Modern technology innovations feature a successive and even recurrent procedure. Intervals between old and new generations of technology are shrinking, and the Internet and Web services have facilitated the fast adoption of an innovation even before the convergence of its predecessor. While the adoption and diffusion of innovations have been studied for decades, most theories and analyses focus on single and one-time innovations. Meanwhile, limited work has investigated successive innovations while lacking user-level analysis, possibly due to the unavailability of fine-grained adoption behavior data. In this study, we present the first large-scale analysis of the adoption of recurrent innovations in the context of mobile app updates, investigating how millions of users consume various versions of thousands of apps on their mobile devices. Our analysis reveals novel patterns of crowd and individual adoption behaviors, which suggest the need for new categories of adopters to be added on top of the Rogers model of innovation diffusion. We show that standard machine learning models are able to pick up various sources of signals to predict whether users in these different categories will adopt a new version of an app and how soon they will adopt it.
1 INTRODUCTION
Modern technology innovation functions in a successive nature. Smartphones did not take over in one shot; many generations of mobile phones rose and replaced older models in the past decades, and many have vanished from memory, leaving version numbers in the ash. Similarly, car models update every couple of years, delivering new versions of autonomous driving. In recent years, a special group of successive innovations has emerged, which update recurrently with much shorter intervals between updates. Mobile apps serve as a prime example, with updates released every several weeks or even every few days. With merely a click on their smart devices, customers can instantly obtain the newest version of the innovation, which is completely different from the adoption of other innovations. We denote such innovations as recurrent innovations. Compared with their impact on how people live and work, how recurrent innovations are adopted is largely unknown to innovation creators, stakeholders, and disseminators. In this work, we study the adoption of recurrent innovations in the case of mobile app updates, in which we treat an app as a technology and a specific version of the app as a recurrent innovation through the lens of Rogers’ theory [58].

The adoption of innovations has been studied for decades since Everett Rogers’ classic book Diffusion of Innovations [58], first published in 1962. As defined in Rogers’ theory, an innovation is “an idea, practice, or object that is perceived as new by an individual or other unit of adoption” and adopters of an innovation are categorized into innovators, early adopters, early majority, late majority, and laggards [58]. The diffusion of innovations theory and its variations have been widely applied to multiple disciplines, such as medical sociology [8], cultural anthropology [3], industrial economics [45], and health care [11], as well as mobile technologies [28, 36] and apps [14, 20, 53, 73]. A substantial body of literature applying Rogers’ theory focuses on single innovations, such as appliances [4, 6], telecommunications services [42], and digital-imaging technologies [37]. Since 1987, as “newer technologies are continually replacing older ones” [54], a thread of research has started to investigate different generations of innovations (or successive innovations) [24, 26, 41, 48, 54, 55], such as integrated circuits (ICs) [54] and IBM mainframe computers [24, 26, 41] and their diffusion. Successive innovations in these studies update on a yearly basis and are distributed with a carrier of physical products. In addition, due to the lack of fine-grained adoption behavior data, findings for individual adopters are not provided.

In recent years, with the widespread uptake of the Internet and smart devices, some cutting-edge innovations, such as mobile apps that have been reshaping our society, are able to update with an unprecedented frequency. This is probably because mobile apps can be delivered to end users without reliance on a physical carrier. Customers can get the newest version of an app, assuming access to the Internet, with one click on their smartphones. An even newer version of the app could be released within just a few days. The very short interval between versions (e.g., weeks for mobile apps) could make the interactions of versions quite different. In addition to mobile apps, more modern technology innovations, such as (mobile) operating systems, browsers, and programming languages, share similar characteristics. With the emergence of these technologies in recent years, understanding the diffusion of recurrent innovations has become more significant and urgent. However, the existing work is not directly applicable considering the changes in the distribution channel, the update frequency, and the cost of adoption on the user side. Indeed, understanding recurrent innovations requires tracking the adopters of different versions of innovations over a long period of time, which has not been feasible in most domains.

It is, therefore, critical to verify whether the existing theories and findings still hold in the context of recurrent innovations. Specifically, the adoption behavior of a user can be largely influenced by the user’s previous adoption and satisfaction with earlier versions of the same technology. Furthermore, the diffusion process of an innovation can be affected by its subsequent updates. As
A public dataset reveals the evolution of the market share of Android, the mobile operating system for Android devices, and Chrome, a popular Web browser, both with multiple continuous versions. As is shown in Figure 1, the diffusion (or the increase of market share) of each version slows down or reverses after a newer version is released, demonstrating evidence of the possible interference between recurrent versions of innovations. Such a pattern already poses a threat to existing conclusions about single innovations. According to Rogers’ theory, the market share of an innovation saturates but does not drop. While this pattern verifies previous findings in the literature on successive innovations, these data do not untangle the adoption behaviors of individual users and whether there exist variations in the tendency of adoption, timeliness of adoption, and order of adoptions of new versions by different users, and, if yes, whether these variations can be explained by the categorization of adopters in the classical diffusion of innovation theory. Indeed, these questions are also left unanswered in the literature of successive innovations.

In this article, we conducted the first systematic analysis of the diffusion of recurrent innovations using a novel dataset that tracks how 17,124,831 Android users adopt 217,285 Android applications collected by Umeng+, a leading third-party data intelligence service provider. This dataset provides a unique case scenario of recurrent innovations in the context of mobile apps. We found that the release of a new version of the same app clearly hinders the diffusion of its precedent versions. When adopting a new version of an app, there exists a significant difference between users who have not adopted a previous version of the app and those who have. While the adoption curve of the former group (new adopters) complies with Rogers’ theory, the latter group (recurrent adopters) presents considerably different patterns. In particular, we identified three novel categories of adopters of recurrent innovations, which are not covered in existing theories: the immediate-adopters, the preservers, and the retro-adopters. Rula et al. [60] studied Web server logs from a major Content Delivery Network (CDN) and found a substantial proportion of requests originated from hosts using out-of-date app versions, which supports the existence of preservers, a group of adopters identified in our analysis. These new categories account for a considerable proportion of adopters of an innovation, which has not been explored by previous efforts. Their interactions with precedent innovations present a clear difference from the rest of the users, clear enough for a machine learning model to distinguish them with decent accuracy.

1https://gs.statcounter.com/android-version-market-share/mobile/worldwide/
2https://gs.statcounter.com/browser-version-market-share
We further investigated whether a user’s behavior in adopting a recurrent innovation is predictable. We found that by using a group of features to represent the properties of the target app (the technology), the characteristics of the user (the adopter), and how the user interacts with previous versions of the app (recurrent innovations of the technology), standard machine learning models are able to predict whether the user will adopt a new version of the app and, if yes, how soon the adoption will happen after the new version is released. The results reconfirm part of the existing theories about single innovations while once again revealing critical new insights into the factors that affect the adoption of a recurrent innovation.

The contribution of this work can be summarized as follows:

- To the best of our knowledge, this is the first large-scale analysis of the diffusion of recurrent innovations. Our work provides a novel perspective that augments the existing theories and models of the diffusion of single innovations while adding to the literature of successive innovations.
- We based our analysis on a comprehensive longitudinal dataset tracking how tens of millions of users adopt 713,935 versions of mobile apps. This provides a unique application scenario and testbed to understand the diffusion of recurrent innovations.
- We found significantly different patterns in the adoption curves of recurrent innovations that cannot be explained by existing theories, through which we identified new categories of adopters in the diffusion process.
- We conducted a systematic predictive study and found salient factors that affect the adoption behavior. Our findings provide insights for app developers to improve their innovation and dissemination strategies.

The rest of this article is organized as follows. We first introduce the background and related work in Section 2 and the dataset in Section 3. We then examine the adoption process of recurrent innovations in detail and propose new categories of innovation adopters in Section 4. In Section 5, we predict the individual adoption decisions of recurrent innovations and investigate the factors that may influence an individual’s decision. We provide a further analysis of the new categories of adopters in Section 6. Finally, we discuss the implications, limitations, and future research directions in Section 7 and conclude the article in Section 8.

2 BACKGROUND AND RELATED WORK

In this section, we review the recurrent innovations in the diffusion of innovation literature and introduce research efforts in understanding the adoption of mobile apps or app versions.

2.1 Recurrent Innovations

Although first studied as independent entities, innovations do have subsequences to overcome their shortcomings. For example, steam locomotives were first developed in 1804 but were gradually replaced by diesel and electric locomotives starting in the 1920s due to efficiency and cost issues. However, conditioned by the status of science and technology, as well as their inherent nature, innovations in history usually update at a rather slow pace. In recent decades, modern technologies have been able to update successively with relatively shorter intervals. Since 1987, researchers have started investigating the diffusion of successive innovations when two consecutive versions can interact, which is not covered by Rogers’ theory, the classic theory for single innovations. For example, Norton and Bass [54] analyzed the shipments of integrated circuits and revealed the diffusion process (which captures the adoption by new customers) and substitution process (which captures the adoption by existing customers) of successive innovations. Norton and Bass [55] also analyzed 12 datasets covering innovations in electronics, pharmaceuticals, consumer
Table 1. Successive Innovations in the Literature

| Innovation                          | Avg. Release Interval | Literature                                      |
|-------------------------------------|-----------------------|-------------------------------------------------|
| DRAMs                               | 3.67 Years            | Norton and Bass [54, 55] (1987, 1992)           |
| SRAMs                               | 4.50 Years            | Norton and Bass [54, 55] (1987, 1992)           |
| Logic Devices                       | 2.00 Years            | Norton and Bass [54, 55] (1987, 1992)           |
| Computer REVs                       | 4.67 Years            | Norton and Bass [55] (1992)                     |
| Computer Units                      | 4.67 Years            | Norton and Bass [55] (1992)                     |
| Disk Drives                         | 3.00 Years            | Norton and Bass [55] (1992)                     |
| Antihypertensives                   | 5.00 Years            | Norton and Bass [55] (1992)                     |
| Blockers and Inhibitors             | 6.50 Years            | Norton and Bass [55] (1992)                     |
| Diuretics                           | 13.00 Years           | Norton and Bass [55] (1992)                     |
| Diapers                             | 19.00 Years           | Norton and Bass [55] (1992)                     |
| Recording Media                     | 17.00 Years           | Norton and Bass [55] (1992)                     |
| Milk Containers                     | 32.00 Years           | Speece and MacLachlan [62] (1995)               |
| IBM Mainframe Computers             | 6.00 Years            | Islam and Meade [24] (1997)                    |
|                                     |                       | Jun and Park [26] (1999)                        |
| Cellular Systems                    | ≥ 8.00 Years          | Islam and Meade [24] (1997)                    |
| Pagers                              | -                     | Kim et al. [30] (2000)                          |
| Cellular Telephones                 | 6.00 Years            | Kim et al. [30] (2000)                          |
| Cordless Telephone 2                | -                     | Kim et al. [30] (2000)                          |
| Cellular Telephones (European Country) | 6.00 Years    | Danhafer et al. [9] (2001)                      |
| Semiconductor Products              | 2.25 Years            | Chien et al. [7] (2010)                         |
| Cellular Telephones (U.S.)          | 11.00 Years           | Jiang and Jian [25] (2012)                      |
| Nike Golf                           | 2.75 Years            | Kreng and Wang [33] (2013)                      |
| Mobile Apps                         | 4.05 Weeks\(^3\)     | Our work                                        |

\(^1\)The average release intervals of innovations are calculated based on data used in the literature. Marked with - if data is not available.
\(^2\)We only list literature that contains real-world innovations.
\(^3\)The average release interval of mobile apps is calculated based on apps studied in Section 5. These apps have multiple versions and a certain user base, which can help reduce potential noise.

The intervals between generations typically span several years.

goods, and industrial goods and found that a newer generation of innovation will drive sales of the older generation to approximately zero. A stream of follow-up work has studied a wide range of successive innovations, including IBM mainstream computers [24, 41], cellular systems [24], cellular telephones [25], milk container technologies [62], and semiconductors [7]. Table 1 presents a summary of the successive innovations with the average interval between consecutive generations, which ranges from 2 years to 32 years.

Recurrent innovations that have emerged in recent years are a type of successive innovations, which have quite different characteristics compared with classic successive innovations. The most observable difference is that the successive innovations in the literature usually take years to release a new generation (see Table 1), whereas the recurrent innovations update with very short intervals. For example, Python 3 has released, on average, two versions each month over the last two years\(^3\) and mobile apps can update every week. How customers adopt such quickly updated innovations is unrevealed in existing work. The high frequency of updates not only relies on substantial resources invested in creating these innovations but also notably benefits from the

\(^3\)https://www.python.org/downloads/
exceptional efficiency of the distribution channels, such as the Internet and Web services. Instead of ordering physical goods and waiting for delivery, customers are able to switch to the newest app through simple operations on their smartphones. Another significant change is the profit model of the innovations. Most mobile apps are free to download, while developers get revenues from in-app purchases and ads [57, 61, 63, 66]. Consequently, pricing is not as important for the adoption of a specific version of recurrent innovations. Moreover, buying or installing a recurrent innovation is not the most desirable indicator of adoption, since how customers use and interact with the innovation is more significant for innovation creators to contribute to their revenue or to help optimize future versions. Our work provides the first systematic analysis of recurrent innovations with a case study on mobile apps using large-scale data on user adoption behaviors.

2.2 Adoption of Mobile Apps

In this study, we viewed mobile apps as technologies and their versions as innovations and investigated how users adopted recurrent versions. A new version is typically released to fix bugs, introduce new features or functions, or modify user interfaces. From the developers’ perspective, user adoption of a new version is important as it could enhance user experience and help promote user engagement, which could contribute to revenue through in-app purchases, advertisement exposure, and reducing the cost of maintaining outdated versions.

There are two modes to install a new version: manual update and auto update, depending on the user’s awareness of the update.

- **Manual Update:** In the manual update mode, users would be aware of any new version before the app is updated to that version. If the apps are managed through app markets, such as Google Play for Android apps and iOS App Store for iOS apps, users can click the update button in the app markets. Some Android app markets and third-party services provide APK files to download and even provide historical versions of apps (such as Wandojia⁴ and APKPure⁵). In this way, Android users can reinstall a version they prefer, which helps explain the retro-adopters found in our analysis (see details in Section 4.3). Users can also be notified of a new version when using an app. Such in-app updates cannot be installed without users’ approval. In some cases, however, users can no longer use the app without approving the update, which is called a forced update (named immediate update by Google Play).
- **Auto Update:** Users can decide to enable auto updates on their smartphone devices. When the auto-update option is on, apps will automatically update to the latest version when eligible. Research has shown that users are conscious of app updates and, thus, some would prefer to manage app updates manually [52]. To understand users’ attitudes towards automatic mobile app updates, Mathur and Chetty [46] conducted a survey with Android users and revealed that users who avoid auto-updates are more likely to have had past negative experiences with software updating, tend to take fewer risks, and display greater proactive security awareness.

The adoption of apps or app versions is usually measured by various indicators, including ratings, reviews, and the number of downloads or uninstalls from app markets [15, 34, 39, 50, 56]. However, these indicators are usually measured with aggregated values and cannot be traced back to individual adopters, which is also a limitation in existing work about successive innovations. A handful of research efforts measure the adoption of apps through surveys targeting specific user populations [29, 32], but it can be rather costly to trace fine-grained behavioral data across app

⁴https://www.wandoujia.com
⁵https://apkpure.com/
versions from a large scale of users in a timely manner. Our dataset provides in-app usage sessions of individual users, which facilitates the understanding of different adopters and factors that affect an individual’s adoption of a recurrent innovation using advanced machine learning models.

A thread of work has studied user adoption of app versions regardless of whether the diffusion of innovation theory is explicitly applied. Möller et al. [49] analyzed how soon a user would update an app in Google Play once a new version is available. They kept track of the installations of a self-developed app published in Google Play and found that half of the users using an old version did not update to a new version within 7 days of its release. Their results also showed that a new version could affect the diffusion of previous versions. These findings comply with the curves of cumulative adopters in our work (see Figure 4). This work provided an initial look at the adoption of recurrent innovations and supporting evidence for our findings with Google Play data, although only one app was studied. Another work [60] studied requests from mobile apps using a dataset covering 3 years of CDN logs. They found a considerable proportion of requests originated from hosts of out-of-date app versions. Their result implies the existence of users left behind (i.e., users that keep out-of-date app versions) and identifies the potential root causes for why these users did not update the app. Other existing work has considered mobile apps as innovations [16] and invested in applying diffusion of innovation models to study the diffusion of specific apps in domains including health [14, 51], traffic [73], crisis [20], and trekking [53], as well as to understand factors such as personality traits [71] and life stage [17], that influence adoption behaviors. For example, Nickerson et al. [53] examined the diffusion of mobile technology and smartphone apps among people who walked the Camino de Santiago, a nearly 500-mile trek in Spain, using a research model that relates categories of the adopter with the beliefs about innovation characteristics and with the adoption with innovations, respectively. They concluded that the model is only partially supported for this domain. In their work, apps are regarded as single innovations, and different versions are not considered recurrent innovations.

3 DATASET

To understand the adoption and diffusion process of recurrent innovations, we used a large-scale app usage dataset collected by Umeng+, a leading third-party business intelligence service provider in China. This dataset recorded user behaviors in Android applications (i.e., apps) that integrate Umeng+’s software development kit (SDK). We randomly sampled 17,124,831 anonymous users who were active during the period from August 20, 2018 to June 30, 2019 and reconstructed their app usage sessions during the same time period. Each session is formulated as a 5-tuple, \(< u, p, v, t_0, t_1 >\), where \(u\) and \(p\) are anonymized identifiers for the user and the app, \(v\) is the version of the app that the user is using, and \(t_0\) and \(t_1\) are the starting and ending timestamps of the session, respectively. Other than the beginning and the end of a session, we did not obtain any information about the actual activities or content of the session. We conducted a series of statistical tests and confirmed that there is no significant difference between the distributions of the sample and the overall population. The sampled dataset includes 17,124,831 users, 217,285 apps, 713,935 app versions, and 17,013,616,656 sessions, covering the period from August 20, 2018 to June 30, 2019.

Ethical Consideration: We took a series of steps to preserve the privacy of involved users in our dataset. First, all users and apps are anonymized by Umeng+ before being made available to the authors. We know only the categories of the apps used by users, which means no users can be traced back through the data. Second, all data are kept within Umeng+’s private servers, which are protected by the company’s firewall. Additionally, the entire analysis is conducted exclusively on the servers of Umeng+, which is strictly governed by Umeng+’s administration.

6https://www.umeng.com/
4 THE ADOPTION PROCESS OF RECURRENT INNOVATIONS

In a period of 10 months, the dataset recorded an average of 3.28 versions per app, which provides a solid basis for studying the diffusion of recurrent innovations. In this section, we provide a detailed examination of the adoption process of recurrent innovations, highlighting how it is both related to and different from the classic innovation diffusion theory.

For analogies, we treat each app as a unique technology and each specific version of the app as a recurrent innovation of that technology. In particular, a version can be recognized as an innovation because it owns relative advantage and leads to significant changes on the part of adopters. Relative advantage refers to the extent to which an innovation is perceived as superior to what it supersedes. An app is usually updated to fix bugs, modify user interfaces, and introduce new features or functions. From the developer’s perspective, these modifications should be significant enough for them to release a new version, which is worth the cost of distribution and users’ adaptation. For example, releasing an update can fix app vulnerabilities and protect users from security challenges, which is critical for the safety of mobile users. From the user’s perspective, their usage behaviors can greatly change in a new version. They may be in favor of the new features, free from annoying bugs, show higher engagement, and even post a higher rating for the app, which demonstrates an improved level of user gratification and suggests a version as advantageous. In addition, the release of a new version may attract new adopters.

The adoption of a recurrent innovation by a user is identified by their first use of the version. Note that this is different from many other types of innovations for which the adoption time is, for example, the time to buy a product or the time to decide to adopt a policy. As previously discussed, recurrent innovations, such as mobile apps, have distinct characteristics compared with single innovations and even classic successive innovations in the literature. As the cost of “buying” an app is usually low in terms of both price (i.e., most apps are free to download) and time, app developers can make revenue through in-app purchases and ads. Therefore, in most cases, starting to use an app serves as a more appropriate indicator of adoption. Our analysis will show that the adoption pattern of new adopters (measured by the time of first use) complies with Rogers’ theory, thereby supporting the validity of the measure of adoption.

To provide a more tangible illustration of the process, we select one video app and one fitness app (referred to as “Video App” and “Fit App” hereafter), both of which are popular within their respective categories.

4.1 Adoption Curves of Recurrent Innovations

The classic innovation diffusion process in Rogers’ theory is featured by the bell-shaped time-of-adoption curve. Users are categorized into innovators, early adopters, early majority, late majority, and laggards according to their adoption time for a single innovation. In the context of fast-evolving recurrent innovations, will the adoption curve still hold the same bell shape? Is there a difference between new adopters of the technology and those who have adopted an earlier version of the technology? Do the adopters of recurrent innovations fall into the same categories? In this section, we start to examine the diffusion process of recurrent innovations through their time-of-adoption curves.

One thing we need to distinguish is that the same version of an app may be recognized as a recurrent innovation for some users but as a brand-new innovation for other users. Indeed, for...
new adopters, or users who haven’t adopted any previous version of the app, a specific version of the app is not different from a single innovation. Thus, we would expect a similar bell-shaped time-of-adoption curve for these users. In Figure 3(a), we plot the number of new adopters for each version of the Video App over a 5-month period. We observe a bell-shaped curve for each version despite some high-frequency jitters likely due to a weekly seasonality. Some new users get on board as soon as a new version comes out and some users wait to adopt the app later, while some users adopt an old version even after a newer version has already been released. The adoption curve of a specific version (a recurrent innovation) largely complies with Rogers’ curve for new adopters of the same app (technology).

Nevertheless, we observe the pattern that once a new version starts to diffuse, there is a sudden drop in the adoption curve of the precedent version. This indicates that even for new adopters, there is an influence between recurrent innovations. Not surprisingly, even a new adopter’s decision depends on the timeliness of information, and the availability of a newer version would drive the attention of users away from an older version.

In comparison, the time-of-adoption curve for recurrent adopters, or users who have adopted an earlier version of the app, exhibits a different pattern, as shown in Figure 3(b). Instead of a slow, gradual increase in the beginning, the curve rises sharply and there exists a strong right-skewness. This indicates that we no longer observe the slow ramping up of early adopters and the early majority. Instead, many recurrent adopters respond promptly to the new version and most
Fig. 4. Cumulative adopters of each version. The y-value of \( v_i \) represents the number of users who have version \( i \) of the app installed as of a given day based on their most recent session of the app.

recurrent adopters update to the new version within days of its release. Such adopters could be fans of the app and update it immediately upon each new release or they may have turned on the auto-update option for the app. Again, the adoption curve of a precedent version drops rapidly once a new version is released, although we can see some recurrent adopters update to a previous version even long after a newer version is released.

The difference between recurrent adopters and new adopters indicates that there exists at least a new category of adopters. Compared with innovators and early adopters in Rogers’ theory, their decisions are even faster, in many cases immediate. Instead of following the reasonable staged processes of adoption (awareness, persuasion, decision, implementation, and continuation), these users make their adoption decisions in no time, almost blindly. For this group of recurrent adopters, we may call them immediate-adopters.

4.2 Cumulative Adopters of an Iteration

Following Rogers’ theory, one intuitive derivation of the bell-shaped adoption curve is the S-shaped curve for cumulative adopters over time, which represents the market share of the innovation, as shown in Figure 2(a). That is, the total number of adopters increases slowly in the beginning (innovators and earlier adopters), faster afterward (early/late majority), and slowly in the end (laggard). Yet with recurrent innovations, such an S-shaped curve may never materialize. In fact, the cumulative adopters of a specific version cannot be calculated as simply the integration of the time-of-adoption curve, since users may transit to newer versions and, therefore, are no longer adopters of the current version being assessed.

The market share of Android and Chrome in Figure 1 sheds light on the cumulative adopters of recurrent innovations. The market share of a certain version rises upon release and falls when a newer version is released. With the fine granularity of the app usage data, we can examine the adoption process on a daily level. In Figure 4, we plotted the number of users of different versions of the Video App and the Fit App over time. We observed consistent patterns of the adoption curve across different versions and different apps.

Upon release of a new version of an app, the number of adopters increases sharply, reaches its peak when a successive version is released, and then declines fast at first and at a slow pace afterward. The steep slopes in both the increasing and decreasing phases following the release of a new version are clearly driven by the recurrent adopters. However, research on successive innovations [55] showed that the demand for an earlier generation continues to grow for a brief period after the introduction of a later one. This further suggests a difference between recurrent
innovations and classic successive innovations. For recurrent innovations, a newer generation influences the adoption of the previous generation instantly, as a new version of an app is able to replace an older one in the app market immediately (although older versions can be accessed in some markets or third-party services). For classic successive innovations, however, there can be latency in the distribution of the newest product while distributors may want to clear their inventory through promotions.

The curves eventually flatten out but surprisingly never reach zero, suggesting that a portion of adopters keep the current version and never adopt newer versions of the same app. Rula et al. [60] identified a notable percentage of requests that run out-of-date mobile apps from CDN logs, which supports the existence of such adopters. This new category of adopters is not covered by any theory of single innovations or successive innovations — we may call them preservers of an innovation.

### 4.3 New Types of Adopters

We observed a significant difference between the diffusion of recurrent innovations and that of single innovations and successive innovations. Specifically, we identified several novel categories of users that exist in the context of recurrent innovations:

- **Immediate-adopters:** These are recurrent adopters who promptly adopt a new innovation of the technology upon its release. In the context of mobile app updates, using a new version immediately upon its release suggests that such adopters are heavy users of this app and desire the app to be up-to-date no matter whether they have the auto-update option on or manually install/update the app. Note that in Rogers’ theory, innovators refer to adopters who want to be the first to try a brand new innovation, whereas in our work immediate-adopters have adopted an earlier version and are eager to adopt a newer version of the same technology.

- **Preservers:** These are adopters of one innovation of the technology who do not adopt newer innovations. They keep an old version (at least within the time frame of our dataset) despite the availability of newer versions. Note that the late majority and laggards in Rogers’ theory would eventually adopt an innovation, whereas for preservers we did not observe their adoption of a newer version in our dataset. In the scenario of mobile app updates, Rula et al. [60] used thresholds such as 100 days and 300 days to define out-of-date versions of mobile apps. Users who keep using these versions may be restricted by outdated devices and operating systems. In addition, preservers may also have the auto-update option off and control all app updates by themselves [52].

- **Retro-adopters:** Although most users eventually adopt newer versions of the technology, some users decide to roll back to an earlier version after adopting a new one. We refer to such users as retro-adopters. Taking mobile app users as an example, retro-adopters would need to manually install a historical version from third-party app markets or services.

It is worth mentioning that the three new categories, immediate-adopters, preservers, and retro-adopters, have never been covered by any existing diffusion theories. Indeed, these categories make sense only when there are multiple, successive innovations available. Moreover, although the specific adoption patterns could be different, the three new categories of adopters can be potentially generalized to all successive innovations. These categories haven’t been observed in existing work possibly due to the lack of fine-grained data on individual users’ adoption behaviors. Our finding suggests that the adopters of successive innovations should be revisited when data are available. The new categories of adopters represent a significant portion of users in our dataset. In our dataset, approximately 57% of versions are made up of more than 20%
immediate-adopters, whereas around 0.5% of versions have more than 20% retro-adopters. The proportion of preservers is even higher, with about 90% of versions having more than 20% preservers. We also found that there exist two types of preservers, including users who abandon the app entirely and users who continue to use the old versions. Both types of preservers do not adopt a newer version. Our analysis made critical discoveries that call for an update of the diffusion of innovation theory in the context of successive innovations and recurrent innovations.

4.4 Uniting Recurrent and Single Innovations

Despite the difference between recurrent innovations and single innovations, the two types of innovations can be unified at a higher level. In a longer time frame, if we view an app as an innovation, then the adoption of this innovation is made up of the adoptions of each of its versions. In other words, the diffusion of a technology over time can be decomposed into the diffusions of all of its recurrent innovations, except that in this case scenario the versions can overlap and interact with each other. Our analysis provides a lens for understanding the rises and falls of these recurrent innovations and their interactions at a finer granularity.

Figure 5 demonstrates the cumulative adopters of an app with the adopters of every version stacked on top of each other. At any time point, the height of each layer represents the market share of the corresponding version and the combined height of all layers represents the total number of users who have adopted the app. The stacked plot confirms the dual roles of a recurrent innovation. On the one hand, it transits existing adopters to the latest version (or occasionally to an earlier version). On the other hand, it draws new adopters and contributes to the increasing adoption of the technology as a whole. The envelope curve of the stacked layers indicates the cumulative adoption of the app in the observed population. However, such a curve does not necessarily follow the S-shape of that of a single innovation, since individual innovations of the technology (individual versions of an app) may have a different appeal or they may appeal to different segments of the population (because of the differences in features, bugs, or operating strategies). These differences open up new opportunities for innovation creators, disseminators, and even competitors.

To summarize, we observed novel and intriguing patterns in the adoption curves of recurrent innovations that the single and successive innovation adoption theory cannot explain. Specifically, we suggest three new categories of adopters to be added into the diffusion of innovation theories: immediate-adopters, preservers, and retro-adopters. While the adoption curves of recurrent innovations are more or less alike, variations exist among different versions of the same app, which implies that the adoption decisions vary per individual user and individual innovation.
Adoption of Recurrent Innovations: A Large-Scale Case Study on Mobile App Updates

Table 2. Features

| Dimension                  | Features                                                                 |
|----------------------------|--------------------------------------------------------------------------|
| D1: properties of the target app | # used days, avg. daily users, # monthly users, avg. daily co-used apps, # versions a month, # versions a quarter, avg. release interval, time of release |
| D2: the user’s interaction with the target app | prop. days using the app in the last week/2 weeks/1 month, # times using the app in the last week, time spent in the app in the last week; # days to adopt the last/second last/fourth last/eighth last version, freq. adopting the last eight versions, std. days to adopt the last eight versions |
| D3: characteristics of the user | # used apps, # active days, # times using apps, time spent in all apps, avg. days using other apps, avg. times using other apps, avg. time spent in other apps; #versions adopted, avg. days to adopt a version by app/version |

5 PREDICTION OF INDIVIDUAL ADOPTION DECISIONS

The analysis in Section 4 revealed differences in adoption behavior among different types of users and different versions of an app. Considering that user adoption of the latest version is vital for developer revenue and user safety, it is essential for developers and market maintainers to forecast user adoption. To further understand the variance in the individual decisions of adopting a recurrent innovation, we were interested in the following questions: is a user’s behavior of adopting a recurrent innovation predictable and, if yes, what kind of factors could explain the decision of adoption? Answers to such questions add value to the innovation diffusion literature and provide implications to developers.

We designed a prediction task to analyze the users’ adoption decisions: whether and how soon a user will adopt a specific version. We used a user’s time of first use of a version as the indicator of adoption. We set up the prediction tasks as follows: for each app that had released a new version in May 2019, we sampled its users who had actively used the app within 30 days prior to the new version release. We then attempted to predict whether these users would use this new version within 30 days (implying they had adopted it) and, if yes, when they would use it for the first time.

5.1 Feature Description

With the fine granularity of the data, we extracted three sets of features (see Table 2). The extracted features consider two key elements of Rogers’ theory: the target app (the technology) and the user (the adopter). All features are calculated using data from within 30 days prior to the release of the target version unless otherwise noted. Note that all features listed in Table 2 are extracted from the 5-tuple session data introduced in Section 3.

The first set of features represents the properties of the technology, that is, the app. These include its popularity: the monthly active days, the (average) daily active users, and monthly active users. Additionally, we extracted the average number of apps that the users of this app interact with on the same day (the number of co-used apps). We also characterized the updating history of the app, that is, the number of versions released in the past month and 3 months (number of versions) and the average interval between the last three releases. Finally, since the in-app usage differs over time [38, 40], the timing of releases might also affect the adoption behavior. Thus, we encoded the day of the week and hour of the day of the release as one-hot features.

The second set of features describes the adopters. From the dataset, we recorded how heavily users used their phone by measuring the number of apps they used, the number of days that they used any apps, the frequency of launching apps, and the total time spent in apps. Furthermore, we measured the per-app usage of other apps not focused on in the analysis by measuring the number of days, time length, and launching frequency. In addition, we measured users’ prior interaction with the recurrent innovations by measuring the number of versions they adopted and the average days to adopt a version.
Given the recurrent nature of the app version release, the last set of features characterizes the users’ interactions with the app prior to the release, including how they used the app and how they adopted prior versions of the app. We measured how adopters used the app using the proportion of days using the app within the most recent week, 2 weeks, and month, the frequency of launching the app, and the total time spent in the app in the recent week. We measured how adopters adopted prior versions of the app using the adoption interval between the release and the adoption of the first, second, fourth, and eighth most recent updates. We also used the likelihood of adopting the last eight versions and the standard deviation of the adoption interval.

5.2 Experiment Setups

5.2.1 Data Preprocessing. To ensure internal validity, we took a few steps prior to conducting the analysis. We selected apps with at least 500 users and versions with at least 100 users in order to reduce noise and filter out test versions. For each app, we set the first version as the version released in May 2019 and only users with active usage logs since April 1, 2019. By cleaning the data in this way, 4,955 different versions and 8,248,388 users were examined in the analysis. Since the official release time is not obtainable due to app anonymity, we set the version release time to the time when the fiftieth user adopted the release. Finally, because the number of users varies a lot across different versions, we adopted a down-sampling strategy to make each version comparable. Specifically, we selected one-third of all versions with the most users to balance the number of versions and the users of each version. This left 1,651 app versions and 1,063,244 observations for the “adopt-or-not” classification, among which 222,432 observations are positive and thus used in the “time-to-adopt” regression. For both tasks, we randomly split the dataset into 80% training and 20% test sets, and applied 5-fold cross-validation on the training set for tuning hyperparameters.

5.2.2 Feature Selection. In practice, some features are likely to be highly correlated with one another, leading to multicollinearity issues that deteriorate the interpretation of the linear models. Following the standard practice, we calculated the pair-wise Pearson coefficient between all pairs of features, except the one-hot features, on the training sets and carefully selected features so that the correlation coefficients between any of them are not higher than 0.7 [13]. We repeated the process for both the classification and the regression tasks. Eventually, we obtained 17 features for both tasks to feed into linear models.

5.2.3 Model Selection. For the classification task, we selected two models: gradient boosting decision tree (GBDT) and logistic regression. We selected four models for the regression task: gradient boosting regression tree (GBRT), ordinary least squares (OLS) regression, ridge regression, and lasso regression. This combination of models was selected because of their performance in similar research tasks (such as app adoption prediction [39]) and their ability to report the effect and significance of different features (see details in Section 5.3.2 and Section 6.2). We used LightGBM\(^9\) for GBDT/GBRT and statsmodels\(^10\) for the other models.

5.2.4 Evaluation Metrics. We used the area under curve (AUC) score and accuracy to evaluate the classification model performance. A larger AUC or a larger accuracy indicates better classification results. We leveraged the majority guess as the baseline. For the regression models, we selected the root mean squared error (RMSE) score and R-Squared as evaluation metrics. A smaller RMSE score and a larger R-squared indicate a better model in the regression tasks.

\(^9\)https://lightgbm.readthedocs.io/en/latest/
\(^10\)https://www.statsmodels.org/stable/index.html
Table 3. Performance of Adopt-or-Not Classifications

|       | AUC   | Accuracy |
|-------|-------|----------|
| GBDT  | 0.8813| 0.8488   |
| LR    | 0.7542| 0.7970   |
| Baseline | 0.5000 | 0.7682 |

Table 4. Performance of Time-to-Adopt Regressions

|       | RMSE  | $R^2$   |
|-------|-------|---------|
| GBDT  | 6.1936| 0.2685  |
| OLS   | 6.8329| 0.1097  |
| Ridge | 6.8330| 0.1097  |
| Lasso | 6.8662| 0.1010  |

5.3 Results

5.3.1 Model Performance. Table 3 shows that both the GBDT and LR models outperform the baseline model in terms of AUC and accuracy. The GBDT model performs the best with an AUC of 0.8813 and an accuracy of 0.8488. This result indicates that the proposed features can be used well by machine learning methods, such as GBDT, to distinguish adopters and non-adopters of a new version.

Table 4 presents the results of the regression task that predicts how long it takes an adopter to update to a new version. Among the four models, the GBDT model achieves the best performance with an $R^2$ of 0.2685 and an RMSE of 6.1936. This result implies that the GBDT model is adequate for the proposed features. The RMSE for predicting the number of days after the release when a user adopts the version is around six, indicating that the period is within a week.

After we saw the predictive powers of the selected features, we further explored the significance of features in the prediction tasks and investigated how they relate to adoption.

5.3.2 Feature Interpretation. We relied on the feature importance scores generated by the GBDT models to select features of interest and the coefficients of features from the linear regression models to understand the direction of the effect. Figures 6 and 7 show several important features for the classification and regression tasks, respectively. Detailed results are in Table 5 in Appendix A.

It can be observed that quite a few features are important in both tasks, which is reasonable as they both reflect the attitude and decision of users in adopting a version. The most important features in the two tasks are from the third dimension, how users interact with the app, with a slight difference in ranking. As for the “adopt-or-not” classification, the most important feature, the frequency of adopting the last eight versions, indicates one’s tendency to adopt versions of this app or the user’s innovativeness. The positive sign of its coefficient in linear regression further indicates that users who have adopted more historical versions of an app also tend to adopt its new version (evidence of recurrent adopters). The most important feature in the “time-to-adopt” regression is the number of days one used the app in the last 2 weeks, followed by the number of days one used the app in the last week. As is reported in Figure 7(b), such features are negatively related to the time to adopt, indicating that if a user is to adopt a new version, a user using the app more frequently will adopt the new version sooner (evidence of immediate-adopters).

The next level of important features are from the first dimension. They describe the properties of the target app, among which the average release interval is the most important for both tasks. A
larger release interval, which means a less frequent release pattern, is related to a higher tendency of adoption and a shorter interval for the users to adopt the version. This finding provides direct insights for mobile app developers in their design of release plans, such as adjusting the release frequency of new versions.

Features such as the number of used apps, the number of active days, the time spent in all apps, etc., also have predictive power. Users using more apps are less likely to adopt a new version and, if they do, it will take more time for them to adopt it (evidence of preservers and that preservers might preserve multiple apps). Additionally, more active days of using any of the apps represent the frequency of using their mobile phone, which is positively related to the adoption decision and negatively related to the days to adopt (a faster adoption). For app developers, aside from promoting user engagement in their own apps, they can also consider collaborating with other apps\(^\text{11}\) to enhance the overall activeness of their adopters in mobile phone usage.

These findings reveal that, in addition to inherent characteristics of the innovation and the adopters, the patterns in the previous versions of a recurrent innovation, including how they were released, how users adopted them, and how adopters interacted with them, can affect users’ decisions regarding adoption.

\(^{11}\)For example, Genshin Impact, a famous action role-playing game, cooperated with Alipay, a third-party mobile payment platform on September 22, 2022. Users can obtain game skin, primogem, and other rewards in the game if they join the activity held by Alipay.
6 UNDERSTANDING THE SPECIAL ADOPTERS

As discussed in Section 4, we propose the existence of three special groups of adopters of recurrent innovations. The characteristics of such adopters (i.e., to adopt or reject an innovation in a different way) provide a chance to mitigate the pro-innovation bias [58] and individual-blame bias, which is the belief that all innovations are assumed positive and should be adopted and the bias of diffusion research that tends to side with the innovator creators while ignoring the audience, respectively. The immediate-adopters who adopted the recurrent innovation quickly suggest they have positive attitudes towards the innovation. The preservers who stayed with the previous innovations showed their loyalty to that specific version or negative attitudes towards the subsequent innovations since they refused to adopt the newest innovation. The retro-adopters who rolled back to previous versions suggest negative attitudes towards the new innovation. Unlike other adopters, the behaviors of adopters in these three categories provided a valuable opportunity to understand polarized opinions towards innovations.

To better understand the special categories of adopters, and hopefully the rationale behind their adoption behaviors, we conducted a correlation analysis between the adoption and the features proposed in Section 5.1 for the three types of adopters. We used 1,651 versions and their corresponding users discussed in Section 5.2 to analyze immediate-adopters and preservers, and a total of 4,995 versions to analyze retro-adopters.

6.1 Adopter Selection

We employed the following criteria to identify the three special types of adopters. To define immediate-adopters, we assessed the sample of versions to identify where the first peak of adoption occurred. In our dataset, 76.73% of versions achieve their first peak within 1 day in the time-of-adoption curve of their recurrent adopters (as illustrated in Figure 3(b)). Based on this observation, we set a threshold of 1 day to adopt to classify the immediate adopters. Using this criterion, our dataset had 53,858 positive observations and 168,574 negative observations. Then, if a user adopted only the first version of an app, which has had more than one version since May 1, 2019, and kept using that first version, the user was classified as a preserver of the first version. We obtained 75,454 positive observations of preservers. We randomly sampled 126,812 negative observations from users who adopted more than one version. Finally, users who adopted a previous version of an app after they had adopted a newer version are considered retro-adopters. We found 19,359 positive observations of retro-adopters and randomly selected 80,000 negative observations from those who did not adopt a previous version.

6.2 Correlation Analysis

In Section 5.3, we analyzed features describing users’ interactions with the target app and identified important features in the “adopt-or-not” and “time-to-adopt” predictions. Motivated by this finding, we selected typical features from this dimension, \(#\text{days to adopt the last version}\) and \(\text{time spent in the app during the last week}\), and explored the potential correlations between the adoption behaviors and the features for each adopter category. Results are shown in Figures 8 and 9.

- **Correlation with the previous adoption.** For all users, the days to adopt the previous version and the days to adopt the target version are positively correlated (see Figure 8(a)). The pattern in immediate-adopters (Figure 8(b)) complied with this finding, as users who take more days to adopt the previous version were less likely to be immediate-adopters of the new version. Figure 8(c) shows that users who took more days to adopt the previous version are more likely to be a preserver of the target version. This is quite reasonable as they could also take a long time to adopt the version subsequent to the target version. The bins in Figure 8(d) show a V-shape pattern, indicating that users who take a very short time or a very long time to adopt the previous version are more likely...
to be retro-adopters. This pattern suggests that immediate-adopters who adopt a version quickly could also decide to roll back to a previous version, while late adopters may have a low level of tolerance to changes.

- **Correlation with the previous usage.** When considering the time a user spent in an app, we observed consistent patterns in its relation to the number of days to adopt (Figure 9(a)), the probability of being an immediate-adopter (Figure 9(b)), and the probability of being a preserver (Figure 9(c)). Logically, this correlation could be explained since users who spend more time in the app are more likely to quickly know that the app can be updated and adopt the updates sooner. Figure 9(d) shows that the probability of a user being a retro-adopter stayed stable with the change in usage time during the previous week, with exceptions at both ends. It could be inferred from the pattern that heavy users of the previous version have weak adaptability to the changes in the target new version, whereas the very light users might be unfamiliar with the app and prefer returning to previous versions.

This analysis provides insights about the behavior of immediate-adopters, preservers, and retro-adopters. More importantly, the clear patterns shown in the correlations suggest that these special adoption behaviors could be sensed and explained by our proposed features.

7 DISCUSSION

In this section, we discuss the implications of our study from both theoretical and practical perspectives, followed by the limitations. We also suggest future research directions based on our findings and existing literature.

7.1 Implications

7.1.1 **Theoretical Implications.** Our study has a number of theoretical implications. We introduced the term recurrent innovations to differentiate from the successive innovations [24, 26, 41, 48, 54, 55] in the literature, with a recurrent innovation’s most observable characteristic being a high update frequency. Distributed by the Internet and Web services, recurrent innovations can be adopted quickly at a relatively low cost, and users’ actual usage behavior (instead of just buying the product) contributes significantly to the creator’s revenue and further development. Such unique characteristics could contribute to a different diffusion process. Indeed, we found that the
cumulative adopters of recurrent innovations showed a distinct pattern from traditional successive innovations (see Section 4.2). This is understandable, as the newest app version can quickly replace older ones in app markets, whereas retailers of other successive innovations, such as the iPhone, may have to deal with inventory and practice a promotional strategy [55]. Our work provides a new perspective for researchers to model innovations that are released recurrently and with adoption behaviors in different fields. Our findings also imply the need to generalize recurrent innovations and extend the theory. We hope our results provide insights for innovation researchers to model the observable differences between recurrent innovations and traditional successive innovations, to reason the difference in diffusion patterns, and to advance the definition of (recurrent) innovations, which is significant, especially in the digital era.

With the testbed of app versions as one of the most typical recurrent innovations, we made basic observations of the patterns of new adopters and recurrent adopters. For example, while the adoption patterns of new adopters followed Rogers’ theory [58], recurrent adopters exhibited distinct patterns. However, due to the lack of profile details of adopters, such as their device model and mobile OS systems, the specific marketplace used for app management, and their demographic information, a more detailed analysis of different adoption patterns across such groups was not feasible in this work. We leave this for future work when data are available. Furthermore, the patterns shared between app versions and other types of recurrent innovations (e.g., Android and Chrome in Figure 1) show the possibility of generalizing our findings to other types of recurrent innovations. More research efforts are required to understand the adoption process of recurrent innovations in other domains.

Our analysis led to the identification of three new categories of adopters: immediate-adopters, preservers, and retro-adopters, which have never been covered by existing diffusion theories [54, 55, 58]. These categories of adopters may exist only when multiple, successive innovations are available, as in our analysis of mobile app versions. Although these new categories were studied within only one type of recurrent innovation (i.e., mobile apps), it is reasonable to generalize these findings to other recurrent innovations and, more broadly, to successive innovations, provided that consumers are able to choose between different generations of a technology. Innovation researchers should consider verifying this idea with recurrent/successive innovations from diverse domains with an advanced and comprehensive framework of innovation diffusion. This may lead to an extension of Rogers’ theory [58] or a new model that can capture the impact of the new adopter categories on the diffusion of innovations proposed in this study.

With the user-level data of adoption behaviors, we were able to identify the special groups of adopters and their characteristics, which may provide a chance to mitigate the pro-innovation bias [58] and the individual-blame bias [58] in existing diffusion theories (see Section 6). In the context of recurrent innovations, consumers have multiple choices of innovations (e.g., different versions of an app) and even multiple choices of technologies (e.g., different apps with similar functions). Thus, it is essential not to assume that every innovation is positive and should be adopted (i.e., pro-innovation bias). Moreover, user modeling and understanding have been a research focus in mobile app development, and we achieved decent prediction results based on features from only usage behaviors. This further implies that diffusion research should consider individual user attributes and behaviors rather than siding with the innovation creators (i.e., individual-blame basis).

The goal of our work was to explore the validity of existing theories of innovation diffusion in the context of recurrent innovations. As the first effort in this direction, our work shows that Rogers’ theory can partly explain the adoption patterns in recurrent innovations. Further development and refinement are required to effectively accommodate the distinction of recurrent innovations.
7.1.2 Practical Implications. We summarize the practical implications as follows. The observed adoption patterns and adopter categories provide a unique lens for user profiling so that app developers can prioritize the development accordingly to meet the demands of different user groups. Recall that adoption was measured by usage behavior, indicating that the adoption patterns directly relate to users’ in-app engagement, and can further impact apps’ revenue from in-app purchases and ads. For example, when there occur significantly more retro-adopters after a certain version, developers should pay attention to locating and addressing the possible issue with the new version to retain users. Similarly, when preservers that haven’t adopted a new version for a long time accumulate to a certain amount, app designers should consider ways to encourage or force such users to the most recent version of their app.

Our work showed that the adoption of recurrent innovations is predictable with fine-grained usage data. Being able to predict whether and when a user will adopt a specific version can help app developers optimize their development strategies. For example, for beta testing [21] of a new version, app developers can target a higher proportion of immediate-adopters to shorten the testing cycle. The prediction results can also help with app promotion [23], which often accounts for considerable marketing expenses [10, 12]. In distribution channels such as app markets, developers have the opportunity to implement a dynamic advertising strategy using the predicted attitudes of users. This strategy enables them to target potential adopters from various categories at different time intervals, ultimately enhancing the return on investment (ROI) from their marketing expenses.

The prediction results can estimate the overall adoption rate over time. Knowing the adoption rate in advance can help innovation creators optimize their release strategy [41, 69]. For example, the prediction of telecommunication markets can be useful for purposes such as planning the provision of plants and switching equipment [47]. Regarding mobile app updates, accurately predicting the rate at which they will be adopted over time is vital for developers to allocate server bandwidth effectively. Furthermore, such predictions enable effective planning for future releases by ensuring that a desired proportion of users have already adopted the current version before the next release, which, in turn, benefits app maintenance.

Finally, the interpretation of features by our prediction models can provide valuable insights for developers, helping them increase adoption and in-app engagement rates. Our models identified a few factors that can potentially impact user adoption, such as the app’s average release interval and the user’s recent time spent on the app. This knowledge can assist app developers in identifying and addressing issues that may deter users from adopting the app, allowing them to make the necessary improvements to boost the adoption process. For instance, developers should consider maintaining a relatively low frequency of version releases since it is positively related to adoption decisions and negatively related to the time users take to adopt. Additionally, developers can offer personalized services to encourage more frequent app usage, which can lead to higher in-app engagement and improve adoption rates for new versions. This, in turn, can enhance the app revenue through various means, such as newly developed content for in-app purchases and optimized ad display. These measures can also help reduce the cost associated with maintaining older versions of the app.

7.2 Limitations

Our study carries several limitations. First, this work focuses on one kind of recurrent innovation; therefore, the results and findings cannot be directly generalized to other domains and broader successive innovations. Considering the natural difference between different kinds of innovations, such as the distribution method (i.e., physically or digitally distributed) and the price of the innovation, the adoption process and the factors that affect the adoption process can be quite different.
However, our study provides a systematic look at a very typical kind of recurrent innovation and provides a foundation for future analysis of other kinds of recurrent innovations (and successive innovations) when data are available. Second, because the dataset is collected by a third-party business intelligence service provider, only apps that use their service are included. This inclusion criterion may introduce a bias in the features used to characterize user interactions with other apps. Additionally, some meta information (such as app names, the type of updates, and the app market used to download the app) is not available in our dataset, which limits further understanding of the observed patterns. However, we argue that by carefully describing apps and their updates with user behavior data, our study has already provided a first and systematic view of the adoption of recurrent innovations using a large-scale dataset. It is feasible for app owners to compare the adoption patterns of their app to the general patterns derived in this article and improve their development and update strategies.

7.3 Future Research Directions

Based on the literature on innovation diffusion, we suggest the following potential future related research directions:

- **Application to specific domains.** Researchers of diffusion of innovation have applied the diffusion models in different disciplines, such as medical sociology [8], cultural anthropology [3], industrial economics, [45] and health care [11]. Recurrent innovations could be observed in any technology where innovations are updated recurrently, including various fields ranging from mobile apps to neural network development. Exploring diffusion patterns of recurrent innovations in such domains would be crucial for different stakeholders, help enhance the understanding of the nature of recurrent innovations, and enrich the diffusion of innovation theory.

- **Characteristics of innovations.** The characteristics of innovations or technologies can impact the adoption process and are one of the key elements in innovation diffusion research. Research efforts have identified the characteristics of innovations from multiple aspects, including relative advantage, compatibility, complexity, trialability, observability, and reinvention [19, 58]. In the context of recurrent innovations, we explored how attributes of mobile apps and their versions (such as app popularity, release frequency, and release time) influence user adoption. Beyond the attributes of mobile apps distilled from our dataset, more research on the innovations themselves is needed to promote the understanding of recurrent innovations and their diffusion. The characteristics to be further studied can include the risk of technologies [5], the compatibility of technologies on different hardware [60], the usability of technologies [35, 67], and the explicit update contents of technologies [70].

- **Characteristics of adopters.** The characteristics of adopters is another key element of diffusion of innovation [58]. In this work, we described the adopters with their interactions with apps and their history of version adoption. We found distinguishable differences between new adopters, existing adopters, and three categories of adopters with unique adoption patterns. Future analysis could be conducted to determine whether such patterns could be explained by other characteristics of the adopters, such as their demographics and personality, understand the innovativeness [58] of adopters towards recurrent innovations, identify the role of different adopters in the diffusion process of recurrent innovations, and determine how adopters’ attitudes towards the innovation (e.g., innovation anxiety [1] and mental depreciation regarding outdated innovations [43]) influence their adoption behaviors. Such questions need to be answered to portray the adopters of recurrent innovations more comprehensively.

- **Communication channels.** Communication channels also influence the spread of an innovation [58]. In our case of mobile app updates, the communication channels could be the apps themselves as they can send notifications to mobile users, the app markets where users can be
notified of new updates, and advertisements in various media. How the different channels and dissemination strategies applied in the channels influence the diffusion of the recurrent innovations needs to be studied.
• **Diffusion in social networks.** The impact of social influence on the dynamics of diffusion has been extensively explored [27, 65] from multiple aspects, including the local network structure, the characteristics of adopted neighbors, the distance to opinion leaders, etc., in the interpersonal networks. Such factors can also influence the diffusion of recurrent innovations.
• **Competition and collaboration of innovations.** Innovations could have competitors and collaborators. Taking the mobile apps as an example, apps with similar functions could be competitors of each other, while an app can collaborate with other apps in ways such as integrating a login authentication service provided by a social network app. Given that the interactions between innovations show an effect on the diffusion of innovations [2, 18, 59, 64, 68], they could also influence the diffusion of recurrent innovations, which is worthy of further study.

8 CONCLUSION

In this article, we presented the first large-scale analysis of the adoption of recurrent innovations in the context of mobile app updates. Our analysis revealed novel patterns of crowd-adopting behaviors with millions of users who consumed the many versions of thousands of Android apps. We identified new categories of adopters to be considered in addition to Rogers’ model of innovation diffusion: immediate-adopters, preservers, and retro-adopters. Furthermore, we showed that standard machine learning models are able to predict users’ decision to adopt a new version of an app by picking up various sources of signals from three groups of features: the properties of the technology, the characteristics of the adopter, and how the adopter interacts with the recurrent innovations of the technology.
APPENDIX

A RESULTS OF ADOPTION BEHAVIOR PREDICTION

Table 5. The Importance and Coefficients of Features in the Classification of Adoption Task and Regression of Adoption Task

| Feature                                           | Classification | Regression |
|---------------------------------------------------|----------------|------------|
|                                                  | GBDT           | LR         | GBDT      | LR          | Ridge    | Lasso    |
| # used days                                       | 0.0514**       | 0.0006***  | 2.8254*** | 2.7543***   | 5.4293*** | 5.5864***|
| avg. daily users                                  | 0.0556**       | 0.0497***  | 5.4351*** | 5.4293***   | 5.5864*** | 5.4293***|
| # monthly users                                   | 0.0543**       | 0.0399***  | 2.0170    | 2.0170      | 2.0170    | 2.0170    |
| avg. daily co-used apps                           | 0.0566**       | 0.0434***  | −0.9210***| −2.6372***  | −6.2233***| −6.3201***|
| # versions a month                                | 0.0120*        | 0.0135**   | −2.3572***| −2.6233***  | −6.3201***| −6.3201***|
| # versions a quarter                              | 0.0175         | 0.0175***  | −0.9210***| −2.6372***  | −6.2233***| −6.3201***|
| avg. release interval                             | 0.0587**       | 0.0355***  | −2.1822***| −2.6560***  | 0.9868*** | 0.9868***|
| time of release                                   |                |            |           |             |          |          |
| prop. days using the app in the last week         | 0.0322         | 1.6085***  | 0.0770    | −5.1717***  | −5.1756***| −5.6423***|
| prop. days using the app in the last 2 weeks      | 0.0777         | 0.0972***  | 0.0777*** | 0.0972***   | 0.0972*** | 0.0972***|
| prop. days using the app in the last month        | 0.0527         | 0.0620***  | 0.0527*** | 0.0620***   | 0.0620*** | 0.0620***|
| # times using the app in the last week            | 0.0145         | 0.0691***  | 0.0145*** | 0.0691***   | 0.0691*** | 0.0691***|
| time spent in the app in the last week            | 0.0294*        | 0.0551**   | −2.9242***| −2.9260***  | −2.9260***| −2.5028***|
| # days to adopt the last version                  | 0.0720**       | 0.0625***  | 9.6361*** | 9.6361***   | 9.4992*** | −0.5172  |
| # days to adopt the second to the last version    | 0.0307*        | 0.0326**   | 16.2809***| 16.2809***  | 16.0200***| 1.2890** |
| # days to adopt the fourth to the last version    | 0.0119         | 0.0163**   | 10.0890***| 10.0890***  | 9.9434*** | 4.3276***|
| # days to adopt the eighth to the last version    | 0.0057*        | 0.0070**   | 7.9489*** | 7.9489***   | 7.7559*** | −3.7478***|
| freq. adopting the last eight versions            | 0.1088         | 3.0095***  | 0.0176    | −1.1999***  | −1.2083***| −1.5455***|
| std. days to adopt the last eight versions        | 0.0627         | 1.1512***  | 0.0730    | 6.2950***   | 6.3635*** | 10.9795***|
| # used apps                                       | 0.0147−0.3030***| 0.0102***  | 4.9629*** | 4.9237***   | 5.1834*** | 5.1834***|
| # active days                                     | 0.0094         | 0.5066***  | 0.0100    | −1.1780***  | −1.1767***| −1.4150***|
| # times using apps                                | 0.0018         | 0.0186***  | 0.0018*** | 0.0186***   | 0.0186*** | 0.0186***|
| time spent in all apps                            | 0.0208         | 0.0187***  | 0.0208*** | 0.0187***   | 0.0187*** | 0.0187***|
| avg. days using other apps                        | 0.0184−0.1418***| 0.0158**   | 0.8631*** | 0.8571***   | 0.7096*** | 0.7096***|
| avg. times using other apps                       | 0.0164         | 0.0164***  | 0.0164*** | 0.0164***   | 0.0164*** | 0.0164***|
| avg. time spent in other apps                     | 0.0177         | 0.0000***  | 0.0177*** | 0.0000***   | 0.0459*** | 0.4820**|
| #versions adopted                                 | 0.0183         | 0.0163***  | 0.0183*** | 0.0163***   | 0.0163*** | 0.0163***|
| avg. days to adopt a version by app               | 0.0212         | 0.3484***  | 0.0180    | 7.2427***   | 7.1126*** | 1.8368** |
| avg. days to adopt a version by version            | 0.0207         | 0.2027***  | 0.0180    | 7.2427***   | 7.1126*** | 1.8368** |

(Significant at the: *5%, **1%, or ***0.1% level.)

REFERENCES

[1] David Agogo and Traci J. Hess. 2018. “How does tech make you feel?” A review and examination of negative affective responses to technology use. Eur. J. Inf. Syst. 27, 5 (2018), 570–599.
[2] Noga Alon, Michal Feldman, Ariel D. Procaccia, and Moshe Tennenholtz. 2010. A note on competitive diffusion through social networks. Inform. Process. Lett. 110, 6 (2010), 221–225.
[3] H. G. Barnett. 1963. Innovation: The Basis of Cultural Change. McGraw-Hill.
[4] Frank M. Bass. 1969. A new product growth for model consumer durables. Management Science 15, 5 (1969), 215–227.
[5] Dario Bonaretti and Diana Fischer-Preßler. 2021. Timeliness, trustworthiness, and situational awareness: Three design goals for warning with emergency apps. In Proceedings of the 42nd International Conference on Information Systems. 1–17.
[6] Holger Bonus. 1973. Quasi-Engel curves, diffusion, and the ownership of major consumer durables. Journal of Political Economy 81, 3 (1973), 655–677.
[7] Chen-Fu Chien, Yun-Ju Chen, and Jin-Tang Peng. 2010. Manufacturing intelligence for semiconductor demand forecast based on technology diffusion and product life cycle. International Journal of Production Economics 128, 2 (2010), 496–509.
[8] James Coleman, Elihu Katz, and Herbert Menzel. 1957. The diffusion of an innovation among physicians. Sociometry 20, 4 (1957), 253.
[9] Peter J. Danaher, Bruce G. S. Hardie, and William P. Putsis Jr. 2001. Marketing-mix variables and the diffusion of successive generations of a technological innovation. Journal of Marketing Research 38, 4 (2001), 501–514.
[10] data.ai. 2023. State of Mobile 2023. https://www.data.ai/en/go/state-of-mobile-2023/

[11] James W. Dearing and Jeffrey G. Cox. 2018. Diffusion of innovations theory, principles, and practice. Health Affairs 37, 2 (2018), 183–190.

[12] Artem Dogtiev. 2023. App Marketing Costs (2023). https://www.businessofapps.com/marketplace/app-marketing/research/app-marketing-cost/

[13] Carsten F. Dormann, Jane Elith, Sven Bacher, Carsten Buchmann, Gudrun Carl, Gabriel Carré, Jaime R. Garcia Marquéz, Bernd Gruber, Bruno Lafourcade, Pedro J. Leitao, et al. 2013. Collinearity: A review of methods to deal with it and a simulation study evaluating their performance. Ecography 36, 1 (2013), 27–46.

[14] Marlene Lynette East and Byron C. Havard. 2015. Mental health mobile apps: from infusion to diffusion in the mental health social system. JMIR Mental Health 2, 1 (2015), e10.

[15] Denzil Ferreira, Jorge Goncalves, Vassilis Kostakos, Louise Barkhuus, and Anind K. Dey. 2014. Contextual experience sampling of mobile application micro-usage. In Proceedings of the 16th International Conference on Human-Computer Interaction with Mobile Devices & Services. 91–100.

[16] Robert G. Fichman, Brian L. Dos Santos, and Zhiqiang (Eric) Zheng. 2014. Digital innovation as a fundamental and powerful concept in the information systems curriculum. MIS Quarterly 38, 2 (2014), 329–A15.

[17] Remo Manuel Frey, Runhua Xu, and Alexander Ilic. 2017. Mobile app adoption in different life stages: An empirical analysis. Pervasive and Mobile Computing 40 (2017), 512–527.

[18] Sanjeev Goyal, Hoda Heidari, and Michael Kearns. 2019. Competitive contagion in networks. Games and Economic Behavior 113 (2019), 58–79.

[19] Trisha Greenhalgh, Robert Glenn, Fraser Macfarlane, Paul Bate, and Olivia Kyriakidou. 2004. Diffusion of innovations in service organizations: Systematic review and recommendations. The Milbank Quarterly 82, 4 (2004), 581–629.

[20] Margarita Grinko, Marc-André Kaufhold, and Christian Reuter. 2019. Adoption, use and diffusion of crisis apps in Germany: A representative survey. In Proceedings of Mensch and Computer 2019. 263–274.

[21] Apple Inc. 2023. Beta testing made simple with TestFlight. https://developer.apple.com/testflight/

[22] Apple Inc. 2023. Engaging users with app updates. https://developer.apple.com/app-store/app-updates/

[23] Apple Inc. 2023. Promoting your apps. https://developer.apple.com/app-store/promote/

[24] Towhidul Islam and Nigel Meade. 1997. The diffusion of successive generations of a technology: A more general model. Technological Forecasting and Social Change 56, 1 (1997), 49–60.

[25] Zhengrui Jiang and Dipak C. Jain. 2012. A generalized Norton-Bass model for multigeneration diffusion. Management Science 58, 10 (2012), 1887–1897.

[26] Duk Bin Jun and Yoon S. Park. 1999. A choice-based diffusion model for multiple generations of products. Technological Forecasting and Social Change 61, 1 (1999), 45–58.

[27] Zsolt Katona, Peter Pal Zubcesek, and Miklos Sarvary. 2011. Network effects and personal influences: The diffusion of an online social network. Journal of Marketing Research 48, 3 (2011), 425–443.

[28] Robert J. Kauffman and Angsana A. Techatassanasoontorn. 2005. International diffusion of digital mobile technology: A coupled-hazard state-based approach. Information Technology and Management 6, 2–3 (2005), 253–292.

[29] Marc-André Kaufhold, Jasmin Haunschild, and Christian Reuter. 2020. Warning the public: A survey on attitudes, expectations and use of mobile crisis apps in Germany. In 28th European Conference on Information Systems. 1–12.

[30] Namwoon Kim, Dae Ryon Chang, and Allan D. Shocker. 2000. Modeling intercategory and generational dynamics for a growing information technology industry. Management Science 46, 4 (2000), 496–512.

[31] Rajiv Kohli and Nigel P. Melville. 2019. Digital innovation: A review and synthesis. Information Systems Journal 29, 1 (2019), 200–223.

[32] Paul Krebs and Dustin T. Duncan. 2015. Health app use among US mobile phone owners: A national survey. JMIR mHealth uHealth 3, 4 (2015), e101.

[33] Victor B. Kreng and Bang Jyun Wang. 2013. An innovation diffusion of successive generations by system dynamics—an empirical study of Nike Golf Company. Technological Forecasting and Social Change 80, 1 (2013), 77–87.

[34] Huoran Li, Wei Ai, Xuanzhe Liu, Jian Tang, Gang Huang, Feng Feng, and Qiaozhu Mei. 2016. Voting with their feet: Inferring user preferences from app management activities. In Proceedings of the 25th International Conference on World Wide Web. 1351–1362.

[35] Tong Li, Mingyang Zhang, Hancheng Cao, Yong Li, Sasu Tarkoma, and Pan Hui. 2020. “What apps did you use?”: Understanding the long-term evolution of mobile app usage. In Proceedings of The Web Conference 2020. 66–76.

[36] Ting-Peng Liang, Chen-Wei Huang, Yi-Hsuan Yeh, and Binshan Lin. 2007. Adoption of mobile technology in business: A fit-viability model. Industrial Management & Data Systems 107, 8 (2007), 1154–1169.

[37] M. J. Liberatore and D. Brem. 1997. Adoption and implementation of digital-imaging technology in the banking and insurance industries. IEEE Transactions on Engineering Management 44, 4 (1997), 367–377.

[38] Xuanzhe Liu, Huoran Li, Xuan Lu, Tao Xie, Qiaozhu Mei, Feng Feng, and Hong Mei. 2017. Understanding diverse usage patterns from large-scale appstore-service profiles. IEEE Transactions on Software Engineering 44, 4 (2017), 384–411.
Adoption of Recurrent Innovations: A Large-Scale Case Study on Mobile App Updates 13:25

[39] Xuan Lu, Zhenpeng Chen, Xuanzhe Liu, Huoran Li, Tao Xie, and Qiaozhu Mei. 2017. PRADO: Predicting app adoption by learning the correlation between developer-controllable properties and user behaviors. Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies 1, 3 (2017), 1–30.

[40] Yun Ma, Ziniu Hu, Dianqian Gu, Li Zhou, Qiaozhu Mei, Gang Huang, and Xuanzhe Liu. 2020. Roaming through the castle tunnels: An empirical analysis of inter-app navigation of Android apps. ACM Transactions on the Web 14, 3 (2020), 14:1–14:24.

[41] Vijay Mahajan and Eitan Muller. 1996. Timing, diffusion, and substitution of successive generations of technological innovations: The IBM mainframe case. Technological Forecasting and Social Change 51, 2 (1996), 109–132.

[42] Alwin Mahler and Everett M. Rogers. 1999. The diffusion of interactive communication innovations and the critical mass: The adoption of telecommunications services by German banks. Telecommunications Policy 23, 10 (1999), 719–740.

[43] Tamar Makov and Colin Fitzpatrick. 2021. Is repairability enough? Big data insights into smartphone obsolescence and consumer interest in repair. Journal of Cleaner Production 313 (2021), 127561.

[44] Daniel J. Mallinson. 2016. Building a better speed trap: Measuring policy adoption speed in the American states. State Politics & Policy Quarterly 16, 1 (2016), 98–120.

[45] Edwin Mansfield. 1985. How rapidly does new industrial technology leak out? The Journal of Industrial Economics 34, 2 (1985), 217–223.

[46] Arunesh Mathur and Marshini Chetty. 2017. Impact of user characteristics on attitudes towards automatic mobile application updates. In Proceedings of the 13th Symposium on Usable Privacy and Security. 175–193.

[47] Nigel Meade and Towhidul Islam. 1995. Forecasting with growth curves: An empirical comparison. International Journal of Forecasting 11, 2 (1995), 199–215.

[48] Nigel Meade and Towhidul Islam. 2006. Modelling and forecasting the diffusion of innovation — A 25-year review. International Journal of Forecasting 22, 3 (2006), 519–545.

[49] Andreas Möller, Florian Michahelles, Stefan Diewald, Luis Roalter, and Matthias Kranz. 2012. Update behavior in app markets and security implications: A case study in Google Play. In Research in the LARGE: Proceedings of the 3rd International Workshop. 3–6.

[50] Elizabeth L. Murnane, Saeed Abdullah, Mark Matthews, Matthew Kay, Julie A. Kientz, Tanzeem Choudhury, Geri Gay, and Dan Cosley. 2016. Mobile manifestations of alertness: Connecting biological rhythms with patterns of smartphone app use. In Proceedings of the 18th International Conference on Human-Computer Interaction with Mobile Devices and Services. 465–477.

[51] Elizabeth L. Murnane, David Huffaker, and Gueorgi Kossinets. 2015. Mobile health apps: Adoption, adherence, and abandonment. In Adjunct Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2015 ACM International Symposium on Wearable Computers. 261–264.

[52] Maleknaz Nayebi, Bram Adams, and Guenther Ruhe. 2016. Release practices for mobile apps — what do users and developers think?. In Proceedings of the 23rd International Conference on Software Analysis, Evolution, and Reengineering. 552–562.

[53] Robert Nickerson, Mark Austreich, and Jamie Eng. 2014. Mobile technology and smartphone apps: A diffusion of innovations analysis. In Proceedings of the 20th Americas Conference on Information Systems. 183–194.

[54] John A. Norton and Frank M. Bass. 1987. A diffusion theory model of adoption and substitution for successive generations of high-technology products. Management Science 33, 9 (1987), 1069–1086.

[55] John A. Norton and Frank M. Bass. 1992. Evolution of technological generations: The law of capture. Sloan Management Review 33, 2 (1992), 66–77.

[56] Ella Peltonen, Eemil Lagerspetz, Jonatan Hamberg, Abhinav Mehrotra, Mirco Musolesi, Petteri Nurmi, and Sasu Tarkoma. 2018. The hidden image of mobile apps: Geographic, demographic, and cultural factors in mobile usage. In Proceedings of the 2013 International Conference on Human-Computer Interaction with Mobile Devices and Services. 1–12.

[57] Thanasis Petsas, Antonis Papadogiannakis, Michalis Polychronakis, Evangelos P. Markatos, and Thomas Karagiannis. 2013. Rise of the planet of the apps: A systematic study of the mobile app ecosystem. In Proceedings of the 2013 Conference on Internet Measurement Conference. 277–290.

[58] Everett M. Rogers. 2010. Diffusion of Innovations. Simon and Schuster.

[59] Xin Rong and Qiaozhu Mei. 2013. Diffusion of innovations revisited: from social network to innovation network. In Proceedings of the 22nd ACM International Conference on Information & Knowledge Management. 499–508.

[60] John P. Rula, Philipp Richter, Georgios Smaragdakis, and Arthur Berger. 2020. Who’s left behind? Measuring adoption of application updates at scale. In Proceedings of the ACM Internet Measurement Conference. 710–723.

[61] Imam Salehudin and Frank Alpert. 2020. No such thing as a free app. In Proceedings of the International Conference on Business and Management Research. 1–8.
[62] Mark Speece and Douglas L. MacLachlan. 1995. Application of a multi-generation diffusion model to milk container technology. *Diffusion of Innovation eJournal* 49, 3 (1995).

[63] Ailie K. Y. Tang. 2016. Mobile app monetization: App business models in the digital era. *International Journal of Innovation, Management and Technology* 7, 5 (2016), 224–227.

[64] Jie Tang, Jimeng Sun, Chi Wang, and Zi Yang. 2009. Social influence analysis in large-scale networks. In *Proceedings of the 15th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*. 807–816.

[65] Thomas W. Valente. 1996. Social network thresholds in the diffusion of innovations. *Social Networks* 18, 1 (1996), 69–89.

[66] Haoyu Wang, Hao Li, and Yao Guo. 2019. Understanding the evolution of mobile app ecosystems: A longitudinal measurement study of Google Play. In *Proceedings of The World Wide Web Conference*. 1988–1999.

[67] Pawel Weichbroth. 2020. Usability of mobile applications: A systematic literature study. *IEEE Access* 8 (2020), 55563–55577.

[68] Lilian Weng, Alessandro Flammini, Alessandro Vespignani, and Filippo Menczer. 2012. Competition among memes in a world with limited attention. *Scientific Reports* 2 (2012), 335.

[69] Lynn O. Wilson and John A. Norton. 1989. Optimal entry timing for a product line extension. *Marketing Science* 8, 1 (1989), 1–17.

[70] Huayao Wu, Wenjun Deng, Xintao Niu, and Changhai Nie. 2021. Identifying key features from app user reviews. In *Proceedings of the 2021 IEEE/ACM 43rd International Conference on Software Engineering*. 922–932.

[71] Runhua Xu, Remo Manuel Frey, Elgar Fleisch, and Alexander Ilic. 2016. Understanding the impact of personality traits on mobile app adoption—insights from a large-scale field study. *Computers in Human Behavior* 62 (2016), 244–256.

[72] Kum Fai Yuen, Xueqin Wang, Li Ting Wendy Ng, and Yiik Diew Wong. 2018. An investigation of customers’ intention to use self-collection services for last-mile delivery. *Transport Policy* 66 (2018), 1–8.

[73] Emmanuel Yujuico. 2015. Considerations in the diffusion of a public traffic app for metro Manila. *Journal of Transport Geography* 42 (2015), 48–56.

Received 18 May 2022; revised 19 July 2023; accepted 4 September 2023