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Investigating the Relationship between Effectiveness of App Evolution and App Continuance Intention: An Empirical Study of the U.S. App Market

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Abstract:

App evolution has been shown to continuously lead to app success from the developer perspective. However, few studies have explored app success from the user perspective, which limits our understanding of the role of app evolution in app success. Building on app evolution literature and the technology acceptance model (TAM), the authors investigate the influence of the effectiveness of app evolution on users' perceived app usefulness and ease of use and their app continuance intention, which is a proxy of app success from the user perspective. Survey data were collected from 299 app users on both the Google Play and AppStore platforms in the U.S. The findings indicate that the effectiveness of strategic evolution and effectiveness of evolution speed directly affect a user's perceived app usefulness, while effectiveness of operational evolution and effectiveness of evolution speed directly affect a user's perceived app ease of use. In addition, perceived app usefulness and perceived app ease of use are two keys that lead to users' app continuance intention. A user's perceived app ease of use affects app continuance intention both directly and indirectly through perceived app usefulness. This study enhances our understanding of the relationship between effectiveness of app evolution and app continuance intention. This is especially important in helping app developers that are small firms or startups with limited resources understand how to retain app users. Limitations and directions for future research are also discussed.

Keywords: App Evolution, Platform Ecosystems, App Continuous Intention, Google Play, AppStore.

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

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1 Corresponding Author

1 Introduction

Mobile devices have become increasingly popular among individuals and organizations in the "Mobile Economy" era (Morgan, 2017; Sivakumaran & Iacopino, 2018). These mobile devices occupy 65% of users' digital media time (Sterling, 2016) and contribute approximately $1 trillion in revenue to the digital market (Sivakumaran & Iacopino, 2018). Associated with the rise in mobile devices are platform-centric ecosystems, which play a major role in today's business. A platform-centric ecosystem consists of a mobile platform and mobile apps. A mobile platform (e.g., Android, iOS) is a software-based platform that provides basic functionalities for mobile devices (Tiwana, Konsynski, & Bush, 2010). Mobile apps complement a platform's functionalities by adding new features to the platform, thereby allowing app users to perform specific tasks on the platform (Liu, Au, & Choi, 2014). Recent industrial studies indicate that approximately 204 billion apps were downloaded onto mobile devices in 2019 (Statista, 2020). Moreover, the revenue is expected to grow from $365.2 billion in 2018 to $935.2 billion in 2023 (Statista, 2019). The app markets have become a very attractive and fast-growing market. Also, app markets have comparatively low barriers to entry and a large number of similar competing apps (Wang, Li, & Singh, 2018). These factors make app markets highly dynamic, in which app success is temporary. How to keep apps profitable in such a competitive market is critical for developers.

Previous studies have examined app success in initial adoption (e.g., app download, app sales) and indicate that an app's visual design (Wang & Li, 2017) and online feedback (e.g., rank, ratings, reviews) (Carare, 2012; Claussen, Kretschmer, & Mayrhofer, 2013, Liang, Li, Yang, & Wang, 2015) play important roles in influencing users' initial app adoption behavior, as measured by app downloads and sales. However, app revenue is largely generated by app continuance use (Adjust, 2020; Delisle, 2017). Recent reports indicate that app retention rates were lower than 30% over the past 8 years, and more than 70% of app users stop using an app in the first three months (Iqbal, 2019). In addition, 25% of app users only used an app once (Rodde, 2018). Thus, understanding what drives app continuance intention will help developers retain users and be successful.

Extending the traditional technology acceptance model (TAM) to continuance use, scholars claim that perceived usefulness and perceived ease of use remain two core factors that help users determine whether to continuously use certain technology (Islam, Mäntymäki, & Bhattacherjee, 2017; Venkatesh, Thong, Chan, Hu, & Brown, 2011). Recent studies have adopted this extended model to identify antecedents of perceived usefulness and ease of use, and their impacts on initial or continuance intention in the app context (Agrebi & Jallais, 2015; Cho, 2016; Hsiao, Chang, & Tang, 2016). Although important insights can be generated from these studies, they only focus on a snapshot of determinants of perceived usefulness and perceived ease of use. Apps are evolvable systems that have the capability to efficiently adapt to serve new purposes and emerging possibilities (Agarwal & Tiwana, 2015). Therefore, understanding how to continuously influence perceived usefulness and perceived ease of use, which are two key influential factors of app continuance intention, is critical to developers, especially those that are small firms or startups that do not have resources for professional, third party marketing services to help them understand their users.

Scholars extend evolutionary perspective, which comes from biological evolution in natural sciences, into the IS field to explain continuous app success (Tiwana et al., 2010). As continuous change that leads to the incremental improvement of an app, app evolution can help an app constantly address changing user preferences (Agarwal & Tiwana, 2015), which may result in app continuance intention. Studies on app evolution mainly take the app developer perspective and focus on evolution speed, which is defined as frequency of app updates in a certain period of time, or the absolute evolution speed (Agarwal & Tiwana, 2015; Tiwana, 2015). However, speed is not the only attribute of app evolution. Given that successful evolution should not only be fast, but also effective (Moore, 1993), evolution content (i.e., what and how an app evolves) is another critical attribute of app evolution. In addition, whether app evolution can influence app continuance intention is determined by end users. Because users can differ in their ability to assimilate app evolution, different users form different perceptions about app evolution (Saffarizadeh, Jabr, & Keil, 2018). Thus, user perceptions on how effectively an app evolves can be a key factor that influences app continuance intention. We therefore integrate the app evolution perspective and technology acceptance model to investigate the influence of effectiveness of app evolution on user perceptions of app usefulness, ease of use, and app continuance intention. By doing so, we are able to advance scholarly understanding of app evolution and provide app developers with actionable insights. Specifically, we seek to address these two research questions:

RQ1: Do effectiveness of app evolution content and evolution speed affect users' perceived app usefulness and perceived app ease of use?

RQ2: Do perceived app usefulness and perceived app ease of use influence app continuance intention?

The rest of this paper is structured as follows. The next section reviews the literature on the technology acceptance model (TAM) and app evolution. A conceptual model is then developed, and hypotheses presented. In the remaining sections, we test the research model empirically and discuss the research implications, limitations, and future research.

2 Literature Review and Hypothesis Development

The *technology acceptance model* (TAM) explains the relationship between a user's perceived usefulness and perceived ease of use, and technology continuous use, which indicates that whether a user decides to continue using a technology is determined by the user's perception of whether such technology is useful and easy to operate (Davis, 1985, 1989). The *evolution perspective* in the app research stream indicates that app evolution can influence a user's perception of an app, which, in turn, leads to better app performance. Combining the app evolution perspective with TAM, we propose that the effectiveness of app evolution can positively affect user perceptions of an app's usefulness and ease of use, which in turn enhances app continuance intention.

2.1 TAM Model and App Evolution

2.1.1 Technology Acceptance Model

The technology acceptance model (TAM), together with other models developed from it (such as TAM2 and UTAUT), is one of the dominant theories in individual-level IS adoption/use/rejection studies. Originally developed by Davis (1989), TAM attempts to understand user intention with regard to the use and acceptance of a technology. When presented with a new technology, users are influenced by two major constructs: perceived usefulness (PU) and perceived ease of use (PEOU) (Abdullah, Ward, & Ahmed, 2016; Turel, Serenko, & Giles, 2011). Perceived usefulness is 'the degree to which a person believes that using a particular system would enhance his or her job performance' and PEOU is "the degree to which a person believes that using a particular system would be free of effort (Davis, 1989)." Over the past three decades, researchers have further developed and extended TAM from different perspectives. For example, Venkatesh and Davis (1996) suggested that both computer self-efficacy and objective usability are important determinants of perceived ease of use. In another study, Venkatesh and Davis (2000) proposed TAM2 and further revealed that social influence processes and cognitive instrumental processes are significant influencers on user acceptance. Meanwhile, other scholars tried to integrate TAM and the task-technology fit model, suggesting that tool and task-related factors can help explain user acceptance (Dishaw & Strong, 1999). Synthesizing the rich literature on IT adoption and use, Venkatesh, Morris, Davis, and Davis (2003) proposed the Unified Theory of Acceptance and Use of Technology (UTAUT), which provides a holistic view of factors that affect technology adoption and use decisions. TAM and its extended models have been applied to explain technology adoption in various contexts, such as online streaming (Lee & Lehto, 2013), and virtual reality device adoption (Manis & Choi, 2019).

Notwithstanding the popularity of TAM and its related models in IT adoption research, there are calls to further develop this important theory. For example, Bagozzi (2007) pointed out, "the absence of a sound theory and method for identifying the determinants of perceived usefulness and perceived ease of use" (p. 245) restricted IS researchers from uncovering novel theoretical insights from the technology adoption/acceptance/rejection research. Venkatesh, Thong, and Xu (2016) further indicated that user acceptance research is at a "crossroads" (p. 329) where possible theoretical contributions from further research should be built on novel theoretical mechanisms. To answer these calls, we integrate the app evolution literature with the TAM model to examine to what extent the effectiveness of app evolution would affect PU and PEOU, which would in turn affect the continuous use of an app. While existing TAM and related models have been extended to explain technology continuous use (Chiu & Wang, 2008; Marinković, Đorđević, & Kalinić, 2020; Venkatesh et al., 2011), one major issue with them is that these models are developed for traditional technologies/systems that mainly go through the lifecycle of adoption, continuous use, assimilation, and discontinuity or retirement. For an evolvable system or application like a mobile app (Agarwal & Tiwana, 2015), continuous use is no longer a one-time decision, but can happen every time the app evolves. The antecedents identified in existing adoption models may not be able to fully explain continuance intention for evolvable apps. Thus, to better understand continuous use in the app market context, we extend the TAM model by identifying app factors that are progressive in nature as antecedents for user perceptions (perceived ease of use, perceived usefulness) on evolvable applications, and how these user perceptions affect user continuance intention. While UTAUT provides a more holistic view of factors that may influence continuous use, we specifically draw on the core components of the original TAM model to capture the essence of this influential theory and maintain parsimony at the same time.

2.1.2 App Evolution and Effectiveness of App Evolution

The evolutionary perspective in the social sciences comes from biological evolution in the natural sciences (Nelson & Winter, 1982; Tellis & Crawford, 1981). Tiwana and his colleagues extend the evolutionary perspective into the IS field to explain continuous app success in app markets (Agarwal & Tiwana, 2015; Tiwana, 2015; Tiwana et al., 2010). In this perspective, apps are considered to be an organism that adapts to the external environment (users, market, platform, etc.) through continuous upgrades. Each app upgrade can be considered as an adaptation. The cumulation of these upgrades forms the evolutionary process of an app. Only those apps that can consistently meet changing market demands and user preferences can survive or succeed in the competition (Agarwal & Tiwana, 2015; Tiwana, 2015).

As Tiwana et al. (2010) said "complex systems that evolve **at a faster rate** and **with greater diversity** are more likely to evolve to achieve better fit with their environment than those that do not possess these traits" (pg.684), indicating that app evolution can be a multi-faceted construct that includes both speed and content. However, previous studies in this research stream often focus on evolution speed only (Tiwana, 2015). For example, Tiwana (2015) specifically mentioned that he emphasizes "the speed of evolution rather than evolution itself" (pg. 267). We argue that app evolution content (e.g., what, and how to evolve the app) can be an equally, if not more, important factor than app evolution speed in app success and use.

To identify the different dimensions of app evolution content, we conducted a content analysis of the app evolution history of ten randomly selected apps from Apple's App Store. The content analysis reveals two major types of evolution content: (a) the addition of new features and/or functions to enrich the user experience and enlarge the user base or (b) the refinement of current features to smooth app operations. Correspondingly, we define **strategic evolution** as the extent to which an app adds new features, and **operational evolution** as the extent to which an app refines existing features. Table 1 presents part of the evolution history of AtmosphereLogger, an app developed by IllllT, to illustrate these two types of evolution content. After releasing its first version, AtmosphereLogger experienced some bug issues, which caused the app to operate poorly. Thus, in the updated version (Version 0.2.1), the app was refined by fixing the operational issues, thereby smoothing out its operation. In a later version (Version 0.2.3), the development team added new export features to gain new functionality. Thus, these upgrades from Version 0.2.1 to Version 0.2.3 included both operational and strategic evolution. Other versions of the app and their associated evolution types are also provided in Table 1.

Table 1. Examples of App Strategic Evolution and Operational Evolution (AtmosphereLogger)

App Version	Content of Evolution	Evolution Type
Version 0.2.3	• Added exporting feature	Strategic
	• Fixed some problems	Operational
Version 0.2.1	• Added exporting feature	Strategic
	• Fixed some problems	Operational
Version 0.1.5	• Improve noise reduction	Operational

In addition, the extant literature on app evolution mainly takes the app developer perspective and focuses on absolute evolution speed (Tiwana 2015). Such theorizing and operationalization cannot capture how users react to content and speed of app evolution. Since app continuance intention is an individual choice and behavior (Chen, Meservy, & Gillenson, 2012), it is not absolute evolution speed but rather how each user perceives the effectiveness of app evolution that shapes their app continuance intention. Such a user perspective of app evolution is supported by Saffarizadeh et al. (2018), in which they argue that users differ in their ability to assimilate app evolution, indicating that users can form different perceptions of app evolution. A similar perspective is proposed in Webiotic (2019) in that too much, too frequent app evolution can burn out users. Therefore, we take the user perspective and propose "the effectiveness of app evolution" as the core construct in this study. We define **effectiveness of strategic evolution** as a user's perception of to what extent an app effectively adds new features, and **effectiveness of operational evolution** as a user's perception of to what extent an app effectively refines existing features. We draw on Tiwana (2015) to define **effectiveness of evolution speed** as user perceptions of the rates at which upgraded versions of an app are effectively released by its developer(s). Figure 1 presents the research model and Table 2 presents the definitions of the major constructs.

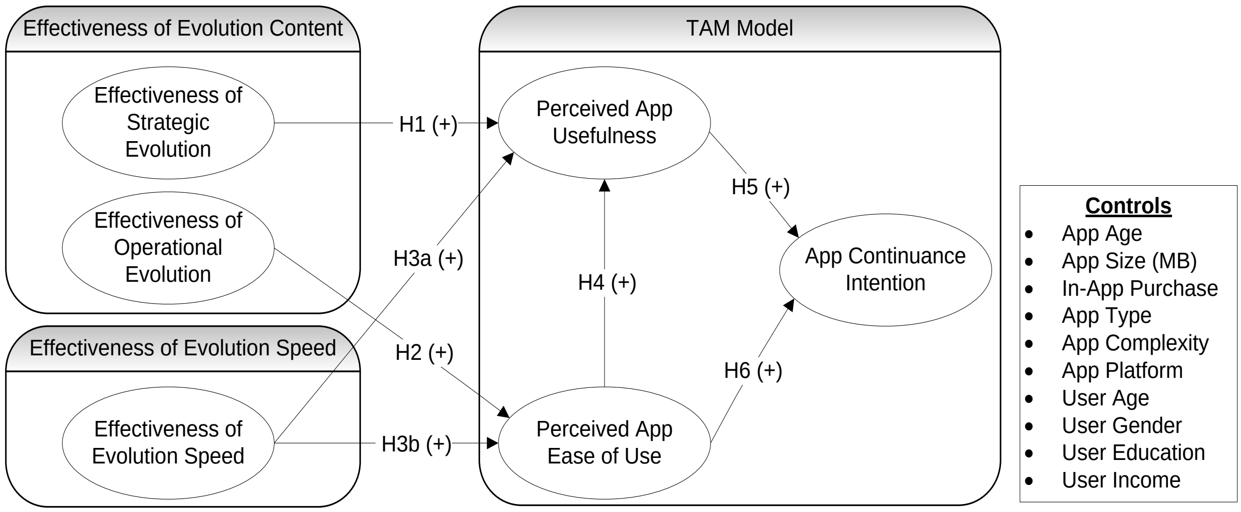

Figure 1. Research Model

Table 2. Main Construct Definitions and Sources

Construct	Definition	Source
Effectiveness of Strategic Evolution	User perceptions of to what extent an app effectively adds new features	Adapted from Pavlou and Gefen 2004; Fang et al., 2014
Effectiveness of Operational Evolution	User perceptions of to what extent an app effectively refines existing features	Adapted from Pavlou and Gefen 2004; Fang et al., 2014
Effectiveness of Evolution Speed	User perceptions of the rates at which upgraded versions of an app are effectively released by its developer(s)	Adapted from Tiwana 2015
Perceived App Usefulness	The degree to which an app user thinks that an app provides useful functionalities	Adapted from Deng, Turner, Gehling, and Prince, 2010; Venkatesh and Goyal, 2010;
Perceived App Ease of Use	The degree to which an app user thinks that using an app will be free of effort	Adapted from Venkatesh and Goyal, 2010
App Continuance Intention	An app user's intention to continue using the same app	Adapted from Venkatesh and Goyal, 2010

2.2 The Role of Effectiveness of Evolution Content

Strategic evolution and operational evolution have different focuses and can affect user perceptions differently. Through strategic evolution, an app can bring new features, such as new functionalities, components, and modules to users. By effectively adding new features, an app can also maintain user interest and counteract negative perceptions of the app's functions, enhancing user perceptions of the app's usefulness. In addition, effectively adding new features can provide an experiential taste of the app's presence and functions, solidifying app users' impressions about the new version's functions. With these positive impressions, users are more likely to form better perceptions of the app's usefulness. Moreover, competition in the app market is a red queen competition, which means competition never stops (Barnett, 2008; Robson, 2005). There are many apps that provide similar functionalities in the app market since original apps often have copycats (Wang et al., 2018). Users may conduct a comparison of features across similar apps in the market (Hamilton, Rust, & Dev, 2017). If an app has fewer features than its competitors, users may think the app is less useful than its competitors. Also, if users find these newly added features to be ineffective, such as having bugs or useless functions, they may determine that the newly upgraded app does not meet their needs, which reduces the perceived usefulness of the app. Thus, we propose:

H1: Effectiveness of strategic evolution is positively related to users' perceived app usefulness.

Apps usually suffer from operational issues, such as bugs and crash issues, due to coding mistakes, inadequate design logic, improper reuse of existing modules, schedule pressures that cause flaws in programming, and inadequate testing before launching to the market (Wong, Li, Laplante, & Siok, 2017). Operational issues can also be caused by regular upgrades to a platform (i.e. Android or iOS). Regular upgrades to a platform may cause some features of an app to stop working on an upgraded version of the platform. These bugs and crashes cause users to exert more effort when using the app, reducing user perceptions of ease of use. Effective operational evolution refines existing features and improves the design. In addition, effective operational evolution reduces operational errors and solve crashes, making an app easier to use with less effort and fewer difficulties. Thus, we propose:

H2: Effectiveness of operational evolution is positively related to users' perceived app ease of use.

2.3 The Role of Effectiveness of Evolution Speed

Effective evolution speed responds to changes in user preferences in a timely manner. Since the app market is highly dynamic with low barriers to entry, an app's developer is likely to receive a steady stream of feedback from users, competing apps, and opportunities opened up by external technological advances (Tiwana, 2015). Feedback from app users may include suggestions such as what kind of functions users want, or complaints about bugs and crashes. Incorporating these suggestions and addressing complaints quickly makes users feel that the developer cares about their concerns and values their opinions, thus increasing their perceptions of an app's usefulness and ease of use. Moreover, promptly incorporating features from competing apps into upgrades can enhance user perceptions of an app's usefulness. In addition, emerging technologies often bring new ideas and opportunities to enrich an app and solve technical issues. Rapid evolution allows an app to incorporate the new ideas and opportunities offered by emerging technologies, thereby improving the app's usefulness in terms of functions as well as reducing user effort to operate the app. However, too much and too frequent app evolution can burn out users (Webiotic, 2019) because users need time to assimilate the changes in each upgrade (Saffarizadeh et al., 2018). Therefore, developers should carefully time the release of new upgrades to meet user expectations. Accordingly, we propose that effectiveness of evolution speed can enhance users' perceived usefulness and ease of use. Thus,

H3a: Effectiveness of evolution speed is positively related to users' perceived app usefulness.

H3b: Effectiveness of evolution speed is positively related to users' perceived app ease of use.

2.4 Perceived App Ease of Use, Perceived App Usefulness, and App Continuance Intention

According to Davis (1989), PU focuses on the benefits of using a system while PEOU focuses on the effort to use a system. When examining user behaviors in system adoption, Davis (1989) suggested that these two perceptions may not be independent, but that PEOU can affect PU. This relationship has been discussed in great detailed in previous research (e.g., Lai & Li, 2004; Agrebi & Jallais, 2015; Ho, Ke, Liu & Chau, 2020). We hypothesize that such a relationship applies to the app market. Generally speaking, if an app is easy to use, a user may have to put less effort into using it and is more likely to explore, appreciate, and enjoy different functions in it. The more effort put into exploring, appreciating, and enjoying the different functions of an app, the better the user experience, leading to higher performance benefits from using the app. This will, in turn, lead to a higher level of PU, especially when there are better alternatives available on the app market. Therefore, we propose:

H4: Perceived app ease of use is positively related to users' perceived app usefulness.

Moreover, TAM posits that perceived usefulness and perceived ease of use determine intention to use (Davis, 1989) because (1) high perceived usefulness makes users believe in the existence of a positive use-performance relationship, and (2) high perceived ease of use means "freedom from difficulty or great effort" (Davis, 1989, pg.320) and effort is a limited resource that a user may allocate to use or continue using a system (Venkatesh & Davis, 2000; Venkatesh & Goyal, 2010; Venkatesh et al., 2016), We believe such relationships exist in app content as well. We argue that users will form a positive opinion when they believe that an app (1) provides necessary functions to satisfy their goals (i.e., high level of usefulness) and (2) does not require too much time and effort to navigate for their goals (i.e., high level of ease of use). Based on the above arguments, we propose the following hypotheses:

H5: Perceived app usefulness is positively related to users' app continuance intention.

H6: Perceived app ease of use is positively related to users' app continuance intention.

3 Research Design

3.1 Measurement Development

We followed the process prescribed by MacKenzie, Podsakoff, and Podsakoff (2011) to develop the survey instrument. We first conducted an extensive review of the literature on TAM and app evolution. Whenever possible, existing validated measures were adopted, or adapted, to ensure the quality of the measurement items. All of the constructs were treated as reflective indicators, and the items were measured using a 7-point Likert scale unless specified otherwise (see Appendix).

To capture the "effectiveness" of app evolution (e.g., strategic evolution, operational evolution, and evolution speed), we adapted existing measures of effectiveness in the IS literature (Pavlou & Gefen 2004; Fang et al., 2014). Specifically, items for the effectiveness of strategic evolution capture whether the newly added features are useful, helpful, reliable, enjoyable, and practical. Items for the effectiveness of operational evolution capture whether the refined features can effectively reduce errors and smooth an app's operation. Items for the effectiveness of evolution speed capture whether the speed of the app upgrades are appropriate, effective, fast, and successful in addressing customer requirements and environmental changes. Items for user's perceived app usefulness, perceived app ease of use, and app continuance intention are adopted from the existing TAM literature (Abdullah et al., 2016; Deng et al., 2010; Venkatesh & Goyal, 2010).

The initial questionnaire was reviewed by four academic professionals in the IS field to assess content validity. In addition, a two-stage sorting process was used to validate the questions and identify ambiguous or inappropriately worded items, thus validating the various scales to be developed (Moore & Benbasat, 1991). 4 student sorters correctly placed 90% and 100% of the items in their corresponding constructs in the first and second rounds. Items were revised based on comments received from the academic professionals and sorters. The revised questionnaire was pilot tested with 104 students at two major universities in the U.S. The items covaried with each other and exhibited high internal consistency or reliability (Cronbach's alpha > .80) (Petter, Straub, & Rai, 2007), providing empirical support to our decision to model these constructs as reflective. Established procedures were followed to examine the validity of measurement items, which showed good convergent and discriminant validity. The pilot test results indicated that the items were of good quality and could be used in the large-scale data collection.

We included ten control variables in the model in order to exclude potential alternative explanations caused by individual differences and app differences. We controlled for users' **age**, **gender**, **income level**, and **education level** as these factors may affect users' app continuance intention (Correa, Hinsley, & De Zuniga, 2010). In addition, the existing literature indicated that app characteristics may also affect app performance (Ghose & Han, 2014; Liu et al., 2014; Tiwana, 2015). We collected subjective data for **app complexity** as well as objective data for **app age**, **app size**, **app type**, **in-app purchase**, and **app platform** using app links provided by respondents and controlled their effects on app continuance intention.

3.2 Data Collection

We collected self-reported survey data from app users (Google Play and AppStore) to test the proposed research model. We used Amazon's Mechanical Turk to recruit potential respondents in the U.S. app market because Mechanical Turk yields comparable samples to those collected from students and individual user panels in the U.S. (Liu & Tang, 2018; Steelman, Hammer, & Limayem, 2014). We asked respondents to recall their use experience with an app on Google Play or AppStore in the most recent three months. To ensure accuracy, respondents were asked to provide the app name and app web link. Nominal incentives were provided to encourage participation.

442 users participated in the study, and 143 were disqualified due to failing to pass our screening questions and/or to provide a valid app website link. After removing these responses, there were 299 valid responses, representing a response rate of 67.65%. Compared to extant studies on apps (Lim, Bentley, Kanakam, Ishikawa, & Honiden, 2014; Rayle, Shaheen, Chan, Dai, & Cervero, 2014), our response rate is appropriate. Table 3 provides the respondent demographics.

To ensure that non-response bias was not a concern in this study, an individual t-test on the means of main constructs was conducted by examining early and late respondents. The first 50 respondents and the last 50 respondents were examined, and the results indicated that the impact of non-respondent bias was minimal in this study.

Table 3. Respondent Demographics

Respondent Age	N	Percent	Respondent Gender	N	Percent
Under 21	39	13.04%	Female	114	38.13%
21 - 30	94	31.44%	Male	185	61.87%
31 - 40	113	37.79%	Respondent Annual Income		
41 - 50	36	12.04%	Below $25,000	108	36.12%
Older than 50	17	5.69%	$ 25,000 – 49,999	94	31.44%
Respondent Education Level			$ 50,000 – 74,999	58	19.40%
High School Diploma	102	34.11%	$ 75,000 – 99,999	18	6.02%
Associate Degree	43	14.38%	$ 100,000 +	18	6.02%
Bachelor Degree	117	39.13%			
Graduate Degree	37	12.37%			

4 Analysis and results

Partial least squares (PLS) is considered to be an appropriate method when the research objective is prediction and theory development and the model is complex (Hair, Ringle, & Sarstedt, 2011; Hair, Hult, Ringle, & Sarstedt, 2016). Thus, SmartPLS was used for measurement validation and model testing, following the approach outlined by Hair et al. (2016) and Ringle, Wende, & Becker (2015).

4.1 Evaluation of Overall Fit of the Saturated Model

To evaluate the overall fit of the saturated model, we examined the standardized root mean squared residual (SRMR), unweighted least squares discrepancy (d_{ULS}), and geodesic discrepancy (d_G) (Benitez, Henseler, Castillo, & Schuberth, 2020; Hair et al., 2016; Henseler et al., 2014). Table 4 reports the values of the discrepancy measures and 99% quantiles of their corresponding reference distribution. The value of the SRMR was below the recommended threshold value of 0.08, and all discrepancy measures were below the 99% quantile of their reference distribution, indicating the model has “good fit”.

Table 4. Results of the Overall Saturated Model Fit Evaluation

Discrepancy	Overall Saturated Model Fit Evaluation			
	Value	HI_{95}	HI_{99}	Conclusion
SRMR	0.039	0.041	0.074	Supported

d_{ULS}	1.251	1.565	1.724	Supported
d_G	0.793	0.947	1.018	Supported

4.2 Measurement Validation

First, an **exploratory factor analysis** (EFA) was conducted, and factors were extracted through principal component analysis (PCA). Two items of app continuance intention and one item of app complexity that had low loadings (less than 0.500) on the appropriate factor and high cross-loadings were removed from the remaining measurement assessments and model testing (MacKenzie et al., 2011). Table 5 reports the results of the exploratory factor analysis, and Table 6 presents the sample's descriptive statistics, correlation, and square root of average variance extracted (AVE). We examined the internal consistency and the convergent and discriminant validity of the construct (Henseler, Ringle, & Sarstedt, 2015; MacKenzie et al., 2011). The appendix shows that Cronbach's α for each of the latent variables exceeded 0.70, suggesting good reliability. All the retained items had loadings above the recommended cutoff of 0.70 (Table 5) and the average variance extracted (AVE) for each construct exceeded the recommended level 0.50 (Table 6) suggesting good convergent validity. Also, all of the items had a much higher loading on their respective constructs than on other constructs (Table 5) and the square root of AVE for each construct was greater than the correlation between each pair of constructs in the model (Table 6). In addition, HTMT Ratio values are less than 0.85 (Table 7). These three results indicate good discriminant validity.

To check for the existence of multicollinearity, the variance inflation factor (VIF) values were computed for all of the constructs. The highest VIF was 1.429, which is well below the acceptable threshold of 10.0, indicating that multicollinearity was less likely to be an issue (Cohen, Cohen, West, & Aiken, 2003).

Table 5. Exploratory Factor Analysis Results

Items	Item Loadings and Cross Loadings							
	PU	EOU	ESE	ACI	EES	EOE	DT	AC
PU_9	**0.826**	0.118	0.026	0.021	0.108	0.121	0.040	-0.023
PU_8	**0.814**	0.020	0.046	-0.021	0.108	0.091	0.011	0.007
PU_7	**0.782**	0.137	0.119	0.030	0.087	0.139	0.027	-0.032
PU_6	**0.756**	0.182	0.095	0.226	0.086	0.132	0.027	0.008
PU_1	**0.726**	0.017	0.132	0.280	0.039	-0.010	0.072	0.067
PU_4	**0.711**	0.294	0.090	0.155	0.055	0.129	-0.100	-0.057
PU_2	**0.690**	0.066	0.029	0.109	0.023	0.013	0.003	0.046
PU_3	**0.679**	-0.067	0.164	-0.011	0.146	-0.134	0.072	0.101
PU_5	**0.667**	0.247	0.065	0.234	0.133	0.154	0.088	-0.044
EOU_4	0.097	**0.840**	0.112	0.052	0.041	0.068	0.036	-0.067
EOU_3	0.116	**0.822**	0.088	0.173	0.100	0.107	0.018	-0.038
EOU_5	0.148	**0.819**	0.057	0.085	0.173	0.112	0.032	-0.059
EOU_6	0.118	**0.814**	0.107	0.129	0.123	0.130	-0.003	-0.063
EOU_2	0.075	**0.764**	0.016	0.106	0.150	0.089	0.004	-0.072
EOU_1	0.186	**0.731**	0.136	0.176	0.042	0.132	0.057	-0.066
ESE_2	0.091	0.108	**0.844**	0.078	0.145	0.239	-0.031	-0.007
ESE_5	0.161	0.145	**0.815**	-0.015	0.127	0.213	-0.040	-0.060
ESE_1	0.096	0.109	**0.792**	0.057	0.143	0.271	-0.023	-0.008
ESE_4	0.083	0.125	**0.776**	0.015	0.190	0.146	0.050	0.070
ESE_3	0.193	0.005	**0.737**	-0.056	0.234	0.168	0.103	-0.007
ACI_1	0.176	0.116	-0.039	**0.878**	0.045	0.046	0.017	-0.067
ACI_4	0.105	0.162	-0.038	**0.850**	0.018	0.102	-0.018	-0.023
ACI_3	0.113	0.133	0.035	**0.834**	0.066	0.037	0.029	-0.076

ACI_2	0.072	0.184	0.017	**0.760**	0.002	0.088	0.009	-0.117
ACI_5	0.218	0.049	0.093	**0.736**	0.103	-0.009	0.039	-0.030
EES_3	0.159	0.160	0.236	0.017	**0.838**	0.100	0.074	0.027
EES_4	0.184	0.164	0.194	0.080	**0.834**	0.171	0.081	0.013
EES_2	0.153	0.178	0.192	0.066	**0.829**	0.182	0.051	-0.055
EES_1	0.162	0.144	0.238	0.105	**0.780**	0.148	0.107	-0.057
EOE_4	0.158	0.144	0.285	0.070	0.183	**0.808**	0.058	0.013
EOE_1	0.073	0.169	0.269	0.089	0.156	**0.789**	0.046	-0.006
EOE_2	0.099	0.165	0.284	0.127	0.163	**0.776**	-0.018	-0.030
EOE_3	0.180	0.207	0.329	0.020	0.129	**0.749**	0.020	-0.009
DT_1	0.077	0.050	0.024	0.017	0.091	0.042	**0.926**	-0.003
DT_3	-0.031	0.013	-0.011	0.108	0.056	0.001	**0.907**	0.053
DT_2	0.112	0.047	0.033	-0.056	0.095	0.033	**0.902**	0.009
AC_3	0.047	-0.080	-0.043	-0.097	-0.008	-0.001	-0.030	**0.930**
AC_2	0.037	-0.033	0.026	-0.104	-0.048	-0.044	0.058	**0.904**
AC_1	0.006	-0.198	0.014	-0.080	0.003	0.022	0.032	**0.901**

Notes: Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization. (**PU**: Perceived App Usefulness; **EOU**: Perceived App Ease of Use; **ACI**: App Continuance Intention; **ESE**: Effectiveness of Strategic Evolution; **EES**: Effectiveness of Evolution Speed; **EOE**: Effectiveness of Operational Evolution; **AC**: App Complexity; **DT**: Deposition Toward Trust)

Table 6. Descriptive Statistics, Correlations, and Square Roots of Average Variance Extracted (n = 299)

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1. ESE	**0.854**															
2. EOE	0.596**	**0.883**														
3. EES	0.493**	0.458**	**0.900**													
4. PU	0.306**	0.307**	0.360**	**0.769**												
5. EOU	0.281**	0.391**	0.368**	0.317**	**0.839**											
6. AC	-0.022	-0.052	-0.058	0.012	-0.198**	**0.924**										
7. ACI	0.104	0.210**	0.199**	0.316**	0.329**	-0.187**	**0.843**									
8. UA	0.066	0.065	0.008	0.238**	0.066	-0.132*	0.065	-								
9. UE	0.093	0.091	0.081	0.259**	0.038	-0.007	-0.059	0.344**	-							
10. UG	0.020	0.045	0.035	0.001	-0.013	-0.062	0.085	0.126*	-0.096	-						
11. UI	0.065	0.085	0.006	0.138*	0.048	0.024	-0.016	0.391**	0.408**	0.035	-					
12. AT	-0.072	-0.110	0.003	0.176**	0.073	0.030	0.126*	-0.082	0.026	0.015	-0.030	-				

13. AS	0.105	0.066	-0.025	-0.148*	0.008	0.091	-0.011	-0.123	-0.165*	-0.005	-0.010	-0.140	-			
14. IAP	0.006	0.036	-0.04	-0.024	-0.068	0.073	-0.059	0.028	-0.007	0.113	0.001	-0.353**	0.169*	-		
15. AP	0.116*	0.082	0.004	0.189**	0.119*	-0.068	0.048	0.357**	0.235**	-0.116*	0.072	0.033	-0.522**	-0.009	-	
16. AA	-0.029	-.0137*	0.049	0.017	0.021	0.045	0.047	-0.147*	-0.100	0.058	-0.003	.466**	0.089	-0.245**	-0.294**	-
Mean	5.609	5.656	5.53	5.828	6.317	2.75	4.684	2.659	2.298	1.381	2.135	0.88	116.435	1.605	1.405	82.391
SD	1.042	1.071	1.093	0.925	0.689	1.138	0.492	1.035	1.069	0.487	1.157	0.326	112.836	0.49	0.498	30.991

**Correlation is significant at the 0.01 level (2-tailed). *Correlation is significant at the 0.05 level (2-tailed).

Note: the diagonals are the square root of the average variance extracted (AVE) for multi-item constructs.

ESE: Effectiveness of Strategic Evolution; **EOE**: Effectiveness of Operational Evolution; **EES**: Effectiveness of Evolution Speed; **PU**: Perceived App Usefulness; **EOU**: Perceived App Ease of Use; **AC**: App Complexity; **ACI**: App Continuance Intention; **UA**: User Age; **UE**: User Education; **UG**: User Gender; **UI**: User Income; **AT**: App Type; **AS**: App Size; **IAP**: In-App Purchase; **AP**: App Platform; **AA**: App Age

Table 7. Heterotrait-Monotrait Ratio of Correlations (HTMT) Results

	1	2	3	4	5	6	7
1. Effectiveness of Strategic Evolution	--						
2. Effectiveness of Operational Evolution	0.660	--					
3. Effectiveness of Evolution Speed	0.538	0.502	--				
4. Perceived App Usefulness	0.336	0.348	0.394	--			
5. Perceived App Ease of Use	0.309	0.430	0.403	0.366	--		
6. App Complexity	0.055	0.058	0.067	0.071	0.218	--	
7. App Continuance Intention	0.116	0.232	0.214	0.365	0.364	0.207	--

Common method bias was assessed after data collection using two analyses outlined in IS studies (Bush, Tiwana, & Rai, 2010; Liu, Armstrong, & Riemenschneider, 2018). First, Harman's single factor test was used to assess common method bias (Harman, 1976; Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). Eight factors emerged from the dataset, accounting for 73.82% of the variance and the first factor explaining 27.45% of the variance. Then, a partial correlation test was performed using **disposition to trust,** a consistent tendency to be willing to trust others (Mcknight, Cummings, & Chervany, 1998), as a marker variable to evaluate the impact of common method bias on observed relationships between constructs (Lindell & Whitney, 2001). We correlated marker variable with the principal constructs and used the smallest positive value to calculate the partial-correlation. The results indicated that changes in the partial correlation were nonsignificant. These two tests suggested that common method bias was less impactful in our dataset.

4.3 Structural Model

A standard bootstrap resampling procedure (5,000 samples) was used to evaluate the significance of the paths (Hair et al., 2016). The significance of path coefficients was tested using a two-tailed t-test. Figure 2 provides the results of the structural model. According to the results, the model explained 20.2% of the variance in perceived app ease of use, 21.1% of the variance in perceived app usefulness, and 22.3% of the variance in app continuance intention. Among the ten control variables, app complexity and user education level had significant negative impacts on app continuance intention, indicating apps that have a complex structure will reduce app continuance intention, and users who have a high education level are less likely to continue using an app.

As shown in Figure 2, both H1, which states that the effectiveness of strategic evolution is positively related to perceived app usefulness ($\beta = 0.143$, $t = 2.099$, $p < 0.05$), and H2, which states that the effectiveness of operational evolution is positively related to perceived app ease of use ($\beta = 0.284$, $t =$

3.610, p < 0.001), were supported. As expected, increased effectiveness of strategic evolution is associated with higher perceived app usefulness and perceived app ease of use.

Next, H3a and H3b, which state that the effectiveness of evolution speed is positively related to an app's perceived usefulness (β = 0.204, t = 2.952, p < 0.01) and perceived ease of use (β = 0.241, t = 3.454, p < 0.001), were also supported. As predicted, an increase in the effectiveness of evolution speed will increase both perceived app usefulness and perceived app ease of use. Hypothesis 4 is also supported, which states that perceived app ease of use is positively related to its perceived app usefulness (β = 0.250, t = 3.773, p < 0.001). This indicates that an increase in perceived app ease of use can increase perceived app usefulness.

Both H5, which indicates that perceived app usefulness is positively related to app continuance intention (β = 0.301, t = 4.497, p < 0.001), and H6, which indicates that perceived app ease of use is positively related to app continuance intention (β = 0.195, t = 2.575, p < 0.01), were also supported. The results confirm that perceived app usefulness and perceived app ease of use are two important forces that affect a user's app continuance intention.

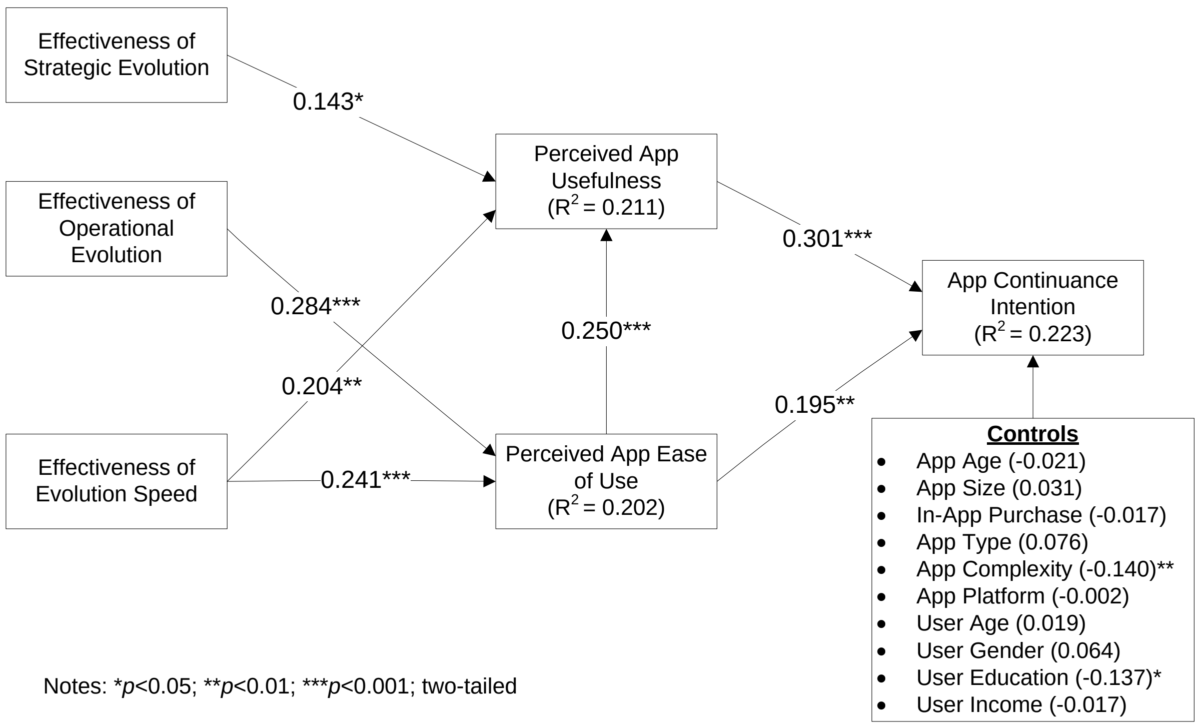

Figure 2. Model Results

4.4 Robustness Check

Three tests were conducted to check the robustness of the test results. To evaluate the stability of the significance of path coefficients, the model was first tested using a different number of samples in the bootstrap resampling procedure (6,000 samples and 7,000 samples). The results indicate consistent significance levels for each path coefficient (Table 8).

Second, two alternative models were tested to check the robustness of the proposed research model. We tested the potential linkage between effectiveness of strategic evolution and PEOU (β = -0.005, t = 0.059) and the linkage between effectiveness of operational evolution and PU (β = 0.107, t = 1.288). In addition, we also tested for the potential direct impacts of effectiveness of strategic evolution (β = -0.111, t = 1.295), effectiveness of operational evolution (β = 0.100, t = 1.342), and effectiveness of evolution speed (β = 0.028, t = 0.326) on app continuance intention. These additional paths are non-significant and including them does not change our proposed model.

Finally, even though we did not propose mediation effects in this study, such effects are embedded in the research model. Thus, we conducted a Sobel test to examine whether perceived app usefulness and perceived app ease of use serve as mediators between effectiveness of app evolution and app continuance intention (Sobel, 1982). The statistics of the Sobel tests were all significant ($p < 0.05$), indicating that perceived app usefulness and perceived app ease of use were mediators among effectiveness of strategic evolution, effectiveness of operational evolution, effectiveness of evolution speed, and app continuance intention.

Table 8. Robustness Check Results (Bootstrapping)

Bootstrapping	5000	6000	7000
Path	T -Value	T - Value	T - Value
App Age -> App Continuance Intention	0.361	0.355	0.359
App Complexity -> App Continuance Intention	**2.878**	**2.817**	**2.858**
Perceived App Ease of Use -> App Continuance Intention	**2.575**	**2.527**	**2.524**
Perceived App Ease of Use -> App Continuance Intention	**3.773**	**3.754**	**3.818**
App Platform -> App Continuance Intention	0.031	0.031	0.030
App Size -> App Continuance Intention	0.411	0.407	0.406
App Type -> App Continuance Intention	1.128	1.115	1.127
Perceived App Usefulness -> App Continuance Intention	**4.497**	**4.461**	**4.473**
Effectiveness of Evolution Speed -> Perceived App Ease of Use	**3.454**	**3.498**	**3.457**
Effectiveness of Evolution Speed -> Perceived App Usefulness	**2.952**	**2.953**	**2.966**
Effectiveness of Operational Evolution -> Perceived App Ease of Use	**3.610**	**3.664**	**3.680**
Effectiveness of Strategic Evolution -> Perceived App Usefulness	**2.099**	**2.103**	**2.097**
In-App Purchase -> App Continuance Intention	0.325	0.324	0.332
User Age -> App Continuance Intention	0.327	0.324	0.327
User Education -> App Continuance Intention	**2.353**	**2.310**	**2.371**
User Gender -> App Continuance Intention	1.177	1.173	1.191
User Income -> App Continuance Intention	0.257	0.254	0.254

5 Discussions

Building on the technology acceptance model and app evolution, this study develops a research model that aims to reveal the influence of the effectiveness of app evolution on user perceived app usefulness, ease of use, and their app continuance intention.

5.1 Research and Managerial Implications

Two research implications emerge from this study. First, this study contributes to the app evolution literature by opening up the black box of the content of app evolution and taking a user perspective to examine how the different aspects of app evolution affect user continuance. Specifically, we draw on the app evolution literature to identify that evolution content should be an equally, if not more, important aspect of app evolution to evolution speed. Further content analysis of app evolution history reveals two types of evolution content, i.e., strategic evolution and operational evolution. This nuanced classification of the aspects of app evolution extends the app evolution literature and advances scholarly understanding of the multi-dimensional nature of app evolution. Moreover, taking users as the stakeholders who can determine whether they want to continue using an app or not, this study complements existing studies that mainly examine app evolution from the developer perspective (Agarwal & Tiwana, 2015; Tiwana, 2015). Following established procedures (MacKenzie et al., 2011), we developed measurement items to capture the effectiveness of app strategic evolution, operational evolution, and evolution speed. The empirical results reveal the different impacts of these aspects of app evolution on shaping users' PEOU and PU. Specifically, we found that the effectiveness of strategic evolution positively influences PU, while the effectiveness of operational evolution positively affects PEOU. In addition, the effectiveness of evolution speed has positive and direct impacts on both PU and PEOU. By delineating the different impacts of evolution content and evolution speed, this study provides a comprehensive understanding of app evolution on app continuance use from the user's perspective.

Second, this study extends the technology acceptance literature by integrating the app evolution perspective with the traditional technology acceptance model (TAM). Unlike traditional information technology and systems in which continuous use is often a one-time decision, such as decision-making process can happen every time an app evolves. The app evolution perspective provides a theoretical lens to explore app factors that are progressive in nature to the continuous use of evolvable systems such as apps. We empirically show that the effectiveness of app evolution can foster a user's continuance intention by improving PEOU and PU. This study therefore answers calls to use a sound theory and method to identify the antecedents of PEOU and PU (Bagozzi, 2007; Venkatesh et al., 2016) and enriches the theoretical account of the TAM in explaining the continuance intention for evolvable systems and applications.

This study also has several important managerial implications for developers. Perceived app usefulness and ease of use still play important roles in influencing app continuance intention in the app market context. These users' perceptions can be influenced by effectiveness of app evolution (strategic evolution, operational evolution, and evolution speed). Understanding factors that influence app continuance intention can help developers retain users and gain profits. The efforts made to effectively evolve an app both in content and in speed can result in a positive change of perceived app usefulness and ease of use. Developers should also notice the varying impacts of different aspects of app evolution on PU and PEOU. By deploying app evolution effectively, a developer can influence app users to continuously use its app and maximize its profits.

5.2 Limitation and Future Research

This study contains several limitations. First, this study draws on the core components of the original TAM model to capture the essence of this influential theory. While this parsimonious approach helped us remain focused and explore the effect of the progressive aspect (evolution) of mobile app development, we acknowledge that alternative acceptance models and theories (e.g., TAM2, UTAUT, and innovation diffusion theory) may provide other possible explanations to the continuance intention of an evolvable application. Future research could draw on these alternative models or theories to examine how the effectiveness of app evolution can affect other factors (e.g., app complexity, observability, compatibility) related to app continuous use. Second, we examined the three evolutionary constructs with cross-sectional survey data, in which the respondent judges these aspects of evolution as a totality. If longitudinal data is available, future research could examine operational and strategic evolution as they occur to see if there is a feedback loop between these two types of evolution and how their interplay changes app continuance intention. A longitudinal research design can also mitigate the impact of reverse causality. In addition, with case or empirical data, a multi-method study can be conducted to check the robustness of our results. Third, the proposed model can be further enriched. For example, platform is also evolvable. How platform evolution will affect the relationships proposed in this study could be an interesting direction to follow. Finally, app evolution is an iterative process that needs the participation of both developers and users. On one hand, developers collect user feedback on PEOU and PU of an app, decide on the evolution content and speed, and hope to keep users continuously using the app. On the other hand, users evaluate the effectiveness of app evolution, form their PEOU and PU, and decide whether they want to keep using an app or not. We only examine this iterative process from the user perspective. Future research could take the developer or both perspectives to provide a more comprehensive understanding of the role of effectiveness of app evolution in app continuance intention.

6 Conclusion

The rise of platform-centric ecosystems creates a highly dynamic app market. Given that app revenue is largely generated from app use, getting users to continuously use an app is a critical issue to app developers, especially to small businesses and startups with limited resources. App evolution has been treated as an important factor that drives app performance. Previous literature focused on app evolution from the developer perspective while ignoring examine the role of app evolution from the app user perspective.

To address the research gap, we focus on the effectiveness of app evolution (content and speed) from the user standpoint and propose a research model to explore the relationship between effectiveness of app evolution and app continuous intention. Using subjective data collected from app users and objective data collected from Google Play, we reveal the intertwined relationships among effectiveness of app evolution, perceived app usefulness, perceived app ease of use, and app continuance intention. These findings help developers understand the role of effectiveness of app evolution in app continuance intention.

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Appendix: Main Constructs, Items and Sources

Construct	Items	Sources
Effectiveness of Strategic Evolution (M = 5.609; SD = 1.042; AVE = 0.730; Cronbach's α = 0.907; CR = 0.931)	I believe that the newly added features (e.g., functionalities, user interfaces, modules, components etc.) are useful	Newly developed based on construct definition and relevant literature (e.g., Pavlou & Gefen 2004; Fang et al, 2014)
	I believe that the newly added features (e.g., functionalities, user interfaces, modules, components etc.) are helpful	
	I believe that the newly added features (e.g., functionalities, user interfaces, modules, components etc.) are reliable	
	I believe that the newly added features (e.g., functionalities, user interfaces, modules, components etc.) are enjoyable	
	I believe that adding New features (e.g., functionalities, user interfaces, modules, components etc.) are practical	
Effectiveness of Operational Evolution (M = 5.656; SD = 1.071; AVE = 0.779; Cronbach's α = 0.905; CR = 0.934)	I feel that it effectively reduces the errors of the app by refining EXISTING features (e.g., functionalities, user interfaces, modules, components etc.)	Newly developed based on construct definition and relevant literature (e.g., Pavlou & Gefen 2004; Fang et al, 2014)
	I feel that it usefully solves the crashes of the app by refining EXISTING features (e.g., functionalities, user interfaces, modules, components etc.)	
	I feel that it significantly improves the quality of the app by refining EXISTING features (e.g., functionalities, user interfaces, modules, components etc.)	
	I feel that it obviously enhances the stability of the app by refining EXISTING features (e.g., functionalities, user interfaces, modules, components etc.)	
Effectiveness of Evolution Speed (M = 5.530; SD = 1.093; AVE = 0.810; Cronbach's α = 0.922; CR = 0.945)	I believe the speed of app upgrade is appropriate to address the customers' requirements and the environmental changes.	Adapted based on construct definition and relevant literature (e.g., Pavlou & Gefen 2004; Fang et al, 2014; Tiwana 2015)
	I believe the speed of app upgrade is effective to address the customers' requirements and the environmental changes.	
	I believe the speed of app upgrade is fast to address the customers' requirements and the environment changes.	
	The speed of app upgrade is successful to address the customers' requirements and the environmental changes.	
Perceived App Usefulness (M = 5.828; SD = 0.925; AVE = 0.592; Cronbach's α = 0.914; CR = 0.928)	I evaluate the app as useless -------------- useful	Deng, Turner, Gehling, & Prince, 2010; Venkatesh & Goyal, 2010
	I evaluate the app as impractical -------------- practical	
	I evaluate the app as unnecessary -------------- necessary	
	I evaluate the app as unfunctional -------------- functional	
	I evaluate the app as unhelpful -------------- helpful	
	I evaluate the app as inefficient -------------- efficient	
	I evaluate the app as ineffective -------------- effective	
	I evaluate the app as harmful -------------- beneficial	
	I evaluate the app as unproductive -------------- productive	
Perceived App Ease of Use (M = 6.317; SD = 0.689; AVE = 0.705; Cronbach's α = 0.916; CR = 0.935)	It is easy for me to become skillful at using the app	Abdullah, Ward, & Ahmed 2016
	I find it is easy to get the app to do what I want it to do	
	My interaction with the app is clear	
	My interaction with the app is understandable	
	I found that the app is easy to use	
	Learning to operate the app is easy for me	
App Continuance Intention (M = 4.684; SD = 0.768; AVE = 0.711; Cronbach's α = 0.492; CR = 0.925)	I intend to continue using the app	Venkatesh & Goyal, 2010
	I predict I would continue using the app	
	I plan to continue using the app	
	I intend to continue using the app in the future.	
	I will always try to use the app in my daily life.	
	I will keep using the app as regularly as I do now. *	

Construct	Items	Sources
	If I could, I would like to discontinue my use of the app.*	
App Complexity (M = 2.750; SD = 1.138; AVE = 0.855; Cronbach's α = 0.915; CR = 0.946)	Compared to other apps with which I am familiar, this app has relatively complex design	Tiwana, 2015
	Compared to other apps with which I am familiar, this app is technically complex to develop	
	Compared to other apps with which I am familiar, this app uses complex development processes	
	Compared to other apps with which I am familiar, this app uses few development tools to build*	
Disposition Toward Trust (M = 3.795; SD = 1.101; AVE = 0.795; Cronbach's α = 0.909; CR = 0.920)	I generally trust other people	Mcknight, Cummings, & Chervany, 1998
	I generally have faith in humanity	
	I generally trust other people unless they give me a reason not to	
* Indicates deleted item; All items excluding App Complexity, App Continuance Intention, and Disposition Toward Trust used the anchors (1 = strongly disagree, 7 = strongly agree). App Complexity, App Continuance Intention, and Disposition Toward Trust used the anchors (1 = disagree, 5 = agree).		

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