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ABSTRACT

Abandonment of software applications can result in significant loses of organizational resources while also undermining the continued success of application developers, vendors, and software support ecosystems. Relatively little attention, however, has been directed toward understanding application abandonment that occurs after applications have been successfully adopted, despite the potentially far-reaching implications of such abandonment and the growing economic and social importance of software applications. We therefore developed a framework based on the four-drives model of motivation to better understand postadoption abandonment decisions and conducted an archival study to test our proposed framework in a hedonically oriented personal-use context. Results of this study suggest that individual motivations to acquire status and experience, bond with others, comprehend and grow, and defend their efforts all have significant implications for the likelihood of application abandonment. Specifically, application-related use activity, in-application user interaction, application complexity, and application commitments were all found to significantly diminish the likelihood of application abandonment.

KEY WORDS

AND PHRASES: Software apps; app abandonment; app discontinuance; hedonic applications; postadoption abandonment; user motivation; four-drives model

Introduction

Abandonment of established attitudes, beliefs, practices, and behaviors occurs with notable regularity and has considerable potential to initiate and foster a wide range of positive and negative outcomes for individuals, organizations, and society. Understanding the nature, basis, and implications of abandonment is, as such, of notable importance to managers. Researchers have thus directed some degree of attention toward understanding individual-level abandonment of various behaviors and beliefs, including purchasing behaviors, personal goals, and online shopping carts [51, 79, 82]. Nonetheless, efforts to understand the abandonment of personal-use software applications in the period after these applications have been successfully adopted have been quite limited [61, 80]. While a notable body of research has sought to understand application adoption, continuance, and switching, this work has not typically considered the possibility that users might simply abandon the use of software applications after some extended period of use. Work that has been conducted in this regard has focused almost exclusively on understanding temporary and permanent abandonment of social networking services. This represents a notable gap in the literature, particularly given that application abandonment decisions can result in significant losses of financial and other resources.

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Developers and vendors typically make large, long-term investments in the ongoing development and marketing of software applications [4]. A wide range of industry reports thus suggest that application abandonment presents a significant challenge to large application development organizations and their smaller competitors [80]. The value of the investments that these organizations make in the development, maintenance, and promotion of an application is severely undermined when this application is abandoned by its users [18]. Such abandonment is a particularly salient issue for developers of personal-use applications with prior work having repeatedly highlighted the difficulties that such developers encounter in their efforts to sustain user engagement [83]. In addition, abandonment of personal-use software applications can be problematic for individual users. While individuals typically invest lower absolute sums of financial and other resources in the applications that they use, the relative levels of monetary and nonmonetary commitments that they make to these applications need not be inconsequential. Considerable time and effort can, for example, be necessary to acquire requisite application expertise [78]. Commitments of time and effort can also be required to acquire status and other rewards, particularly when using hedonically oriented applications. The value that is derived from this time and effort is, however, limited once an application has been abandoned [28]. Improved understanding of application abandonment is, as such, important to improving consumer satisfaction, fostering more effective use of personal and organizational resources, and supporting the continued success of application developers and vendors.

Given the potential costs of postadoption abandonment decisions and the limited attention that such decisions have received, we sought to address the question of what motivates individuals to abandon hedonically oriented personal-use software applications after they have successfully adopted these applications. Our focus on personal-use applications was driven by their growing salience and by research indicating that organizations and organizational users are far more likely to replace rather than abandon applications that they have successfully adopted [20, 28]. Abandonment of personal-use applications occurs, in contrast, with considerable regularity [82]. In addressing our research question, we offer one of the first studies aimed at understanding consumer abandonment of hedonic software applications in the period after use of these applications has become well established. Such efforts are of particular importance given the growing economic significance of these applications. Gaming industry revenues were, for example, forecast to exceed US$175 billion in 2020 and have recently been growing at an annual rate of 9% [5]. Digital games have thus been identified as being among the most popular forms of entertainment and as having significant consequences for organizations and the global economy [41, 96]. In addition, the insights we provide are of considerable relevance to organizations that are increasingly relying upon the gamification of a wide range of business applications to induce and maintain the engagement of employees and other users such as customers [83, 93]. Absent a sound understanding of the drivers of abandonment, such organizations are at some risk of wasting significant resources on gamification initiatives that generate poor or even negative returns.

Theoretically, we present an overarching framework for understanding the abandonment of personal-use software applications that is rooted in established theory of human motivation. We also test this framework via an empirical study that yields insights of practical relevance to information system (IS) researchers and software development organizations. In addition, our framework can be used to support future abandonment

research that adopts a range of research methodologies, including survey research, experiments, mathematical modeling, and research that draws on the growing abundance of real-time user behavior data. Our inquiry commenced with a review and analysis of prior abandonment research across a broad spectrum of organizationally relevant domains. This was followed by a more focused, in-depth review of recent research related to application end-of-life decisions. These efforts aimed to identify salient motivations that underlie application abandonment. Themes that emerged from our review process led to the creation of a general research framework based on the four-drives model of human motivation [66] and formulation of research propositions that identify broad-based motivations to abandon software applications. Specific research hypotheses were then developed to reflect the nature of hedonic, personal-use software applications, and these hypotheses were tested via an archival study [37]. The following sections elaborate on our work, commencing with the development of our research framework and hypotheses. This is followed by a discussion of our methodology, data analysis, and results. We conclude with a discussion of our key findings, limitations of our work, and some notable opportunities for future research related to abandonment.

Research Foundations

Abandonment involves the giving up of something that is currently being used, pursued, or consumed [82]. Hence, while abandonment of personal-use applications can lead users to redirect their time to other activities such as meeting with friends or watching videos, application abandonment is quite distinct from upgrade, replacement, and switching behaviors [28, 54]. In particular, application abandonment does not involve efforts to persist with the same use-related behaviors by either installing an update to an existing application or switching to an alternative application that supports the same general tasks, practices, interests, or behaviors. Instead, abandonment represents a decision to discontinue the use of an application that has been used in the past without adopting an alternative application in its place. Prior research has examined application abandonment or discontinuance that takes place during the period that falls shortly after initial application adoption [e.g., 3, 11]. During this period, application users are primarily seeking to understand an application and assess its relative merits and limitations. They are typically not dependent on the application to perform needed tasks, they have relatively little commitment to use of the application, and use of the application has not yet been incorporated into their habits or routines [58, 77]. This initial trial period thus represents a period that is quite different from the more routine, habitual nature of ongoing application use [67]. Specifically, the individual-level abandonment decisions that are the focus of our work are typically made in light of a far greater degree of application comfort, familiarity, expertise, and dependence [30, 85].

Following a successful trial period, it can be expected that users will typically engage in continued application use for an extended period of time. Prior work has thus examined a wide range of cognitive and affective influences that lead users to persist in such use [e.g., 16, 55]. These influences include those that reflect user appraisals of the application in question such as its usefulness, as well as various affective states such as the level of satisfaction that an application generates. While such influences have been found to foster continued application use, it has been widely recognized that application discontinuance

decisions are often driven by forces that are quite distinct from those that underlie application adoption and continuance [80]. Researchers have thus explored the possibility that users might choose to discontinue their use of an application in favor of an alternative application that meets the same general needs [e.g., 17, 43, 54]. Work in this domain has, for example, examined factors such as dissatisfaction that can push users to switch to alternative applications, as well as factors that discourage switching, such as the benefits that a status quo application provides [15, 57]. Finally, related work has considered the possibility that users will opt to upgrade applications rather than replace them [e.g., 94] and the possibility that users will abandon and then re-adopt an application [e.g., 97].

In contrast with efforts to understand application continuance and switching, relatively little work has examined the possibility that users might opt to simply abandon the use of an application after some extended period of use. Work that has been conducted in this regard has focused almost exclusively on understanding temporary and permanent abandonment of social networking services [80]. This research has placed considerable emphasis on influences such as guilt, stress, fatigue, and social indifference [e.g., 34, 61, 87]. While important, the focus of this work on the relatively unique context of social networking services imposes some limits on its capacity to generalize to the abandonment of hedonic and other personal-use applications where social pressures, relational commitments, and desires to remain connected to strong social networks are less salient. We therefore conducted a general review of research that has examined abandonment behavior across a broad cross section of disciplinary contexts at multiple levels of analysis (Appendix A). This work suggests four broad categories of forces as providing bases for decisions to abandon products, practices, and behaviors. The first of these categories centers on various assessments of the value being provided by the product, practice, or behavior. The second focuses on the scope that is available for the product, practice, or behavior to respond to changing needs and circumstances. The third category reflects commitments that have been made to the product, practice, or behavior, and the fourth relates to general tendencies to mimic the abandonment decisions of others.

While our general review of abandonment research provided some basis for understanding application abandonment decisions, these decisions are somewhat distinct from decisions to abandon consumer products, managerial practices, and many of the other phenomena that were examined by the work included in the review. We therefore undertook a subsequent review of information system-related end-of-life decision-making research conducted over the past 5 years to develop a richer understanding of the motivations that underlie the full spectrum of postadoption end-of-life decisions that are made for personal-use applications (Appendix B). As noted previously, this body of work encompasses multiple, distinct forms of end-of-life decisions, including decisions to switch from the use of an established application to a suitable replacement and decisions to temporarily discontinue the use of an application [74, 80]. Hence, although we only identified one study in this recent work that appeared to examine postadoption abandonment [100], the end-of-life focus of the work meant that we were able to draw on it to further inform the understanding of abandonment that we initially derived from our multidisciplinary review.

The objective of our second review was to identify salient, broad-based themes that encompass the many varied factors that contribute to application end-of-life decisions. For example, approximately half of the studies in our review were focused on examining application switching or replacement behavior (Appendix B). As such, many of the

constructs in this work such as switching costs, switching benefits, and alternative attractiveness are not specifically relevant to application abandonment. Nevertheless, the broader notions of application commitment and application value that these constructs convey remain relevant. We therefore identified all direct antecedents of end-of-life decisions in the research that we reviewed and extracted overarching themes via an approach that is analogous to that used in open coding (Appendix C). We then returned to the theoretical foundations of prior work to further develop and refine our understanding of the motivations behind application abandonment. While a surprising number of studies relied on relatively little in the way of explicit theory, by far the most prominent theoretical foundation in the work we examined was the push-pull-mooring (PPM) framework. Originally developed to provide an account of human migration behavior [e.g., 38, 92], the salience of the PPM framework in individual-level postadoption application end-of-life decision-making research reflects the large proportion of this research that has focused primarily on application switching behavior. However, the inherent tension that the PPM framework posits between an application that is being used and an alternative application tends to limit its relevance as a model for understanding application abandonment. Similarly, other prominent theoretical foundations such as the Technology Acceptance Model (TAM), Expectation Confirmation Theory (ECT), and the Unified Theory of Acceptance and Use of Technology (UTAUT) appear to be better suited to understanding application adoption and continuance rather than application abandonment [10, 21, 89, 90]. In contrast, the four-drives model of human motivation provided a general account of the motivations that underlie human behavior that was also in accord with the themes we had identified as underlying motivations to abandon software applications [1, 63].

The four-drives model of human motivation argues that the psychological mechanisms underlying human motivations are linked to our efforts to fulfill one of the four fundamental human needs of acquisition, bonding, comprehending, and defending [53, 66]. Prior work suggests that fulfilling each of these needs is associated with distinct regions of the brain such that they represent unique sources of motivation that can operate both independently and in parallel [1, 66]. The four motivations posited by the four-drive model have evolved throughout the course of human history in response to the salient problems confronted by humanity. As such, they have come to represent relatively stable drivers of human behavior that are rooted in our biological and psychological makeup [1]. As suggested by Table 1, the most salient themes that emerged from our literature searches also aligned very well with the four motivational drives posited by the four-drives model, thus providing some cross-validation for the results of our search and coding efforts. As a result, the four-drives model was used as theoretical grounding for the formulation of four research propositions concerning the motivations for application abandonment. In the following discussion, we draw on these propositions to identify research hypotheses that we then test empirically (Table 2). The research model that we ultimately develop is presented in Figure 1.

Acquire

The first of the four drives underlying human motivation is the drive to acquire valuable resources, opportunities, experiences, and status [66]. This drive appears to arise in the limbic system of the brain and it seems to be rooted in the innate biological need to survive

Table 1. Applying the Four-Drives Model of Motivation to Application Abandonment Decisions.

Drive	Drive description	Abandonment literature theme	End-of-life literature themes	Proposition
Acquire	The drive to acquire encompasses motivations to obtain scarce resources, including physical products, experiences, and status.	Value	Value, affect	Individuals will be motivated to abandon applications that are not being used to obtain hedonic and/or utilitarian benefits.
Bond	The drive to establish and develop social connections and relationships with other humans.	Imitation	Social influence	Individuals will be motivated to abandon applications that offer less potential to bond with and feel strong connections with others.
Comprehend	The drive to collect information, assess, understand, learn, create, and explore. In essence, this drive is about satisfying our curiosity and making sense of the world.	Evolution	Currency, complexity, ability	Individuals will be motivated to abandon applications that offer less latitude to learn and grow.
Defend	The drive to protect against threats to valued accomplishments, status, and beliefs. The drive to defend aims to create a sense of security, stability, and confidence.	Commitment	Commitment, risk	Individuals will be motivated to abandon applications that do not notably represent past commitments or provide a sense of security and stability.

Table 2. Summary of Research Propositions and Their Associated Hypotheses.

Drives	End-of-life literature themes	Propositions	Hypotheses
Acquire	Value, affect	Individuals will be motivated to abandon applications that are not being used to obtain hedonic and/or utilitarian benefits.	H1a: The likelihood that an application will be abandoned is increased when use activity is low. H1b: The likelihood that an application will be abandoned is increased when extra-use activity is low.
Bond	Social influence	Individuals will be motivated to abandon applications that offer less potential to bond with and feel strong connections with others.	H2a: The likelihood that an application will be abandoned is increased when the application does not support user interaction. H2b: The likelihood that an application will be abandoned is increased when the application is unpopular. H2c: The likelihood that an application will be abandoned is increased when the application rating is low.
Comprehend	Currency, complexity, ability	Individuals will be motivated to abandon applications that offer less latitude to learn and grow.	H3a: The likelihood that an application will be abandoned is reduced when the application is complex. H3b: The likelihood that an application will be abandoned is reduced for newer applications. H3c: The likelihood that an application will be abandoned is reduced when the application is being maintained by its developer. H3d: The likelihood that an application will be abandoned is reduced when the application is being extended by its user community.
Defend	Commitment, risk	Individuals will be motivated to abandon applications that do not notably represent past commitments or provide a sense of security and stability.	H4a: The likelihood that an application will be abandoned is greater when a user has made less nonmonetary commitment to the application. H4b: The likelihood that an application will be abandoned is greater when the user has not made a monetary commitment to the application.

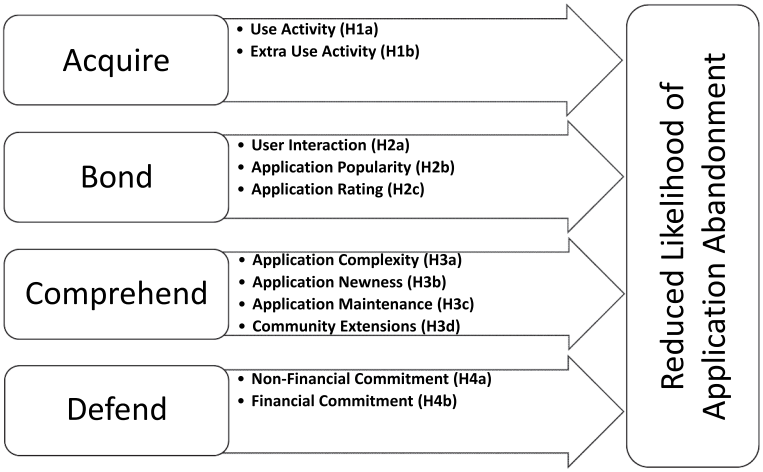

Figure 1. Research Model

[1]. Given the importance of survival to human existence, acquiring valuable resources and experiences tends to induce positive emotions, while failing to obtain such resources and experiences often leads to negative emotions such as dissatisfaction and frustration. Hence, the first source of motivations to abandon applications relates to the means by which individuals acquire value or benefits from applications. In broad terms, prior work identifies hedonic and instrumental benefits as the two key forms of value that can be derived from applications [49, 88]. Hedonically oriented benefits reflect the emotive benefits of application use, such as personal enjoyment and pleasure that users derive from such use. In contrast, instrumental benefits are related to the utilitarian value that is derived from the use of applications to support tasks and meet goals. Both the presence and absence of hedonic and instrumental benefits of application use feature prominently in models of application end-of-life decision making. Application value, defined as any psychological or utilitarian benefit provided by an application, was thus identified as a potentially salient influence on application abandonment. While survey research has often operationalized this value via measures of perceived usefulness and perceived enjoyment, application value encompasses a wide range of notions, including user satisfaction, application efficiency, and return on investment [49]. A notable body of IS literature thus reports that various forms of application value are of considerable importance to continued use of information systems and related services by individuals [e.g., 14, 84, 89].

Although the value of software applications takes different forms, a well-established tenet of both marketing and information systems research is that applications that provide value are used regularly, for extended periods of time, and with some degree of frequency [39, 42]. Such intensity of use is the mechanism by which applications provide users with utilitarian and/or psychological benefits such as satisfaction [23]. As a result, application use frequency and duration have been reported as particularly significant predictors of subsequent application use [45, 46]. It is therefore expected that limited application use activity will significantly increase the likelihood that a hedonically oriented application is subsequently abandoned, as it suggests that the application is not meeting the drive to acquire valued resources, experiences, or status. However, in addition to the direct value that is derived

from application use activity, consumer research also reports that consumers who value product brands are more likely to engage in other brand-related activities, such as posting to online communities that are associated with these brands [71]. Users who value an enterprise information system have been similarly observed to actively engage in a wide range of extra-use activities, such as demonstrating system capabilities to prospective users and contributing to ongoing system development [68]. A growing body of research further suggests that extra-use activities such as contributing to application changes, communicating with other users, and consulting with application experts can induce a greater sense of application value among those users who engage in these activities [9]. Hence, given the opportunities that are available for hedonically oriented application users to meet their drive to acquire through such extra-use activities, we expect that:

H1a:*The likelihood that an application will be abandoned is increased when use activity is low.*

H1b:*The likelihood that an application will be abandoned is increased when extra-use activity is low.*

Bond

The second drive posited to underlie human motivation by the four-drive model is the drive to bond with family, friends, and others and to connect with various social structures such as clubs and associations [66]. Rooted in the hypothalamus, the drive to bond reflects the survival advantages attained by individuals who cooperate to achieve mutually beneficial goals [1]. These advantages are such that humans have evolved to feel negative emotions such as isolation and loneliness in the absence of social connections and bonding. The desire to connect and bond thus suggests that users will be less likely to abandon applications that facilitate social interactions. While the potential to engage in social interaction is perhaps most evident in services such as those provided by social network service providers, this capacity is also integral to a wide range of personal-use applications ranging from fitness applications that permit the sharing of success stories to games that permit and even encourage various forms of user interaction. Given the strength of the drive to bond, it is generally expected that hedonically oriented applications that support such interactions will be less likely to be abandoned.

In addition to the potential for direct interaction through application environments, application ecosystems provide a range of other mechanisms by which application users can bond and connect with others. Specifically, within the context of personal-use applications the Internet has dramatically increased the extent to which the behavior of other application users can be observed and acted upon [24]. This is evident in the growing salience of information cascades and the notion of social proof [24, 72]. In the absence of perfect or complete information, people are inherently inclined to believe that the actions and choices of others are based on superior information. As a result, they tend to mimic these actions and choices when they have been observed. This can create an information cascade, as an observed choice leads others to make the same choice, with each successive choice being viewed as further social proof of the merits of the initial choice. Such informational cascades have been used to explain how media content and technologies spread through populations [24, 48] and how application use is impacted by the

observable use decisions of other users [31, 95]. Online consumers are, for example, more likely to attend to songs that have accumulated a large number of downloads [76], while book sales increase significantly when their popularity is revealed through rankings on highly regarded bestseller lists [81]. Hence, given that low popularity calls into question the social legitimacy, value, and relevance of an application [72], there is considerable potential for declining application popularity to be similarly noticed and acted upon by users of hedonic applications.

Online environments also provide other mechanisms for users to bond and feel connected with application developers and other users [27]. In this regard, user ratings offer one of the most salient channels for understanding the opinions of other application users. Within rapidly changing consumer contexts such as ours, application ratings offer real-time indications of the extent to which applications are valued by their user communities. Although direct personal experience with an application can diminish the impact of such information on user impressions, the drive to bond suggests that peer influences and vicarious learning continue to influence user impressions of value [98]. As a consequence, the negative social signal evident in low application ratings has the potential to foster abandonment of hedonic and other personal-use applications [12, 33]. This potential is heightened by general desires among users to maintain social status and self-esteem [36]. Such desires can encourage abandonment of a low-rated hedonic application as users seek to avoid the sense of social disconnection that can come from being affiliated with an application that is not widely valued. Hence, we expect that both direct and indirect sources of social bonding and connection will influence abandonment decisions such that:

H2a:*The likelihood that an application will be abandoned is increased when the application does not support user interaction.*

H2b:*The likelihood that an application will be abandoned is increased when the application is unpopular.*

H2c*:The likelihood that an application will be abandoned is increased when the application rating is low.*

Comprehend

The third key driver of human motivation is the drive to understand and make sense of our environment and the context in which we live [66]. Novelty in our environment presents significant threats and notable opportunities. We have, therefore, evolved visual and other sensory systems that draw our attention to this novelty and motivate us to explore, understand, and explain what we encounter [1]. Understanding and explaining our world provides a sense of growth and development that is fundamentally rewarding since it gives us some mastery over our current circumstances and helps us to adapt to changing circumstances. As a result, we tend to experience frustration and a sense of helplessness when efforts at understanding and sense making fail [66]. The drive to comprehend thus suggests that the likelihood of application abandonment will be notably influenced by forces that impact the currency and complexity of an application. Current applications provide

a sense of the novelty that we have been biologically programmed to explore, and application complexity has significant implications for efforts to explore and understand applications.

Information system researchers have long recognized the salience of application complexity to application use behavior, with constructs such as usability and ease of use having been posited as key drivers of both initial and continued application use [21, 49]. This salience reflects our innate drive to comprehend, and it can thus be expected that application complexity will also have a significant influence on the likelihood of application abandonment [99]. The direction of this influence is, however, somewhat unclear for hedonically oriented applications. In the case of utilitarian applications such as those used to support work tasks, prior research suggests that complexity will generally have negative implications for user satisfaction and continued application use, as it impedes understanding in a context where application use is simply a means to an end [25]. Implications of complexity at the organizational level of analysis are, however, somewhat less clear, with some work having reported, for example, that complexity does not significantly impact application replacement intentions [29]. Such ambiguity is further heightened in the context of hedonically oriented personal-use applications. While prior work suggests that excessive complexity in such applications might induce discontinuance, a notable degree of complexity is required to garner sufficient levels of user interest in these applications [56]. In essence, greater complexity in a hedonically oriented application provides its users with richer opportunities to explore and understand in accordance with the drive to comprehend. We therefore expect that the general tendency will be for application complexity to be viewed positively by the users of hedonically oriented applications such that it will reduce the likelihood of application abandonment.

In addition to the desire to explore and understand our environment, the drive to comprehend also encompasses our desire to attend to the new and novel. This innate desire suggests that the likelihood of application abandonment will be lower for newer applications. However, it is also important to recognize that application updates and revisions can introduce considerable novelty to older applications. Software applications can be revised on a regular basis to maintain their currency, respond to changing user needs, and thereby create a sense of novelty or newness that fuels the drive to comprehend. Application updates aimed at enhancing feature sets have, as such, been reported to encourage continued application use [26]. Application changes and revisions can therefore be similarly expected to play a role in reducing the likelihood that hedonically oriented applications will be abandoned [2, 70].

Although a wide range of stakeholders can encourage and contribute to application changes and revisions, vendors and users are the two key sources of such changes in the context of hedonically oriented software applications. Vendors typically drive ongoing evolution of software applications through their efforts to maintain and improve these applications via regular, ongoing development, testing, and release of application patches and enhancements. Such efforts introduce new application capabilities and address application shortcomings across the entire postrelease period [2]. Ongoing release of vendor updates is, therefore, a fundamental source of novelty that can induce the drive to comprehend in application users [29, 64]. Furthermore, once an application has been released to end users, its developer has access to user comments and feedback that can be used to identify sources of user dissatisfaction [13]. This information can direct future development efforts toward those

user needs and desires that will be most likely to continue to nurture the drive to comprehend among application users. Hence, ongoing developer-led efforts to maintain application currency are generally expected to diminish the likelihood of application abandonment.

In contrast with application vendors, the users of hedonically oriented applications are typically not responsible for maintaining application currency in the same way that end-user organizations might be responsible for maintaining their business systems. Nevertheless, to engage users and enhance development efforts, some vendors opt to open elements of these applications to modifications and extensions by their user communities. Within the game development industry there is a long tradition of developers permitting users to create and share application modifications free of charge [e.g., 6]. The scope that user communities are afforded to undertake such modifications and extensions ranges from minor alterations of user interfaces to the creation of sophisticated stand-alone product conversions [6]. Hence, while developer-led maintenance is frequently an important contributor to application currency, user-developed application enhancements can also forestall application obsolescence and bring a sense of newness to hedonically oriented applications [35]. In addition, unlike vendor-led development, user-led development is not bound by the demands of an often broad and diverse user base. As a result, user-led changes can be more experimental in nature and more tailored toward very specific user interests and preferences. Developer-led changes and user-led changes are, as such, complimentary contributors to the currency of hedonic applications. Hence, in aggregate, the drive to comprehend leads us to hypothesize that:

H3a:*The likelihood that an application will be abandoned is reduced when the application is complex.*

H3b:*The likelihood that an application will be abandoned is reduced for newer applications.*

H3c:*The likelihood that an application will be abandoned is reduced when the application is being maintained by its developer.*

H3d:*The likelihood that an application will be abandoned is reduced when the application is being extended by its user community.*

Defend

The final drive of the four-drive model of human motivation is the drive to defend [66]. A natural precondition for survival is a desire to defend against external threats to ourselves, our possessions, our friends and families, our beliefs, and our accomplishments [66]. Rooted in the limbic region of our brain, the drive to defend is evident in the fight-or-flight response that is integral to the behavior of many living organisms, including humans [1]. Successfully defending against external threats induces feelings of security and confidence, while failure to do so leads to fear and resentment [66]. In extreme circumstances, the motivational desire to defend can make individuals highly resistant to any form of change [63]. As such, the drive to defend suggests that the various commitments that users make to the use of an application will significantly reduce the likelihood that this application will be abandoned. Such commitments arise as

a consequence of investments of time and other resources that are known to foster dedication to a wide range of behaviors, practices, and beliefs irrespective of their current value [e.g., 30, 101]. The drive to defend thus yields a form of persistent dedication to a software application that can be expected to reduce the likelihood of application abandonment. Specifically, prior work suggests the salience of both monetary and nonmonetary commitments to an application in reducing the likelihood of application abandonment [29, 62].

Nonmonetary commitments encompass past actions that build support for a practice or behavior, such as regular repetition, accumulation of expertise, and the development of related practices. Over time such commitments lead to accomplishments, social relations, and beliefs that people are motivated to defend. Organizations are, for example, less likely to abandon practices when they have accumulated extensive experience with these practices and when the practices are aligned with other organizational decisions and activities [30, 101]. Nonmonetary commitment to personal-use software applications is, however, especially evident in the time that users have dedicated to installing these applications, becoming proficient in their use, and acquiring status. Such investments in learning, expertise development, and reputation building will generally contribute to heightened use [50, 86]. In addition, accumulation of expertise can create positive feedback loops as it helps application users to use an ever broader range of the capabilities that an application provides [75]. There is, as a result, sound reason to expect that application experience fosters commitment to an application that reflects the motivation to defend [20, 32, 40].

Monetary commitments are evident in the various financial investments in a product, practice, or behavior. Such commitments can notably decrease abandonment behavior, as suggested, for example, by literature related to IS project escalation [e.g., 91]. This stream of literature has repeatedly argued that the inability of organizations to abandon failing IS projects is rooted in a sunk cost effect. Rather than halting their losses, organizations tend to double down and "throw good money after bad," relying on prior monetary commitments to defend continued investments in failing projects. As such, the revenue model used to generate income from a personal-use application can have significant implications for its abandonment by altering the nature and timing of the monetary commitments that are made to the application [22]. Specifically, under a pay-to-use revenue model, users must purchase an application prior to using it, while under free-to-use models, users can access at least basic functionality for free and then pay at a later time for added content or functionality [19, 52]. Revenue models that call for an initial investment of financial resources induce a degree of application commitment that goes beyond what might be rationally expected [7]. Users who make an up-front investment of financial resources to gain access to an application can struggle to evaluate this application independent of their investment and are therefore more likely to defend their purchase by continuing to use the application [47]. Hence, we expect that both monetary and nonmonetary commitments will impede the abandonment of personal-use software applications such that:

H4a:*The likelihood that an application will be abandoned is greater when a user has made less nonmonetary commitment to the application.*

H4b:*The likelihood that an application will be abandoned is greater when the user has not made a monetary commitment to the application.*

Methodology

Anonymous individual-level data were collected at two separate points in time from a large desktop application ecosystem (Steam) that delivers primarily hedonically oriented personal-use applications. The public application programming interface (API) of this ecosystem made it possible to collect anonymous data that document the use of applications hosted on the platform at the level of individual users. However, owing to limitations in the platform API, the time spent using each application could only be collected for 2-week blocks rather than on a daily basis. As a result, our data collection effort establishes the time that each of our targeted users spent using each of the applications in their application portfolios during each of the 2-week blocks included in our initial and follow-up data collection windows.

We undertook an initial data collection project from December 2015 through to February 2016 that targeted 37,461 users randomly selected from a list of users active on the platform's discussion board. This method of sampling was adopted because a list of all platform users was not publicly available. Our first round of data collection identified the time that each of the 37,461 targeted users spent using each of the applications in their application portfolio in each biweekly data collection period. Our initial dataset thus included 972,166 dyadic user–application records. Although the size of our data collection window was limited by computational capabilities and data storage capacity, it was more than sufficient to identify the applications that individuals were using at the time of the initial data collection period. To ensure that the applications included in our final dataset were being actively used, we restricted our initial set of user-application records to those applications that had been used by their user for at least 30 minutes during our initial data collection period. A time of 30 minutes was chosen to ensure that use of the applications in our dataset had moved beyond initial exploration to active use. This yielded a dataset of 93,077 user–application dyads encompassing 16,754 users. Parallel to this effort we collected data on application characteristics using the APIs provided by the Steam platform, as well as a custom script that was designed to collect data on the discussion board activity of the users in our dataset. We further engaged in manual data collection efforts to complement and ensure the completeness of our automated data collection. We then consolidated all data into a single dataset such that one row captured all data related to a specific user–application dyad. Following removal of observations with missing data, our dataset included approximately 45,000 user–application dyads.

Identifying Abandonment

To identify instances where users had abandoned the use of an application, we undertook a second round of data collection approximately 18 months later, in August 2017. As the targeted platform reports the total number of minutes that an individual has used an application since adding it to their portfolio, we were able to identify applications that had not been used since our initial data collection window. This was accomplished by

comparing total minutes of use at the time of initial data collection with total minutes of use at the time of the second round of data collection. Approximately 20% of the user–application dyads in our dataset represented applications that had not been used by the user since our initial data collection. Given that 18 months had passed between our initial and follow-up data collections, the observed disuse was deemed to be permanent in nature. This assessment was in accord with prior work that has argued that a minimum of 6 months is required for discontinuance to be considered permanent [65, 100]. However, the observed discontinuance could indicate that a user had either abandoned the application or replaced it with a functionally equivalent alternative application. Hence, to establish that an application had truly been abandoned, we drew on the fact that the application ecosystem permits users to categorize applications using tags. An application was thus deemed to have been abandoned if its user had not used it since our initial data collection period and did not use any other application in the same category within a 1-month window surrounding the time of discontinued use. Approximately 7.6% of our observed last use events were thus identified as abandonment events. After removing user–application dyads that represented replacements and users who had abandoned the entire Steam platform and for whom data were thus unavailable, we were left with a dataset of 17,510 user–application dyads representing abandoned and nonabandoned applications.

Independent Variables and Control Variables

Although the second round of data collection was necessary to identify applications that had been abandoned, final use of abandoned applications took place during our initial data collection period. Abandonment was therefore deemed to have taken place after the period when we last observed an individual using an application. For example, the application depicted in Figure 2 would be deemed to have been abandoned by its user as of the end of the sixth observation block. Most independent variables were thus measured in the period of last observed use. However, this approach was not suitable for measuring use activity and extra-use activity. Prior work indicates that a high level of use activity encompasses use behavior that is recent, frequent, and of notable duration or intensity [39, 42, 44]. Since it is not possible to establish use recency and frequency without evaluating behavior across some period of time, we opted to examine a 6-period (12-week) window. It was felt that this window was sufficiently large to adequately assess the recency and frequency of application use without being excessively large. Nonetheless, we conducted robustness checks using different time windows, and these checks yielded similar results.

Our use activity measure was constructed as an index that incorporates the recency, frequency, and duration of application use in the 6 periods up to the last observed use event. To create this index we first determined use recency by counting the number of periods from the last observed use event to the use event that preceded it. For example, in Figure 2 it is necessary to go back 3 periods from the last use event to identify the most recent previous use

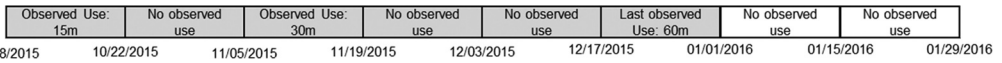

Figure 2. Illustrative Example of Data Collection for a Single User–Application Dyad

Table 3. Construct Definitions and Operationalizations.

Construct	Definition	Operationalization
Acquire		
Use activity	Direct interaction with an application through its user interface.	Index calculated by averaging measures of recency, frequency, and duration of use during the six 2-week periods up to the last observed use of the application.
Extra-use activity	Nonuse engagement with an application.	Binary variable that equals 1 if a user posted at least once to the discussion board of the application during the six 2-week periods up to the last observed use of the application.
Bond		
User interaction	Extent to which the application enables in-application user interactions	Binary variable that equals 1 if an application supports any kind of in-application user interaction and 0 if the application does not support such interactions.
Application popularity	Extent to which the use of an application is widespread.	Maximum number of users simultaneously using an application during the period of the last observed use of the application.
Application rating	Collective, user-driven assessment of the value of an application.	The total number of positive reviews that an application had received as of the period of its last observed use divided by the total number of reviews it had received at that time.
Comprehend		
Application complexity	The breadth and depth of sophistication of an application.	The amount of space, in gigabytes, that an application requires to be installed on a user's hard drive.
Application age	The time that an application has been on the market.	The time, in years, since the application was initially released to the market.
Application maintenance	Creation and release of patches and/or enhancements for an application by its developer.	Binary variable that equals 1 if an application received a software update at some point during the period of the last observed use of the application.
Community extensions	Creation and release of extensions for an application by its user community.	Volume of user modifications, in gigabytes, released for an application in the period of the last observed use of the application.
Defend		
Nonfinancial commitment	Dedication to use of an application over time.	Cumulative time, in hours, that a user spent using an application since adding it to their application portfolio as of the period of the last observed use of the application.
Financial commitment	Monetary investments that are made in an application.	A binary variable that equals 1 if it was necessary to purchase an application before use.

event. Second, we calculated use frequency as the number of periods during which an application was used in the 6 periods up to the last observed use event. There are, for example, 3 such periods for the user–application dyad depicted in Figure 2. Third, we calculated use duration as the total number of minutes that a user spent using an application during the 6 periods up to the last observed use event (105 minutes in Figure 2). This final measure was subsequently scaled to align it with our measures of use frequency and recency by dividing the full range of use duration in our dataset into 6 equally sized groups. A 6-point measure of use duration for each user–application dyad was then determined by establishing which of these 6 groups corresponded to the application dyad's total use time. Finally, to prevent collinearity issues and capture the multidimensional nature of use activity, we averaged our measures of recency, frequency, and duration to create our use activity measure. Our measure of extra-use activity was similarly constructed by examining the 6 periods up to the last observed use event. However, given that contributions to online communities are much rarer, we operationalized extra-use activity as a simple binary variable that equals 1 if a user posted at least once to the discussion board of the application during the 6 periods up to the last observed use event. Our measure of extra-use activity thus captures the general tendency of a user to engage with an application outside of regular use behavior, rather than the absolute level of contribution behavior. A summary of all construct definitions and variable measures is provided in Table 3.

In addition to the constructs of interest, we included a variety of setting specific control variables in our analysis. First, we included a binary variable that indicates whether the application was developed by an independent developer (Developer Resources). Independent developers often have fewer resources at their disposal that might result in systematic differences in the likelihood of application abandonment. Second, we controlled for the total time that a user has dedicated to using all applications on the Steam platform in the 6 periods up to the last use event. This control was included to account for the possibility that individuals who dedicate considerable time to the platform will be less likely to abandon applications. Third, we accounted for the fact that some application developers release paid application content, commonly referred to as downloadable content (DLC), by adding a control variable that equals 1 if the developer released such content in the period of last use. Fourth, we included a set of 6 binary variables to control for the different application genres that are present in our dataset. While all applications in our dataset are gaming applications, there may be some degree of heterogeneity between individual genres. As such, we controlled for whether the developer of the application marketed their application as belonging to the Action, Adventure, Role-Playing, Strategy, Simulation, or Sports genre. Finally, we include three period fixed effects to control for time effects.

Analysis And Results

Table 4 provides descriptive statistics, variance inflation factors (VIFs), and correlations for the core variables in our final model. Of the 17,510 user–application dyads in our sample, approximately 8% represent abandonment events. Use activity averages 2.65, while extra-use activity is relatively rare with only 3% of users posting to an application's discussion board. With respect to social influence, ~72% of observations are associated with applications that enable some form of in-application user interaction. Further, the average application in our sample has more than 107,000 concurrent users. Applications are generally positively reviewed, with the mean rating being 89 out of 100. The average application in

Table 4. Descriptive Statistics and Correlations.

Variable	Mean	SD	VIF	1	2	3	4	5	6	7	8	9	10	11	12
Abandonment	0.08	0.27	—	1.00											
Use activity	2.65	1.60	1.29	−0.19*	1.00										
Extra-use activity	0.03	0.17	1.04	−0.04*	0.14*	1.00									
User interaction	0.72	0.45	1.47	−0.09*	0.11*	−0.01	1.00								
Application popularity ('000s)	107.80	229.11	2.30	−0.09*	0.32*	−0.01	0.26*	1.00							
Application rating	0.89	0.09	1.51	0.00	0.02	−0.05*	−0.06*	0.17*	1.00						
Application complexity	15.05	18.55	1.77	−0.09*	0.13*	0.05*	0.06*	0.03*	−0.41*	1.00					
Application age	3.10	2.58	1.82	−0.02	−0.02	−0.06*	0.17*	0.04*	0.40*	−0.27*	1.00				
Application maintenance	0.28	0.45	1.58	−0.06*	0.05*	0.03*	0.06*	−0.06*	−0.12*	0.21*	−0.19*	1.00			
Community extensions	2.42	4.49	1.81	−0.07*	0.15*	−0.01	0.18*	0.54*	0.25*	−0.01	0.27*	0.05*	1.00		
Nonfinancial commitment	201.42	434.76	1.43	−0.10*	0.35*	0.07*	0.15*	0.38*	0.08*	0.02	0.13*	0.05*	0.17*	1.00	
Financial commitment	0.85	0.36	1.30	0.01	−0.08*	0.00	−0.09*	−0.08*	0.13*	0.03*	0.15*	−0.27*	0.13*	−0.17*	1.00

* $p < 0.01$.

Table 5. Results.

	Logit		Mixed effects	
Variable	(1)	(2)	(3)	(4)
Use activity	−0.342***	−0.022***	−0.405***	−0.023***
	(0.023)	(0.002)	(0.028)	(0.002)
Extra-use activity	−0.575*	−0.037*	−0.587	−0.034
	(0.334)	(0.022)	(0.368)	(0.021)
User interaction	−0.246***	−0.016***	−0.304***	−0.017***
	(0.073)	(0.005)	(0.089)	(0.005)
Application popularity	−0.000	−0.000	−0.001	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Application rating	−0.051	−0.003	−0.145	−0.008
	(0.405)	(0.026)	(0.443)	(0.025)
Application complexity	−0.017***	−0.001***	−0.020***	−0.001***
	(0.003)	(0.000)	(0.003)	(0.000)
Application age	−0.020	−0.001	−0.019	−0.001
	(0.015)	(0.001)	(0.019)	(0.001)
Application maintenance	−0.318***	−0.021***	−0.384***	−0.022***
	(0.092)	(0.006)	(0.107)	(0.006)
Community extensions	−0.024***	−0.002***	−0.030***	−0.002***
	(0.009)	(0.001)	(0.011)	(0.001)
Nonfinancial commitment	−0.002***	−0.000***	−0.002***	−0.000***
	(0.001)	(0.000)	(0.000)	(0.000)
Financial commitment	−0.253***	−0.016***	−0.329***	−0.019***
	(0.097)	(0.006)	(0.115)	(0.007)
Developer resources	−0.187**	−0.012**	−0.212**	−0.012**
	(0.080)	(0.005)	(0.094)	(0.005)
User budget	−0.003***	−0.000***	−0.004***	−0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
DLC release	0.076	0.005	0.099	0.006
	(0.234)	(0.015)	(0.281)	(0.016)
Constant	0.096		0.015	
	(0.364)		(0.405)	
Genre controls	Yes	Yes	Yes	Yes
Week-fixed effects	Yes	Yes	Yes	Yes
AIC	8,251	—	8,169	—
BIC	8,430	—	8,355	—
Log likelihood	−4,102.45	—	−4,060.29	—
Number of users	8,066	8,066	8,066	8,066
Number of applications	662	662	662	662
Number of observations	17,510	17,510	17,510	17,510

Notes: Columns (1) and (2) show results of a logistic regression with (1) showing the raw coefficients, and (2) reporting marginal effects. Similarly, column (3) shows the raw coefficients for a mixed-effect model, and (4) shows the marginal effects. To account for intracluster correlations, we cluster standard errors at the user level for (1) and (2). For the mixed-effect model, we allow the intercept to vary on the user level. With *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

a user–application dyad is 15.05 gigabytes in size and 3.1 years old. Approximately 28% of applications received a software update during the observation period, and the mean level of user-generated content received by an application was 2.42 gigabytes per observation period. Table 4 also shows that 85% of observations are associated with applications that require an up-front financial commitment. The mean level of nonfinancial commitment, measured as the total time that a user has utilized an application, is 201.42 hours. In terms of control variables, we find that 63% of observations are associated with independent developers and that users in our sample spend an average of 138.5 minutes per observation period using applications on the Steam platform. Finally, 2% of observations relate to user

application dyads where the developer released DLC in the period of last use. None of the variables included in our analysis raised multicollinearity concerns as indicated by low VIF values.

Analysis of our sample is complicated by its hierarchical nature. In particular, one user can use multiple applications and can thus be represented multiple times in our dataset. As a consequence, we needed to account for possible intracluster correlations within user clusters. Mixed-effects models account for such correlations by splitting variance into a fixed portion that is constant across users and a random portion that is unique to individual users. We therefore constructed a mixed effects logistic regression model as well as a conventional logistic model where we clustered the standard errors at the user level (Table 5). Although our dataset also contains multiple observations for some applications, we allowed for random intercepts between users rather than applications as this reflects the fact that users select applications rather than vice versa. Nonetheless, we estimated a model where intercepts could differ across applications to ensure the robustness of our findings. This alternative model yielded results that were similar to those that we report in Table 5.

Model Selection and Performance

To assess the appropriateness of the logit model relative to the mixed-effects model and evaluate overall classification accuracy we performed a series of postestimation tests. Specifically, we performed a likelihood ratio test and compared the AIC and BIC values of the two models. These assessments suggested that the mixed-effects model outperformed the conventional logit model. In addition, since the goal of the models is to predict abandonment, we assessed and compared the classification accuracy of both models by first dividing our dataset into a training sample that included 70% (12,257) of the total observations and a hold-out sample that included the remaining 30% (5,253) of observations. In constructing these samples, we ensured that the average rate of abandonment remained constant across samples. Logit and mixed-effects models were then constructed using the training sample and the classification accuracy of these models was assessed (Appendix D). To perform this assessment, we translated each model's predicted probability into a binary outcome variable that denoted either abandonment or continuance. Given that our dataset was highly imbalanced with respect to the two possible outcomes, it was necessary to establish the probability threshold that would be used to discriminate between these two outcomes since reliance on a default threshold of 0.5 would have yielded an artificial increase in false negatives [69]. As our data were obtained via a random sample that was expected to be representative of the population, we identified an optimal threshold value through calculation of the Youden index, which aims to establish a threshold that maximizes the sum of true positives and true negatives [59]. Using this threshold value, the logit specification of the model achieved a modest classification accuracy of 71.4% (Appendix D). However, the classification accuracy of the mixed effects model is notably higher at 91.8%. This provides further evidence to support the superiority of the mixed-effects model. Finally, having obtained estimates of classification accuracy for both the logit and mixed effects models, we assessed out-of-sample classification accuracy for each model using the hold-out sample. To do this we predicted abandonment using the coefficient estimates obtained from the training data. Classification accuracy was 71.5% for the

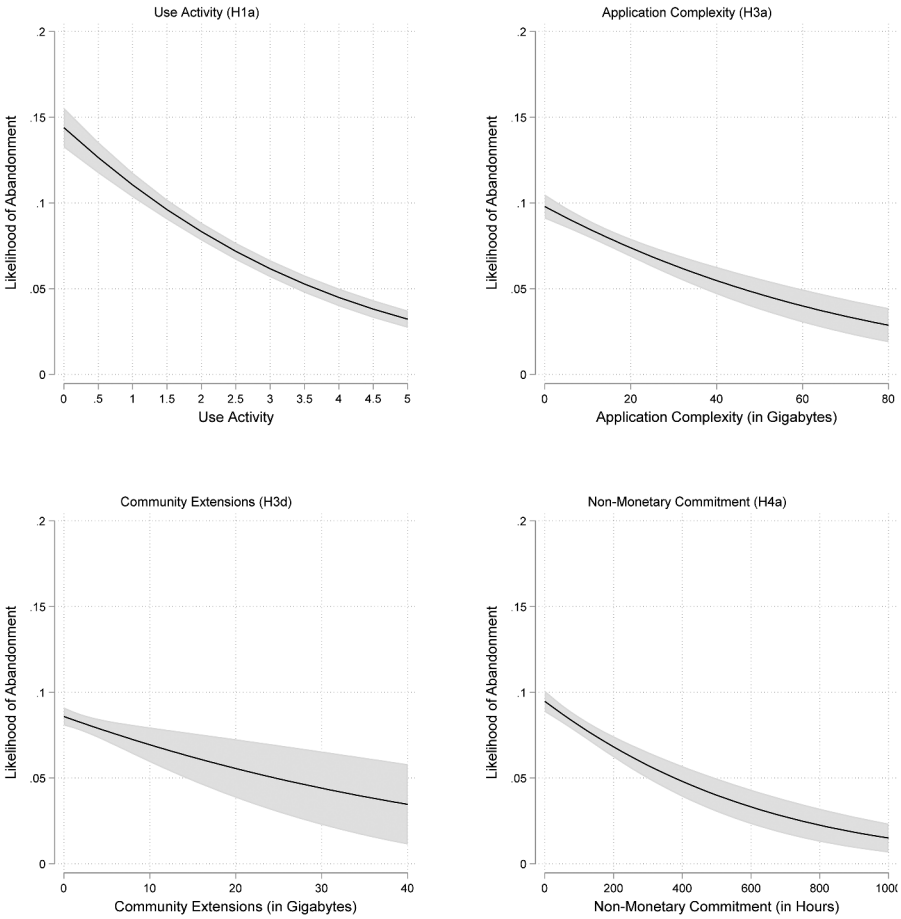

Figure 3. Graphical Illustrations of Marginal Effects Note: These figures show the marginal effects on the likelihood of abandonment for continuous predictors in our model. Shaded areas in the graphs correspond to the 95% confidence intervals.

conventional logit model and 92.4% for the mixed effects model. These values further underscore the merits of the mixed effects model and demonstrate consistency in classification accuracy between training and holdout data.

Hypotheses Testing

Having found that our mixed-effects model provides good predictive power and is superior to our conventional logit model, we evaluated our hypotheses using the results reported in column (3) of Table 5. Based on the coefficients and significance tests reported in this table we find support for all hypotheses except H1b (extra-use activity), H2b (application popularity), H2c (application rating), and H3b (application age). To understand the magnitude and practical significance of our results, we examined the calculated marginal effects reported in column (4) of Table 5. We first discuss the results for binary predictors before

Table 6. Split Sample Analysis.

Variables	(1) User Interaction	(2) No user interaction	(3) Difference
Use value	−0.421***	−0.361***	−0.06
	(0.041)	(0.046)	
Nonuse value	−0.843	−0.347	−0.496
	(0.526)	(0.528)	
Application popularity	−0.001***	−0.013***	0.012***
	(0.000)	(0.004)	
Application rating	0.907	−1.311*	2.218***
	(0.593)	(0.752)	
Application complexity	−0.018***	−0.030***	0.012*
	(0.004)	(0.006)	
Application age	−0.081***	0.050	−0.131***
	(0.027)	(0.032)	
Application maintenance	−0.364**	−0.507**	0.143
	(0.143)	(0.200)	
Community extensions	0.011	−0.040***	0.051*
	(0.022)	(0.015)	
Nonfinancial commitment	−0.002***	−0.004***	0.002*
	(0.000)	(0.001)	
Financial commitment	−0.389***	−0.429*	0.04
	(0.147)	(0.238)	
Developer resources	−0.224*	−0.405***	0.181
	(0.134)	(0.151)	
User budget	−0.004***	−0.003***	−0.001*
	(0.001)	(0.001)	
DLC release	0.443	0.058	0.385
	(0.428)	(0.400)	
Constant	−1.328**	1.316*	−2.644**
	(0.530)	(0.714)	
Genre controls	Yes	Yes	
Week-fixed effects	Yes	Yes	
Observations	12523	4987	
Log likelihood	−2517.04	−1532.55	

Notes: This table shows the results of testing for systematic differences in coefficients between a sample containing only those applications that support in-application user interactions (column 1) and those that lack this functionality (column 2). Results of the two individual regressions have been combined using seemingly unrelated estimations techniques and standard errors have been clustered at the user level. Column (3) reports the results of a Wald test for differences in coefficients. With *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

moving to continuous predictors, given that interpretation of the latter is rendered somewhat more difficult due to the inherently nonlinear nature of our logit model. For the three statistically significant binary predictors (user interaction, application maintenance, and financial commitment), the marginal effects reported in column (4) of Table 5 represent instantaneous rates of change in the probability of abandonment. Hence, the likelihood of abandoning an application that supports some form of user interaction is, on average, 1.7% lower than for an application that lacks such support. Similarly, recent developer maintenance activity reduces the likelihood of abandonment by 2.2% and applications that require a monetary commitment are 1.9% less likely to be abandoned.

To explore the effect of the statistically significant continuous predictors we plotted the marginal predicted probability of abandonment at different levels of the focal variable while holding all other variables at their means (Figure 3). With respect to H1a, we find evidence that use activity in the preceding 12 weeks has a strong negative influence on the likelihood of abandonment. Limited use activity is associated with a likelihood of abandonment of

around 15%. In contrast, the likelihood of abandonment falls to under 5% for users with high levels of use activity. We further observe that increased application complexity is associated with a notable decrease in the likelihood of abandonment in accordance with H3a. We also see that application extensions provided by the user community have a significant negative effect on the likelihood of abandonment in accordance with H3d. In this case, the likelihood of abandonment falls from approximately 10% for applications without user extensions to under 5% when notable levels of such extensions are being posted by the user community. Finally, with respect to H4a and the influence of nonmonetary commitment, we observe that the likelihood of abandonment falls from ~10% for users with limited nonmonetary commitment to ~2% for users with high levels of such commitment.

Additional Analysis

To shed further light on our results and assess the robustness of our findings, we conducted some post hoc analysis. Specifically, we split our sample into two groups based on whether a user–application dyad represents an application that supports some form of in-application user interaction. This split was motivated by the possibility that the process of application abandonment for applications that support in-application user interactions might be systematically different from those that do not support any such interactions. In the latter case, user retention and experience are primarily driven by user interaction with the application and the content provided by its developers. For the former case, a notable portion of the user experience might reflect social interactions that take place within the application. Since most of the applications in our sample (73%) support some form of in-application interaction, effects for applications that do not support such interactions might be masked.

Split sample analysis was adopted over the alternative of including interaction terms in our model because we did not have specific hypotheses for interaction terms. As such, it would have been necessary to include interactions for all variables in our model to yield results that are comparable to those generated with our split sample analysis. In addition, split sample analysis is both simple and easy to understand. Finally, split sample analysis is suited to our data because it can be divided into two distinct, meaningful categories based on whether support is provided for in-application user interaction. Hence, we conducted separate analysis on our two subsamples and tested for differences in the coefficients obtained from these two subsamples (Table 6). Since split sample analysis does not provide direct tests of statistical significance, as would be the case for interaction terms included in a regression model, we tested for differences in coefficients by combining the covariance matrices of the individual logit regressions using seemingly unrelated estimation techniques. In so doing, we accounted for the nested nature of the data by clustering standard errors on the user level. This process allowed us to test for the equality of individual coefficients using a modified Wald test. Columns (1) and (2) of Table 6 report the coefficients obtained for applications that support in-application user interaction and those that lack such support, while column (3) reports differences between these two estimates and the significance of these differences.

Results of our split sample analysis reveal some interesting differences. Specifically, application popularity and application rating have significantly stronger implications for the abandonment of applications that do not support any form of in-application user

interaction. This suggests that indirect opportunities for bonding can substitute for direct forms of bonding when the latter are unavailable. A similar observation can be made for application complexity and community extensions, both of which are more likely to reduce the likelihood of application abandonment for applications that do not support in-application user interaction. This suggests that the motivation to comprehend can substitute for the motivation to bond in reducing the likelihood of abandonment. Finally, our results indicate that older applications that support in-application user interactions are less likely to be abandoned than older applications that lack such support. This suggests that support for in-application interaction can offset the negative consequences of application aging. Hence, although the general pattern of results in our split sample analysis is in alignment with our main analysis, the split sample analysis also reveals some interesting differences.

Discussion

Abandonment of software applications is an overlooked phenomenon of notable importance to managers and consumers. We therefore developed a framework for understanding motivations behind application abandonment that is based on two separate reviews of prior work and grounded in the four-drives model of human motivation. Drawing on this foundation, we presented four general propositions concerning the abandonment of software applications. We then formulated research hypotheses in accordance with these propositions and empirically tested our hypotheses using an archival dataset collected over a 2-year period. This dataset documents the application abandonment behavior of more than 8000 users of more than 660 hedonic personal-use software applications, and it thus provides a novel opportunity to understand application abandonment based on the actual behavior of a relatively large sample of application users. Results of our analysis indicate that, in general terms, application abandonment decisions can be significantly influenced by the motivations of individuals to acquire status and experience, bond with others, comprehend and grow, and defend their efforts.

In broad terms, we present a theoretical model for understanding application abandonment that is predicated on fundamental human motivations and grounded in prior research that has examined abandonment in general and IS end-of-life decision making in particular. This framework is both broadly inclusive and based on innate human tendencies that are stable and enduring [66]. As such, it provides some degree of integration and cohesiveness to existing IS end-of-life research, particularly the not inconsequential body of this work that has relied on relatively limited theoretical foundations. We thus believe that our effort to review and develop the theoretical foundations of prior work represents an important contribution that can provide stronger grounding for future research related to application abandonment, as well as other end-of-life phenomena such as application switching and upgrading. While specific research hypotheses may vary depending on context and the phenomenon being examined, the research propositions that we present are based on innate human motivations and they thus provide guidance to researchers examining end-of-life decisions in a wide range of contexts. Prior work suggests, for example, that the abandonment of social media services tends to be dominated by influences related to the drive to bond. However, our work indicates the potential salience of a broader range of motivations while simultaneously identifying the theoretical basis for these motivations.

In addition to offering a broad-based theoretical contribution to the literature, our research also offers interesting empirical insights that are of significance to researchers and practitioners alike. As a starting point, our analysis provides robust evidence that the motivational drive to acquire achievement and status through application use activity has a broad and strongly negative influence on the likelihood of application abandonment. Specifically, in accordance with prior work related to application adoption [89], we find that frequent, recent, and intense application use activity significantly reduces the likelihood that a personal-use application will be abandoned. The importance of application use activity is such that it can, on average, reduce the likelihood of application abandonment by well over 10%. Hence, although the general result was anticipated based on prior work in the domains of application continuance and switching, the strength and economic significance of the influence that we demonstrate are quite compelling. In contrast, our results provide only limited evidence that extra-use activity, in the form of contributions to an application's user community, has significant implications for the abandonment of personal-use applications. Specifically, the negative impact of extra-use activity on the likelihood of application abandonment is only significant in our conventional logistic regression model. Nevertheless, given the notable body of work demonstrating the power of such activity to engage users [8], we believe that it is still reasonable to expect that users who are engaged in application-related extra-use activities can derive the achievement, experience, and status needed to fill the drive to acquire. The limited prevalence of such activity among the users in our dataset means, however, that this effect is not statistically significant in our mixed effects model. As such, we feel there is considerable opportunity to further explore the implications of extra-use activity for application abandonment.

While our work indicates that the drive to acquire is a powerful motive force behind application abandonment decisions, we also find strong evidence to suggest that the drive to bond can be a similarly powerful motivation. Specifically, personal-use applications that support some form of in-application user interaction are significantly less likely to be abandoned. By providing a mechanism for users to meet their needs to bond and connect, these applications fill important human needs. In addition, our work indicates that the implications of the drive to bond can be complex. In particular, while application popularity and application rating did not significantly influence the likelihood of application abandonment in our main analysis, results of a subsequent split sample analysis suggest that application popularity and rating do significantly influence the likelihood of abandonment for applications that do not support in-application user interactions. As such, it seems that personal-use applications can support a wide range of direct and indirect mechanisms to meet user needs to bond and connect with others. While the specific nature of these mechanisms may vary depending on the applications in question, there would appear to be considerable opportunity to further explore the full spectrum of these mechanisms.

In contrast with many physical products, software applications hold notable potential to evolve in response to changing circumstances. This flexibility imbues applications with the capacity to remain relevant to their users even as these users pursue new interests and confront changing needs. This suggests that software applications have considerable potential to meet user motivations to comprehend and grow even over extended periods of time. This is supported by our finding that ongoing developer efforts to maintain and update applications can significantly reduce the likelihood that these applications will be abandoned, irrespective of whether they support in-application user interaction. In addition, we

find that greater application complexity also reduces the likelihood that the hedonically oriented applications in our dataset will be abandoned. The effect of application complexity is, however, significantly stronger for applications that do not support in-application user interactions. This suggests that the drive to comprehend and grow can serve as a partial substitute for the drive to bond when applications provide relatively limited opportunities to meet this latter need. We also find some evidence that developer maintenance efforts can be complemented by user efforts to create and share application extensions with other members of an application's user community, particularly for applications that do not support in-application user interactions. For these applications, our split sample analysis indicates that community extensions significantly reduce the likelihood of application abandonment. Such extensions can be particularly responsive to user needs, given that they can be released with few of the constraints that impede the release of formal software updates. As such, they can support user motivations to learn and grow when needs for bonding and connection may not be fully met.

Finally, we demonstrate the importance of the drive to defend for application abandonment. Once users make monetary and nonmonetary commitments to an application, our results suggest that they are motivated to defend these commitments such that greater commitments lead to significantly reduced likelihood of application abandonment. Specifically, the need to purchase an application was found to significantly reduce the likelihood that users would abandon this application. Similarly, nonmonetary commitment, as evidenced in dedication to use of an application over time, was also observed to reduce the likelihood that individuals would abandon hedonically oriented software applications. In addition, the impact of monetary and nonmonetary commitments on the likelihood of application abandonment is evident in both our main model and our split sample analysis. This suggests that these commitments are of broad-based importance. Our work thus indicates that users will grow increasingly reluctant to abandon applications as their monetary and nonmonetary commitments to these applications accumulate. This is in accordance with work that demonstrates that prior resource commitments undermine the willingness of decision makers to make economically rational choices [e.g., 7, 91]. Hence, while continued use of redundant or unnecessary applications may provide users with some value, there is notable risk that users will fail to pursue more economically rational uses of their time as a consequence of their motivation to defend the extensive commitments they have made to the use of these applications.

Implications for Practice

Given the negative consequences of abandonment for application developers, our work offers a number of important insights for practicing managers. First, our finding that abandonment is significantly more likely to occur in the absence of monetary commitments is of value to developers that rely on business models that provide free or low-cost applications and then generate revenue streams from microtransactions within the application environment [19]. More generally, our finding that both monetary and nonmonetary application commitments can reduce the likelihood of application abandonment suggests that developers would benefit from a wide range of initiatives aimed at understanding and nurturing various forms of application commitment. Application abandonment might, for example, be reduced by seeking application endorsements from users who appear to be at

some risk of abandonment or by inviting these users to participate in application testing programs. In addition, the salient role of developer maintenance and community extensions in reducing application abandonment highlights the need for developers to build evolvability into their applications. Such evolvability should be central to initial application design and then leveraged throughout an application's life cycle to support user motivations to comprehend and grow. This can be achieved via the regular release of application updates and by encouraging application users to actively engage in the processes of application evolution. Such engagement can include creation and posting of application content to application user communities as well as active participation in developer led evolution through, for example, participation in focus groups or submissions of suggestions for application improvements. Finally, in general terms, we provide quantitative, empirically grounded understanding of the relative impact of the four motivational drivers of human behavior on the likelihood that personal-use applications will be abandoned. Such practical insights can be used to guide developer planning and resource allocation to the most effective mechanisms for reducing abandonment.

Limitations

Our research examined application abandonment in a hedonically oriented personal-use context. As such, questions can be asked concerning its relevance to more utilitarian contexts. We believe, however, that the general understanding of the motivations underlying application abandonment offered by our framework provides guidance to IS researchers working in a broad range of contexts, including those that are more utilitarian in nature. In addition, given the large and growing importance of personal-use applications, we believe that the insights we offer are of direct relevance to a significant and growing group of researchers and practitioners. A second limitation of our work is that we examine only application abandonment events, rather than the entire process of application abandonment. As a consequence, we are unable to comment on the possibility that a significant period of decommitment or deescalation of use-related activity may be necessary to move users from the emergence of some form of abandonment intention to the actual abandonment behavior that we observe [60, 98]. Nevertheless, although we were not seeking to offer a process-oriented view of abandonment, we believe that our research provides foundational insights for those researchers who might seek to examine the entire application abandonment process in more depth. Further to this, the data that we analyze are relatively cross-sectional in nature. This can constrain the causal inferences that are possible. Our dependent variable was, however, measured subsequent to the measure of our independent variables, which supports at least some degree of causal inference. Finally, our research examined application abandonment that took place within a relatively limited time period. We are, therefore, unable to provide insights concerning how the motivations behind abandonment may be changing over time, as might, for example, be occurring as new technology trends emerge. By focusing on a relatively narrow time period we are, however, able to examine these motivations without confounding influences that might be introduced as technologies evolve over time. Hence, although we encourage more longitudinal inquiry, a strength of our research is that our findings are unlikely to have been impacted by technological innovations and other contextual changes that take place over time. We therefore believe that we offer a significant contribution to the literature despite some of

the limitations that have arisen due to our specific research focus and the challenges associated with collecting data that documents actual application abandonment events over extended periods of time.

Future Research

Our initial examination of individual-level application abandonment suggests a wide range of future research opportunities. In broad terms, there are opportunities for research that seeks to triangulate our findings using alternative methods such as surveys and experiments, alternative approaches to analysis such as survival analysis, and alternative measures for constructs such as application use activity. More specifically, further in-depth examination of how community contributions impact abandonment and the types of contributions that most strongly support the drive to comprehend would be of considerable value to both research and practice. Further to this, there would seem to be considerable opportunity to explore the full spectrum of mechanisms that might be used by applications to support the drive to bond and to examine the implications that each of these might have for application abandonment. In addition, there are numerous opportunities to extend our split sample analysis to explore how the influences that we have identified interact with each other and how they might be moderated by other contextual factors [37]. Also, as suggested previously, there are some opportunities to explore abandonment as a process that occurs over time rather than as a discrete event. Such inquiry could help to better understand variation in the rate at which individuals progress toward abandonment and the forces that alter this process [98]. It might, for example, be that the abandonment events we observe mark merely the endpoint of a process that extends for some period of time as user motivations weaken [82]. Inquiry in this area could be guided by the four-drives model of human motivation, which our work suggests is well suited to exploring application abandonment. In addition, an interesting line of inquiry would be to explore how other forms of application commitment such as acquiring application certifications might foster the drive to defend. Further to this, it could also be the case that users who are engaged in an application community identify themselves as committed users of the application and are thus less likely to abandon their use of the application [73].

Conclusion

We drew upon the four-drives model of human motivation to develop a research model that provides a basis for understanding the motivations behind decisions to abandon the use of hedonically oriented personal-use software applications. We then tested this model using a dataset that documents the use behavior of more than 8000 users. Results of our analysis demonstrate the importance of the drives to acquire, bond, comprehend, and defend in reducing the likelihood of application abandonment. Split sample analysis further demonstrates how these motivational drivers can operate in parallel and substitute for each other. The work that we report thus provides empirically grounded guidance to practitioners seeking to reduce the likelihood of application abandonment. It also provides a theoretically grounded, empirically validated framework for understanding abandonment that can be used to guide a wide range of research initiatives related to the abandonment of software applications as well as other beliefs, behaviors, attitudes, and assets of managerial importance.

Disclosure Statement

No potential conflict of interest was reported by the authors.

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Appendix A. Research Examining the Basis for Abandonment Decisions

Study	Focal outcome(s)	Research context	Methodology	Basis for abandonment	Abandonment driver themes	Level of analysis
Becker [1]	Abandonment of traditional budgeting practices	Four organizations of different sizes operating in various industries	Case study	Insider agency is essential to the deinstitutionalization needed to abandon entrenched organizational practices.	Commitment	Organizational
Bennett [2]	Abandonment of online donations	Individuals who had abandoned the donation page of a British child care charity	Survey	Affordability, lengthy process, requests for excessive personal information, and uncertainty about the wisdom of donating were found to foster abandonment of online donations.	Value	Individual
Boulianne and Cho [3]	Abandonment of quality assurance imprimaturs	North American publicly traded telecommunications organization	Case study	Questions about the value of an imprimatur and abandonment of the imprimatur by other organizations lead to its abandonment.	Value, imitation	Organizational
Burns and Wholey [4]	Abandonment of corporate structures	Large or teaching hospitals operated in the United States during the period from 1961 to 1978	Quantitative archival	Abandonment by referent organizations leads to abandonment of corporate structures.	Imitation	Organizational
Finkelstein and Gilbert [7]	Abandonment of pharmaceuticals	Eight pharmaceutical products released in the United States during the period 1963–1972	Quantitative archival	Abandonment of pharmaceuticals does not appear to be driven by opinion leaders.	Imitation	Societal
Gaba and Dokko [9]	Abandonment of corporate venture capital practices	Organizations identified as having been engaged in corporate venture capital practices	Quantitative archival	Abandonment is impeded by organizational experience with a practice and managerial experience with a practice. Drivers of abandonment are moderated when abandonment takes place among referent organizations.	Commitment, imitation	Organizational
Gill [11]	Abandonment of expert systems	Commercial expert systems developed prior to 1988	Survey	User resistance, inability to retain system expertise, operational difficulties, and changing organizational priorities lead to abandonment of expert systems.	Evolvability, value	System
Greenwood et al. [12]	Abandonment of medical technology	U.S. health care organizations	Quantitative archival	Financial incentives and scientific efficacy encourage organizational abandonment of technologies.	Value	Organizational

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Study	Focal outcome(s)	Research context	Methodology	Basis for abandonment	Abandonment driver themes	Level of analysis
Greve [13]	Abandonment of corporate strategies	Abandonment of a music format by U.S. radio stations in 12 states during the period 1984–1993	Event study	Abandonment by reference groups fosters abandonment. Larger organizations are less likely to abandon a strategy.	Imitation, commitment	Organizational
Henttu-Aho and Järvinen [14]	Abandonment of budgeting	Five Finnish industrial organizations	Case study	Decoupling of practices is key to the deinstitutionalization needed to abandon organizational practices.	Commitment	Organizational
Hogg [15]	Negative consumption	Undergraduate management science students at a British university	Multimethod qualitative	Aspirations and changing roles can lead to the abandonment of products and behaviors.	Value, Evolvability	Individual
Jacoby et al. [17]	Disposition of consumer products	Residents of a U.S. city	Survey	Personal characteristics, product characteristics, and situational factors all foster product disposition.	Decision-maker characteristics, value, evolvability, commitment	Individual
Kim [18]	Abandonment of online purchase behavior	Korean online shoppers	Survey	Vendor distrust and dissatisfaction with product quality undermine plans to repurchase.	Value	Individual
Knoke [19]	Abandonment of administrative structures	The 267 largest U.S. cities during the period 1900–1942	Quantitative archival	Imitation of geographically proximate cities fosters abandonment of administrative structures.	Imitation	Organizational
Kukar-Kinney and Close [21]	Online shopping cart abandonment	Online U.S. consumers	Survey	Concerns about pricing and use of shopping carts for research or entertainment all contribute to shopping cart abandonment.	Value, commitment	Individual
Maguire and Hardy [27]	Abandonment of DDT use	Use of DDT in the United States	Case study	Abandonment driven by problematization that undermines the institutional support for a practice.	Value	Societal
Nilsson et al. [30]	Abandonment of a governmental policy instrument	Renewal energy policy in the European Union	Case Study	Lack of strong lobby efforts, experience with policies, and concerns about security, innovation, and competitiveness foster abandonment of government policy initiatives.	Value, commitment	National

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Study	Focal outcome(s)	Research context	Methodology	Basis for abandonment	Abandonment driver themes	Level of analysis
Rajamma et al. [33]	Online shopping cart abandonment	U.S. undergraduate students and their associates	Survey	Abandonment is driven by risk, waiting time, and expectations that completing the transaction will be inconvenient.	Value	Individual
Rao et al. [34]	Abandonment of stock analyst coverage of stocks	Analysts covering NASDAQ listings during the period 1987–1994	Quantitative archival	Abandonment of behavior is more likely when others are abandoning the behavior and when adoption of the behavior was driven by imitation.	Imitation	Individual
Rao et al. [35]	Abandonment of culinary traditions	Abandonment of classical cuisine in France during the period 1970–1997	Quantitative archival	Abandonment by others and the potential for notable reputational gains through abandonment contribute to abandonment of culinary traditions.	Value, imitation	Individual/ organizational
Rich [36]	Diffusion and abandonment of innovations	Analytical model	Computational simulation	Short-term performance pressures can lead to adoptions that are abandoned; costs that are clearer than benefits can also lead to abandonment.	Value	Organizational
Roster [37]	Consumer disposal of possessions	Consumers aged 22 to 75 years	Qualitative interviews	Abandonment of possessions involves a process of personal change and evolution until the individual no longer identifies with the possession.	Evolvability	Individual
Stizmann and Bell [42]	Goal abandonment	Diverse pool of subjects recruited online	Experimental	Subconscious messages of underachievement can foster goal abandonment.	Value	Individual
Strang et al. [43]	Abandonment of management techniques	Analytical model	Computational experiments	Shift in the focus of high-quality consultants to alternative management techniques fosters abandonment of a technique by reducing its popularity.	Value, imitation	Organizational
Tang et al. [45]	Abandonment of the following of social media brand fan pages	Users of the social media site Sina Weibo	Survey	Dissatisfaction with the quality of information, changing interests, failure of page to meet expectations, and lack of affinity with the brand all foster abandonment.	Value	Individual
West and Dedrick [48]	Abandonment of computer architecture standards	Personal computer architectures of the 1990s	Case study	Innovations that bridge incompatible standards can lead to abandonment of some of these standards.	Evolvability	Industry
Younkin [49]	Abandonment of the practice of unrelated corporate diversification	U.S. Fortune 500 organizations	Quantitative archival	Abandonment is the final stage in a process of de-commitment that is driven by normative pressures and declining organizational performance.	Value, commitment	Organizational
Zuckerman [54]	Corporate divestitures	Publicly held U.S. organizations during the period 1985–1994	Quantitative archival	Organizational profitability and coverage by many analysts reduce the likelihood of divestiture. Smaller divisions, younger divisions, and divisions not aligned with other divisions are more likely to be abandoned.	Value, commitment	Organizational

Appendix B. Recent Information System End-of-Life Research

Study	Focal outcome(s)	Research context	Methodology	Information technology (IT) artifact
Chen et al. [5]	Discontinuance behavior	Mobile shopping in Taiwan	Experiment	Shopping app
Fang and Tang [6]	Switching behavior	Taiwanese instant messaging users	Cross-sectional survey	Instant messaging app
Fu et al. [8]	Discontinuance behavior	Social network service users	Cross-sectional survey	Social network service
Gan and Li [10]	Continuance intention	Chinese instant messaging users	Cross-sectional survey	Instant messaging app
Huang et al. [16]	Discontinuance intention	Mobile fitness application users	Cross-sectional survey	Fitness app
Köse et al. [20]	Continuance and discontinuance intention	European drivers	Cross-sectional survey	Gamified driver assistance app
Li and Ku [22]	Switching behavior	Taiwanese consumers	Cross-sectional survey	Online commerce sites
Lin et al. [23]	Switching intention	Telecommunications customers in Taiwan	Cross-sectional survey	Mobile phone operating system
Liu et al. [24]	Switching behavior	Game users in China	Cross-sectional survey	Social network game
Luqman et al. [25]	Discontinuance intention	Social network service users in Pakistan	Cross-sectional survey	Social network service
Luqman et al. [26]	Discontinuance intention	Chinese smartphone-based users of social network services	Cross-sectional survey	Social network service
Nawaz et al. [28]	Discontinuance intention	Social networking users	Cross-sectional survey	Social network service
Ng [29]	Discontinuance, re-adoption, and continuance commitment	Twitter users	Cross-sectional survey	Micro blogging app
Osatuyi and Turel [31]	Use reduction intention and behavior	U.S. social network service users	Longitudinal survey	Social network service
Peng et al. [32]	Switching intention	Chinese instant messaging users	Cross-sectional survey	Instant messaging app
Salo and Makkonen [38]	Switching behavior	Finnish mobile application users	Interviews and open-ended questionnaires	Mobile applications
Salo et al. [39]	Switching intention and other responses to negative application use incidents	Finnish and U.S. mobile application users	Interviews and open-ended questionnaires	Mobile app
Shokouhyar et al. [40]	Switching intention and use reduction intention	Social networking users	Cross-sectional survey	Social network service
Sibona et al. [41]	Continuance intention	Social network service use	Cross-sectional survey	Social network service
Sun et al. [44]	Switching intention	Chinese mobile instant messaging	Cross-sectional survey	Instant messaging app

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Study	Focal outcome(s)	Research context	Methodology	Information technology (IT) artifact
Turel [46]	Discontinuance intention	Social network service users	Cross-sectional survey	Social network service
Wang et al. [47]	Upgrade intention	Taiwanese users of desktop computers	Cross-sectional survey	Desktop operating system
Yu et al. [50]	Switching intention	Turkish, Taiwanese, and Thai Internet users	Cross-sectional survey	Web browser
Zhang et al. [51]	Discontinuance intention	Chinese social network service users	Cross-sectional survey	Social network service
Zhao et al. [52]	Discontinuance behavior	Firefox add-on users	Archival	Firefox app
Zhao et al. [53]	Abandonment	Chinese social network service users	Interviews	Social network service

Appendix C. Key Themes Underlying Application End-of-Life Decisions

Theme	Constructs
Ability	Experience with change, behavioral control, personal innovativeness, purchasability, awareness of behavioral problem
Affect	Guilt, technostress, fatigue, exhaustion, strain, regret, trust
Commitment	Application experience, familiarity, habit, inertia, financial switching cost, process switching cost, relational switching cost, switching costs, replacement risk, addiction to use, data lock-in, user commitment
Currency	Availability of complementarities, support availability, application age, application innovativeness, number of application versions released, time since last update, application update released, technical compatibility, opportunity to self-fix, vendor recovery resources
Risk	Perceived threat, security risk, perceived privacy risk, privacy concern
Social influence	Average daily users, critical mass of users, number of downloads, user base, future expectations for user base, user ratings, marketplace recommendations, pressure to use from social groups, number of peers using application, number of reviews available, social norms, subjective norms, interpersonal relationships, sense of community
Complexity	Complexity, convenience, ease of use, effort costs, search and setup costs, similarity to other apps
Value	Preference, application deficiencies, capability shortcomings, low content quality, poor interaction design, quality of communication, alternative attractiveness, application value, efficiency, enjoyment, functional deprivation, functional value, lifestyle compatibility, monetary deprivation, monetary rewards of alternative, need, value, switching benefits, switching value, satisfaction, social benefit, social value, use frequency, use value, use recency, costs of system compliance, usefulness

Appendix D. Classification Matrices

Logit model (Threshold= 0.09)			
Training data (classification accuracy = 0.714)			
Predicted		*Observed*	
	Continuance	Abandonment	Total
Continuance	8,099	286	8,385
	71.52%	30.65%	
Abandonment	3,225	647	3,872
	28.48%	69.35%	
Total	11,324	933	12,257
Holdout data (classification accuracy = 0.715)			
Predicted		*Observed*	
	Continuance	Abandonment	Total
Continuance	3,481	124	3,605
	71.73%	31.00%	
Abandonment	1,372	276	1,648
	28.27%	69.00%	
Total	4,853	400	5,253
Mixed-effect logit model (threshold= 0.09))			
Training data (classification accuracy = 0.918)			
Predicted		*Observed*	
	Continuance	Abandonment	Total
Continuance	10,410	86	10,496
	91.93%	9.22%	
Abandonment	914	847	1,761
	8.07%	90.78%	
Total	11,324	933	12,257
Holdout data (classification accuracy = 0.924)			
Predicted		*Observed*	
	Continuance	Abandonment	Total
Continuance	4,495	39	4,534
	92.62%	9.75%	
Abandonment	358	361	719
	7.38%	90.25%	
Total	4,853	400	5,253