Nudging Digital Entrepreneurs: The Influence of the Google Play Store Top Developer Award on Technological Innovation

Abstract

Purpose – We study how an online mobile app store uses an award signal to encourage entrepreneurs to engage in technological innovation. We depart from signaling theory and derive hypotheses to examine the underlying feedback and re-signaling mechanism on entrepreneurial behavior and technological innovation.

Design/methodology/approach – The study collated multi-sourced and longitudinal data of 349 top mobile app entrepreneurs on the UK Google Play Store. Using the information on release date and permission technologies, their apps were compared with the nearest rivals' prior apps to measure functionality novelty and explorative behavior. We then tested our hypotheses using accelerated failure time parametric models.

Findings – Our study extends the literature on signaling by showing that: (1) the top developer award signal served to nudge entrepreneurs to improve the functionality novelty of their apps and those who succeeded were less likely to switch to another product category, (2) the award signal created a window of opportunity for non-award entrepreneurs to respond and those who released new apps around the midpoint of a normal app development cycle significantly improved the likelihood of winning the award in a subsequent round of award-giving, and (3) the effect of functionality novelty on winning the award was more pronounced when non-award entrepreneurs pursued more explorative than exploitative behavior in app development.

Originality – The results offer novel insights into an understudied area, specifically the influence of online award signals on motivating entrepreneurs to pursue technological innovation. The research also highlights the crucial role played by the app store as an intermediary signaler.

1. Introduction

Numerous research studies have delved into how online signals are employed by signalers to convey quality information and influence consumer behavior (Kirmani and Rao, 2000; Wells *et al.*, 2011). However, there has been relatively limited exploration of the connection between online signals and entrepreneurial behavior related to technological innovation (Bergh *et al.*, 2014, 2019). A recent shift is redirecting the focus from considering the signaling process solely as conveying quality information to a more strategic use of signals for nudging innovation behavior. For example, platforms such as the Google Play Store utilize their annual award signals to subtly manage their ecosystem (Foerderer *et al.*, 2021). Similarly, OpenStreetMap employs endorsement signals to steer innovation towards new content development (Hukal *et al.*, 2020). Despite this shift prompting a re-examination of online signals, the constitution of these signals and the involvement of intermediaries such as app stores in the signaling process remain inadequately explored.

Previous research rooted in signaling theory (Spence, 1973) primarily addresses concerns related to the nature of quality signals themselves, often overlooking the fundamental mechanisms that underline the signaling process (Dimoka *et al.*, 2012; Rice, 2012). In the context of app stores, quality-related issues are being addressed through recommendations (Shi and Raghu, 2020), user reviews (Bickart and Schindler, 2001; Tang *et al.*, 2014), and consideration sets (Helmers *et al.*, 2019) to guide consumer behavior. However, existing studies on online signals largely neglect the impact of these signals on the entrepreneurial behavior linked to technological innovation (Troise, Ben-Hafaïedh, *et al.*, 2022).

This study aims to understand how an online signal triggered by receiving the top developer award from the Google Play Store can influence entrepreneurial behavior towards technological innovation. We approach this inquiry from the perspective of leading mobile app entrepreneurs in the UK, with a focus on the mechanisms that connect award signals with technological innovation. Our hypothesis development draws from the signaling theory in three distinct ways. First, beyond merely transmitting quality information, awards serve as a strategic resource that app stores employ to generate unique value that is difficult for competitors to replicate (Gallus and Frey, 2016). This is because an award can signal the app store's strategic intentions to potential entrepreneurs, thereby guiding more favorable behavior (Frey and Gallus, 2017). Second, award signals can trigger a feedback loop that encourages non-award entrepreneurs to use the apps of the award recipients as benchmarks (Asante *et al.*, 2022). Those who successfully introduce innovative functionality are more likely to secure the same award in subsequent rounds of recognition. This effect is particularly pronounced when entrepreneurs undertake extensive exploratory efforts in their app development. Finally, an award signal also opens up an opportunity window for the non-award entrepreneurs to respond.

We validate these hypotheses through an examination of the UK Google Play Store and its top developer award, which proves to be an appropriate context for two key reasons. Firstly, it allows us to observe the actions of all the award recipients by gathering temporal and technical data linked to their apps prior to receiving the award. Secondly, we can identify their nearest competitors based on the consideration sets that the Google Play Store used to group similar apps for consumers to consider downloading. This study offers several unique theoretical and practical insights. Primarily, it uncovers the latent feedback and re-signaling mechanisms by delving deeper into the strategic and competitive impacts of award signals on entrepreneurial behavior tied to technological innovation. Furthermore, our study adds to the literature on using online signals as gentle nudges to increase innovation behavior. Lastly, it contributes to the signaling literature on the role of app stores as intermediaries in the signaling process.

The rest of the paper proceeds as follows. The next section briefly reviews the literature on online signals. Following that, we present the development of the research hypotheses, which delve into the composition of online signals through the lens of feedback and re-signaling. Subsequent sections elaborate on our research methodology and present the findings of this study. Finally, we conclude by discussing the study's contribution to theory and practice.

2. Theoretical Background

In the context of an app-driven economy, app developers assume the role of entrepreneurs, constituting a pivotal resource that complements mobile app stores (Jacobides *et al.*, 2018). While the digital landscape fosters entrepreneurial behavior that might be financially prohibitive in traditional mediums (Nambisan, 2017), the continuous influx of new apps into the markets amplifies the challenges tied to assessing and ensuring quality, a persistent hurdle in the mobile app industry (Arora *et al.*, 2017). Even though an app's quality will be known eventually, its quality-related information might not be available beforehand (Chia *et al.*, 2012; Tiwana and Bush, 2014). This information asymmetry may lead certain consumers to acquire subpar apps (Liu *et al.*, 2014), consequently missing out on high-quality offerings (Ghose and Han, 2014). Furthermore, within an oversaturated market of complementary products, entrepreneurs might opt to switch to different markets (Boudreau, 2012). Some might resort to tactics such as copying (Luo *et al.*, 2011), cloning (Zhou *et al.*, 2012), fraudulent practices (Chia *et al.*, 2012), and other malicious behaviors (Felt *et al.*, 2011). These challenges not only escalate the expense of quality control for platform owners (Basole and Karla, 2012; Ghose and Han, 2014) but also render the signaling of quality a formidable task for entrepreneurs.

The current body of literature on platform management suggests two primary approaches The first approach leans towards hard management strategies, including control measures (Kapoor and Agarwal, 2017), boundary resources (Ghazawneh and Henfridsson, 2013), and competitive tactics (Foerderer *et al.*, 2018). In contrast, the second approach leverages online signals such as awards (Foerderer *et al.*, 2021; Gallus, 2017) and social nudges to steer contribution behavior (Zeng *et al.*, 2022).

However, the underlying signaling process remains underdefined in three key aspects. Firstly, previous studies tend to compartmentalize the roles of signaler and receiver (Ebbers and Wijnberg, 2012; Higgins and Gulati, 2006). For example, in an entrepreneur-investor relationship, despite being distinct roles, an investor can also re-signal through feedback (Alsos and Ljunggren, 2017). Consequently, the roles of the signaler and receiver can interchange through a mechanism of feedback and re-signaling. Moreover, app stores, functioning as intermediaries, can assume both roles in the signaling process. Yet, this intermediary role is frequently overlooked. Secondly, in addition to quality signals, there exist other types of signals, such as peer awards (Burtch *et al.*, 2022), platform endorsements (Hukal *et al.*, 2020), and description and demonstration signals (Zhou *et al.*, 2022), which convey supplementary strategic and competitive information. How this additional information influences entrepreneurial behavior, particularly in the context of award dissemination, remains less understood. It is possible that non-award entrepreneurs might respond differently. Existing research on award signals, for instance, implies that non-award entrepreneurs react with less competition and exploitation (Burtch *et al.*, 2022; Foerderer *et al.*, 2021), potentially underestimating the influence of online signals in nudging innovation behavior.

Building upon previous research in signaling (Connelly *et al.*, 2011), this study extends the exploration of the fundamental feedback and re-signaling mechanism. It aims to discern how award signals can nudge entrepreneurs to engage in technological innovation, circumventing the need for overly controlling platform management approaches (Altman *et al.*, 2022). Since entrepreneurs often encounter similar initial entry conditions, we examine award signals as a form of feedback that exerts both strategic and competitive impacts on entrepreneurial behavior.

2.1 Signaling and Feedback

Signaling theory has traditionally been applied across various offline contexts and markets, spanning areas such as employment (Spence, 1973), education (Bedard, 2001), commodities (Akerlof, 1970), and initial public offerings (Certo, 2003; Cohen and Dean, 2005). More recently, attention has turned to online economies, including the crowdfunding market (Ahlers et al., 2015; Troise et al., 2022). While many of these studies aim to analyze the signaling process between two individuals and the conditions under which agents reveal private information at a cost (Riley, 2001), they often overlook the underlying mechanisms. Such studies often assume that once signals become visible, receivers can use the information to infer the underlying quality. However, recent research has questioned this assumption, revealing that signal interpretation can vary among individual receivers (Kim and Jensen, 2014). Furthermore, recent investigations have unveiled that feedback initiates a re-signaling process (Alsos and Ljunggren, 2017), involving multiple actors, each of whom might interpret and react to the initial signal differently (Drover *et al.*, 2018; Kim and Jensen, 2014).

This study advances the understanding of the interplay between feedback and re-signaling within an app store environment. A classic signaling theory comprises five key components (Connelly *et al.*, 2011): the signaler, signal, receiver, feedback, and signaling environment. To illustrate, the introduction of a new app to the app market serves as a positive signal (Cucculelli and Ermini, 2012; Landoni *et al.*, 2020), making the entrepreneur introducing the app the signaler, the app store, and its consumers the receivers. Consumer reviews and recommendation function as forms of feedback (Jozani *et al.*, 2023). Additionally, another form of signal arises when an app is algorithmically co-listed with others in a "consideration set", aiding the "consider-then-purchase" decision. Furthermore, app stores play the role of intermediary signalers by bestowing awards. In this scenario, award-giving functions as feedback for re-signaling to both recipients and their non-award counterparts. The intricate exchange of signals, facilitated by feedback and re-signaling, establishes app stores as signaling environment. Each actor interprets and responds to these online signals with varying degree of discernment. To visualize this dynamic process between signals, feedback, and re-signaling, Figure 1 illustrates the introduction of a new app to an app store (at time *t*), the subsequent feedback and re-signaling through awards and reviews at time *t*+1, and the eventual decision to compete or switch (at time *t+2*).

[Insert Figure 1 here]

The process begins with the focal entrepreneur (A) introducing an app (App_a) to the app store. The app's functional attributes act as a visible signal representing the entrepreneur's less conspicuous competence in terms of quality. Subsequently, the app store evaluates the app's novelty in functionality to determine its eligibility for an award. Additionally, another set of signals emerges from the consideration set, where the focal entrepreneur typically examines their nearest rivals' prior apps across various technological dimensions. Where a rival entrepreneur (B) secures an award ahead of the focal entrepreneur, it inevitably shapes the focal entrepreneur's subsequent actions, including resource allocation for competition against rivals or contemplating a switch to another product category.

While these two parallel processes share some interconnectedness, prior research has rarely examined them concurrently. The signal that emerges from introducing a new app in response to competition can be interpreted either positively or negatively concerning the focal entrepreneur's intentions and commitment (Krishnan and Bhattacharya, 2002). Thus, award signals play a pivotal role in the feedback and re-signaling mechanism, which could impact both entrepreneurs who receive awards and those who do not, within the context of technological innovation.

3. Research hypotheses

Recent studies on platform management have highlighted the utilization of both “soft” and “technical” strategies for nudging entrepreneurs into technological innovation. For example, the Firefox platform exercised input control over the progression of its modularized extensions (Tiwana, 2015), while Facebook selectively rewarded apps that effectively engaged users (Claussen *et al.*, 2013). These examples underscore how the app store and their associated technological platforms (such as the Google Play Store and the Google Android operating system) are apt to capitalize on their distinct access to market and technical information, aiming to shape entrepreneurial behavior. Consequently, armed with valuable insights into technical advancements and market trends, app stores can strengthen their role as intermediaries conveying strategic information. When it comes to enhancing existing offerings, app stores might seek to mitigate the uncertainties tied to product functionalities sought by customers while concurrently spurring additional development and contribution towards technological innovation.

In a traditional business ecosystem, producers often resort to external searches to gather information about competing products (Anderson and Tushman, 1990). For example, they analyze purchasing patterns to discern users’ technological preferences and how these preferences evolve over time (Utterback, 1994). In the case of mobile apps, app stores have exclusive access to technical and market information, enabling them to evaluate the novelty of newly added app functionalities in relation to existing apps. Armed with this proprietary knowledge and insights into the utilization of new and pre-existing technologies, app stores can categorize apps with similar functionalities into a consideration set within the same product category. While not a direct intention for entrepreneurs, this placement can inadvertently accelerate technological innovation.

Under the feedback and re-signaling framework (as shown in Figure 1), entrepreneurs are likely to pay attention to competitive signals emanating from the consideration set, which exerts a dual impact on their search endeavors. Firstly, it narrows down the potential scope for product innovation (Maggitti *et al.*, 2013). Secondly, incorporating rival apps into a consideration set broadens "*sampling opportunities from the pool of technological possibilities*" (Levinthal and March, 1981, p. 313). This shared focus yields both advantages and drawbacks for entrepreneurs and their nearest rivals. While it fosters learning and exploration, it also introduces the potential for delayed product innovation and, in some cases, earlier exit. Entrepreneurs striving to glean insights from rival apps by introducing distinctive and novel functionality are more likely to capture the attention of app stores. Drawing lessons from the success of other entrepreneurs' research and development endeavors can reduce search costs, as these successes offer clear indications of effective and ineffective strategies (Katila and Chen, 2008). In such scenarios, entrepreneurs who benchmark against their nearest rivals, co-listed within the same consideration set, are more inclined to introduce innovative functionalities that garner app store recognition, including winning the top developer award. However, investing in improving functionality tied to specific product categories can hinder the reusability of bespoke functionalities in other categories. This has led to the following hypotheses:

Hypothesis 1a. *Entrepreneurs who introduce functionality novelty that competes with their nearest rival apps are more likely to win the top developer award.*

Hypothesis 1b. *Entrepreneurs who introduce functionality novelty that competes with their nearest rival apps are less likely to switch to developing apps in another product category.*

With the app store functioning an intermediary signaler, award signals can redirect the signaling flow between the signaler and receiver (Connelly *et al.*, 2011). For example, if an app store intends to stimulate the growth of a new product category, then award-giving can serve to influence entrepreneurs' choices regarding resource allocation towards that specific category (Lin *et al.*, 2011). When an app store bestows an award on a rival app prior to the focal entrepreneur's turn, the award signifies the app store's strategic intent. In addition to technological insights gained from comparing with rival apps, the award affords the focal entrepreneur the ability to assess market expectations and decide whether to adopt similar technologies. However, if there are misconceptions regarding online signals, entrepreneurs might opt for actions with lower opportunity costs, such as copying and cloning, which can ultimately compromise the overall quality of the signaling environment. Nevertheless, considering that the "window" for app-based market interaction is confined by the interface size of most mobile devices (Liu *et al.*, 2014), the use of consideration sets can impact how entrepreneurs develop apps and the strategies they employ to compete with rivals.

Given the associated costs and risks, particularly if awards prove unreliable signals of quality (Jordan *et al.*, 2017), their scarcity bestows app stores with a distinctive ability to guide internal competition among entrepreneurs, influencing entrepreneurial behavior, including app development choices and timing for market introduction.

Entrepreneurs recognize that when launching a new app, users require time to acclimate to its functionalities (Kim *et al.*, 2016; Liu *et al.*, 2014). An elevated level of app churn, marked by frequent releases, updates, and notifications, can lead to user disengagement (Bavota *et al.*, 2015; Guerrouj *et al.*, 2015). For example, Facebook shifted its approach by favoring apps that maintain user engagement through infrequent releases while penalizing those with frequent, unnecessary updates and notifications (Claussen *et al.*, 2013). Consequently, entrepreneurs who recognize the inverse relationship between release frequency and user experience are inclined to adjust their release timing based on pertinent market signals (Rietveld and Eggers, 2018).

Previous studies indicate that despite receiving the same signal, receivers are likely to interpret it differently and respond to varying extents (Vanacker *et al.*, 2020). Awards can potentially offer a dependable signal to navigate the challenge of timing product releases. In essence, awards signify an opportune window for entrepreneurs to take action. It is plausible that the commencement of awards bestowed upon a specific entrepreneur will sustain the app store's attention amid heightened downloads and sales performance, making it advantageous to introduce a new product in proximity to the award's inception.

Recent research underscores that awards can also benefit other co-listed apps within the same product category in terms of sales performance. This positive spillover effect persists until approximately the midpoint between rival and focal app releases (Soh and Grover, 2020). This midpoint serves as a focal point of attention, making it more challenging for apps released after this juncture to capture the app store's focus, potentially prompting the focal entrepreneur to switch to another product category. This has led to the following hypotheses.

Hypothesis 2a. *Entrepreneurs who introduce apps after a midway point from the onset of the award signal are less likely to win the top developer award.*

Hypothesis 2b. *Entrepreneurs who introduce apps after a midway point from the onset of the award signal are likely to switch to developing apps in another product category.*

Award signals can also signify entrepreneurial setbacks for non-award entrepreneurs, offering a clear indication that their conventional app development approaches were ineffective. This becomes particularly pronounced when an award-winning app is placed alongside the focal entrepreneur's app, prompting non-award entrepreneurs to make either incremental or radical adjustments. The existing literature on entrepreneurial failure suggests that those who manage to rebound will reallocate resources (Ucbasaran *et al.*, 2013), and notably engage in explorative behavior (Hu *et al.*, 2017).

Much like adept inventors, capable entrepreneurs are open to feedback and capable of revisiting and revising their strategies (Maggitti *et al.*, 2013). These developmental alterations are intrinsic and can be gauged by examining distinctive changes between two successive apps across the exploitation-exploration spectrum. In comparison to gradual changes linked to exploitative behavior, exploratory behavior demands more resources and time for implementation. Appropriately timed introduction of the next app allows non-award entrepreneurs to methodically assess the less-obvious quality aspects of their awarded rivals (Drover *et al.*, 2018). In this sense, the optimal timing from the commencement of the award signal enables non-award entrepreneurs to avoid hasty market entry with subpar apps. However, excessive delay in response time might signal the inability of non-award entrepreneurs to develop a superior product to compete with the award-winning rivals. Thus, the response time to the award signal interacts with exploratory behavior to determine the shift towards winning an award in a subsequent round of award allocation. Here, the app store perceives appropriate response time as a favorable signal when coupled with high levels of exploratory behavior. As exploratory behavior exacts a toll on the focal entrepreneur, they might also choose to broaden their exploratory scope by transitioning to another product category to enhance the prospects of their app-based ventures' sustainability (Lee and Raghu, 2014). This has led to the following hypotheses:

Hypothesis 3a. *Entrepreneurial explorative behavior moderates the relationship between response time and transition to winning the top developer award, such that entrepreneurs who engage in explorative behavior are likely to win the award around the midway point.*

Hypothesis 3b. *Entrepreneurial explorative behavior moderates the relationship between response time and transition to switching, such that entrepreneurs who engage in explorative behavior are likely to switch to developing apps in another product category around the midway point.*

While functionality novelty, grounded in discernible attributes, conveys the intrinsic quality tied to technological innovation, entrepreneurs must also communicate their readiness to embrace a path aligned with the app store's expectations, even in the face of R&D costs and opportunities forgone. High-quality signals frequently result from an intricate, resource-intensive process involving the delicate balance of intricate technology utilization and user-friendliness. Entrepreneurs who cultivate a nuanced comprehension of the challenges inherent in this equilibrium are more likely to gain distinctive proprietary insights and expertise on managing the interplay between exploitation, exploration, and functionality novelty. As the resource-intensive actions remain inconspicuous to users, entrepreneurs who merge less apparent behaviors with more observable attributes (Paruchuri et al., 2021; Plummer et al., 2016) are more prone to capture the app store's attention. In essence, the amalgamation of exploratory behavior in app development, alongside the discernible signal stemming from app functionality novelty, not only renders expensive actions visible but also bolsters the reliability of functionality novelty as a hallmark of quality. This combination is liable to remain challenging for rivals to replicate over time. Consequently, if entrepreneurs solely prioritize functionality novelty without engaging in exploratory actions, their apps are less apt to garner the app store's notice. Likewise, channeling R&D endeavors exclusively into the creation of bespoke functionality confined to a specific category can hinder the versatility of such functionality across different product categories. Thus, this has led to the following hypotheses:

Hypothesis 4a. *Explorative behavior moderates the relationship between functionality novelty and transition to winning the award, such that entrepreneurs who invest more in functionality novelty but engage in less explorative behavior offer a weaker signal to win the top developer award.*

Hypothesis 4b*: Explorative behavior moderates the relationship between functionality novelty and transition to switching, such that entrepreneurs who focus on improving app functionality than engaging in explorative behavior is less capable to switch to another product category.*

4. Methodology

4.1. Empirical context, sample, and data sources

The current study collected publicly accessible information from the Google Play Store. Given the theoretical framework built on feedback and re-signaling, the study acquired detailed data concerning all UK award recipients on the Google Play Store from 2009, when it was known as the Android Market, through 2014. This timeframe was selected due to the ongoing nature of award allocation during this period, which granted entrepreneurs heightened visibility and promotion on the Google Play Store. In contrast, the annual awards introduced in 2016, announced in May at Google's developer conference (see Foerdere et al., 2021), fell short of capturing the intricate interplay of award signals, entrepreneurial behavior, and technological innovation over time.

To gain a comprehensive understanding of the dynamic signaling process, a Python program was developed to scrape data from the UK Google Play Store by systematically traversing the website for publicly available content. Given the regular updates to the website's content, the program was executed periodically from February 2014 to July 2014, during which a total of 1,340,505 unique app IDs from 232,397 developers were recorded. Over this span, 365 entrepreneurs were recognized as top developers on the UK Google Play Store. Collectively, they contributed to 3,542 apps, with an average of 9.7 apps per award recipient, compared to the general developer average of 5.7 apps.

To verify the apps development history of the award recipients before receiving the top developer award, as well as their nearest rivals' prior apps grouped within a consideration set by the Google Play Store for potential consumer downloads, historical archival services like archive.org and the Wayback Machine Internet Archive were employed. Addressing concerns regarding selection bias in our sampling (see Zhou et al. 2022), we opted for the nearest rival's prior app of the award recipient as our comparison group. Calculating the time elapsed between the release date of the nearest rival's prior app and the award recipient's app enabled a more precise estimation of the transition time towards receiving an award or opting to shift to different product categories.

[Insert Figure 2 here]

We use Figure 2 to illustrate our data sampling framework centered around two mobile app entrepreneurs, denoted as A and B. Entrepreneur A launched his first app (A_1) at time t_1, followed by entrepreneur B's rival app (B_1) at t_2. Both entrepreneurs vied within the same product category. By considering the release dates of a focal app and its nearest rival, we computed the response time – specifically, the initial response cycle between A_1 at time t_1 and B_1 at time t_2: *Response Time* = $B_1t_2 – A_1t_1$. Similarly, when entrepreneur A introduced his second app (A_2) at time t_3 as a response to B_1, the response time for A to B was calculated as *Response Time* = $A_2t_3 – B_1t_2$. In this illustrative scenario, involving the app and its nearest rival's release date, there were four responses from A and three from B. In the third instance, entrepreneur B earned the top developer award based on his third app, B_3, at time t_6. Consequently, entrepreneur A reacted by launching his fourth app, A_4, which subsequently secured the top developer award at time t_7. For each focal entrepreneur, we employed mean-centering on every response time, facilitating the scaling of individual entrepreneur's response time and enabling the identification of midpoint response to test our research hypotheses.

Furthermore, the study collected information relating to the types of permission technologies used by apps to determine their functionality novelty. These permission technologies vary depending on an app's intended functionality (Felt *et al.*, 2011; Sarma *et al.*, 2012) and offer access privileges to data. For example, a "read contacts" permission provides access to individuals listed in the phone directory. Often, new permission technologies were introduced, and older ones were phased out, especially in response to changes in hardware and security requirements across diverse mobile app devices. Typically, Android apps operate as virtual machines on user devices. To access data, information, settings, or external networks on or off the device, entrepreneurs employ a blend of permission technologies to deliver distinct functionality. As such, permission technologies empower entrepreneurs to develop and enrich app usability and service offerings. In theory, a greater availability of newer permission technologies equips entrepreneurs to innovate and create fresh apps capitalizing on these advancements. However, practically speaking, an excessive number of newer permission technologies could lead to extended runtime and potential slowdowns in app functionality rendering. Hence, in 2015, Google introduced a novel permission model, labeled “runtime permissions”, permitting apps to solicit specific permissions from users when they are needed.

4.2. Dependent, independent, and control variables

The study involves two dependent and three independent variables. The first dependent variable, termed “award-winning”, pertains to the duration taken for an entrepreneur to shift from a non-award to attaining the status of an award recipient. Additionally, we represented the award status using a dummy code, wherein “1” signifies an award entrepreneur and “0” denotes a non-award entrepreneur. In cases where an entrepreneur introduced a single app and received the top developer award, we calculated the transition time based on their nearest rival’s prior app that was encompassed within the same consideration set. It is worth noting that seven award recipients did not possess a nearest rival, as they were the first to introduce an app in a given product category, thereby promptly earning the top developer award. This particular circumstance led to a reduction in the final sample size, resulting in 349 entrepreneurs being included for analysis.

[Insert Figure 2 here]

The second dependent variable, termed “transition to switching”, hinged on the utilization of product category information as metadata to identify instances when the focal entrepreneur shifted to a distinct product category. This switching status was encoded with “1” indicating a switch to a different product category, while “0” indicated remaining within the same category.

The first independent variable, labeled “functionality novelty”, leveraged the permission set of the nearest rival’s prior app, co-listed within the same consideration set, to assess disparities and commonalities vis-à-vis the focal entrepreneur’s app. As of the research period, Android provided entrepreneurs with a choice of over 135 permissions to shape app functionalities. We gauged an app’s functionality novelty through the Levenshtein distance matrix (Levenshtein, 2001), a string metric for gauging similarities and disparities between two appss (Navarro, 2001). To illustrate, the Levenshtein distance signifies the minimal number of individual edits (such as insertion, deletion, or substitution) required to transform one app into the other. The assessment unfolded in two main steps. Initially, permission technologies commonly employed by both the rival and focal app were filtered out. The remaining permissions were those solely used by either the rival or focal app. These permissions were unique to one app, and not the other, encapsulating functionality novelty as the proportion of distinct permissions in comparison to the nearest rival’s prior app. This metric was subsequently normalized within a range from 0 to 1, with 0 signifying that the focal app employed the same permission set as the rival app, and 1 signifying that the focal app employed an entirely different permission set.

Similarly, the aforementioned process was replicated to ascertain the second independent variable, termed “explorative behaviour”. However, in this case, it entailed tracking within-subject changes, capturing disparities and commonalities between two consecutive apps developed by the same focal entrepreneur. This measure encapsulated a less obvious signal pertaining to the focal entrepreneur's inclination to partake in explorative or exploitative development activities. With values spanning from 0 to 1, a lower score denoted a preference for exploitative over explorative behavior, while a higher score indicated a preference for explorative over exploitative behavior.

The third independent variable pertains to the “response time”, as previously discussed (as shown in Figure 2), which serves as a metric for assessing the timing of the focal entrepreneur's introduction of a new app. Building on prior research (Soh and Grover, 2020), we divided the response time into four quantiles. This division enabled the examination of interactive effects involving explorative changes over four distinct periods following the award date.

Moreover, a set of individual-level control variables were incorporated. These variables encompass the average user review score, the count of non-award entrepreneurs' apps, the count of award apps within the product category, a pricing dummy, and a game dummy. The "average user review score" emerged from the total number of stars assigned to a focal app divided by the number of reviewers. This metric is particularly pertinent in relation to quality assessment (Godes and Mayzlin, 2004; Tang *et al.*, 2014). It holds significance in scenarios involving experience goods, where product/service quality is only ascertainable ex-post, following purchase (Nelson, 1970).

The second and third control variables encompassed the existing count of non-award entrepreneurs' and award apps prior to the launch of the focal app within the same product category. Earlier studies have indicated a strong link between this behavior and the quest for innovation (Katila & Chen, 2008). In essence, the number of new entrants can function as a signal of market significance. This behavior also aligns with the prevailing product strategy within an app-based market, where similar apps are co-listed for potential purchase. This form of co-listing may drive user growth but can concurrently intensify competitive pressures.

The "pricing dummy", the fourth control variable, hinged on metadata detailing whether the app was offered for free, carried a price tag, or incorporated an in-app purchase option. The inclusion of this variable aligns with previous research illustrating its connection to app entrepreneurs' switching behavior (Lee *et al.*, 2021). In the final sample, a majority (46.1%) featured in-app purchases, followed by 28% offering free apps and 25% presenting paid apps. Lastly, the "game dummy", as the final control variable, encompassed whether the focal entrepreneur exclusively released game apps, given that games were the predominant product category (comprising 63%) within the study period. A summary of all variable statistics utilized in the estimation is provided in Table 1.

[Insert Table 1 here]

4.3. Analytical Approach – Model Specification

We conducted estimations using accelerated failure time (AFT) parametric models, employing the generalized structural equation modeling (*gsem* module) in Stata (Bartus *et al.*, 2013). Unlike discrete-time event history analysis, the AFT model assumes that a covariate's effect is to either accelerate or decelerate the transition time by a constant factor. This approach is particularly well-suited for estimating the impacts of independent variables on the transitions to winning an award and to switching. Within the gsem framework, a simultaneous equation approach was employed to control for shared unobserved characteristics associated with award-winning and switching. This entailed accounting for correlated disturbances specific to each equation.

To address robustness, the two transitions were estimated separately. This comparison allowed us to directly assess the extent of selection bias. For instance, if early switching had a negative effect on the transition to winning an award, the act of switching would be negatively correlated with the underlying factors contributing to award-winning within the present entrepreneur sample.

For estimating the transition to award-winning, we specified a Weibull distribution to accommodate the steep drop-offs often observed in the data when award-winning and app release coincided (Tavassoli Hojati *et al.*, 2013). Conversely, when estimating the transition to switching, we employed a lognormal distribution. This choice was made based on the assumption that the transition to switching was likely to exhibit an initial increase followed by a decrease over time (Bartus *et al.*, 2013).

While the unit of analysis was at the individual level, the data structure encompassed multiple levels with apps nested within entrepreneurs. This implies that an entrepreneur could have released multiple apps. Thus, random intercepts were specified in the aforementioned estimations to account for these multi-level dependencies.

[Insert Table 2 about here]

5. Findings

Table 2 presents the outcomes of our hypothesis testing. Model 1a and Model 1b comprise solely control variables. Model 2a and Model 2b incorporate all independent variables, while Model 3a and Model 3b introduce their interactive effects. The last two columns of Table 2 provide additional checks on the main findings, displaying the results of separately estimating the transition to winning an award and the transition to switching.

The coefficients reflect incremental changes in the log duration of the transition time taken by the focal entrepreneur to achieve top developer award status and the log duration of the transition time required for the focal entrepreneur to switch to a different product category. A positive coefficient signifies a lengthier duration for entrepreneurs to reach award-winning or switching.

Hypothesis 1a posited that entrepreneurs who introduced novel functionalities to compete with their nearest rivals were more likely to win awards. The coefficients of functionality novelty in Model 2a ($p < 0.001$) support Hypothesis 1a by being negative and statistically significant. Hypothesis 1b suggested that entrepreneurs introducing functional novelty to rival apps were less inclined to switch to another category. The positive and significant coefficient of functionality novelty in Model 2b ($p < 0.001$) backs Hypothesis 1b.

Hypothesis 2a anticipated that non-award entrepreneurs introducing apps after the midway point of the award signal onset were less likely to win awards. The coefficients of response time at the 3rd and 4th quantiles in Model 2a are both positive and significant, indicating that introducing new apps from the midway point onward substantially reduced the likelihood of award-winning. Thus, Hypothesis 2a is supported.

Hypothesis 2b predicted that non-award entrepreneurs introducing apps after the midway point of the award signal onset were inclined to switch to other categories. While the coefficient of response time at the 4th quantile in Model 2b is negative and significant ($p < 0.001$), the coefficient at the 3rd quantile is not. Therefore, the findings offer partial support for Hypothesis 2b. They suggest that, rather than remaining in the same category, non-award entrepreneurs were prone to switch to different categories in the last quantile from the award signal's onset.

Hypothesis 3a proposed that explorative behavior moderated the relationship between response time and the transition to award-winning around the midway point of the award signal’s onset. The positive and significant ($p < 0.05$) coefficient of the interaction between explorative behavior and response time in Model 3a, specifically in the fourth quantile, aligns with Hypothesis 3a. Figure 3a reveals that elevated explorative behavior accelerated the transition to award-winning from the second quantile onwards. This supports Hypothesis 3a, indicating that non-award entrepreneurs engaging in explorative behavior were more likely to win awards around the midway point of the award signal’s onset.

[Insert Figure 3a about here]

Hypothesis 3b postulated that explorative behavior would moderate the relationship between response time and the transition to switching. Specifically, it anticipated that entrepreneurs who exhibited explorative behavior would be inclined to switch to different product categories from the midway point onward. This hypothesis gains support from the negative and significant coefficient ($p < 0.001$) of the interaction between explorative behavior and response time in the fourth quantile of Model 3b (Table 2). The significant interaction effect is illustrated in Figure 3b, underscoring that non-award entrepreneurs with high explorative behavior were prone to switching despite introducing apps in the last quantile from the onset of the award signal.

Moving to Hypothesis 4a, it projected that explorative behavior would moderate the relationship between functionality novelty and the transition to award-winning. The interaction coefficient between explorative behavior and functionality novelty is both positive and significant ($p < 0.001$). Figure 4a visually portrays this significant interaction effect. It reveals that non-award entrepreneurs who prioritized creating apps with novel functionalities but invested less in explorative behavior conveyed a weaker signal for winning the award. The figure underscores that lower explorative behavior diluted the positive impact of high functionality novelty on winning awards.

Lastly, Hypothesis 4b posited that explorative behavior would moderate the relationship between functionality novelty and the transition to switching. The interaction coefficient between explorative behavior and functionality novelty is negative and significant ($p < 0.05$). Figure 4b visually represents the significant interaction effect, indicating that entrepreneurs who concentrated on delivering apps with high functionality novelty were inclined to remain in the same product category and postpone switching to another category.

[Insert Figures 4a & 4b about here]

5.1. Robustness Checks

To ensure the robustness of our findings, we conducted several additional analyses. Initially, we addressed the potential influence of selection bias in our estimates by separately estimating the transition to award-winning and the transition to switching, as recommended by Bartus et al. (2013). The outcomes of these separate estimates are presented in the last two columns of Table 2. Notably, when compared to Model 3a and Model 3b, the key coefficients aligned with our research hypotheses and exhibited effects in the anticipated directions. This consistency held true despite the presence of negatively correlated residuals between the transition to award-winning and the transition to switching, signifying the existence of unobserved factors that exerted opposing impacts on these two transitions. Importantly, despite this significant correlation, the results remained largely robust.

Additionally, we conducted analyses to address potential endogeneity concerns arising from control variables like pricing and average user review, which might be outcomes of winning awards. The inclusion of such variables in the estimation could potentially lead to control problems and reverse causality issues (Angrist and Pischke, 2008). Therefore, we re-estimated our models excluding these two control variables. The resulting outcomes remained consistent with our main findings, reaffirming the stability of our results.

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6. Discussions

6.1. Main findings

The results not only strongly support our hypotheses but also align consistently with the theoretical underpinnings of how award signals influence entrepreneurial behavior and technological innovation (Altman *et al.*, 2022). In essence, the top developer award signal spurred entrepreneurs to enhance functionality novelty. This signifies that the award signal offers entrepreneurs a more directed strategy (Frey and Gallus, 2017; Gallus and Frey, 2016), encouraging them to utilize rival apps as benchmarks for innovation and competition (Asante *et al.*, 2022). Furthermore, those entrepreneurs who actively engaged in explorative behavior exhibited a higher propensity to attain the top developer award and displayed a greater inclination to pivot their app development efforts towards a different product category. This explorative behavior not only drives entrepreneurs to expand their app-related endeavors but also aligns with the trend of adopting a broader approach (Lee and Raghu, 2014). Interestingly, engaging in explorative behavior while introducing new apps around the midway point significantly heightened the prospects of winning the award. These insights, drawn from the behavior of non-award entrepreneurs, contribute valuable perspectives to the existing literature, which has primarily focused on award recipients (Foerderer *et al.*, 2021).

6.2. Theoretical Contributions

The present study departs from conventional signaling theories (Akerlof, 1970; Connelly *et al.*, 2011) and focuses on the intricate interplay of feedback and re-signaling within online app stores. Our examination centers around the influence of award signals from an app store, along with the co-listing of apps in consideration sets, on entrepreneurial behavior and technological innovation. Our study makes three distinct contributions to the existing literature.

Firstly, we delve into the interaction between observable attributes and behavior within an online environment, revealing the strategic and competitive influence of award signals on entrepreneurial behavior and technological innovation. This intricate relationship becomes evident through the interactive effects of functionality novelty and explorative behavior on award-winning and switching. Our findings illustrate that developing apps with increased functionality novelty accelerated the path to award-winning, particularly when accompanied by less-visible explorative behavior. This combined approach garnered the app store's attention, positioning entrepreneurs favorably for the top developer award. This insight complements prior research, which often examines signaling effects from a single-receiver perspective or revolves around supply-demand dynamics (Nikolay *et al.*, 2011). Our emphasis on ongoing feedback and re-signaling processes provides a novel insight, an aspect less explored in current signaling (Foerderer *et al.*, 2021; Zhou *et al.*, 2022) and award literature (Frey and Gallus, 2017; Gallus and Frey, 2016). This connection between feedback, re-signaling, and entrepreneurial behavior enriches our understanding of entrepreneurial agency in the digital landscape (Nambisan, 2017; Tani *et al.*, 2022).

Secondly, our research offers an innovative perspective from the standpoint of non-award entrepreneurs. We challenge the notion that non-award entrepreneurs simply mimic award recipients by producing more apps in the same category. Instead, we find that they adopt an alternative approach, embracing functionality novelty and exploration in app development to challenge award recipients (Agarwal *et al.*, 2023). This perspective counters prior studies indicating that platform awards might inadvertently encourage more exploitative rather than explorative behavior (Foerderer *et al.*, 2021).

Furthermore, our study delves into the role of app stores as intermediary signalers, exploring the co-constitutive interplay of feedback and re-signaling among multiple actors within the online app ecosystem. This constitutive viewpoint provides a nuanced understanding of how award signals shape entrepreneurial behavior and technological innovation. Specifically, entrepreneurs strategically use award signals to navigate their app ventures, incorporating explorative behavior to effectively compete with rivals and expand beyond a single product category. Conversely, our findings demonstrate that entrepreneurs who balance technological innovation and explorative behavior are more likely to attract the mobile app market's attention and broaden their ventures.

Lastly, our empirical model supports the conceptualization of online platforms as intermediary signalers. Given the complexity of deciphering quality signals concerning the adept use of digital technology (Troise, Ben-Hafaïedh, *et al.*, 2022), a unique information asymmetry emerges regarding the concealed actions taken by various stakeholders to assess quality beforehand (see Troise, Matricano, et al., 2022). By accessing proprietary knowledge of review-submitted apps, it seems the Google Play store can curate desired qualities tailored to specific market segments (Pollock and Gulati, 2007). Coupled with co-listing rival apps, the award signal transforms into an effective feedback mechanism, re-signaling entrepreneurs and influencing their behavior towards technological innovation. This perspective highlights the multi-dimensional role of award signals, shedding light on their capacity to convey quality and competitive insights to fellow entrepreneurs, guiding their investment, development choices, and market understanding. This extends our comprehension of the intricate relationship between entrepreneurs, awards, and the potential for technological growth.

In the context of entrepreneurial innovation, entrepreneurs navigate the same initial set of constraints and controls imposed by technology use, leading to inherent variation. This aligns with a constitutive approach to technological innovation, emphasizing an ongoing process where entrepreneurs adapt innovation by leveraging new and existing technologies. Entrepreneurs effectively internalize innovation as they integrate recognition and creation into a constitutive process (Garud *et al.*, 2014). In essence, award signals, such as the top developer award, encourage entrepreneurs to experiment with available technologies, reflecting their technological adeptness and entrepreneurial ingenuity.

6.3. Practical Implications

Our present study yields valuable insights for both app stores and mobile app entrepreneurs. Firstly, app stores can leverage the subtle nudging effect achieved by co-listing apps in a consideration set. By strategically arranging diverse apps from both award recipients and non-award entrepreneurs within this set, app stores can experiment with different configurations to foster explorative behavior and stimulate technological innovation. This experimental approach, conducted via quasi-experimental methods, can yield behavioral data that informs the more effective utilization of awards. Ultimately, this would lead to enhanced app quality in the stores. Consequently, investing resources to refine consideration sets while promoting healthy competition among entrepreneurs becomes a crucial endeavor.

Secondly, app stores can utilize the act of award-giving to convey not only quality but also strategic and competitive information, encompassing market trends and technological advancements. However, striking a delicate balance between using awards to communicate quality and to impart strategic value for technological innovation is imperative. This brings forth a discussion on the efficacy of annual awards. The introduction of an annual award, such as Google Play Store's in 2016, aims to honor exceptional apps and the developers behind them. Yet, compared to the ongoing award process, annual awards might dilute the subtle nudging impact on non-award entrepreneurs. It is plausible that non-award entrepreneurs are more likely to heed a dynamically evolving award signal that conveys up-to-date market and technological insights, rather than an annual event where such information might be outdated.

Moreover, entrepreneurs who attune themselves to award signals are likely to uncover fresh business prospects and decide whether to persevere in their current product category or venture into new ones. Our findings underline that solely focusing on functionality novelty might not yield the desired outcomes, as R&D efforts could go unnoticed by app stores. Additionally, investing in specialized functionality could hinder adaptability across different product categories. Conversely, the results advocate for an experimental approach via explorative behavior, suggesting that embracing risk-taking and innovation might yield better long-term results compared to incremental approaches through exploitation. Given the rapidly evolving landscape of mobile technologies, which often render existing ones obsolete, entrepreneurs must remain attuned to the market's signals to align with its expectations.

Lastly, our study challenges the assumption within signaling theory that once a signal is generated, it will automatically bridge the information gap between parties. Recent research underscores that despite exposure to the same signals, receivers may interpret and comprehend them differently, influenced by factors such as heuristic versus systematic processing, and the interplay of human and market conditions. Our model offers practical implications for evaluating and measuring quality signals from a behavioral standpoint, focusing on less overt attributes like functionality novelty and explorative behavior in app development.

7. Conclusions

In conclusion, this study investigates how the Google Play award signal influences the behavior of top UK mobile app entrepreneurs to align with the app store's expectations. By utilizing a longitudinal and multi-sourced dataset, the findings underscore the influential role of award-giving and consideration sets in shaping entrepreneurial actions. Entrepreneurs who respond to the award signal are significantly more likely to achieve the top developer award, demonstrating the effectiveness of these signals in driving desired entrepreneurial behavior.

Moreover, our research sheds light on the pivotal role of successful rival apps as benchmarks for driving technological innovation. Entrepreneurs who ventured into functional novelty while embracing explorative behaviour emerged as strong contenders for the top developer award, expanding their entrepreneurial horizons. This novel focus on feedback and re-signaling introduces a fresh perspective to the connection between entrepreneurial behaviour and technological innovation, enriching both theoretical understanding and practical applications (Nambisan, 2017).

From a practical standpoint, this model offers market owners an insightful blueprint for cultivating online environments that foster entrepreneurial behaviors conducive to sustained technological innovation, all while minimizing excessive managerial control (Altman *et al.*, 2022). By reconceptualizing app stores as strategic signaling arenas, particularly by unpacking the intricate interplay between feedback and re-signaling, policymakers can gain deeper insights into effective market regulation. As the study advances the scholarly discourse, it lays the groundwork for future research endeavors to delve even deeper into the complexities of signaling dynamics and the significance of online signals in driving entrepreneurial innovation. This foundational framework paves the way for more nuanced and comprehensive investigations, enriching our understanding of the multifaceted landscape of entrepreneurial behavior and its interaction with digital markets.

While the current model is grounded in data from the Google Play store, the validity of the signaling framework is applicable to various digital contexts. Future research could expand the model to encompass other online markets and their associated platforms, such as the Apple app store and its iOS platform. Although some study variables might not be publicly accessible, exploring whether market signals like awards and consideration sets yield similar effects on entrepreneurial behavior and technological innovation across different platforms would provide valuable insights.

Utilizing a dataset linked to a UK IP address, this study employed a 2-level structure encompassing apps nested within entrepreneurs. To enhance the analysis, future research could widen the scope by incorporating geographical locations. However, comprehending the mechanics of cross-level signaling would necessitate theoretical development, considering behavioral strategies at the firm level (Schijven and Hitt, 2012). While previous research has often focused on identifying the most credible signaling source, our study hones in on app store awards as sources of quality, strategic, and competitive information. Other sources, such as third-party assessments, could also shape behavior relevant to technological innovation. Comparative studies that examine the impact of multiple signaling sources, particularly when employing diverse quality assessment criteria, would provide valuable insights.

Furthermore, with the mobile app market's exponential growth – reaching a record 38.4 billion new app downloads in Q1 2023 (Data.ai, 2023), companies like Google, Apple, and Kindle are actively exploring new business models and innovations (Tani *et al.*, 2022). Subscription services like Google Play Pass, Apple Arcade, and Kindle Unlimited provide curated access to apps or services. Investigating how such inclusions influence entrepreneurs' app development strategies, particularly in comparison to non-selected apps, presents an intriguing avenue for future research.

However, the present findings should be interpreted in light of several limitations. Primarily, the study's design aimed to mitigate internal validity threats through the use of behavioral data, complementing other sources like interviews for deeper insights (Claussen *et al.*, 2013). Additionally, although the focus lies on the impact of award signals on entrepreneurial behavior, understanding how these signals interact with user perceptions of quality and their potential to mitigate self-selection and confirmation bias – as highlighted in previous studies (Sun, 2012) – could provide a more nuanced understanding.

Lastly, it is worth noting that our data were censored once the focal entrepreneur received the award, preventing an examination of post-award dynamics. In the context of the Google Play app store, once an entrepreneur receives the top developer award, the status remains. Subsequent research could delve into how entrepreneurs leverage this award status to gain a competitive edge over their counterparts. Additionally, an intriguing avenue for exploration lies in comparing this scenario with the Apple app store, where recommendations manifest as a top 300 chart (Lee and Raghu, 2014). Here, dropping off the chart could potentially initiate a distinct cycle of technological innovation and entrepreneurial behavior. Consequently, a longitudinal comparison of the effects stemming from various recommendation mechanisms could yield further valuable insights.

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FIGURE 1.

A dynamic model of online signals, feedback, and re-signaling.

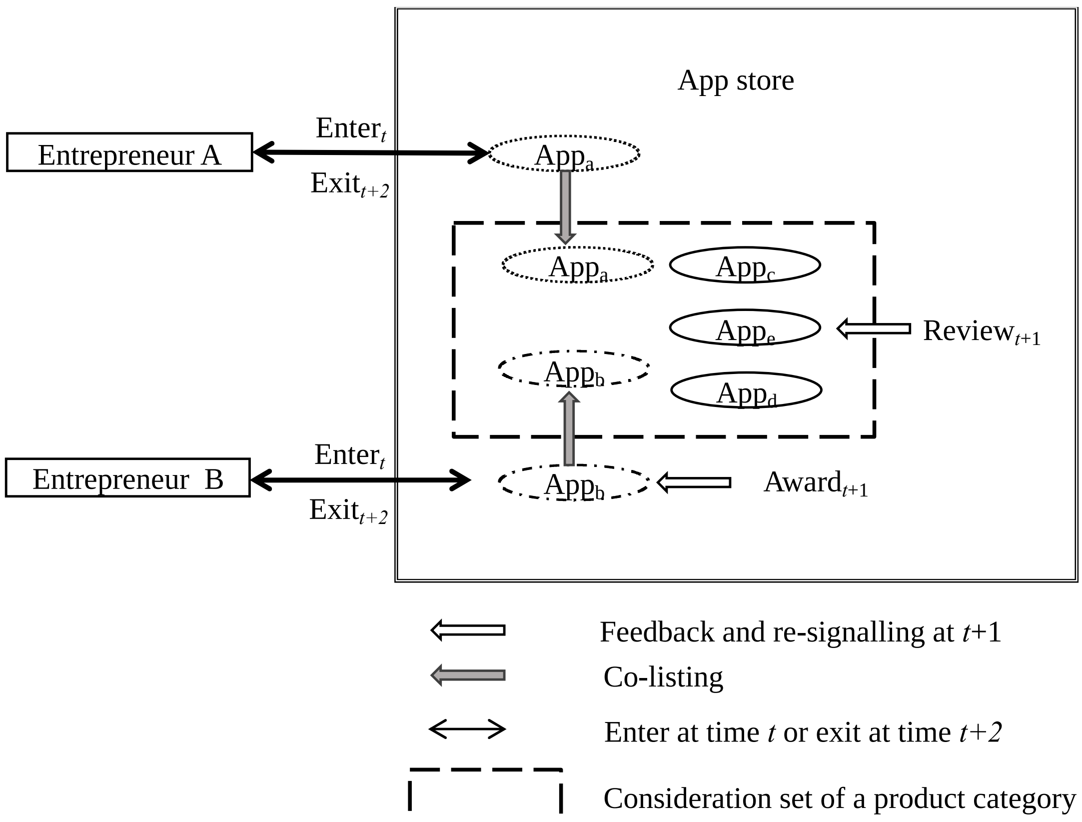

FIGURE 2. An illustration of the data sampling framework of the study.

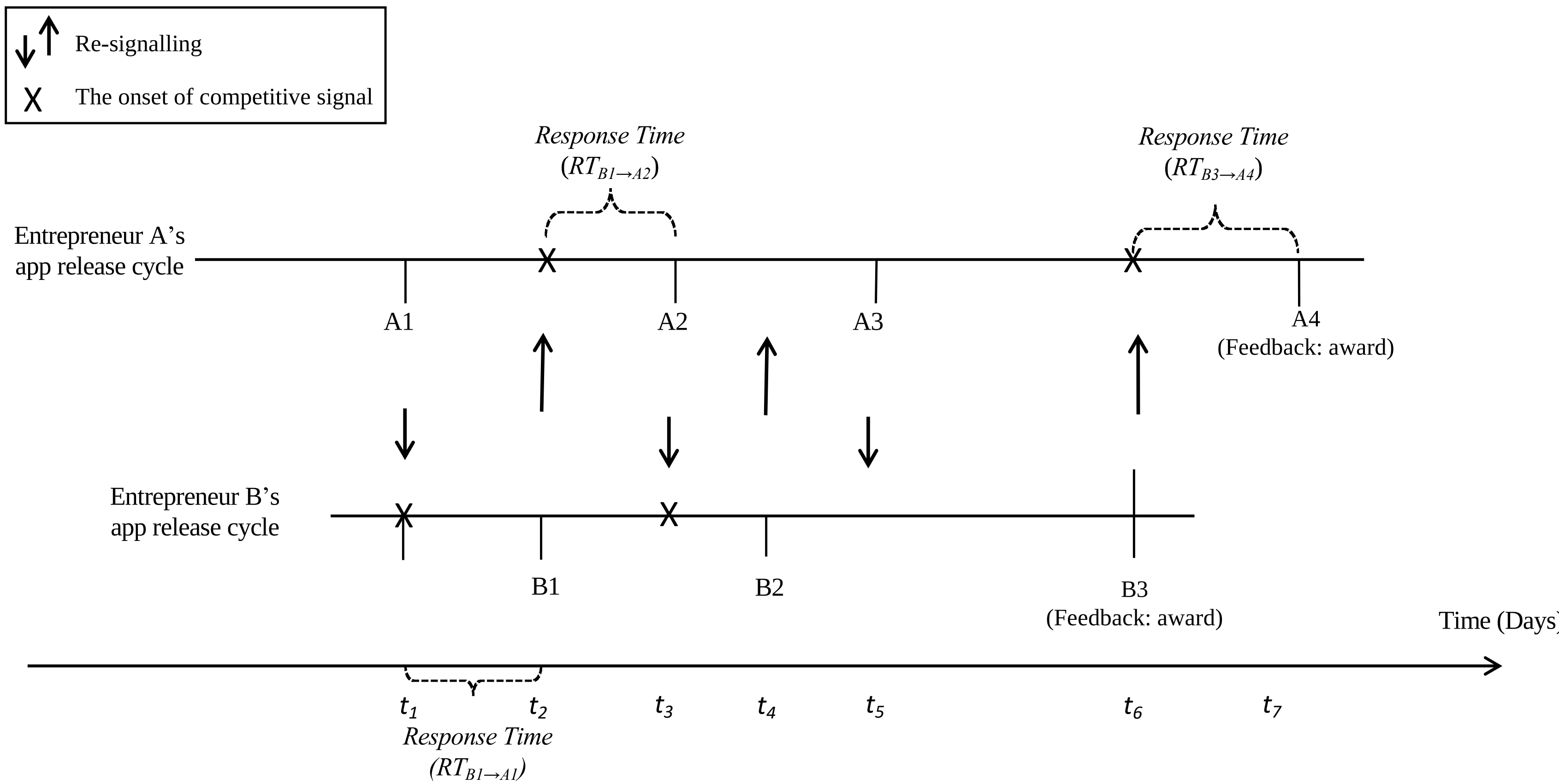

FIGURE 3a.
Interaction term: explorative behavior and response time on transition to award-winning.

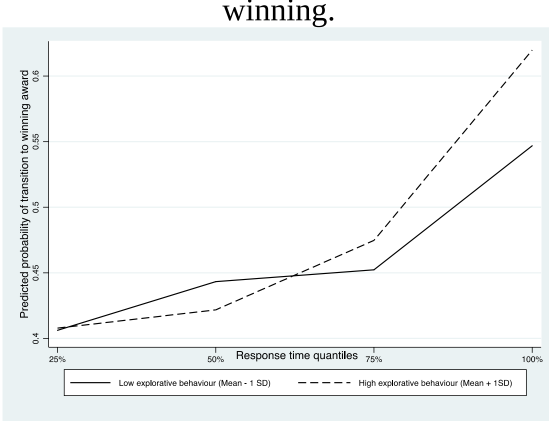

FIGURE 3b.
Interaction term: explorative behavior and response time on transition to switching.

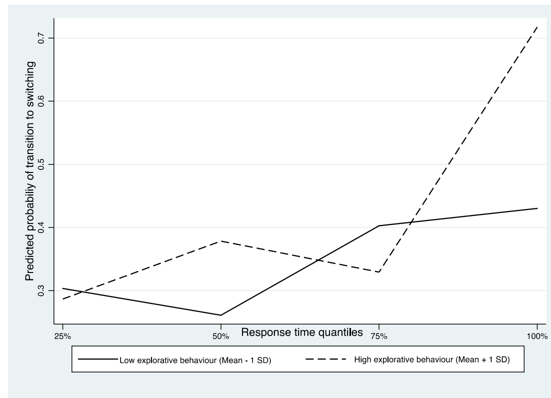

FIGURE 4a.
Interaction term: explorative behavior and functionality novelty on transition to award-winning.

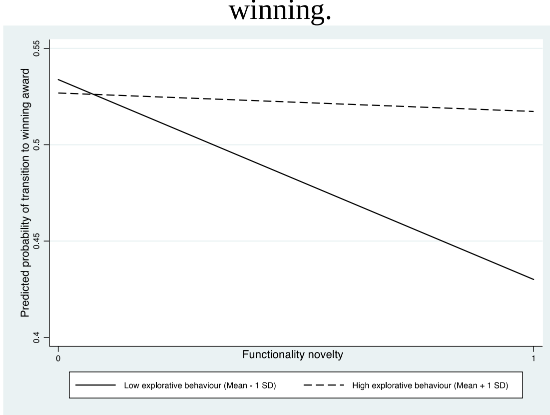

FIGURE 4b.
Interaction term: explorative behavior and functionality novelty on transition to switching.

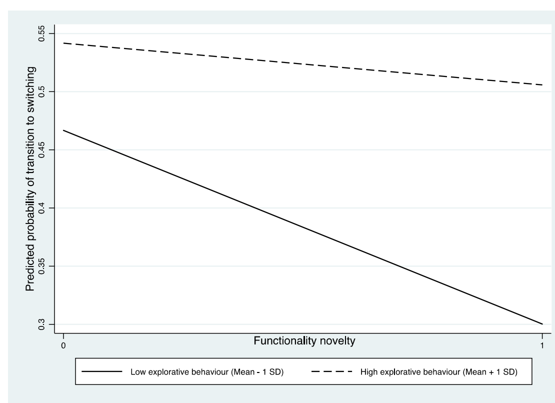

TABLE 1.
Descriptive statistics for all the variables used in the analysis.

		Observations	Mean	SD	Min	Max
Dependent variables						
Time to Award-winning		1990	297.19	382.77	0.00	1595.22
Time to Switching		1990	22.80	80.02	0.00	1274.06
Independent variables						
Functionality Novelty		1990	0.36	0.29	0	1
Explorative Behavior		1990	0.16	0.27	0	1
Response Time	*1st Quantile*	305	-0.94	0.05	-1	-0.82
	2nd Quantile	328	-0.54	0.20	-0.82	-0.13
	3rd Quantile	428	0.13	0.24	-0.12	0.81
	4th Quantile	929	1.00	0.02	0.82	1
Control variables						
Pricing Dummy	*Free*	746	–	–	–	–
	In-app purchase	821	–	–	–	–
	Paid	423	–	–	–	–
Game Dummy						
	No	1097	–	–	–	–
	Yes	893	–	–	–	–
Review score		1990	4.14	0.39	0.00	5.00

Note. The final sample included 349 entrepreneurs with 1990 observations. Time is measured in days.

TABLE 2.
Estimated the effects of the top developer award on the transition to award-winning and switching.

	Transition time modeled jointly with common observed errors						Transition time modeled separately	
	Award-winning (Model 1a)	Switching (Model 1b)	Award-winning (Model 2a)	Switching (Model 2b)	Award-winning (Model 3a)	Switching (Model 3b)	Award-winning (Full)	Switching (Full)
Explorative X Response								
< 25%					-0.743	-2.793	-1.443	-3.467
					(0.777)	(1.665)	(0.794)	(2.009)
50%					0.646	1.127	1.136	0.242
					(0.764)	(1.966)	(0.789)	(2.297)
> 75%					2.545*	-6.010***	3.093**	-6.906**
					(1.065)	(1.881)	(1.056)	(2.183)
Explorative X Functionality					3.945***	-3.782*	3.946***	-4.018′
					(0.868)	(1.796)	(0.837)	(2.142)
Explorative behavior			0.213	-1.160	-1.294*	1.656	-1.132	1.617
			(0.370)	(1.132)	(0.627)	(1.450)	(0.702)	(1.715)
Response time								
< 25%			0.416	-0.330	0.641	0.517	1.034**	0.665
			(0.234)	(0.522)	(0.359)	(0.783)	(0.381)	(0.967)
50%			0.954***	-0.185	0.801*	-1.107	1.103**	-1.038
			(0.287)	(0.705)	(0.379)	(0.972)	(0.401)	(1.145)
>75%			2.700***	-2.067***	2.581***	-1.401	2.730***	-2.096*
			(0.377)	(0.632)	(0.437)	(0.736)	(0.454)	(0.874)
Functionality novelty			-1.251***	2.160***	-2.377***	2.712***	-2.561***	2.765***
			(0.288)	(0.543)	(0.383)	(0.611)	(0.386)	(0.712)
# Award apps	0.059*	0.278***	0.127***	0.229***	0.132***	0.225***	0.203***	0.197**
	(0.028)	(0.062)	(0.033)	(0.063)	(0.034)	(0.060)	(0.034)	(0.070)
# Non-award apps	0.042	0.220***	0.100***	0.155***	0.103***	0.150***	0.130***	0.181***
	(0.023)	(0.040)	(0.023)	(0.043)	(0.025)	(0.042)	(0.022)	(0.047)
Pricing dummy								
In-app purchase	-0.137	-0.364	-0.305	-0.266	-0.352	-0.162	-0.302	-0.203
	(0.183)	(0.360)	(0.197)	(0.376)	(0.201)	(0.352)	(0.198)	(0.392)
Paid	0.061	-0.418	0.087	-0.200	-0.004	-0.122	0.030	-0.088
	(0.221)	(0.524)	(0.233)	(0.566)	(0.237)	(0.540)	(0.230)	(0.606)
Game dummy	-0.807***	-0.303	-0.197	-0.593	-0.190	-0.506	-0.282	-0.793*

	(0.173)	(0.363)	(0.201)	(0.383)	(0.219)	(0.354)	(0.208)	(0.397)
Review	0.104	0.747*	-0.085	1.079*	-0.174	1.009*	-0.197	1.164*
	(0.153)	(0.388)	(0.166)	(0.483)	(0.175)	(0.474)	(0.180)	(1.164)
Constant	-7.337***	-1.1946	-10.362***	-2.087	-9.314***	-2.523	-10.600***	-2.369
	(0.808)	(1.660)	(1.132)	(2.117)	(1.212)	(2.153)	(1.246)	(2.402)
Log SD of the residuals	0.507***	1.025***	0.710***	0.978***	0.687***	0.945***	0.759***	1.103***
	(0.049)	(0.095)	(0.069)	(0.102)	(0.077)	(0.101)	(0.078)	(0.086)
Correlation of residuals		-7.795***		-6.297***		-5.668***		
		(0.887)		(0.967)		(0.907)		

Note. N =349 with 1990 observations. □p < 0.06, * p < 0.05; **p < 0.01; *** p < 0.00l; robust standard errors included in brackets.