
	(0.553)	(0.078)	(0.078)	(0.167)	(0.022)	(0.021)
Observations	187,461	187,461	187,461	187,461	187,461	187,461
R-squared	0.001	0.578	0.579	0.001	0.629	0.631

Note: Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Interestingly, in contrast to our findings about how introducing new features affect app usage in Table 3 for socially-orientated apps, we find that, in Table 4, Column 3, the presence of new features in the update does not appear to significantly moderate the effect of app updates on usage time for self-oriented apps. This lack of significance indicates that, unlike socially-oriented apps, self-oriented apps do not show reduced usage time in response to new feature changes introduced through app updates. Columns 4 to 6 report similar results when looking at app usage frequency. We find that app updates are associated with an increased in app use frequency after accounting for individual fixed effects. Meanwhile, introducing new features through app updates does not significantly moderate this connection for self-orientated apps.

Together, Tables 3 and 4 also collectively examine whether the moderating effect of update type (new features vs. bug fix) varies by socially-oriented and self-oriented apps. Recall that in Table 2, we find that introducing new features weakens the positive relationship between app updates and subsequent app usage. Building on this, the results in Tables 3 and 4 show that this negative moderating effect is statistically significant for socially-oriented apps, whereas this moderating effect is not statistically significant among self-oriented apps. These findings support ***H3*** that the negative moderating effect of update type (new feature vs. bug fix) on post-update user engagement is stronger for socially-oriented apps than for self-oriented apps.

6 Robustness Check

We performed a robustness check by accounting for the day in the week when the updates were launched (i.e., Monday, Tuesday, Wednesday, Thursday, Friday, Saturday, and Sunday), with Monday as the reference group. Tables 5, 6, and 7 present the robustness check results. We primarily compared the results reported in columns 3 and 6 from each table since those comprised the regression model that accounted for app updates, new features, and individual fixed-effects.

Table 5. Robustness Check, Combined App Usage Time and Frequency, Add the Day of Week when Updates were Launched

	(1)	(2)	(3)	(4)	(5)	(6)
	App usage time			App usage frequency		
Controlled for new feature	No	No	Yes	No	No	Yes
Individual fixed effect	No	Yes	Yes	No	Yes	Yes
Update	1.385**			1.880***		
	(0.690)			(0.535)		
After	1.309**	2.872***	2.879***	0.507	2.405***	1.590***
	(0.606)	(0.244)	(0.324)	(0.442)	(0.160)	(0.212)
After*update	3.224***	2.568***	3.322***	1.771***	1.203***	1.595***
	(0.701)	(0.283)	(0.377)	(0.516)	(0.185)	(0.247)
After*new feature			-0.016			1.892***
			(0.494)			(0.323)
After*new feature*update			-1.647***			-0.968***
			(0.570)			(0.373)
Day of week (Tuesday)	-0.410**	0.167	0.168	0.501***	0.922***	0.920***
	(0.196)	(0.213)	(0.213)	(0.126)	(0.139)	(0.139)
Day of week (Wednesday)	-2.595***	-2.405***	-2.402***	-0.715***	-0.550***	-0.553***
	(0.210)	(0.213)	(0.213)	(0.139)	(0.140)	(0.140)
Day of week (Thursday)	1.906***	2.150***	2.153***	2.485***	2.677***	2.674***
	(0.230)	(0.212)	(0.212)	(0.157)	(0.139)	(0.139)
Day of week (Friday)	-0.318	-0.129	-0.133	0.776***	0.919***	0.922***
	(0.218)	(0.208)	(0.208)	(0.146)	(0.136)	(0.136)
Day of week (Saturday)	4.028***	4.073***	4.060***	3.912***	4.147***	4.158***
	(0.222)	(0.210)	(0.210)	(0.152)	(0.137)	(0.137)
Day of week (Sunday)	2.572***	2.728***	2.726***	1.723***	1.901***	1.903***
	(0.193)	(0.208)	(0.208)	(0.124)	(0.136)	(0.136)
Constant	29.897***	30.451***	30.455***	19.530***	20.273***	20.269***
	(0.580)	(0.077)	(0.077)	(0.444)	(0.050)	(0.050)
Observations	352,842	352,842	352,842	352,842	352,842	352,842
R-squared	0.002	0.626	0.626	0.002	0.707	0.707

Note: Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

As shown in Table 5, columns 3 and 6, app updates increased the average time of app usage by 3.322 minutes and the frequency of opening the app by 1.595 times, respectively. Meanwhile, incorporating new features reduced the time spent on apps by 1.647 minutes and the number of times opening the apps by 0.968. The main analysis, as reported in Table 2, columns 3 and 6, shows nearly identical results, indicating a 3.310-minute increase in app use duration and 1.588 additional app openings due to updates. Although the robustness check results showed changes in the coefficient values compared to those from the main analysis, we concluded that those changes were marginal given the values of standard errors. The rest of the robustness check, reported in Tables 6 and 7, based on different app categories is highly similar to those from the main analysis. Therefore, we concluded that our findings are robust. We have also performed the parallel trend assumption check for all our analysis, and found our analysis fits the parallel trend assumption for DID analysis. Figures for parallel trend illustrations can be found in Appendix B.

Table 6. Robustness Check, App Usage Time and Frequency (WeChat and QQ), Add the Day of Week when Updates were Launched.

	(1)	(2)	(3)	(4)	(5)	(6)
	App usage time			App usage frequency		
Controlled for new feature	No	No	Yes	No	No	Yes
Individual fixed effect	No	Yes	Yes	No	Yes	Yes
Update	-0.806			0.479		
	(1.207)			(0.992)		
After	5.783***	6.643***	4.159***	3.575***	5.489***	2.672***
	(1.166)	(0.468)	(0.653)	(0.915)	(0.353)	(0.492)
After*update	3.076**	2.549***	4.359***	1.967*	1.484***	2.765***
	(1.325)	(0.533)	(0.747)	(1.044)	(0.402)	(0.563)
After*new feature			5.111***			5.796***
			(0.937)			(0.706)
After*new feature*update			-3.769***			-2.740***
			(1.067)			(0.804)
Day of week (Tuesday)	0.838**	1.126***	1.133***	1.470***	1.936***	1.948***
	(0.344)	(0.383)	(0.383)	(0.258)	(0.289)	(0.289)
Day of week (Wednesday)	-2.632***	-2.533***	-2.525***	-0.947***	-0.682**	-0.666**
	(0.372)	(0.384)	(0.383)	(0.284)	(0.289)	(0.289)
Day of week (Thursday)	4.659***	4.768***	4.787***	5.202***	5.456***	5.492***
	(0.415)	(0.382)	(0.382)	(0.321)	(0.288)	(0.288)
Day of week (Friday)	0.875**	0.889**	0.922**	2.023***	2.086***	2.143***
	(0.394)	(0.373)	(0.373)	(0.303)	(0.282)	(0.282)
Day of week (Saturday)	7.964***	7.709***	7.746***	8.268***	8.305***	8.368***
	(0.401)	(0.379)	(0.379)	(0.310)	(0.285)	(0.285)
Day of week (Sunday)	3.563***	3.780***	3.785***	3.208***	3.455***	3.464***
	(0.340)	(0.374)	(0.374)	(0.255)	(0.282)	(0.282)
Constant	41.314***	40.462***	40.450***	33.975***	33.507***	33.489***
	(1.046)	(0.282)	(0.282)	(0.854)	(0.213)	(0.213)
Observations	165,381	165,381	165,381	165,381	165,381	165,381
R-squared	0.006	0.614	0.615	0.006	0.650	0.650

Note: Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

7 Discussion

Today, mobile apps have become an important aspect of individual life due to their added communication efficiency and convenience, which could help individuals better manage their daily activities (Al-Shamaileh & Sutcliffe, 2023). Among the various functionalities and benefits brought by mobile apps, the increasing social engagement and efficient communication from app usage could be the most crucial benefits that attract app users (Harari et al., 2020). While numerous studies have revealed the importance of updates in maintaining app popularity at the app level, the connection between updates and individual app usage remains understudied. To fill this gap, we used a novel empirical approach, which combines propensity score matching and a difference-in-difference model, to examine the causal effect of app updates on personal app usage by two categories of apps: self-oriented apps and socially-oriented apps.

Table 7. Robustness Check, App Usage Time and Frequency (Weibo and Zhihu), Add the Day of Week when Updates were Launched.

	(1)	(2)	(3)	(4)	(5)	(6)
	App usage time			App usage frequency		
Controlled for new feature	No	No	Yes	No	No	Yes
Individual fixed effect	No	Yes	Yes	No	Yes	Yes
Update	1.341**			0.514**		
	(0.668)			(0.203)		
After	-0.635	0.241	2.118***	-0.113	0.261***	0.948***
	(0.534)	(0.234)	(0.300)	(0.157)	(0.065)	(0.083)

After*update	2.100***	1.926***	2.334***	0.564***	0.423***	0.541***
	(0.620)	(0.275)	(0.354)	(0.184)	(0.076)	(0.098)
After*new feature			-4.792***			-1.753***
			(0.480)			(0.133)
After*new feature*update			-0.679			-0.173
			(0.561)			(0.155)
Day of week (Tuesday)	-1.364***	-0.665***	-0.634***	-0.174***	0.037	0.048
	(0.207)	(0.215)	(0.214)	(0.057)	(0.059)	(0.059)
Day of week (Wednesday)	-2.466***	-2.210***	-2.159***	-0.426***	-0.361***	-0.343***
	(0.219)	(0.215)	(0.215)	(0.060)	(0.060)	(0.059)
Day of week (Thursday)	-0.334	-0.031	0.058	0.260***	0.337***	0.369***
	(0.226)	(0.214)	(0.214)	(0.063)	(0.059)	(0.059)
Day of week (Friday)	-1.121***	-0.924***	-0.873***	-0.076	-0.022	-0.004
	(0.219)	(0.209)	(0.209)	(0.061)	(0.058)	(0.058)
Day of week (Saturday)	1.082***	1.023***	1.015***	0.665***	0.628***	0.625***
	(0.220)	(0.211)	(0.210)	(0.062)	(0.058)	(0.058)
Day of week (Sunday)	1.822***	1.826***	1.820***	0.556***	0.551***	0.549***
	(0.203)	(0.209)	(0.209)	(0.054)	(0.058)	(0.058)
Constant	19.280***	19.708***	19.730***	5.591***	5.786***	5.794***
	(0.570)	(0.158)	(0.157)	(0.170)	(0.044)	(0.044)
Observations	187,461	187,461	187,461	187,461	187,461	187,461
R-squared	0.002	0.579	0.580	0.002	0.630	0.631

Note: Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

First and foremost, we found that app updates relate to an increased frequency of app openings and more time spent on apps among all app users. This finding is consistent with the literature discussed in the Section 2.1, which highlights app updates as an important source for fulfilling new feature demands from users, stimulating user curiosity and engagement, and maintaining app attractiveness to users (Lee & Raghu, 2014; Nayebi et al., 2016). A couple of reasons could help explain this finding. Firstly, app updates often inherit bug fixes, improved app-to-device compatibility, and security, which can improve the user experience, resulting in prolonged app usage among users (Mathur & Chetty, 2017). Moreover, user expectations about app enhancement from updates could also trigger increased usage following updates (Wang et al., 2017). In other words, since app users often expect a better user experience from updates, they are more likely to test out apps after updates and see if the new version meets their expectations. This behavioral response may not be surprising, as app updates reflect developer responsiveness or attention to app quality, which determines system satisfactions and usages (DeLone & McLean, 1992, 2003). In addition, our finding is in line with prior research in the marketing domain, which has shown that app update is an essential step for maintaining market competence and consumer engagement (Lee & Raghu, 2014). This is because a successful update often results in better consumer reviews and ratings, which could help further expand the consumer base and add business value (Katewa & Jain, 2022). Furthermore, apps now also serve as a critical information channel for marketing communication, where consumers actively seek product-related information, compare service features, and seek consumer reviews for products offered by retailers. Therefore, from the perspective of consumers, app updates not only enhance technical performance but also contribute to perceived transparency and brand credibility from correcting misinformation and updating new offerings, which can influence subsequent ratings and engagement behaviors. Thus, this finding has important implications, considering the immensely large consumer group of mobile devices and the increasing competition in the mobile app industry (Kesler et al., 2020).

Based on the findings mentioned above, the present study contains theoretical contributions to the information system domain. Specifically, the present study contributes to a more contextualized understanding of user engagement of technology in information systems. Drawing on the Information Systems Success theory, which links system quality to user engagement through user satisfaction (DeLone & McLean, 1992, 2003), we refine this framework by showing that not all system quality improvements have the same effect. Bug fixes, as incremental quality improvements, tend to reinforce satisfaction and encourage continued usage, while feature introductions may disrupt established routines and reduce engagement in socially oriented apps. We further distinguish immediate exploratory use from sustained use, showing that feature-introducing updates may trigger short-term curiosity and app openings, whereas bug-fixing updates more reliably translate into longer-run engagement due to reduced failure risk and lower learning costs. This indicates that the pathway from system quality to satisfaction and use is not uniformly positive, but rather contingent on contextual factors such as app orientation. In this way, our findings add a boundary condition to the IS Success model, suggesting that the effectiveness of system quality improvements depends not only on the type of update but also on the nature of the application in which it is embedded. Each update functions as a new quality signal that resets user expectations and reactivates the chain from quality to satisfaction to use. In our panel analysis, this sequence recurs across releases. App openings and time spent increase immediately after an update. Bug fix releases are more likely to sustain the increase because they remove small problems, whereas feature releases often create a short testing spike and, especially in the socially-oriented apps in our sample, can reduce ongoing engagement when routines are disrupted. The effect stabilizes until the next release, at which point the sequence begins again, yielding a dynamic view of IS success in mobile settings. Thus, our study highlights the need to consider contextual factors, such as app orientation, when evaluating the impact of app updates, which intends to improve app quality or functionality, on user engagement.

Our analysis also revealed an interesting pattern that introducing new features in updates reduces app usage for socially-oriented apps, while no such connection was identified for self-oriented apps. Although the detailed reasons that cause the heterogenous effect of new features based on app categories need further investigation, the negative connection between introducing new features and reduced app usage is not surprising and can be explained by the well-developed technology adoption conceptual framework (Lai, 2017). Specifically, the theoretical model posits that technology adoption is largely dependent on perceived ease of use and perceived usefulness (Sugandini et al., 2018). Therefore, the reduced app usage from introducing new features could be attributed to reduced ease of use due to the new functionalities from updates, which require users to spend more effort familiarizing themselves with the changes (Xiao & Spanjol, 2021). Therefore, our findings also underscore the importance of considering user capabilities to master new features from app updates. While app update is an important source for offering new features based on user demand, the effectiveness of these updates depends on whether users can easily adapt to the changes introduced. This adds to the Information Success conceptual framework that users' technology capability is another important determinant of system engagement, apart from system quality.

Our paper also carries practical implications. First, app developers and product managers should evaluate whether feature changes align with user expectations and the functional orientation of apps, especially when updates are intended to promote user engagement. For example, Instagram's shift toward algorithmic Reels from a photo-centric platform, received strong pushback from users who felt these changes deviated from the app's original purpose (Lorenz, 2022). This case shows that updates misaligned with user expectations or app orientation can generate dissatisfaction and reduce user engagement, regardless of their technical sophistication. Likewise, our findings underscore the importance of implementing easily understandable app feature introductions that help users quickly master the new functionalities following updates.

8 Limitation

While, in this study, we present empirical evidence on the relationship between app updates and app usage, there are several limitations that should be acknowledged. First of all, due to the availability of data, our analysis is based on user behavior in a single national context, which may limit the generalizability of our findings to other regions. Prior research has shown that technology acceptance can vary across different countries (Straub, 1994). Therefore, future research could extend this work by examining the relationship between app updates and app usage in a different country to assess the contextual determinants of update-rated user behaviors.

Second, due to the availability of data and the information collected, our causal analysis did not include an ample amount of control covariates related to the socio-demographic factors of app users, such as external marketing campaigns, presence of competitor apps, or possible seasonal variation in user behavior. Although our results are robust after controlling for time-variant updates, future research that includes social determinants could yield a more accurate estimation when data are available (AlSaleh & Thakur, 2019). Complementary methods, including longitudinal field experiments or other econometrics approach, such as the instrumental variable regression, could strengthen causal inference in future studies.

Third, our paper focused on the four apps (i.e., WeChat, QQ, Zhihu, and Weibo), which we think could serve as good representations for socially-oriented and self-oriented apps in the marketplace today. However, due to the nature of our data, the majority of app usage observations come from these four apps, and our data analysis mainly focuses on the impact of updates on these apps. This means that our findings may not fully generalize to other types of apps, such as gaming apps. Additionally, as discussed earlier, these apps offer both socially-oriented and self-oriented features. Despite this limitation, our main goal is to examine the impact of updates on app usage, so this limitation does not dramatically decrease our research contribution. Future studies could use newly emerged, highly popular apps like ChatGPT or gaming apps, given the rapid technological development in society (Stocchi et al., 2022).

Fourth, our data come from the backend database of a single software development firm in China, which may raise concerns about generalizability. While the dataset offers unique advantages by capturing individual-level app usage behaviors with high accuracy, it is not representative of all app categories, platforms, or geographic regions. Patterns of app engagement may differ in other national or institutional contexts due to cultural, regulatory, or technological differences. Thus, our findings should be interpreted with caution, and future research could extend the analysis by using multi-source data from diverse platforms and markets to validate and broaden the applicability of our results.

Additionally, since our dataset was drawn from a population of individuals who were either interested in or at risk of excessive mobile app use, this context may have influenced the types of users included in the dataset and could potentially bias behavioral patterns relative to the general population. Future research should test similar or extended hypotheses on broader samples of general mobile app users to validate and expand upon our results. At the same time, we urge scholars to exercise extreme caution when working with similar datasets, as such data may carry heightened privacy risks. Researchers should follow their institutional IRB guidelines to ensure that all studies meet established ethical standards.

Finally, our finding that incorporating new features through updates can reduce app usage among socially-orientated apps but not for self-orientated apps. This extends the literature that shows new features as generally beneficial to user experience and promote user engagement (Nayebi et al., 2016). However, our paper does not dive further into the determinants that lead to this heterogenous effect of app types. Therefore, future research could examine user-level factors such as perceived task complexity or social expectations that may influence responses to new feature introductions in app updates.

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Appendix A

Table A1. Summary of Definition of the Covariates in PSM

Variable Name	Variable Definition
Social app usage frequency	The number of times a user opened apps in the social category.
Social app usage time	The duration of time a user spent on apps in the social category.
Financial app usage frequency	The number of times a user opened apps in the financial category.
Search app usage frequency	The number of times a user opened apps in the search category.
Shopping app usage frequency	The number of times a user opened apps in the shopping category.
Musical app usage frequency	The number of times a user opened apps in the music category.
Musical app usage time	The duration of time a user spent on apps in the music category.
Food app usage frequency	The number of times a user opened apps in the food category.
Camera usage frequency	The number of times a user opened cell camera.
Camera usage time	The duration of time a user opened cell camera.
Educational app usage frequency	The number of times a user opened apps in the education category.
Educational app usage time	The duration of time a user spent on apps in the education category.
Travel app usage frequency	The number of times a user opened apps in the travel category.
Travel app usage time	The duration of time a user spent on apps in the travel category.
Work-efficiency app usage frequency	The number of times a user opened apps in the work-efficiency category.
Work-efficiency app usage time	The duration of time a user spent on apps in the work-efficiency category.
Health app usage frequency	The number of times a user opened apps in the health category.
Health app usage time	The duration of time a user spent on apps in the health category.

Table A2. PSM Matching Quality Check

Variables	Mean score		t-score	p-value
	Treatment group	Control group		
Social app usage frequency	121.14	120.93	0.48	0.634
Social app usage time	152.9	153.52	-1.11	0.266
Financial app usage frequency	2.6843	2.6731	0.55	0.581
Search app usage frequency	14.494	14.512	-0.23	0.82
Shopping app usage frequency	11.203	11.282	-0.82	0.411
Musical app usage frequency	7.3695	7.4174	-0.92	0.359
Musical app usage time	6.3448	6.4391	-1.73	0.083
Food app usage frequency	0.65717	0.65103	0.74	0.462
Camera usage frequency	9.0536	9.1281	-1.34	0.181
Camera usage time	6.6159	6.6834	-1.37	0.171
Educational app usage frequency	4.6739	4.7258	-1.12	0.261
Educational app usage time	6.4884	6.5797	-1.33	0.185
Travel app usage frequency	1.4821	1.4538	1.68	0.094
Travel app usage time	1.5545	1.5251	1.56	0.119
Work-efficiency app usage frequency	8.2732	8.2769	-0.08	0.934
Work-efficiency app usage time	6.3801	6.3901	-0.2	0.844
Health app usage frequency	0.67008	0.67249	-0.3	0.768
Health app usage time	0.73633	0.74522	-0.77	0.439

Appendix B

Over the course of our study, we found that people used more socially-oriented apps than self-oriented apps. WeChat, in particular, is the app that people spend most of their time with and use most frequently compared to other apps. On average, individuals spend 57 minutes opening it 44 times per day. Zhihu, on the other hand, is the least frequently used one compared to others, with an average usage time of 12 minutes and 3 times of app opening per day. Table B1 provides summary statistics regarding the duration (in minutes) and frequency of app usage among individuals.

Table B1. Summary Statistics of App Usage (Time Duration and Frequency)

	mean	sd	min	max	n
Combined app usage					
App usage time	32.484	53.143	0	290.523	352,842
App usage frequency	21.663	39.340	0	212.000	352,842
QQ usage					
App usage time	39.338	57.993	0	217.368	101,342
App usage frequency	36.455	49.634	0	181.000	101,342
WeChat usage					
App usage time	57.283	71.825	0	290.523	64,039
App usage frequency	43.508	52.542	0	212.000	64,039
Weibo usage					
App usage time	26.932	43.352	0	151.064	106,189
App usage frequency	8.427	12.928	0	46.000	106,189
Zhihu usage					
App usage time	11.651	23.018	0	82.636	81,272
App usage frequency	3.300	6.205	0	22.000	81,272

Appendix C

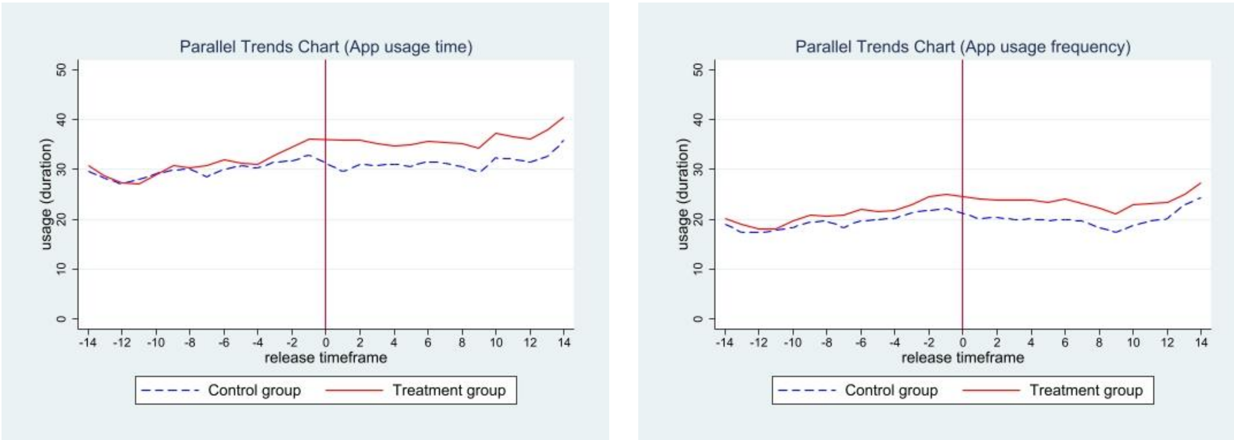

Figure 1. DID Assumption Check. Pre-update Time Shows Nearly Parallel Trends Between the Control and the Treatment Groups. All Four Apps Usage Combined.

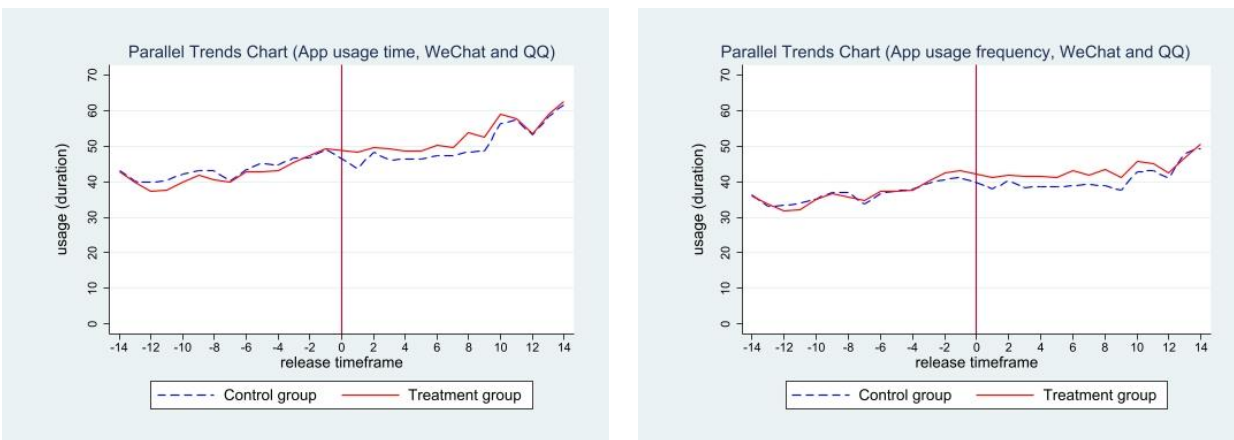

Figure 2. DID Assumption Check. Pre-update Time Shows Nearly Parallel Trends Between the Control and the Treatment Groups. Wechat and QQ Usage Combined.

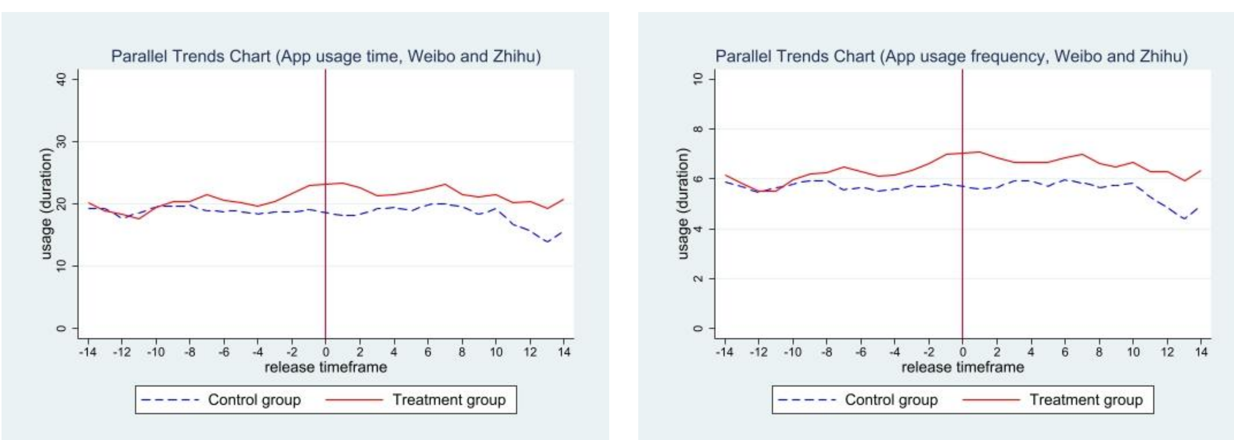

Figure 3. DID Assumption Check. Pre-update Time Shows Nearly Parallel Trends Between the Control and the Treatment Groups. Weibo and Zhihu Usage Combined.

Appendix D

This appendix provides regression charts with the 95% confidence interval on the coefficients in the main analysis (i.e., the regression models that include types of app updates as the moderator in Tables 2 to 4).

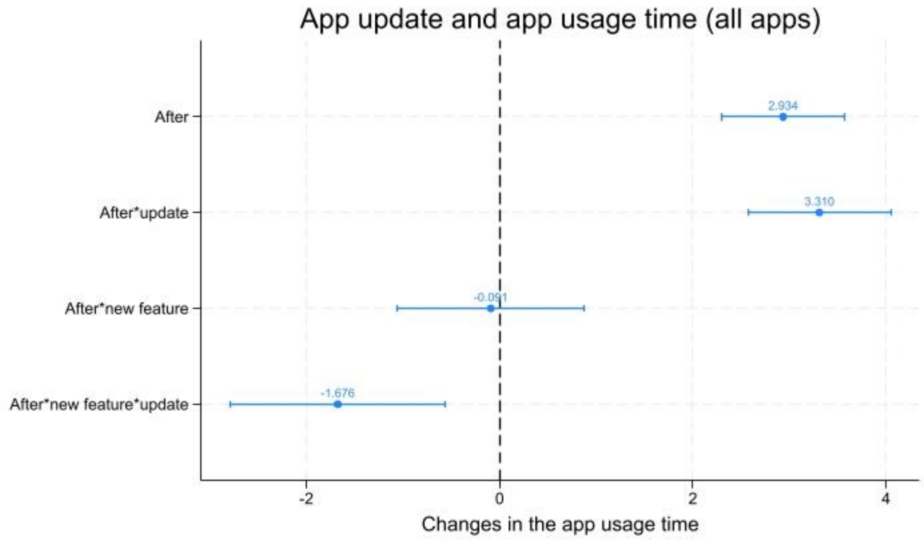

Figure 4, App Updates and App Usage Time (All Apps).

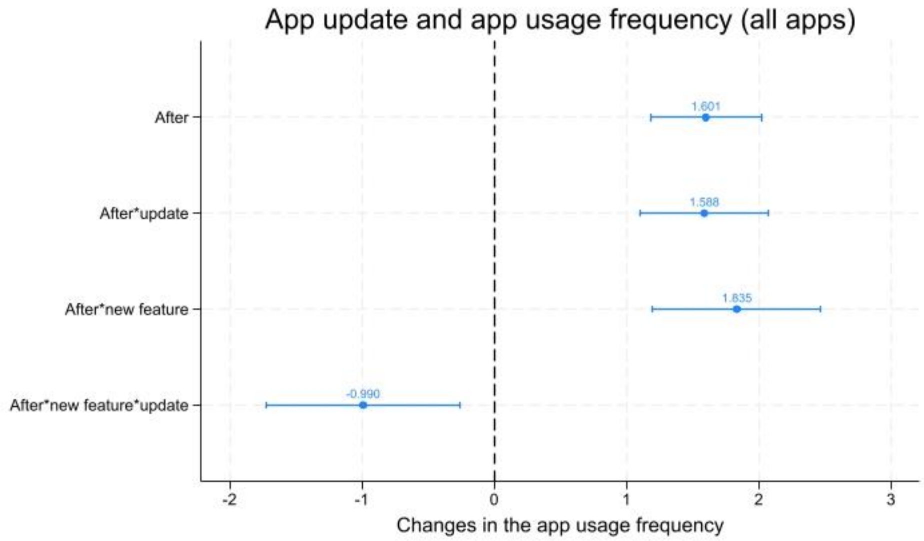

Figure 5. App Updates and App Usage Frequency (All Apps).

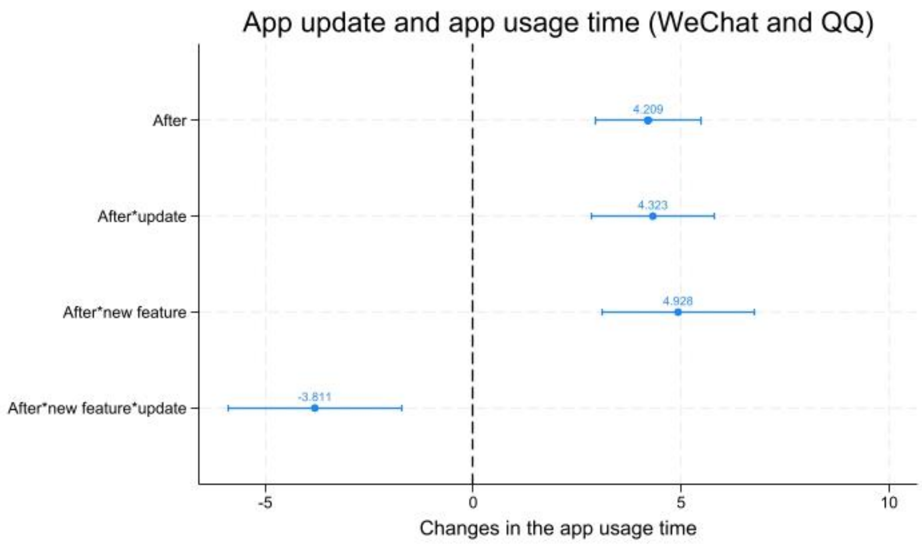

Figure 6. App Updates and App Usage Time (WeChat and QQ).

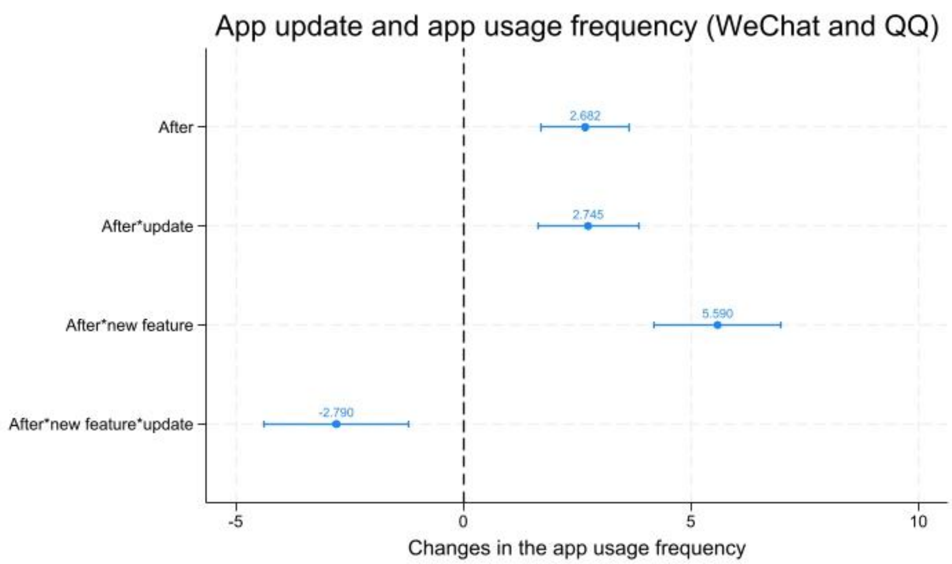

Figure 7. App Updates and App Usage Frequency (WeChat and QQ).

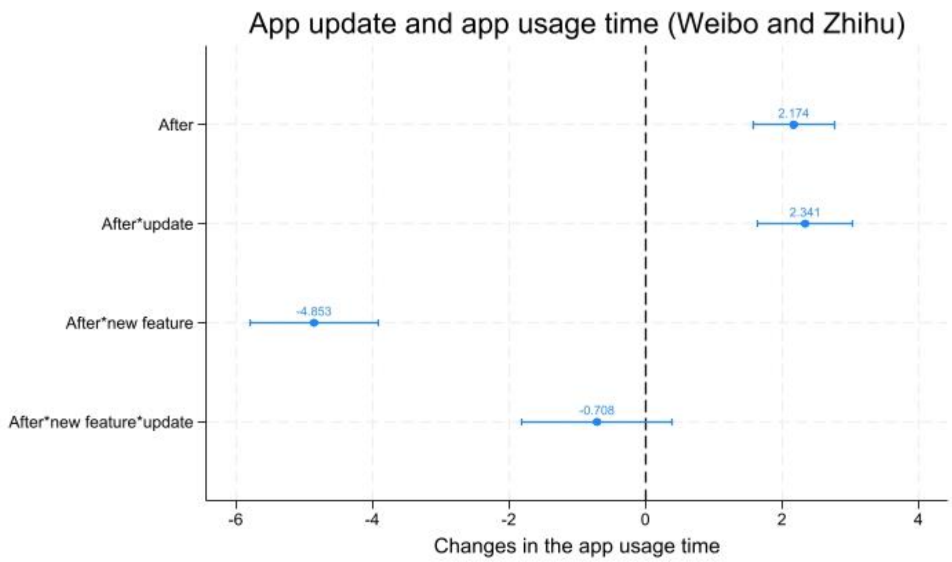

Figure 8. App Updates and App Usage Time (Weibo and Zhihu).

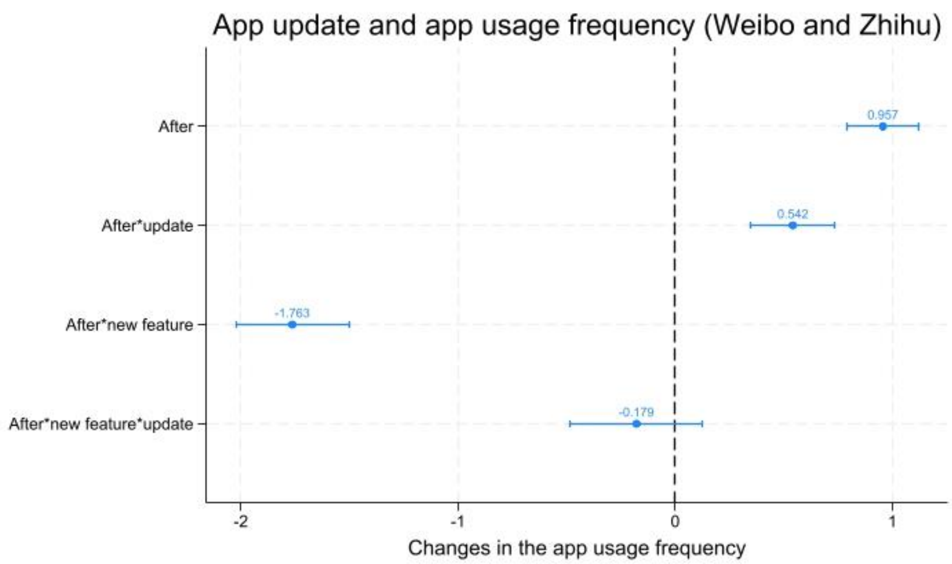

Figure 9. App Updates and App Usage Frequency (Weibo and Zhihu).

Appendix E

This appendix presents a robustness check using standard transformations (i.e., $\ln(y+1)$) of the dependent variables, app usage time and app usage frequency, and then re-runs the DID analysis. Overall, the estimates of the treatment effects of app updates and the introduction of new features are fairly consistent with those in Tables 3 to 5.

Table E1. Robustness Check, Regression Analysis, Combined App Usage Time and Frequency

	(1)	(2)	(3)	(4)	(5)	(6)
	App usage time			App usage frequency		
Controlled for new feature	No	No	Yes	No	No	Yes
Individual fixed effect	No	Yes	Yes	No	Yes	Yes
Update	0.178***			0.178***		
	(0.027)			(0.025)		
After	-0.080***	-0.010	-0.022**	-0.074***	0.014**	0.000
	(0.020)	(0.008)	(0.011)	(0.018)	(0.006)	(0.008)
After*update	0.157***	0.109***	0.139***	0.120***	0.076***	0.102***
	(0.023)	(0.009)	(0.012)	(0.021)	(0.007)	(0.010)
After*new feature			0.028*			0.031**
			(0.016)			(0.013)
After*new feature*update			-0.068***			-0.060***
			(0.019)			(0.014)
Constant	1.904***	2.018***	2.018***	1.679***	1.784***	1.784***
	(0.023)	(0.003)	(0.003)	(0.021)	(0.002)	(0.002)
Observations	352,842	352,842	352,842	352,842	352,842	352,842
R-squared	0.004	0.686	0.686	0.004	0.759	0.759

Note: Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix E2. Robustness Check, Regression Analysis, App Usage Time and Frequency (WeChat and QQ)

	(1)	(2)	(3)	(4)	(5)	(6)
	App usage time			App usage frequency		
Controlled for new feature	No	No	Yes	No	No	Yes
Individual fixed effect	No	Yes	Yes	No	Yes	Yes
Update	0.063*			0.081**		
	(0.037)			(0.036)		
After	0.046	0.060***	-0.052***	0.024		-0.050***
	(0.030)	(0.012)	(0.016)	(0.029)		(0.014)
After*update	0.100***	0.075***	0.128***	0.085***	0.126***	0.117***
	(0.034)	(0.013)	(0.019)	(0.033)	(0.006)	(0.017)
After*new feature			0.231***			0.234***
			(0.023)			(0.021)
After*new feature*update			-0.114***			-0.116***
			(0.026)			(0.024)
Constant	2.572***	2.621***	2.622***	2.549***	2.606***	2.600***
	(0.032)	(0.003)	(0.003)	(0.031)	(0.003)	(0.003)
Observations	165,381	165,381	165,381	165,381	165,381	165,381
R-squared	0.002	0.696	0.697	0.002	0.724	0.725

Note: Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix E3. Robustness Check, Regression Analysis, App Usage Time and Frequency (Weibo and Zhihu)

	(1)	(2)	(3)	(4)	(5)	(6)
	App usage time			App usage frequency		
Controlled for new feature	No	No	Yes	No	No	Yes
Individual fixed effect	No	Yes	Yes	No	Yes	Yes
Update	0.182***			0.133***		
	(0.034)			(0.024)		
After	-0.110***	-0.060***	-0.005	-0.067***	-0.021***	0.031***
	(0.024)	(0.011)	(0.014)	(0.017)	(0.007)	(0.010)
After*update	0.162***	0.127***	0.152***	0.107***	0.078***	0.099***
	(0.027)	(0.013)	(0.017)	(0.020)	(0.009)	(0.011)
After*new feature			-0.141***			-0.133***
			(0.022)			(0.015)
After*new feature*update			-0.052			-0.042
			(0.056)			(0.048)
Constant	1.369***	1.487***	1.488***	0.982***	1.064***	1.066***
	(0.028)	(0.004)	(0.004)	(0.020)	(0.002)	(0.002)
Observations	187,461	187,461	187,461	187,461	187,461	187,461
R-squared	0.004	0.614	0.614	0.004	0.643	0.644

Note: Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

About the Authors

Pengcheng (P.C.) Wang is an Assistant Professor of Information Systems and Security at Kennesaw State University. His research explores the intersection of technology and human behavior, focusing on cryptocurrency investor decision-making, human-AI interaction, application development, and information security. He has published in various outlets, including Finance Research Letters, the International Journal of Bank Marketing, and the Journal of Systems and Information Technology, as well as in multiple international conference proceedings. He earned his Ph.D. in Computer Information Systems from Georgia State University, where he developed his interdisciplinary expertise bridging behavioral research and cybersecurity. His current projects examine how emerging digital technologies influence user risk perception, financial decision-making, and ethical technology use.

Zefeng Bai is an assistant professor of business administration at The Williams School of Commerce, Economics and Politics of Washington and Lee University. He holds a PhD in Business Analytics from Bentley University. His research primarily centers on causal inference and data analytics, with a particular focus on consumer behaviors in cryptocurrency markets, artificial intelligence (AI) adoption, and long-term asset management strategies. He has publications in different outlets, including Journal of Experimental and Behavioral Finance, Journal of Consumer Affairs, and International Journal of Bank Marketing. He also served as a reviewer for journals, such as European Journal of Information Systems, Behaviour & Information Technology, and Journal of Information Technology.

Kambiz Saffari (Saffarizadeh) is an assistant professor of information systems at the University of Texas at Arlington. His research mainly focuses on artificial intelligence (AI) alignment, human-AI collaboration, and algorithmic decision-making. He has published in various outlets, including MIS Quarterly, the Journal of Management Information Systems, and the Journal of the Association for Information Systems. Saffarizadeh is a recipient of the Rising STARs Award from the State of Texas and has been recognized as an AIS Distinguished Member. He has also received AIS Community Leadership recognition for his service as co-founder and president of the Iranian Scholars Chapter by the Association for Information Systems. He has developed several courses on emerging technologies, machine learning, and mobile application development. He holds a PhD from Georgia State University. Before joining academia, he spent several years in software development and managerial roles in the industry.

Chuang Wang is a professor at School of Business Administration, South China University of Technology. Her research focuses on IT challenge and negative issues, human-AI collaboration, electronic commerce etc. Her work has appeared in leading academic journals such as Information System Research, Journal of Management Information Systems, Journal of the Association for Information Systems, Decision Support Systems, Journal of the Association for Information Science and Technology, Information & Management, Information Processing and Management, etc.