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https://pubsonline.informs.org/journal/isre

INFORMATION SYSTEMS RESEARCH
Vol. 36, No. 2, June 2025, pp. 1054–1077
ISSN 1047-7047 (print), ISSN 1526-5536 (online)

Does David Make A Goliath? Impact of Rival's Expertise Signals on Online User Engagement

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Received: May 7, 2022
Revised: February 11, 2023; October 28, 2023; June 29, 2024
Accepted: July 22, 2024
Published Online in Articles in Advance: September 5, 2024

https://doi.org/10.1287/isre.2022.0282

Abstract. How does information on a rival's expertise influence the focal user's engagement in online competitive settings? Online competitive settings differ fundamentally from other online contexts, such as e-commerce and social media platforms, explored in the prior work. This contextual distinction, we argue, is important as it determines the relationship between information about others and the focal user's engagement. The relevance of this question relates to broader theoretical ambiguities concerning the effects of status and past performance as relative and absolute signals of expertise. Our findings are based on a field experiment in which we modified the multiround mobile two-player gaming app interface, randomly exposing players to rival's status and past performance signals. We measure the focal user's engagement regarding their decision to continue the game after each round. As a baseline, we find that the focal user is less likely to continue the game if the rival exhibits higher current performance. However, the rival's status and past performance signals create strong contingencies wherein the principle effect of current performance is stronger if the rival has a high status or moderate past performance. Further, these contingent effects are partly predicated on the focal player's motivation to compete. These findings offer several important implications for driving user engagement in online competitive settings and meaningfully advance our current understanding of the effects of status and past performance information on online engagement.

History: Anandasivam Gopal, Senior Editor; Yili (Kevin) Hong, Associate Editor.
Supplemental Material: The online appendices are available at https://doi.org/10.1287/isre.2022.0282.

Keywords: player engagement • status • performance • digital games • field experiment

1. Introduction

In many online settings, examining informational antecedents of user engagement remains an important research endeavor (Oestreicher-Singer and Zalmanson 2013). In this space, the majority of the prior work has focused on digital contexts such as e-commerce and social media. For instance, Burtch et al. (2018) showed that disclosing information about others' past reviews drives the focal user's review authorship. Similarly, Aral and Walker (2014) reported a manifold increase in the focal user's engagement when they received a suitable message from friends. More generally, these studies substantiate the assertion that information about other users influences the focal user's engagement.

However, this overarching claim masks a significant complexity. Namely, the underlying logic driving the effects of informational antecedents is highly contextual, so the explanation may not operate if the underlying online context changes fundamentally. For instance, the "social contagion" argument by Aral and Walker (2014) differs from the "social norm" argument by Burtch et al. (2018), although both studies assert the same overarching claim concerning information about other users. However, the use of social norms as the explanation makes sense as Burtch et al. (2018) study a context in which behavior is relatively prosocial (writing reviews). In short, we argue that by examining diverse digital settings, one can meaningfully expand the current understanding of how and why information about other users influences the focal user's engagement. Our work is a step in this direction as we examine the influence of rival information on focal user engagement in the context of online competitive settings.

Studying this context is important, given its fundamentally distinct nature from settings studied predominantly in the prior work. Specifically, in an online competitive setting, the focal user hopes to realize private benefits (i.e., winning an ongoing competition) by reducing the chances of rivals receiving similar benefits. Such "zero-sum" fallout of engagement is less common in settings such as e-commerce and social media. For instance, in crowdsourcing contests, which have emerged as a prominent online competitive setting, the user engages to perform better than their rivals in a given contest (Lee et al. 2018). Similarly, in many digital games, a given player engages to defeat their rivals. Given this distinction, the mechanisms and explanation depicted in the prior work may be somewhat insufficient in explaining how and why informational antecedents pertaining to rivals drive engagement in online competitive settings.

This assertion is based on the fact that, in a competitive setting, the focal user seeks to defeat their rival and hence would be interested in assessing the rival's expertise. Consequently, informational antecedents of engagement in online competitive settings would pertain largely to the rival's expertise. Prior work on competitive settings offers corroborative evidence, showing that the rival's expertise shapes the focal individual's behavior. (Flynn and Amanatullah 2012). Our study augments this baseline assertion by identifying two distinct representations of a rival's expertise: *status as a relative and past performance as an absolute signal of expertise*. This conceptualization, rooted in prior work (Malter 2014, Teplitskiy et al. 2022), relates to several theoretical ambiguities.

First, in competitive settings, the effect of rivals' status on an individual may be open to debate (Zhang et al. 2019). On the one hand, competing against a high-status rival may demotivate the focal player from competing (Flynn and Amanatullah 2012). On the other hand, the presence of a high-status rival could afford learning benefits to the focal player, and hence, the focal player may even prefer to compete against a high-status rival (Zhang et al. 2019). Second, although conventional wisdom suggests that status and past performance are substitutable signals of expertise of the focal individual, more recent studies show that the two signals may exert independent effects on others' behavior toward the focal individual (Washington and Zajac 2005). Thus, although the representational difference between the two signals is evident, whether the signals distinctly shape others' behavior toward the focal individual remains uncertain. Thus, our work also addresses these broader theoretical uncertainties, in addition to advancing the literature on online user engagement.

We further contextualize the question of the effects of relative and absolute expertise signals by considering the presence of another expertise indicator prevalent in online competitive settings: the *rival's current performance* (Whetten 2009). Simply put, the information-rich interfaces in online competitive settings saliently disclose the rival's current performance. Moreover, such information about the rival drives the focal user's behavior and participation in the competitive setting. For instance, Yang et al. (2023) investigated the effect of providing information on the rival's current performance as running distance covered in an online fitness platform. Ventura et al. (2019) found that when focal players were aware of their rival's current performance, they exerted greater efforts. Thus, beyond the impact of the rival's status and past performance signals, which are more historical, the role of the rival's current performance is also crucial. Therefore, our research question is as follows:

Research Question. *How does relative and absolute information about the rival's expertise influence the focal user's engagement, given the rival's current performance?*

We address this question using a randomized field experiment followed by an online survey. For the experiment, we collaborated with the makers of a two-player competitive mobile game. In addition to suiting our research question, this empirical context is also pertinent given the increasing prominence of mobile gaming. The global market for mobile gaming is expected to cross the 150 billion USD threshold, making mobile gaming apps critical to the growth of global gaming revenue (Statista 2023a, b). More importantly, in mobile gaming, monetization mainly occurs through purchases and advertising in an ongoing game, and to that extent, the economic outcome of a game for the developer is contingent on the engagement the game elicits (Rutz et al. 2019). Thus, for a game developer, increasing user engagement remains a key objective. Unfortunately, doing so is a highly nontrivial problem as the supply of mobile games is ever-increasing (Statista 2023c). To this end, game developers introduce interface-level design changes (Gu et al. 2022). Through the present study, we hope to offer recommendations to game developers on whether and how rival status and past performance information should be revealed.

Although we later provided details on the mobile app, experiment design, and execution (see Section 3), the key institutional details are as follows: Each game consisted of two players and was played across five rounds. In each round, a player "attacked" their rival with the description of an English word along with four choices from which the rival had to select the correct word fitting the description. A round was completed when each player attacked their rival once. At the end of each round, each player was shown correct answers along with the performance of both players in the current game. The player had an option of whether to continue to the next round or exit the game. In the experiment, we randomly matched players to rivals of varying expertise for each game session. During gameplay, relative and absolute information signals about the rival's expertise were selectively revealed.

Consistent with the prior literature, we depicted status as a lexical hierarchy (i.e., gold, silver, and bronze labels) or as a percentile value. In contrast, the rival's past performance was shown as the count of wins or outcomes of the last five games played. For the focal user, the precise representation of these signals was determined at the time of installation of the game by the user. Thus, for the given user, while rivals changed across games, the representation of rivals' expertise remained consistent. Our main outcome variable, that is, the focal user's decision to continue the game after a given round, was captured by logging related events using Firebase for each user gameplay session. The experiment, conducted over a three-month window (Sep–Nov 2022), attracted more than 4,000 distinct players, resulting in 71,099 observations.

Our estimates, based on the field experiment, reveal several important findings. First, as a baseline, we find that the more correct answers by the rival (current performance), the less likely is the focal user to continue the game beyond a given round ($\beta = -0.2164$, $p < 0.001$). Second, we find this baseline effect to be contingent on the rival's status and past performance signals. The baseline effect of the current performance was significantly stronger for rivals with high status ($\beta = -0.0706$, $p < 0.10$). Next, we find a similar contingent effect for rivals with moderate performance ($\beta = -0.0802$, $p < 0.05$). Lastly, we find that the contingent effect of the rival's Status signal is stronger if the focal user has a higher competitive motivation ($\beta = -0.0800$, $p < 0.05$). At the same time, we find no equivalent result for the past performance signal ($\beta = -0.0068$, $p > 0.05$).

We also conducted an additional survey on a popular microtask platform (*prolific*) to ascertain whether the status and past performance signals were indeed viewed in relative and absolute terms. During the survey, we presented participants with four game screens, which were used during the main field experiment. Each screen contained a varied representation of the rival's expertise (e.g., one screen showed the status as a lexical hierarchy while the other showed past performance as three wins out of five). We asked participants to select options that they considered most useful for evaluating the given player's relative position amongst a pool of other players. The majority of the participants exclusively selected the screen with status signal ($n = 263$, 62.32%) as the information important to make that assessment. Further analysis revealed a statistically significant association ($\chi^2 = 142.48$, $p < 0.001$) between participants' preferred signal for determining the relative position of their rival and their justifications for selecting particular expertise information. These findings lend credence to the argument that the two expertise signals were indeed viewed differently.

Our research has a number of implications, discussed in greater detail in Section 5.2. For instance, our work builds on and extends previous work on the informational drivers of user engagement in an online competitive setting, which is fundamentally different from the empirical contexts such as e-commerce and social media, which are studied frequently in the previous work. This distinction of empirical context is significant because it allows us to broaden the pool of the informational antecedents and underlying explanations of their effect on user engagement (Bianchi et al. 2012, Kane et al. 2014). Next, the interaction effects that combine a rival's expertise signals (status and past performance) with more "immediate" signals (current performance) underscore how these signals shape the focal user's behavior. These findings relate to the broader arguments about how status and cognate information drive behavior (Bitektine 2011, Kim and King 2014). Further, the heterogeneous effects of motivation to compete on our key findings reveal the motivational underpinnings of user behavior. Specifically, advantages accrued by rivals with higher status are contingent on the focal user's underlying motivational frame (Flynn and Amanatullah 2012). In addition, our study recommends a more dynamic disclosure of rivals' expertise signals, wherein the disclosure can be made more or less salient and contingent on the rival's current performance.

2. Background Literature

2.1. Informational Drivers of User Engagement

User engagement has been an outcome of interest for the prior work involving online settings (Table in Online Appendix A). The rationale for this interest stems from the economic implications of user engagement. For instance, Ye et al. (2009) revealed a substantial positive link between consumer reviews and hotel business outcomes. They showed that the presence of positive feedback on online review platforms increased the average bookings made by focal users. Hu and Krishen (2019) investigated the contextual aspects of online reviews, emphasizing the problem of information overload that negatively affected user engagement, eventually influencing sales. Gunaratne et al. (2018) showed that users relied on algorithm-generated recommendations in the case of financial advisory platforms (Gunaratne et al. 2018).

Amongst the antecedents of user engagement, the role of information about other users is crucial (Table A1, Online Appendix A, and Table 1). For instance, Duan et al. (2009) showed that the count of prior downloads of software tools relates positively with the subsequent downloads the software attracts. Likewise, in content websites like online news media, the focal user's engagement is affected by engagement (e.g., news consumption) by other users (Oestreicher-Singer and Zalmanson 2013). Similarly, in e-commerce platforms, information pertaining to the review activity of other users influences the focal user's review contributions (Burtch et al. 2018). These studies indicate that the information about other users significantly influences the focal user's engagement.

Table 1. Information Signals as Drivers of Online User Engagement

Reference	Context	Antecedent/s	User engagement outcome	Key findings
Huang et al. (2017)	Online movie reviews	Expert and peer opinions	Sentiments in user-generated content	Authors find that the influence of experts and peer information on users is significantly higher in times of informational uncertainty.
Burtch et al. (2018)	Online retail	Financial incentive and information on peer engagement	Quality of reviews	The study showed the indirect effect of peer information. Findings reveal that financial incentives combined with information on peer contributions positively affect the quality of online reviews contributed by users.
Wang et al. (2018)	Online reviews of food outlets	Recognition of online review contributors	Willingness among customers to buy and recommend others to buy	In the case of positive reviews, endorsements of review contributors by giving badges, etc., lead to more favorable outcomes. No similar relationships were observed for negative reviews.
Fu et al. (2018)	Online product reviews website	User membership tier and customer status	Review writing behavior and review helpfulness	Users with a higher membership tier i.e. higher status produce lower-quality of reviews, at the same time their reviews were perceived as more helpful by others. Thus, Status of users informs not just their engagement at online platforms but also effects how other users perceive their engagement.
Chen et al. (2019)	Online customer reviews	Endorsement of prior customer reviews	Quantity of subsequent customer reviews	Differential effect of manager's response to positive and negative customer reviews. More specifically, the paper discourages larger public responses to negative reviews.
Meservy et al. (2019)	Online network forums for programming and software development	Contextual cues and information quality	Likelihood of adopting a solution or recommendation at the online forum	No effect of content quality was observed on the likelihood of solution adoption. Interestingly, authors find that contextual cues, particularly those pertaining to the community, significantly influence the likelihood of evaluating a solution for adoption.
Fujita et al. (2020)	Affiliate marketing on social media	Awareness of other users' actions on the brand page	Focal user engagement with the brand page	Increased engagement behavior by other users and perceived similarity with them among focal users leads to stronger institutional identification.
Huang et al. (2021)	Massive online open courses	Call to action by informing about peer participation and upcoming deadlines.	Assignment completion and time to complete the same	Differential effects of peer information viz a viz warning (deadline indicating) in the call to action. Information about peers, along with financial incentives, is associated with higher chances of assignment completion and a shorter time to completion.
Deodhar et al. (2023)	Mobile application	Expert and peer opinion	Content consumption and content organization	Authors find uneven effects of expert and peer information signals across content consumption and content organization actions, that is, ladder of participation.
This study	Online Competitive setting	Rival's status and past performance information	User engagement in two-player mobile game	The rival's status and performance information signals act as contingency as they drive the focal player's engagement, given the rival's in-game performance. However, the effect is not uniform for status and performance signals.

Driving this assertion is a range of explanations. However, all such explanations and mechanisms are unlikely to operate simultaneously, and the specifics of the online context determine the legitimacy of a mechanism. For instance, in the social media context, the presence of interpersonal network ties renders *social contagion*, spread through information about other users, highly relevant (Aral and Walker 2014). In contrast, in e-commerce, where such ties are much less salient, social contagion is less relevant. Instead, information about others drives the focal user's behavior by creating a *social norm* such that the information discloses a socially acceptable behavior (Burtch et al. 2018). More generally, we argue that the underlying mechanism driving the relationship between information about others and the focal user's engagement is highly context specific.

Consequently, the empirical examination of diverse online contexts can significantly expand the current understanding of how informational antecedents drive the focal user's engagement. This argument is consistent with the growing emphasis on making the context more central (Whetten 2009), including in studies of online contexts (Kane et al. 2014). Given this background, the present study examines informational antecedents of user engagement in online competitive settings.

Notably, online competitive settings differ fundamentally from others, such as social media and e-commerce. The difference occurs from the fact that in a competitive setup, the focal user engages to "win" by defeating rival users. For instance, studies on online contests and tournaments examine predictors of user participation (Zhang et al. 2019). There, the zero-sum dynamics play out wherein few players win, whereas the rest merely spend resources with virtually no payoff (Liu et al. 2014). Given this fact, we argue that user engagement in online competitive settings would differ fundamentally from that in other prevalent online contexts, such as social media and e-commerce, in which competition between users is largely absent. This difference, we argue, would imply that mechanisms underlying the effects of informational antecedents would be rather distinct from those examined in the prior work on the effect of information about others on the focal user's engagement (Table 1).

With this background, we present the main assertion on which the study is based: in online competitive settings, a user would be sensitive to information about their rivals' expertise because such information would aid the user in inferring their chances of winning. However, besides the notable exceptions of Bockstedt et al. (2022) and Deodhar et al. (2022), how such information influences the focal user's engagement remains largely understudied. To this end, we draw from the prior work on status and past performance, along with their behavioral implications. Specifically, we note that status and past performance may act as distinct signals of expertise, wherein status acts as a relative signal, whereas past performance acts as an absolute signal (Washington and Zajac 2005). Furthermore, as elaborated subsequently, the empirical assessment of the two expertise signals addresses a broader theoretical tension, which we elaborate on in the subsequent sections.

2.2. Effect of Rival's Status in Competitive Settings

As a powerful social attribute, status is often construed in relative terms, such as an explicit hierarchy (Deodhar et al. 2022). Regardless of its precise implementation, however, there is a general consensus that status indicates expertise such that higher status conveys higher expertise. However, in competitive settings, the effect of the rival's status (relative signal of expertise) on the focal user's behavior is ambiguous.

One stream of studies suggests that the high status of a rival creates a strong competitive barrier for the focal player as the latter gets "psyched out" competing against such a rival (Flynn and Amanatullah 2012). Similar findings by Prato and Ferraro (2018) reveal that hiring a high-status employee reduces the performance of incumbent employees, albeit asymmetrically. Further, players in a contest may be distracted or overwhelmed by the presence of high-status opponents, potentially causing their performance to suffer (Baumeister and Showers 1986). Along similar lines, in competitive settings, withdrawal of effort from the primary actor is related to a higher valuation of the rival (such as from their status) and a lower expectation of success (Bandura 1977, Carver et al. 1979). Thus, one stream of studies suggests that in online competitive settings, a rival's higher status could reduce the focal player's willingness to compete and reduce their engagement.

In contrast, competing against a high-status rival could lead to greater learning and opportunities for improvement. Given these benefits, the focal user's engagement should be higher when competing against a high-status rival. Prior work offers corroborating evidence, including in online settings. For instance, Zhang et al. (2019) showed that, in crowdsourcing contests, a contestant might benefit from competing against a "superstar" and hence may deliberately choose to do so. Other cognate arguments suggest that the presence of a high-status rival could act as an inspiration, elevating the focal player's behavior (Moore and Kim 2003), wherein the player may set higher goals, invest more time, and exert more effort to match their rival in a competitive setting (Vance and Colella 1990, To et al. 2020). Thus, prior work also indicates the positive side of competing against a high-status rival. Given these countervailing arguments regarding the effects of the rival's status on the focal user's engagement, further empirical assessment is warranted. Our study addresses this gap.

2.3. Status and Past Performance Dichotomy

Additionally, there is some ambiguity concerning the differential effects of status and past performance as expertise signals (Malter 2014, Bowers and Prato 2018). As argued previously, these signals convey distinct information (Table 2) as status provides a relative assessment (e.g., percentile), whereas past performance offers the absolute assessment (e.g., percentage) of expertise. For instance, Washington and Zajac (2005) referred to win and loss as indicators of absolute expertise of basketball teams, whereas the *preferential* treatment a team receives as a status indicator. Similarly, Teplitskiy et al. (2022), in their work on comparing the influence of papers, used percentile-rank based on the paper's citation count as a status indicator and recent citation count as the measure of the paper's performance. Lastly, Smirnova et al. (2022) discretized profile views and scores, using quantile distributions, into three status tiers: low, medium, and high, bringing in the sense of relativity to the measure.

However, beyond the representational differences between status (*relative* signal of expertise) and Past Performance (*absolute* signal of expertise), prior work remains equivocal about their effects. On the one hand, the conventional argument suggests that status and past performance would be tightly coupled, such that status and past performance may have a similar influence to the extent that one reinforces the other (Smirnova et al. 2022). For instance, Kilduff et al. (2010) showed that basketball teams with high status and strong recent performance were more likely to be perceived as rivals, indicating that the two signals are comparable. Similarly, Bothner et al. (2012) investigated the relationship between the current performance of golfers and their score (status), reflecting their position in the pecking order against other rivals. They found that status acquired positively affects current performance. In summary, prior evidence suggests that status and performance-based signals of expertise would be highly concurrent.

However, recent work shows that the effects of these signals may not be so comparable, given, perhaps, their separate conceptual foundings (Piazza and Castellucci 2014). For instance, Washington and Zajac (2005) analyzed the team selection data for the basketball tournament. They find that the status of the team significantly predicts the likelihood of receiving the invitation to the tournament, disconnected from the team's past performance. Simcoe and Waguespack (2011) examined the influence of the author's name on publication rates, highlighting the enduring nature of status hierarchies within academic publishing. Their findings indicate that proposals benefit from the inclusion of an author selected for the leadership position, that is, a high-status author, regardless of the author's current research and academic performance. Roberts and Sterling (2012) found that wineries that recruited winemakers from high-status wineries were able to command higher prices for their wines without any significant changes in the wine's ratings or critical reviews. Lastly, Malter (2014) investigated the impact of status on product prices, using the classification of wine producers in the Médoc region of France as an indicator of high status. The finding of this study is that status has a symbolic effect on prices, which either increases or remains consistent despite the decrease in uncertainty about the product rating (performance signal).

In summary, there is growing evidence to show that status and past performance, as signals of expertise, may exert distinct effects on the observer's behavior. We argue that further empirical work is warranted, given these competing streams of work. Our study is a step in that direction.

2.4. Role of Current Performance in Competitive Setting

In addition to the relative and absolute expertise signals drawn from the literature on status and past performance, another ubiquitous expertise signal in competitive settings is current performance. Yet again, prior work indicates competing effects of current performance. Suggesting a positive effect, Kilduff (2014) showed that when rivals are closely matched in an ongoing competition and aware of such equivalence, they shift focus toward outperforming the rival. Similarly, Williams et al. (2015) found that informing cyclists about their rivals' current performance enhanced their performance. However, studies also show the negative effect of knowing a rival's current performance (Bartling et al. 2015). For example, Bothner et al. (2007) analyzed data from NASCAR races and found that drivers were more likely to crash when their position was threatened, potentially leading to them exiting the race entirely. Next, Chen et al. (2019) found that informing users about their rivals' current performance negatively impacted their engagement and performance. Further, knowing the rival's current performance also drives the focal player's behavior in an ongoing competition. For instance, when winning is rewarded, users appear to rely on the current performance of others to gauge their chances of success and subsequently decide their level of engagement (Brabham 2010, Mo et al. 2018). In summary, much like relative (status) and absolute (past performance) signals of expertise, the rival's current performance also has a seemingly complex effect on the focal user's actions and behavior. To conclude, the present study examines a salient cohort of expertise signals that, as indicated in prior work in competitive settings, exhibit ambiguous effects on the focal individual's behavior.

3. Empirical Details

3.1. Institutional Details

Our empirical estimation is based on a randomized field experiment conducted using a mobile game, in which

Table 2. Highlighting the Relative and Absolute Operationalization of Expertise in Previous Work

Article reference	Relative expertise (status operationalization)	Absolute expertise (performance operationalization)	Key findings
Merton (1968)	Eminence in the academic field indicated by publicly recognized rewards such as the Nobel Prize	Count of discoveries made in the past	Readership, citation of academic articles, and additional research support received are positively correlated with the author's status. Authors with higher status obtain greater recognitions and rewards for performing a similar task than a corresponding lower-status actor.
Benjamin and Podolny (1999)	Winery's status using network centrality using data of regional affiliations	Average of quality of wine measure over a period of three years	High-status wineries have greater market opportunities as they can charge more for bottles of equivalent quality. Furthermore, the authors find that the effects of status indicators are not contingent on the availability of objective information (such as quality of wine over three years).
Phillips and Zuckerman (2001)	Occupying positions of eminence indicated by affiliations with other high-status (publicly renowned) institutions	Recent performance using forecast inaccuracy	Authors find that both low-status and high-status actors are more inclined to defy norms because they either have less to lose or enjoy considerable security regardless of their actions.
Hsu (2004)	Access to network resources	Count of deals closed and previous valuation quality	High-status venture capitalists have an advantage because entrepreneurs are willing to accept a discount on the valuation of their startup in order to access the network ties of these venture capitalists.
Washington and Zajac (2005)	Quantifying and comparing the privileged treatment of college basketball teams at the tournament	Win and loss counts	High-status teams are given preferential treatment or consideration for participation in the tournament.
Stewart (2005)	Rank label (e.g., apprentice, master)	Skill related certificate count	Recognition by higher-status others within the open-source community is associated with a higher likelihood of being positively assessed or recognized for their contributions to open-source projects.
Simcoe and Waguespack (2011)	Occupying leadership position considered eminent in the context	Count of previous publications	The findings reveal that high-status authors receive greater attention and approval of their work.
Roberts and Sterling (2012)	Network and ties with prominent individuals in the context	Quality ratings and score	Authors find that wineries employing high-status winemakers are able to command higher prices for their wines without any significant changes in quality ratings or scores. An interesting boundary condition to this effect of status is geographical proximity.
Bendersky and Shah (2012)	Rank ordered within group for peer ratings	Overall course grade	People with high status at the end performed better, but gaining or losing status itself wasn't linked to better performance.
Bothner et al. (2012)	Score for each player in the network, reflecting their position in the pecking order based on their win or loss against others	Win or loss	Performance increases with status, but only up to a point. Once someone achieves extremely high status, their performance actually starts to decline.
Azoulay et al. (2014)	Occupying position considered eminent in the context	N/A	Status signals boost performance but at the same time it has diminishing returns. Author report boundary condition as influence of status is more pronounced under uncertain situations (for instance, lesser-known authors in this study).
Malter (2014)	Historical ranking (identification with category that has longstanding reputation)	Quality rating	Price premium associated with high status increases when quality information becomes more readily available.

Table 2. (Continued)

Article reference	Relative expertise (status operationalization)	Absolute expertise (performance operationalization)	Key findings
Correll et al. (2017)	Indicated by linguistic markers, such as the brand name of a high-status manufacturer or a supermarket label indicating relatively low status	Objective evaluation of taste and quality using scores	Authors find that status hierarchies persist in meritocratic systems despite contradictions with personal preferences or ground truths.
Sharkey and Kovács (2018)	Recipient of awards relevant in context	N/A	Status positively effects sales of books, but this effect is contingent on visibility of user's actions. Visibility of outcome enhances the relevance of status.
Fu et al. (2018)	User membership tier	Review helpfulness score	Users having higher status produce lower-quality of reviews, at the same time their reviews were perceived as more helpful by others. Thus, Status of users has differential effect on their performance indicators (helpfulness).
Drivas and Kremmydas (2020)	The journal ranking is based on the AJG/ABS list	Count of citations	The study's results indicate that when journals had an upgrade in their status, the papers published in those journals tended to receive more citations.
Deodhar et al. (2022)	Color-coded groups were assigned to the participants based on their ratings in the online crowdsourcing platform	N/A	Users status significantly influences the attention and assessments they receive.
Teplitskiy et al. (2022)	Percentile rank among all published papers in that year based on the count of citations received by the article	Citation count	Authors find that displaying citation-related percentile details colors the perception of readers such that papers with fewer citations than the median were perceived to be of lower quality, and this effect was statistically significant.
To et al. (2022)	Percentile and low high tiers. Occupying position of importance within team	Objective score. Win and loss count	Authors provided evidence for bidirectional relationship between status hierarchy and performance such that past performance determines status and status in turn effects recent performance.
This study	Lexical hierarchy (gold, silver, bronze) and percentile	Win count and win loss sequence	Contingent effect of rival's high status and moderate performance signal on user engagement. Further, we find motivational underpinnings for contingent effect of status signal and no similar effects for past performance signal.

Note. N/A, Not applicable.

we exogenously provided information on the rival's status and past performance to the focal user. Further, mobile games have become a significant area of economic activity, with average revenue per user reaching 150 USD and global revenue projected to exceed 200 billion USD in 2027 (Statista 2023b). But, generating and maintaining user engagement remains a perennial problem for mobile games (Connolly et al. 2012). To this end, game developers rely on the interface, among other artifacts, to engage players, wherein interfaces offer a rich mix of information signals such as the rival's current performance, status, and past performance. For example, the link between user engagement and disclosing rival information, such as position on the leaderboard (social hierarchy) and count of badges or points acquired (performance in past games) (Deterding 2011, Peng and Hsieh 2012, Park and Kim 2019), is well documented and leveraged by the game developers. These informational signals are devised to enable the focal user to compete effectively against their rival (Weibel et al. 2008).

Our specific empirical context is a mobile gaming app titled Word Fighter-2.[1] The app included a two-player, multiround game in which a given player engaged in English vocabulary-based challenges[2] with a rival. The typical workflow of a game is as follows (Figure B.1, Online Appendix B): Every new game session starts with the player (player 1), who is automatically matched with a random rival (player 2) (Figure 1). Once matched, the player could not seek an alternate rival within the

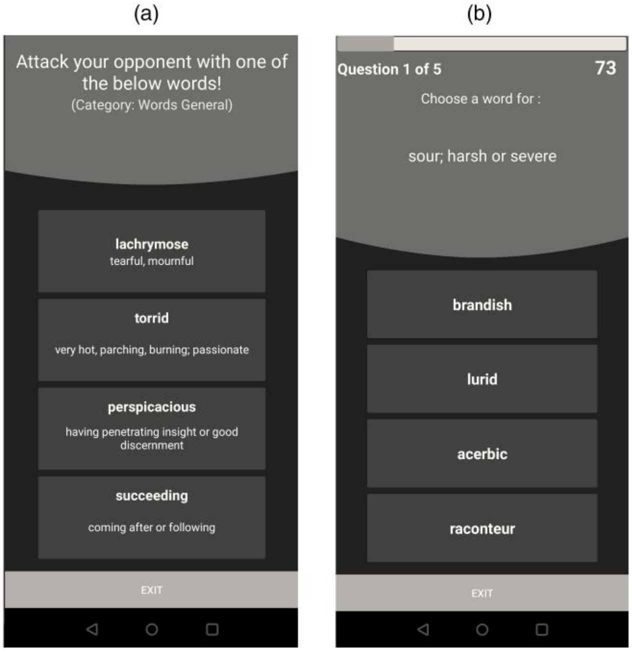
Figure 1. Matching with a Random Player

same game. If player 1 is playing their first game after installing the app, they are asked to fill out a short survey. Importantly, the survey collected data on crucial parameters such as self-reported prior expertise in English vocabulary, the purpose of using the app (e.g., preparing for a competitive exam), and ratings on two motivations, namely, to compete and perform better in an English-language based game or to learn and improve their English vocabulary. For these attributes, the player used a five-point scale to record their responses.

As the next step, the matched players competed in a five-round game. At the start of each round, player 1 selects a word from four candidate words (Figure 2(a)). This initial list of four words is randomly generated and drawn from an established word bank used in preparation for competitive exams. The description of the chosen word's meaning (selected by player 1), framed as a question, is then used to "attack" player 2. Next, player 2 is shown the description of the chosen word along with four words (Figure 2(b)). The only overlap between the lists shown to the two players is the chosen word. For scoring a point in the round, player 2 has to select the word that they believes matches the description. Before submitting the answer, player 2 is unaware of the word selected by player 1 in that round. Once player 2 answers the question, players' roles switch. In that case, player 2 "attacks" player1 with the same workflow but with a different set of word options. A round in the game is defined as one complete turn of each player "attacking" their rival with a word. A game is considered finished when five rounds have been played between the two players.

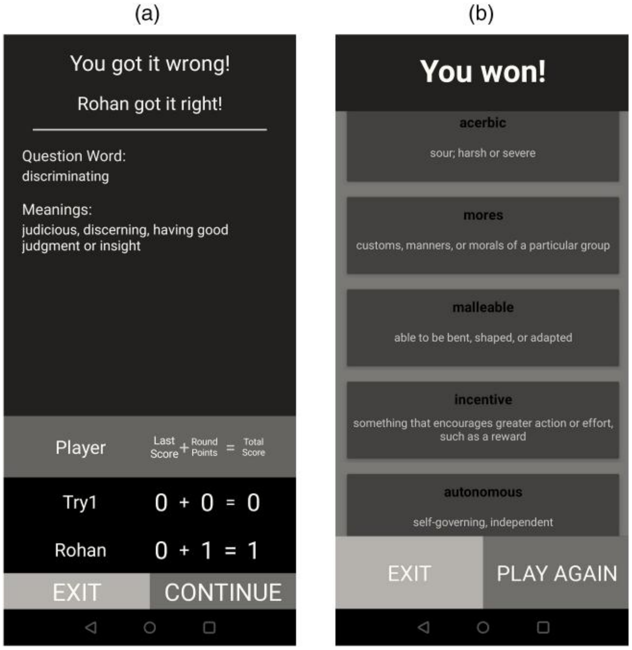
In its default version, at the end of each round, the game is designed to reveal the scores of both the player's

Figure 2. (a) Player Selects a Word and (b) Description of the Chosen Word



scores to each other (Figure 3(a)). This information remains the same in the subsequent versions made for this study. To understand the computational logic of players' scores,[3] consider the following scenario: Suppose at the end of the first round, player 1 correctly answers the question, whereas player 2 gives an incorrect answer, and then player 1 is awarded one point, whereas player 2 is awarded zero points. In the subsequent round,

Figure 3. (a) Round Result Disclosure and (b) Game Result Disclosure



if both players answer each other's questions correctly, resulting in a tie for the ongoing round, then none of the players are awarded any points. Once the five rounds are completed, the player with the higher score is named the winner of the game (see Figure 3(b) for the screen shown to the players at the end of the game). Finally, a player can choose to leave a game during any of the rounds as well as upon the game's conclusion.

3.2. Programming Rivals

For our study, we partnered with the app developers and introduced salient changes to the game while retaining its core workflow (see Figure B1 in Online Appendix B for the workflow of the game). The key aspect of our experiment, given our research question, was devising information on rival's status and past performance. Doing so, however, presented an important challenge. Namely, if we were to exogenously attribute status and past performance signals to a human player, they may question the logic and credibility of these signals. Further, the human player may alter their behavior in unpredictable ways once made aware of the attribution of status and past performance. If left unchecked, these considerations could jeopardize our ability to attribute engagement outcomes to the status and past performance signals. To overcome these challenges, we devised a set of bots precalibrated with distinct status and past performance signals assigned randomly and kept orthogonal (Table C1, Online Appendix C). Thus, a bot may have a high status (e.g., gold level) and low past performance (e.g., zero to one wins out of the previous five games; Figure 4). During the data collection window (September–November 2022), each human player competed against these bots. Further, each bot was assigned a human name. Lastly, we ensured that the focal user could not ascertain the programmed nature of their rival.

Another potential challenge was increasing the plausibility of the bot's expertise information. To this end, we correlated the bot's current performance (i.e., the maximum number of correct answers in a game) with information on its past performance. For example, if the past performance indicated four wins in the previous five games, the bot was programmed to correctly answer a minimum of four questions, provided the game is played in its entirety (Table 3).[4] However, no such mapping was created for the status information to ensure that relative expertise remained orthogonal to other signals of rival expertise. It is important to note that the mapping depicted in Table 3 was never revealed to the human player, avoiding any confounding effects. Further, although the bot's correct answer count in a game was correlated to their past performance signal, the specific questions that the bot answered correctly were randomly determined in a game. As a result, it was unlikely that a human player could estimate the rival's chances of correctly answering a given question based on information on their past performance.

Figure 4. Rival Expertise Information

As discussed previously, the game round starts with the human player attacking the bot by selecting a word from their wordlist (Figure 2(a)). In the background, the bot simultaneously selects a word from a given list to attack the human player. Once the human player sends the selected word to the bot, the very next screen displays the word that the bot has selected. Each round concludes with the focal user responding to the bot's attack from a list of four words. The results of each round are revealed when both parties, that is, focal user and bot, register their response. To make this workflow realistic in terms of the time a bot takes in a round, we included a random delay of up to five seconds (see Online Appendix D for a detailed explanation of delay workings). In each round, this interval of five seconds is randomly divided into "waiting time for bot's attack" (i.e., time taken by the bot to choose a word) and "response time for bot" (i.e., time taken by the bot to respond to the human player's chosen word). In summary, we attempted to make the bot's activities in the game appear more human-like. These behavioral rules for bots were consistent throughout the duration of the experiment.

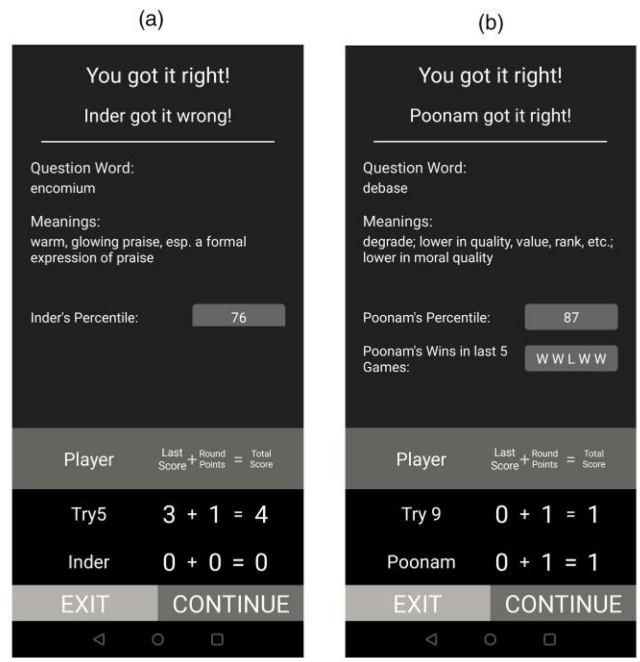
Table 3. Mapping Between the Bot's Prior Performance [Wins] and Correct Answers in the Focal Game

Count of prior games won (out of 5)	Number of correct answers by the bot in the focal game
0	0 or 1
1	0 or 1
2	2 or 3
3	2 or 3
4	4 or 5
5	4 or 5

In addition to randomly assigning status and past performance information to each bot, we also introduced randomization in information disclosure. First, we randomly paired a human player with a bot. Second, at the start of the game, the player would be shown information on the rival's expertise in one of the following ways: no information (the default interface of the game), only status, only past performance, or both information. Third, to control for the nature of the rival's information, we also randomized the informational representation (see Online Appendix C). For instance, for some human players, the status information of their respective bots was shown as a percentile, which is a widely employed representation of status (Berri and Simmons 2009, Smith and Faris 2015). Although for others, it was shown as a lexical hierarchy, namely gold, silver, and bronze (Edwards et al. 2018, Yang et al. 2022).

Similarly, performance information is displayed either as the count of wins or the order of outcomes from the previous five games. Thus, regardless of the representation, status information was relative in nature, whereas past performance information was absolute. In summary, our experiment introduced a robust system of randomization, facilitating the causal inference of the rival's status and past performance information on the focal user's engagement. To improve the salience of this information on the rival's expertise, we displayed them after each round along with the results of the round (i.e., points scored by each player; Figure 5, (a) and (b)).

Figure 5. (a) Rival Status After Round Result and (b) Rival Status and Past Performance After Round Result



3.3. Data Collection and Variable Description

Our experiment lasted over a contiguous window of three months, from September 2022 to November 2022. During the experiment, a total of 4,710 users downloaded the Word Fighter-2 application from the Google Play store (see Figures B2–B4 in Online Appendix B for the details on the download activity during the experiment window) and filled out the initial survey. Of this sample, 4,131 users started playing at least one game, generating 71,099 observations. Each observation pertained to a {*player i, game g, round, r*} tuple. We collected the data by tracking events (e.g., whether the player exited after a given round) as the human player engaged with the Word Fighter-2 app. We used a react-tracking application programming interface (API) and a user interaction tracking library embedded within the app.[5] Additionally, we recorded the timestamps of these events and the Current Performance of both the focal user and the bot.

The principal outcome variable in the study is engagement, which is operationalized as an indicator variable (*ContinuedAfterRound*). The variable is coded as one if the focal user i continued the game g after a given round r. Otherwise, the variable takes the value of zero. Next, our independent variables include the rival's status (*Status Tier*) and performance (*Performance Tier*). An important point to be considered is that information about rivals is revealed in distinct formats. For instance, *Status Tier* is disclosed to some players as a percentile (a continuous representation of status information) but to some as a lexical hierarchy (a discrete ordered representation of status information). To ensure measurement parity between them, we discretize the continuous informational representations. The discretization rules are given in Table 4. Lastly, we calculate the count of correct answers by a rival in the game g up to round r (*RivalCorrectAnswers*).

We introduced several controls to make our estimates further robust. Specifically, we controlled for the number of games played by player i before game g (*PriorGameCount*), as well as for the number of correct answers up to round r by player i playing game g (*PlayerCorrectAnswers*). In addition, we also included dummy vectors for the date of the gameplay to account for time trends. Lastly, we included the dummies to capture the information representation format (e.g., rival's status shown as either percentile or a lexical hierarchy) accounting for the effects of information format on the focal user's engagement.[6] Table 5 summarizes the variable operationalization, whereas Tables 6 and 7 provide descriptive statistics and pairwise correlation.

Table 8 depicts the validity of our randomization. In reporting these mean comparisons, we ascertain whether the distribution of rivals' expertise, as indicated by status and past performance information, across the human player's pool of games is disconnected from the human player's self-reported characteristics, namely, their English expertise and motivational underpinnings.[7] As Table 8

Table 4. Discretization of Status and Performance Information

Rival information tiers	Performance as count	Performance as list	Status as percentile	Status as tiers
High performance	4 to 5 wins in the prior 5 games	4 to 5 wins as outcome in the prior 5 games	NA	NA
Moderate performance	3 to 2 wins in the prior 5 games	3 to 2 wins as outcome in the prior 5 games	NA	NA
Low performance	0 to 1 win in the prior 5 games	0 to 1 win as outcome in the prior 5 games	NA	NA
High status	NA	NA	Above 66 percentiles	Gold
Moderate status	NA	NA	Between the 33 and 66 percentiles	Silver
Low status	NA	NA	Between 0 and 33 percentiles	Bronze

Note. NA, Not applicable.

Table 5. Variable Descriptions

Variable name	Description	Measure
Status Tier	The discrete measure of the rival's status 0 = If status information is not shown 1 = Low status 2 = Moderate status 3 = High status	Independent variable
Performance Tier	The discrete measure of the rival's performance 0 = If performance information is not shown 1 = Low performance 2 = Moderate performance 3 = High performance	Independent variable
Rival Correct Answers	Number of correct answers by the rival of focal player i in the game g before round r	Independent variable
Continued After Round?	A dummy variable coded as 1 if the player i continued the game g after a given round r	Dependent variable
Player Correct Answers	Number of correct answers by a focal player i in the game g before round r	Control variable
Prior Game Count	Number of games played by a focal player i before the game g	Control variable

Table 6. Descriptive Statistics of Key Variables

	Descriptive at a game level			Descriptive at a round level	
Statistics	Prior game count	Status tier	Performance tier	Rival correct answers	Player correct answers
Standard deviation	8.2797	1.1568	1.1399	1.1244	1.1869
Minimum	0	0	0	0	0
Maximum	85	3	3	4	4
Average	4.3896	1.377	1.3731	0.9446	1.2741

Table 7. Pairwise Correlation

Variables	Continued after round?	Performance tier	Status tier	Prior game count	Rival correct answers	Player correct answers
Continued After Round?	1					
Performance Tier	0.0038	1				
Status Tier	−0.0075	0.0171*	1			
Prior Game Count	0.0399*	0.0309*	0.0416*	1		
Rival Correct Answers	−0.2093*	0.0073	−0.0010	0.0193*	1	
Player Correct Answers	−0.2981*	0.0098*	−0.0026	0.0693*	0.5167*	1

*$p < 0.05$.

Table 8. Randomization Checks of Key User Traits Across Status and Past Performance Levels

Proportion of games with	Self-reported English expertise	Competitive motivation	Learning motivation
No Status Information	$F = 1.14$ ($p = 0.3351$)	$F = 0.35$ ($p = 0.8428$)	$F = 1.45$ ($p = 0.2147$)
High-Status Rival	$F = 0.55$ ($p = 0.6980$)	$F = 0.41$ ($p = 0.7980$)	$F = 0.72$ ($p = 0.5796$)
Moderate Status Rival	$F = 0.66$ ($p = 0.6214$)	$F = 0.71$ ($p = 0.5847$)	$F = 1.07$ ($p = 0.3707$)
Low-Status Rival	$F = 0.23$ ($p = 0.9192$)	$F = 0.62$ ($p = 0.6508$)	$F = 0.40$ ($p = 0.8094$)
No Past Performance Information	$F = 0.24$ ($p = 0.9169$)	$F = 0.31$ ($p = 0.8730$)	$F = 1.07$ ($p = 0.3680$)
High Past Performance Rival	$F = 0.05$ ($p = 0.9960$)	$F = 0.16$ ($p = 0.9601$)	$F = 0.18$ ($p = 0.9507$)
Moderate Past Performance Rival	$F = 0.45$ ($p = 0.7697$)	$F = 0.41$ ($p = 0.7985$)	$F = 0.85$ ($p = 0.4928$)
Low Past Performance Rival	$F = 0.47$ ($p = 0.7575$)	$F = 1.34$ ($p = 0.2514$)	$F = 0.88$ ($p = 0.4721$)

shows, for different values of each of these player characteristics, mean proportions of games across status and past performance levels are statistically indistinguishable.

3.4. Econometric Specifications

The econometric specification below indicates the relationships empirically tested (Equation (1)). In this equation, i indexes the focal user, g indexes the current game, and r indexes the ongoing round in that game. On the left-hand side (LHS), we capture the log-odds ratio of our key dependent variable, which is an indicator variable (*ContinuedAfterRound*). On the right-hand side (RHS), τ_w and $\alpha_{i,g}$ indicate effects of the *date* and *representation* vectors. Coefficients β_2 and β_3 correspond to the effects of the *rival's status* and *performance information*, whereas β_1 represents the effect of the number of correct answers by the rival. β_4 and β_5 capture the contingent effects of status and performance information, respectively. Next, β_6 and β_7 indicate the estimated effects of control variables. Finally, ε_{igr} captures the error term. The regression equation for our full model to estimate the main and interaction effects of performance and status tiers on user engagement takes the following form:

$$
\begin{aligned}
&Log\left(\frac{ContinuedAfterRound_{igr}}{1-ContinuedAfterRound_{igr}}\right)\\
&=\beta_0+\alpha_{ig}+\tau_w+\beta_1\times RivalCorrectAnswers_{igr-1}+\beta_2\\
&\quad\times RivalStatusTier_{ig}+\beta_3\times RivalPerfTier_{ig}+\beta_4\\
&\quad\times RivalCorrectAnswers_{igr-1}\times RivalStatusTier_{ig}+\beta_5\\
&\quad\times RivalCorrectAnswers_{igr-1}\times RivalPerfTier_{ig}+\beta_6\\
&\quad\times PlayerCorrectAnswers_{igr-1}+\beta_7\times PriorGameCount_{ig-1}+\varepsilon_{igr}
\end{aligned} \tag{1}
$$

4. Analysis

4.1. Main Analysis

The results of the estimates computed using logistic regression are reported in Table 9. We find that the rival's status and past performance information exert no direct significant effect on the focal user engagement (Model 1). However, the rival's correct answers (current performance) decrease the likelihood of the focal user continuing the game after the given round ($\beta = -0.2164$, $p < 0.001$, Model 1). Next, we observe significant contingent effects of the rival's status and performance information. We find that the effect of the rival's correct answers in an ongoing game on the player's engagement increases significantly if the rival has high status ($\beta = -0.0706$, $p < 0.1$, Model 2) compared with nondisclosure of rival status. In contrast, we find correct answers in an ongoing game by rivals with low or moderate status exhibit no significant comparable effects (Model 3) compared with the nondisclosure of rival status. Further, we see a significant negative interaction effect ($\beta = -0.0802$, $p < 0.05$, Model 3) whereby the baseline effect of the rival's correct answers in an ongoing game is stronger if the rival has moderate performance compared with nondisclosure of past performance. Further, we find no such effect for rivals bearing high or low-performance information. Lastly, we find that in a fully specified model (Model 4), these estimates retain their sign and significance. In addition, we report interaction plots (Figure 6, (a) and (b)) depicting the contingent effects of status and performance information. These figures are consistent with our interpretation of the interaction terms.

4.2. Robustness Checks

To further ascertain the stability of our findings, we subject the baseline effects reported in Model 4 (Table 9) to several robustness checks. As described in Table 4 (Section 3.3), we discretized the percentile-based status signal, resulting in three categories. As the first robustness check, we assess whether our key findings are susceptible to the choice of these thresholds. To this end, we re-estimate the effects using alternate status discretization thresholds (Smirnova et al. 2022) (described in Table 10). The new estimates (Models 5 and 6) show that the

Table 9. Contingent Effects of Status and Performance Information on Engagement Outcomes

Dependent variable = *Did the player continue after the current round?*	Model 1 Main effects	Model 2 Status interaction	Model 3 Performance interaction	Model 4 Full model
Low Performance	0.1366	0.1352	0.1472*	0.1454*
	(0.0867)	(0.0865)	(0.0872)	(0.0869)
Moderate Performance	0.0732	0.0714	0.1118	0.1085
	(0.0872)	(0.0869)	(0.0883)	(0.0880)
High Performance	0.1122	0.1094	0.1252	0.1217
	(0.0870)	(0.0867)	(0.0872)	(0.0870)
Low Status	−0.0779	−0.0746	−0.0793	−0.0758
	(0.0861)	(0.0871)	(0.0864)	(0.0874)
Moderate Status	−0.0921	−0.0899	−0.0935	−0.0908
	(0.0875)	(0.0887)	(0.0878)	(0.0890)
High Status	−0.1074	−0.0738	−0.1085	−0.0753
	(0.0870)	(0.0883)	(0.0873)	(0.0887)
Prior Game Count	0.2821***	0.2816***	0.2829***	0.2824***
	(0.0385)	(0.0384)	(0.0385)	(0.0384)
Rival Correct Answers	−0.2164***	−0.1964***	−0.1842***	−0.1651***
	(0.0139)	(0.0248)	(0.0234)	(0.0312)
Player Correct Answers	−0.8554***	−0.8555***	−0.8556***	−0.8556***
	(0.0203)	(0.0203)	(0.0203)	(0.0203)
Rival Correct Answers × *Low Status*		−0.0087		−0.0083
		(0.0365)		(0.0365)
Rival Correct Answers × *Moderate Status*		−0.0061		−0.0066
		(0.0363)		(0.0364)
Rival Correct Answers × *High Status*		−0.0706*		−0.0689*
		(0.0363)		(0.0364)
Rival Correct Answers × *Low Performance*			−0.0260	−0.0263
			(0.0358)	(0.0358)
Rival Correct Answers × *Moderate Performance*			−0.0802**	−0.0784**
			(0.0346)	(0.0346)
Rival Correct Answers × *High Performance*			−0.0311	−0.0307
			(0.0361)	(0.0361)
Intercept	1.2314**	1.2228**	1.2250**	1.2168**
	(0.4870)	(0.4852)	(0.4856)	(0.4838)
N	60,671	60,671	60,671	60,671
Pseudo-R^2	0.1405	0.1406	0.1406	0.1407
Date dummies	Yes	Yes	Yes	Yes
Representation dummies	Yes	Yes	Yes	Yes

Note. Robust standard errors clustered on user are reported in parentheses.
*$p < 0.10$; **$p < 0.05$; ***$p < 0.001$.

Figure 6. (a) Rival Current (In-game) Performance and Status Tier Interaction and (b) Rival Current (In-game) and Past Performance Tier Interaction

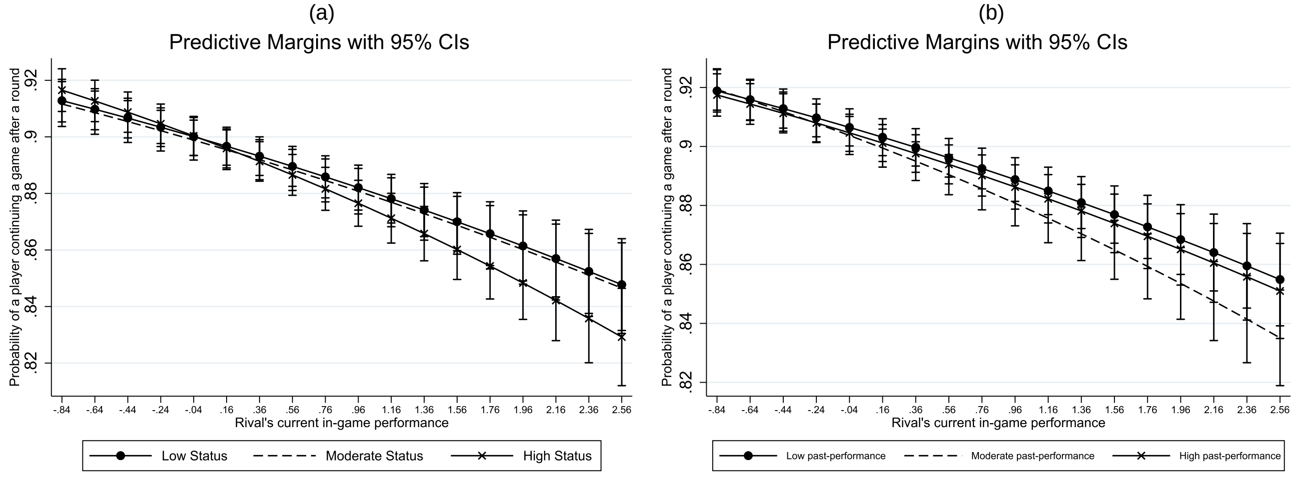


Table 10. Alternate Status Thresholds Used for Discretization

Statue tiers	First alternate status threshold	Second alternate status thresholds
High Status	≥79 percentiles	≥80 percentiles
Moderate Status	<79 and ≥40	<80 and ≥20
Low Status	<40 and ≥0	<20 and ≥0
Method Used for Discretization	Creating three segments based on percentile values (using Stata's xtile command)	Utilizing perceptual (80-20 classification) interpretation of percentile

contingent effects of status and performance information remain qualitatively unchanged (Table 11). Therefore, our findings may not be fully explained by the choice of thresholds for the discretization of the percentile-based status signal.

We further test whether the estimates are robust to the choice of the estimator. To this end, we calculate the coefficient estimates with probit (Model 7) and linear probability models (Model 8). The estimates are consistent, indicating that our findings are not predicated on the estimator choice. Next, we also test whether the estimates are predicated on the potential outliers. To this end, we removed observations of users whose count of played games during the experiment window exceeded the average count by more than two standard deviations (n = 2,294). The estimates (Model 9; Table 12) show no meaningful change in our key results. Thus, our results are reasonably robust to the presence of potential outliers.

Next, we consider the possibility that the focal user's decision to continue beyond the current round may be

Table 11. Robustness Checks: Status Thresholds Used for Discretization

Dependent variable = *Did the player continue after the current round?*	Model 5: First alternate status threshold	Model 6: Second alternate status thresholds
Low Performance	0.1451*	0.1452*
	(0.0869)	(0.0869)
Moderate Performance	0.1082	0.1083
	(0.0880)	(0.0880)
High Performance	0.1217	0.1218
	(0.0870)	(0.0870)
Low Status	−0.0732	−0.0621
	(0.0864)	(0.0900)
Moderate Status	−0.0979	−0.0940
	(0.0889)	(0.0863)
High Status	−0.0649	−0.0583
	(0.0907)	(0.0912)
Prior Game Count	0.2826***	0.2827***
	(0.0384)	(0.0384)
Rival Correct Answers	−0.1653***	−0.1651***
	(0.0312)	(0.0312)
Player Correct Answers	−0.8556***	−0.8557***
	(0.0203)	(0.0203)
Rival Correct Answers × *Low Status*	0.0049	−0.0071
	(0.0357)	(0.0398)
Rival Correct Answers × *Moderate Status*	−0.0335	−0.0180
	(0.0353)	(0.0332)
Rival Correct Answers × *High Status*	−0.0658*	−0.0689*
	(0.0391)	(0.0395)
Rival Correct Answers × *Low Performance*	−0.0253	−0.0259
	(0.0358)	(0.0358)
Rival Correct Answers × *Moderate Performance*	−0.0792**	−0.0790**
	(0.0346)	(0.0346)
Rival Correct Answers × *High Performance*	−0.0298	−0.0305
	(0.0361)	(0.0361)
Intercept	1.2218**	1.2212**
	(0.4837)	(0.4842)
N	60,671	60,671
Pseudo-R^2	0.1408	0.1407
Date dummies	Yes	Yes
Representation dummies	Yes	Yes

Note. Robust standard errors clustered on user are reported in parentheses.
*$p < 0.10$; **$p < 0.05$; ***$p < 0.001$.

Table 12. Robustness Checks: Alternative Regression Models and Outlier Presence

Dependent variable = *Did the player continue after the current round?*	Model 7 Probit	Model 8 LPM	Model 9 Sensitivity to outliers
Low Performance	0.0679	0.0101	0.1514*
	(0.0456)	(0.0071)	(0.0861)
Moderate Performance	0.0451	0.0050	0.1154
	(0.0461)	(0.0071)	(0.0875)
High Performance	0.0550	0.0085	0.1370
	(0.0454)	(0.0071)	(0.0867)
Low Status	−0.0334	−0.0072	−0.0936
	(0.0459)	(0.0069)	(0.0857)
Moderate Status	−0.0418	−0.0083	−0.1188
	(0.0467)	(0.0070)	(0.0870)
High Status	−0.0343	−0.0095	−0.1006
	(0.0464)	(0.0070)	(0.0862)
Prior Game Count	0.1393***	0.0180***	0.3622***
	(0.0193)	(0.0022)	(0.0399)
Rival Correct Answers	−0.0959***	−0.0173***	−0.1628***
	(0.0169)	(0.0041)	(0.0316)
Player Correct Answers	−0.4291***	−0.0819***	−0.8720***
	(0.0104)	(0.0024)	(0.0200)
Rival Correct Answers × Low Status	−0.0071	−0.0027	−0.0049
	(0.0196)	(0.0045)	(0.0372)
Rival Correct Answers × Moderate Status	−0.0037	−0.0032	−0.0085
	(0.0196)	(0.0045)	(0.0372)
Rival Correct Answers × High Status	−0.0377*	−0.0107**	−0.0684*
	(0.0197)	(0.0046)	(0.0372)
Rival Correct Answers × Low Performance	−0.0108	0.0006	−0.0259
	(0.0193)	(0.0046)	(0.0364)
Rival Correct Answers × Moderate Performance	−0.0377**	−0.0068	−0.0816**
	(0.0188)	(0.0046)	(0.0353)
Rival Correct Answers × High Performance	−0.0132	−0.0002	−0.0266
	(0.0193)	(0.0046)	(0.0366)
Intercept	0.6955**	−0.0938***	1.2296**
	(0.2832)	(0.0040)	(0.4849)
N	60,671	60,710	58,377
Pseudo-R^2	N/A	0.098	0.0996 (R^2)
Date dummies	Yes	Yes	Yes
Representation dummies	Yes	Yes	Yes

Notes. Robust standard errors clustered on user are reported in parentheses. N/A, Not applicable.
*$p < 0.10$; **$p < 0.05$; ***$p < 0.001$.

predicated on the outcome of the round. Namely, we included a dummy variable, coded as one if player i answered the question correctly in round $r-1$ in game g. This dummy variable is included as a control. The key estimates remain qualitatively similar (Table 13), suggesting that the contingent effects of the rival's status and past performance information may not be explained fully by the focal user's activities in the given round. We did not include this variable in the main analysis because it restricts the consideration set to those players who continued beyond the first round.

4.3. Heterogeneity on Motivation

Lastly, we analyzed to determine whether the observed effects of rival status and past performance information on the focal user's engagement are dependent on the player's motivational makeup. In particular, we argue that the *motivation to compete* vis-à-vis *motivation to learn* may play a crucial role in shaping the observed effects. Prior empirical work supports this assertion. For instance, Flynn and Amanatullah (2012) showed that when competing against a high-status rival, the focal user loses motivation to compete, leading to lower performance. Thus, Flynn and Amanatullah (2012) depicted an inhibiting effect of a high-status rival. In contrast, Zhang et al. (2019) showed that the focal user may "learn more" by competing against a high-status rival. Thus, a high-status rival may also prove beneficial. These competing effects, we argue, are predicated on the focal user's motivational frame.

To assess these effects, we modified our econometric specification (Equation (1)), incorporating a three-way interaction to examine the contingent effects on the player's motivation. The estimates are provided in Table 14 (Model 11), and the corresponding three-way interaction is shown in Figure 7. We find that the effect of a high-status

Table 13. Controlling for Previous Round Correct Answer (Dummy Variable)

Dependent variable = *Did the player continue the game after the current round?*	Model 10
Low Performance	0.1902**
	(0.0930)
Moderate Performance	0.1677*
	(0.0932)
High Performance	0.1837**
	(0.0935)
Low Status	−0.1252
	(0.0933)
Moderate Status	−0.1163
	(0.0949)
High Status	−0.1187
	(0.0944)
Prior Game Count	0.2867***
	(0.0370)
Rival Correct Answers	−0.1316***
	(0.0328)
Player Correct Answers	−1.2974***
	(0.0242)
Player Previous Round Correct Answer	1.3138***
	(0.0378)
Rival Correct Answers × *Low Performance*	−0.0264
	(0.0381)
Rival Correct Answers × *Moderate Performance*	−0.0962**
	(0.0366)
Rival Correct Answers × *High Performance*	−0.0511
	(0.0387)
Rival Correct Answers × *Low Status*	0.0080
	(0.0390)
Rival Correct Answers × *Moderate Status*	−0.0076
	(0.0382)
Rival Correct Answers × *High Status*	−0.0631*
	(0.0380)
Intercept	1.0917***
	(0.1902)
N	47,171
AIC	29,023.9702
BIC	29,786.2237
Pseudo-R^2	0.1815
Day fixed effects	Yes
Representation fixed effects	Yes

Note. Robust standard errors clustered on user are reported in parentheses.
*$p < 0.10$; **$p < 0.05$; ***$p < 0.001$.

rival is more pronounced when the focal user possesses a greater level of competitive motivation ($\beta = -0.0800$, $p < 0.005$). The graphical depiction of this interaction effect is consistent with our interpretation. In Figure 7, the slope of the curve is higher in the right panel (*high competitive motivation*) compared with that in the left panel (*low competitive motivation*). However, we find no comparable effect concerning the rival's past performance information. At the same time, our key effects retain signs and significance. Thus, our analysis reveals that the focal user's motivation to compete is a strong contingency mainly for status information.

Next, we rerun the same analysis with the focal user's motivation to learn as the contingency. Interestingly, we find no significant interaction between either of the information about expertise and motivation to learn (Table F2, Online Appendix F). A possible explanation for this lack of effect is that in our context, there is no "grand reward" awarded over a player's activities over time. As a result, perhaps, we find no effect equivalent to that reported by Zhang et al. (2019).[8] However, this assertion requires further empirical assessment. Nonetheless, this asymmetry in the contingent effects of learning and competitive motivations suggests that the influence of rival expertise information remains predicated on the focal user's motivational frame in nuanced ways.

4.4. Follow-up Study

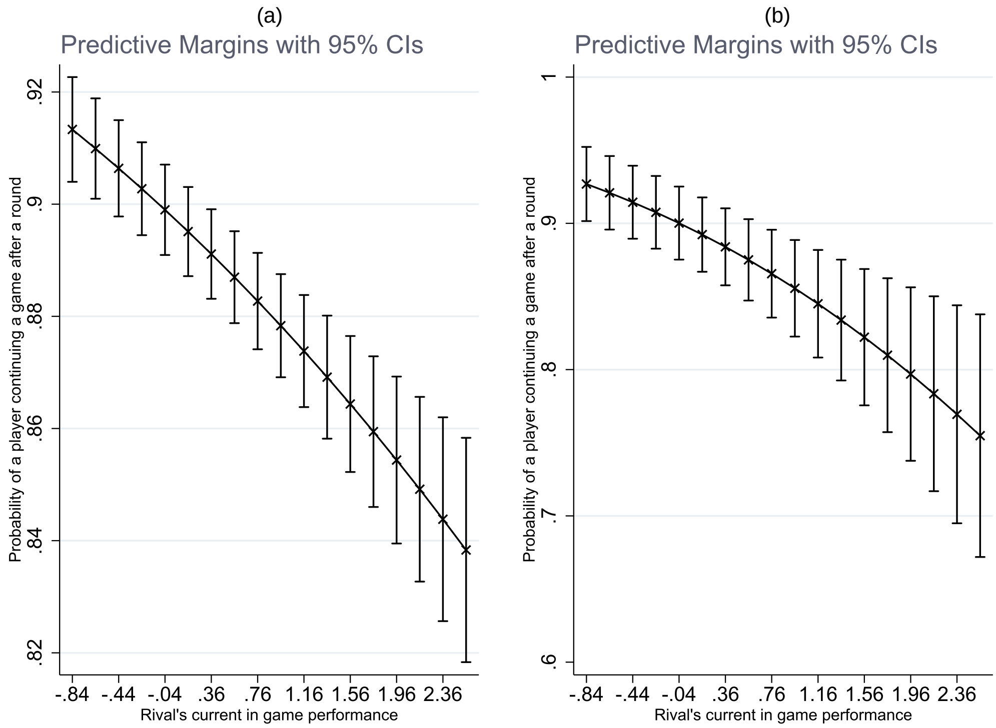
Thus far, the findings underscore the differentiated effects of the rival's status and past performance as expertise signals. However, the core assertion that the

Table 14. Three-Way Interactions Involving Player Competitive Motivation

Dependent variable = *Did the player continue after the current round?*	Model 11 Three-way interaction
Low Performance	0.1476*
	(0.0874)
Moderate Performance	0.1109
	(0.0885)
High Performance	0.1236
	(0.0874)
Low Status	−0.0753
	(0.0873)
Moderate Status	−0.0919
	(0.0887)
High Status	−0.0764
	(0.0884)
Prior Game Count	0.2819***
	(0.0385)
Rival Correct Answers	−0.1642***
	(0.0313)
Player Correct Answers	−0.8563***
	(0.0203)
Rival Correct Answers × *Low Status*	−0.0078
	(0.0366)
Rival Correct Answers × *Moderate Status*	−0.0059
	(0.0365)
Rival Correct Answers × *High Status*	−0.0689*
	(0.0365)
Rival Correct Answers × *Low Performance*	−0.0274
	(0.0357)
Rival Correct Answers × *Moderate Performance*	−0.0783**
	(0.0347)
Rival Correct Answers × *High Performance*	−0.0316
	(0.0362)
Competitive Motivation	−0.0196
	(0.0418)
Low Status × *Competitive Motivation*	0.0021
	(0.0474)
Moderate Status × *Competitive Motivation*	0.0044
	(0.0453)
High Status × *Competitive Motivation*	0.0265
	(0.0470)
Low Performance × *Competitive Motivation*	0.0134
	(0.0463)
Moderate Performance × *Competitive Motivation*	0.0301
	(0.0454)
High Performance × *Competitive Motivation*	0.0460
	(0.0463)
Rival Correct Answers × *Competitive Motivation*	0.0370
	(0.0346)
Low Status × *Rival Correct Answers* × *Competitive Motivation*	−0.0724**
	(0.0351)
Moderate Status × *Rival Correct Answers* × *Competitive Motivation*	−0.0161
	(0.0360)
High Status × *Rival Correct Answers* × *Competitive Motivation*	−0.0800**
	(0.0344)
Low Performance × *Rival Correct Answers* × *Competitive Motivation*	−0.0227
	(0.0355)
Moderate Performance × *Rival Correct Answers* × *Competitive Motivation*	−0.0068
	(0.0347)
High Performance × *Rival Correct Answers* × *Competitive Motivation*	0.0249
	(0.0366)
Intercept	1.2163**
	(0.4893)
N	60,671
Pseudo-R^2	0.1411
Date dummies	Yes
Representation dummies	Yes

Note. Robust standard errors clustered on user are reported in parentheses.
$^*p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.001$.

Figure 7. Rival's Status Tiers, Current (In-game) Performance and Focal Player's Motivation Interaction



two signals are indeed viewed in relative and absolute terms is not tested explicitly. To this end, we report the findings of a follow-up study designed as an online survey. This study involved 422 individual participants recruited from *Prolific*, a popular microtask platform (Peer et al. 2022). Given that our empirical setup in the main study involved a two-player mobile game, we recruited participants with a certain propensity to play such games for at least three hours per day, either on a mobile or on a PC. The survey required just under two minutes to complete, and each participant was compensated fairly in accordance with Prolific's policies.

At the start, a recruited participant was redirected from Prolific to a QuestionPro survey link. First, they were required to read and confirm their comprehension of survey-related instructions. Namely, each participant was asked to imagine playing a two-player mobile game that has received more than ten thousand downloads. Next, participants were told to view four distinct screens, each depicting different information about a player's expertise. Each screenshot (refer to Figures H1–H4, Online Appendix H) depicted the rival's expertise signal. For "status" signals, we showed a lexical hierarchy (gold, silver, bronze) (Screen-2) and percentile (Screen 3). For "past performance" signals, we showed the count of wins in the past five games (Screen 1) and the win-loss sequence of the outcomes of the past five games (Screen 4). In look and feel, in addition to the actual representation of expertise signals, these screens were identical to the ones used in the main field experiment. After seeing these screens, each participant was asked to select one or more screens that provided the most useful expertise signal for positioning their rival among a pool of other active players.[9] After selecting the screens, participants were asked to briefly explain their responses.[10] We use these responses later to delve further into the respondents' reasoning for choosing specific screens.

Table 15 shows that the majority of the participants exclusively selected status signal screens (n = 263, 62.32%). In contrast, at 22.27%, the proportion of participants who exclusively selected performance screens was considerably lower (n = 94). Lastly, 65 participants (15.40%) selected both status and performance screens. Thus, prima facie, there is a greater reliance on status to assess the relative expertise of an individual. Next, the cross-tabulation of responses in Table 15 indicates that the majority of participants who selected status signals did not select past performance signals. Further, we

Table 15. Cross-Tabulation of Response to Survey Questions

	Performance information selected		
Status information selected	No	Yes	Total
No	0	94	94
Yes	263	65	328
Total	263	159	422

Note. Pearson χ^2 = 200.04; p = 0.0000.

conducted chi-square tests to examine the association between selecting status information and selecting past performance information. We found a significant association between selecting status and past performance signals (chi-squared = 200.0438, $p < 0.001$). Collectively, these findings reveal that users primarily rely on status information to determine their position among a pool of players, that is, status indicates the expertise of the rival in relation to other players.

Next, we delve into the qualitative explanations from respondents for their choice of screens. To this end, two independent coders (the first author and a research associate who was not associated with this study earlier) analyzed all the participant's text responses to the final question on the survey and developed an open coding scheme (Creswell and Poth 2016). Then, the coders jointly developed a selective coding scheme. This scheme categorized participant responses into three broad categories reflecting each participant's reasoning. Note that at the time of developing this classification scheme, each coder did not know where the other coder had categorized the given respondent.

Relative Comparison of Expertise: *The focus was on how the selected information screen positioned the rival player relative to other players (e.g., "gold indicates a top player").*

Absolute Indicator of Expertise: *The emphasis was on the selected information screen directly providing the player's skill level (e.g., "Win count shows how many games they've won").*

Unclear Rationale: *The response was ambiguous or did not provide clear reasoning for the choice.*

Then, both coders independently allocated each participant's responses to one of the selective code categories. We found a significant level of agreement between the coders (Cohen 1968). Namely, the resulting kappa value was 0.86 ($\sigma = 0.035$, $Z = 25.29$), which exceeds the threshold for chance agreement, indicating an acceptable level of consensus between the coders (Vieira et al. 2010, Wang et al. 2019). The summary of qualitative responses is provided in Table 16.

Finally, we conducted a chi-square test to examine the association between the qualitative response categories and the participant's initial selections (both status and past performance, past performance only, or status information only). The statistically significant result ($\chi^2 = 142.48$, $p = 0.0000$) indicates the type of rival's expertise information participants preferred (status or past performance) and their underlying reasoning (relative or absolute) for that preference are indeed associated (see Tables I1–I2, Online Appendix I, for the results). In summary, the follow-up survey reveals that the two signals of expertise are indeed viewed differently in the online competitive setting, with status being perceived as a relative signal and performance as an absolute signal.

Table 16. Categorization of Qualitative Response

Assessment of expertise	Frequency	Percent
Absolute	89	21.09
Relative	215	50.95
Unclear	118	27.96
Total	422	100.00

5. Conclusion

5.1. Summary of Key Findings

Our study is intended to examine how information about rivals influences the engagement of a focal user. To this end, we reported findings based on a field experiment conducted in an online competitive setting. We find that the rival's current performance (i.e., correct answers in an ongoing game) reduces the focal user's chances of continuing the game. Next, we find the contingent effects of relative (*status*) and absolute (*past performance*) signals of the rival's expertise. Precisely, estimates reveal that the primary negative effect of the rival's current performance is stronger for rivals with either high status or moderate performance. Further, we find that the contingent effect of the interaction between a rival's high status and current performance is stronger if the focal user is more competitively motivated. However, we do not observe a similar interaction effect concerning the focal user's motivation to learn. Finally, a follow-up study based on an online survey corroborates our assertion that status and past performance expertise signals are indeed viewed in relative and absolute terms, respectively.

5.2. Implications

Our findings have several implications. Firstly, our study contributes to the existing body of literature on the informational drivers of online user engagement. Our contribution stems from examining a fundamentally different context—*online competitive settings*—where the applicable mechanisms for the effects of information antecedents would be qualitatively different from those reported in the prior work (Burtch et al. 2016). In competitive settings, we argue that the focal user would be primarily interested in the rival's expertise information (Zhang et al. 2019) because such information may help the player in assessing their chances of winning the competition. Therefore, typically employed mechanisms, such as *social norms* and *social contagion,* may be insufficient to explain how informational antecedents influence the focal user's engagement. Addressing this gap, we show that the effects of information on the rival's *relative* and *absolute* expertise signals have distinct and significant implications. To that extent, our work adds to the known repository of explanations of how information signals influence online user engagement (Table 1).

Second, our study contributes to the literature on the effects of status and past performance in competitive settings (Washington and Zajac 2005). Contrary to the conventional wisdom, recent work has shown that status and past performance may operate independently. Our work advances this literature by showing that, at least in online competitive settings, status (as a *relative* signal of expertise) and past performance (as an *absolute* signal of expertise) influence engagement indirectly; that is, by reshaping the baseline effect of the rival's current performance. Further, the corroborative insight from the follow-up study indicates that status and past performance are indeed processed separately when the focal user attributes expertise to their rival. On a related note, the study also shows that in online competitive settings, the inference of the rival's expertise may be contingent on how expertise is revealed. That is, more "accumulated" expertise signals, such as past performance and status, may generate different framings to assess the more "immediate" expertise signals (Kim and King 2014).

The interaction effects further unpack the distinction between status and past performance expertise signals. First, given that compared with having an unknown status, the rival's *high status amplifies.* However, the *low status does not weaken* the baseline influence of the rival's current performance, suggesting that the broader expertise framing, at least when conveyed through a relative signal, may be an asymmetric lens that users adopt to interpret the rival's current performance. This finding is particularly interesting as it indicates that status may not always be viewed as a continuum (i.e., high to low status) but rather a discrete order wherein only higher positions create differentiations. However, the moderate and lower status positions, in their influence, are comparable to having unknown status. To an extent, this finding is consistent with the assertion that unknown status is often seen as comparable to low status in a social context (Bitektine 2011).

Next, the finding that a moderate level of past performance strengthens the baseline effect of the rival's Current Performance is also rather intriguing. At the outset, it shows that past performance and status influence the focal user's engagement differently. A possible explanation for this effect is that under moderate past performance, there would be greater uncertainty about the rival's absolute expertise. Therefore, current performance, also in some ways an absolute signal of expertise, would attain greater importance. The basis for this claim is, once again, the rationale for the focal user to assess rival-specific expertise signals: *to assess the chances of winning*. To this end, the focal user may engage in a rather involved search process (Phillips et al. 2014), seeking to reduce the uncertainty about the rival (e.g., the rival's expertise). Therefore, the focal user is likely to rely differentially on more informative signals (e.g., high/low current performance is more informative than moderate past performance). We do not see such an effect for moderate status as the two signals operate rather differently (Bitektine 2011). That said, more work is warranted to further tease out the underlying explanation for the interaction effect involving the past performance as an expertise signal.

Our subsequent contribution is in identifying the role of the focal user's motivational frame as an important contingency. Namely, we find that the greater the competitive motivation of the focal player, the stronger the contingent effect of the rival's high status. Although the relationship between the advantages accrued to actors because of their status and motivation has seen some research attention Willson (1983), we advance this literature by modeling the effect of motivational heterogeneity among actors. Overall, our findings are aligned with the insights of Simcoe and Waguespack (2011) and Azoulay et al. (2014), suggesting that the effect of status may have considerable boundaries in terms of level of expertise, motivation, and information format.

Lastly, our findings offer important practical recommendations. Given the finding that rival expertise information can dramatically shape the focal user's engagement, we recommend dynamically adjusting the salience of rival information, especially when a rival holds a high status or exhibits moderate past performance. Thus, we go beyond the usual recommendations, such as whether the player hierarchy or leaderboard. Instead, we recommend designers disclose player information in a competitive setting based on the actual gameplay. As per our findings, doing so may significantly enhance user engagement in competitive online settings. Next, based on the finding that competitively motivated players are more influenced by status information, we recommend that the motivational traits of players should be recognized, and the interface can be customized accordingly.

5.3. Limitations and Future Research

Our findings should be viewed in light of certain limitations. First, our empirical context is a two-player, multiround game. Therefore, additional work is required to ascertain whether the findings extend to multiplayer settings wherein viewing and responding to rival expertise information may be more cognitively taxing. Further, the participants in the study, attracted through Facebook advertisements, were from a single country (India). Thus, although the exogenous treatments mitigate concerns regarding the potential influence of player culture and game context (duration and number of players), we suggest readers exercise caution when generalizing these findings to participants from different countries.

On a related note, nationality may also afford status, resulting in added status-borne effects. Given these possibilities, we call for additional research to include player nationality in online competitive settings (Bockstedt et al. 2016).

Furthermore, it is crucial to recognize that for our analysis, information on the rival's expertise (*status and past performance*) was discretized into three levels. Subsequent research endeavors may investigate whether the observed effects persist with adding additional levels or removing existing levels while conveying information about rivals to the focal user. On a related note, further empirical exploration is warranted for the contingent effect of the moderate levels of past performance. Although we do offer some explanation, drawing from Bitektine (2011), our empirics do not test the same explicitly. Researchers may also investigate observed effects by introducing complexities related to the gameplay timeline for the calculation of status and past performance signals. Another limitation is that we consider a single binary engagement outcome: the player's decision to continue playing the game. Future work can examine other important outcomes, such as length of engagement. Our penultimate limitation is that, although we programmed rivals as bots replicating human-like gameplay, we did not explicitly test how convincing their humanness was to the focal players. Future research can compare engagement outcomes with bots versus human rivals. Finally, we do not consider the variation in the bot's response time, which, although varied exogenously, is not captured by the game. Therefore, we call for further research to investigate temporal variations in rival response time as an important determinant of engagement.

Endnotes

[1] The suffix 2 in the application name Word Fighter-2 denotes a two-player game. The title was chosen by developers at the time of the game's release and has nothing to do with application versioning. For this study, exclusively, modifications were made in the original game. The mobile application Word Fighter-2 with changes related to rival programming and data gathering was only made accessible for download for the duration of the study.

[2] The game is built using a standard word list for GRE preparations https://magoosh.com/gre/best-and-worst-gre-word-lists/as base vocabulary for challenge design.

[3] The scores are displayed to the focal user but information captured includes whether the focal user got the answer right in that round and the same was captured for the rival.

[4] Refer to Table D1 (Online Appendix D) for mean comparison of proportion of games played by focal players with rivals of varied "current performance" across the four groups (i.e., no signal, only status signal, only performance signal, both signals). We find no significant variation in the "nature of the rival", that is, bot's current performance, with respect to status and past performance signals' revelations of our focal players.

[5] The app sent the user data to the Firebase Real-Time database, where it was stored as events identified for tracking user and rival (bot) activities. To retrieve this data for analysis, the JSON blob was exported from the Firebase web dashboard. The exported data were then transformed into csv for analysis. This process enabled real-time collection of user activity data, as well as efficient retrieval and analysis of the data.

[6] Refer to Table E1 (Online Appendix E) for player-level estimation of the direct effect of status and performance signal representation on proportion of completed games.

[7] Refer to Table E2 (Online Appendix E) for randomization check of human player, that is, focal user's self-reported traits across grouping based on rival's status and performance signal revelations.

[8] In the empirical context that Zhang et al. (2019) study, the platform offers a reward based on performance over time (https://www.topcoder.com/tc?module=Staticandd1=digital_runandd2=2006_des_prizes). As a result, the focal user may be motivated to learn early on to increase their chances of performing well over time and winning the said reward.

[9] The verbatim text of the corresponding question was "We will show you four game screens (4 options) with a randomly picked rival's name along with the information on their game statistics in a popular two-player mobile game. Based on the information on those screens, you have to select one or two screen/s which contain information that allows you to conclusively make comparison of the rival with all other active players. (Multiple select question)."

[10] To this end, we asked the following question on the survey: "Can you tell us reasons for your choices/selection in previous question? (minimum seven words)."

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