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RESEARCH ARTICLE

# POPULARITY FEEDBACK AND ADAPTATION STRATEGIES IN ONLINE DATING: A SOCIAL COMPARISON PERSPECTIVE[1]

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*Digital platforms are increasingly employing informational nudges to motivate user participation. This paper examines the provision of popularity information as a feedback mechanism and its impact on users' adaptation strategies. Leveraging ego utility theory and self-determination theory, we hypothesize that comparative popularity information—information that facilitates social comparison—will trigger different reactions based on gender and popularity level. In collaboration with an online dating service provider, we designed and conducted two randomized field experiments in which we provided popularity feedback to platform users and investigated their post-feedback behavioral changes in two adaptation strategies: the selectiveness in choosing potential partners (i.e., selectivity calibration) and the frequency of their online profile modifications (i.e., self-marketing). In the first experiment, where we revealed information about their popularity relative to other users, we found that those who received low-popularity feedback significantly increased self-marketing efforts and lowered their selectivity, but the opposite was observed in individuals who received high-popularity feedback. We also found that men readily made adaptations to their selectivity calibration and self-marketing, whereas women's behaviors were more persistent as they exhibited little strategic change. We then conducted a second experiment in which we revealed absolute popularity instead of comparative popularity and observed no significant changes in adaptation strategies. Comparing the outcomes of the two experiments, we argue that it is the social comparison information associated with comparative popularity that drives user behavioral changes.*

**Keywords:** Popularity feedback, comparative feedback, social comparison, two-sided platforms, matching markets, online dating, gender difference, randomized field experiments

## Introduction

Digital platforms often leverage *popularity information* to boost content viewership. For example, video streaming platforms such as YouTube routinely promote trending videos based on their recent popularity. Reddit, a social news aggregator, uses upvotes and downvotes to determine posts' visibility on the site. Besides its role in directing the attention of content viewers, popularity information can serve as a feedback mechanism that informs content creators how well their content is received by the target audience, and earlier research has shown that content creators respond to it with various coping strategies (Li et al., 2018; Rosenthal-von der Pütten et al., 2019).

More generally, revealing popularity information on digital platforms often leads to strategic, adaptive behaviors (Goes et al., 2014). However, prior studies of online platforms have primarily examined the role of popularity information in stimulating the contribution of user-generated content (UGC) (Huang et al., 2019; Zhu et al., 2013). In contrast, it

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is unclear if and how popularity information would influence user behavior in online matching markets. Notably, matching markets require a different set of strategies of utilizing popularity information because the participants in a matching market are usually constrained by a limited capacity (Sönmez, 1997). In the rental property market, for example, an apartment can only be rented to one tenant at a time; similarly, in the ride-hailing market, a driver can only serve one customer at a time. Social media websites, in comparison, have an almost unlimited capacity to provide content to many viewers at the same time. Due to these differences, matching markets often suffer from the problem of congestion (Arnosti et al., 2021; Ashlagi et al., 2020)[2], which, in contexts of online dating, results in a market where the demand of one side is concentrated in a small set of highly attractive users on the other side (Huang et al., 2022). Clearly, promoting the most popular individuals on an online dating platform in the same manner that UGC platforms promote popular content will likely backfire and exacerbate congestion. However, if popularity information can be leveraged to modify user behavior to divert attention away from the most popular population or prompt the less popular individuals to better market themselves, it can help alleviate the congestion issue and improve matching efficiency.

In this work, we study the impact of popularity feedback on two-sided matching platforms by examining users' subsequent *adaptation strategies* in the context of an online dating platform. Drawing upon prior work (Baumeister & Hutton, 1987; Ellison et al., 2006; Heino et al., 2010; Hirschman, 1987), we focus on two strategies that are commonly employed by participants on online matching platforms: (1) a *self-marketing* approach, where users improve self-presentation through online profile management to highlight their desirable attributes, maximize their exposure and lower search costs for others, and (2) a *selectivity calibration* approach, which involves users strategically adjusting their degree of selectivity based on the supply of potential partners and their own desirability. A few elements set our work apart from earlier studies in this area. First, unlike recent studies of popularity information on dating platforms that use the popularity of potential partners as the manipulation (Bojd & Yoganarasimhan, 2022; Huang et al., 2022), the information we provide in the experiments reflects the popularity of the focal user—therefore it is a form of *feedback*. Second, we manipulate the presentation of popularity information in both comparative and absolute forms, allowing us to contrast the resulting outcomes under these different conditions, and delve deeper into the underlying mechanism.

Notably, our work draws from the online dating literature, which has highlighted gender differences in experiencing congestion (Jung et al., 2022; Piskorksi, 2014; Bapna et al., 2016), in matching preferences (Fisman et al., 2006; Hitsch et al., 2010), and—of particular relevance to this paper—in the impact of different types of information provision (Bapna et al., 2016, 2022; Huang et al., 2022; Jung et al., 2022). Most relevant to our study is the work showing the impact of revealing (or hiding) *identifying* information in heterosexual matching markets (Bapna et al., 2016, 2022) and the provision of *potential candidates'* demand information (Huang et al., 2022). Noting that the effects of identity revelation and peer population information have been shown to vary both by the gender and popularity of the user, we are particularly interested in understanding the heterogeneous effects of gender and popularity level in the impact of popularity feedback on users' self-marketing and selectivity calibration strategies.

Thus, we aim to answer the following research questions:

**RQ1:** *Will popularity feedback on online dating platforms influence the focal users' (i.e. the receivers of the feedback) adaptation strategies (i.e., in terms of* ***self-marketing*** *and* ***selectivity calibration****)?*

**RQ2:** *To what extent is the effect heterogeneous, i.e., among focal users with varying levels of popularity, or between men and women?*

**RQ3:** *What is the mechanism underlying individuals' responses to popularity feedback on dating platforms, the degree of the user's popularity or their relative popularity ranking among peers?*

In collaboration with one of the leading online dating service providers in the U.S., we designed and conducted two randomized field experiments in which we provided users in the treatment group with information regarding their popularity, whereas users in the control group received no such intervention. Given the importance of social comparison in the context of social media (Chen et al., 2010; Gerson et al., 2016), we started with *comparative popularity*—the relative ranking of one's popularity among peer users on the same side of the market—as the intervention in the first experiment. Our analyses yielded several interesting results. First, we found that the effect of comparative popularity feedback on an individual's adaptation strategy is contingent on their popularity level as revealed in the feedback.[3] Regarding *selectivity calibration*, we found that individuals who learned

[2] We define congestion in the sense of Roth (2018, p. 1613), i.e., "the accumulation of more time-consuming activities than can easily be accommodated in the time available."

[3] Our study examines how users react to revealed comparative popularity. It is beyond the scope of our study to explore how users interpret their popularity feedback in relation to their expectations.

that they had low popularity significantly relaxed their selectiveness, while those who learned that they had high popularity became more selective in choosing whom to pursue. In terms of *self-marketing*, however, we found that individuals with low popularity significantly increased their effort in managing and updating their online profiles in their attempt to catch up (Eriksson et al., 2009), while the opposite was observed for high-popularity individuals, showing evidence of "coasting" on the part of high achievers (Bénabou & Tirole, 2002). Importantly, because the treatment message does not provide suggestions regarding strategies to improve one's popularity, any user's action is of their own initiative in response to the popularity information.

Second, we discover considerable gender differences in the way users adjust their adaptation strategies in response to the feedback of comparative popularity. Examining *selectivity calibration*, we found that men adjusted their selectivity readily in response to their own popularity as revealed in the feedback, but women were more persistent in their selectivity and their reactions were insensitive to their revealed relative standing. Such differences also emerged in the *self-marketing* strategy. For men, the less popular individuals increased the intensity of online profile management, while the more popular ones reduced it; for women, in contrast, the less popular individuals appeared to become discouraged and reduced their profile update efforts, and we observed no significant change among highly popular individuals in managing their self-presentation. In summary, our findings suggest that post-feedback responses are far less prominent among women than among men. Such heterogeneity across genders resonates with prior literature showing that men and women have different competitive preferences in various contexts and men respond more positively to competition (Croson & Gneezy, 2009; Gneezy et al., 2003; Niederle & Vesterlund, 2007).

To disentangle the social comparison mechanism associated with comparative feedback (Buunk & Gibbons, 2007; Gibbons et al., 1994; Huang et al., 2019) from competing explanations—such as a "saliency" effect (Chetty et al., 2009) or a "knowledge of result" effect (Klueger & DeNisi, 1996)—which are often associated with absolute feedback, we conducted a second randomized experiment in which we revealed to the users their *absolute popularity* instead of their comparative popularity in the feedback message and observed the subsequent changes in adaptation strategies. Interestingly, we observed no significant changes in adaptation strategies—neither in the aggregate population nor in the subpopulations of different popularity levels or genders—following the manipulation of the second experiment. These contrasting outcomes between turning the competitive aspect of the popularity information on and off provide strong support for the role of social comparison as the driver of the post-feedback behavioral changes.

## Related Literature

### *Peer Feedback on Digital Platforms*

Peer feedback on digital platforms differs from *performance feedback* that has been examined under the context of education or workforce management (Azmat & Iriberri, 2010, 2016; Bandiera et al., 2015; Blanes i Vidal & Nossol, 2011; Eriksson et al., 2009; Kuhnen & Tymula, 2012) in several important aspects. First, unlike the settings of education and workforce management in which performance is evaluated by a central "authority" (e.g., a supervisor or a teacher), on digital platforms, favorable reception is usually determined by peer users on the same platform in a decentralized fashion, often through some "voting" mechanism (Gallaugher & Ransbotham, 2010). Furthermore, existing performance feedback literature almost exclusively centers on the relationship between feedback and agents' subsequent effort, whereas digital platforms, due to their multisided nature, enable a more diverse space of coping strategies, which cannot be adequately captured by simple effort metrics. For example, job seekers on online resume platforms such as LinkedIn may use several ways to attract the attention of potential employers, including describing, in detail, their past work experiences and qualifications, making new connections to increase visibility, or asking for endorsements from coworkers.

IS research has begun to examine the effect of peer feedback on digital platforms, typically focusing on motivating UGC creation (Brzozowski et al., 2009; Huang et al., 2019). For example, research has shown that social comparison associated with peer feedback increases contribution to online communities in the setting of rating movies (Chen et al., 2010), that a larger population of peers causes individuals to write not only more online product reviews but also higher-quality reviews (Wang et al., 2019), and that the effect of peer feedback on the task performance of Wikipedia contributors depends on the receiver's prior experience (Zhu et al., 2013). Earlier studies have also reported that peer recognition is a powerful driver of knowledge contribution in online user support forums (Jabr et al., 2014; Jin et al., 2015). Moreover, Moon and Sproull (2008) showed that the implementation of systematic quality feedback systems leads to high-quality knowledge contribution and the retention of contributors.

Most relevant to our study is a small cluster of studies that have examined peer feedback on digital platforms where the feedback conveys information about the content's or creator's *popularity*, and how this influences the receiver's post-feedback behavior. For example, Goes et al. (2014) identified a "popularity effect" in online product reviews: as an individual gains more subscribers/followers, they write more product reviews with increasing objectivity, and their product ratings become more negative on average but also more varied. Toubia and Stephen (2013) argued that as an individual's number of followers on Twitter increases, their intrinsic utility and image-related utility lead to opposite effects on the volume of their posting activities: evidence from their field experiment suggests that intrinsic utility is more prevalent when an individual has fewer followers, but image-related utility becomes more important when individuals amass more followers.

In the context of online dating, two recent studies have examined the role of revealing user popularity information. Bojd and Yoganarasimhan (2022) found evidence that individuals temper their preference for popular people due to fear of rejection. Huang et al. (2022) showed that disclosing peers' popularity information helps mitigate congestion and improve matching efficiency in online dating. While both studies investigated how users react to demand information about *potential mates*, the information manipulation in our study is a form of *feedback*—i.e., it provides the popularity information of the *focal user*. Moreover, by contrasting the presentation of popularity information in comparative and absolute terms, our work underscores the vital role of social comparison—a concept overlooked in the two earlier studies—in designing popularity feedback.

## Online Dating and Adaptation Strategies

With people increasingly turning to the internet to seek dates and romantic relationships, there is a small but burgeoning body of literature on online dating, or "the use of Internet services designed to facilitate interactions between potential romantic partners" (Heino et al., 2010, p. 428). Through technology-enabled features and tools, such as online profiles and private messaging, online dating platforms capture unusually rich information on their users, allowing researchers to investigate interesting new research questions (Bapna et al., 2016; Burtch & Ramaprasad, 2016; Hitsch et al., 2010).

A few studies have specifically focused on an individual's strategies in online dating. Broadly speaking, these strategies fall under two categories: (1) searching, filtering, and approaching one's potential mates on such platforms, and (2) determining one's self-worth and controlling self-presentation (Baumeister & Hutton, 1987). For example, applying the market metaphor to online dating, earlier studies have documented some specific adaptation strategies commonly adopted by participants of online dating, such as assessing one's own "market value," going out on as many dates as possible so as to maximize one's "inventory," or avoiding people whose profile contains only one blurry photo (Heino et al., 2010). In our setting, we are particularly interested in examining how focal users change these *adaptation strategies* in response to their popularity feedback.

We primarily focus on two adaptation strategies practiced by most users of online dating services that can be readily measured under the research context. First, it is well known that the dating and marriage market displays features of assortative matching (or homogamy) on social status, age, income, and education (Abramitzky et al., 2011; Blossfeld, 2009; Choo & Siow, 2006; Pencavel, 1998), and individuals often employ a *selectivity calibration* strategy that involves adjusting the degree of selectiveness in their searches for potential partners. Adopting a restrictive set of criteria for potential mates will likely limit one's choices. Considering a broad set of potential partners with a loosely specified attribute space, on the other hand, results in greater screening costs. Heino et al. (2010) documented that individuals strategically adjust their level of selectivity based on the supply of potential partners and their own perceived desirability, e.g., broadening the age and weight criteria for potential dates as one ages and therefore becomes less attractive.

Second, users can also employ a *self-marketing* strategy that involves managing their online profile to appeal to a wider audience, lower the search cost for others, and maximize their online visibility. Prior research suggests that in social interactions individuals highlight their desirable attributes as marketable assets that are sought after by potential partners (Hirschman, 1987), and in the online space, an important tool for self-presentation is one's online profile—the "first and primary means of expressing one's self during the early stages of a correspondence and can therefore foreclose or create relationship opportunities" (Ellison et al., 2006, p. 423). Ellison et al. (2006) further presented a detailed discussion of self-presentation strategies in online dating, highlighting a tension between the motive of portraying an *ideal self* and the desire to reveal an authentic, *actual self* (Higgins, 1987). Some also argue that due to reduced physical cues and asynchronous communication, online identities are more prone to self-censorship and selective self-presentation (Walther, 1996; Walther & Burgoon, 1992). Nevertheless, such a *self-marketing* strategy through computer-mediated communication helps people construct a digital self and use the digital likeness to communicate their real-life identity (Jensen Schau & Gilly, 2003).

The two adaptation strategies we examine in this work—self-marketing and selectivity calibration—have important implications for downstream outcomes in the dating process. Indeed, researchers have found that subsequent contacts and matching outcomes are impacted by both users' strategic self-presentation (Whitty, 2008; Finkel et al., 2012) and their selectivity (Finkel et al., 2009; Jung et al., 2022). As Finkel et al. (2012) (Figure 2) illustrated, profile creation/updating and profile browsing are central activities in online dating that directly lead to subsequent steps of establishing initial contact, meeting face-to-face, and developing offline relationships. In addition, Jung et al. (2022) showed that users in online dating strategically modify their selection criteria as their choice capacity changes, which influences matching outcomes greatly. Therefore, our systematic examination of these adaptation strategies can not only increase the understanding of how individuals shape these strategies in response to popularity feedback but can also shed light on how such feedback may lead to changes in subsequent user engagement and matching outcomes.

## Theory

### *Social Comparison in Online Dating*

Social comparison is defined as individuals' pervasive tendency or drive to engage in comparison with others, often with an interest in acquiring comparative knowledge (Gerber et al., 2018; Kruglanski & Mayseless, 1990). Social comparison is an important way for individuals to obtain information for self-evaluation (Festinger, 1954), enhance or maintain self-esteem (Smith & Insko, 1987), and learn to adapt to challenging environments (Tarakci et al., 2018). As a result, social comparisons are often used as a tool to influence individual behavior. On social media platforms, it has been shown that information regarding viewer responses to UGC can unintentionally invoke social comparison processes due to its public nature (Krasnova et al., 2015). Digital platforms are increasingly using information that involves social comparison, such as popularity, to increase user engagement. Although earlier research has shown that popularity feedback leads to significant changes in the receivers' behavior, such as their content creation strategies on social media (Goes et al., 2014; Toubia & Stephen, 2013), it remains unclear if—and how—such information can be provided to influence user behavior in matching markets such as online dating.

Social comparison is frequently observed in romantic relationships, and research has shown that it is more likely to occur when the comparison target is a close friend and the comparison factor is more relevant to the individual (Morry & Sucharyna, 2016, 2019). Relatedly, Buunk et al. (2001) showed that downward social comparison results in greater relationship satisfaction. Thomas et al. (2023, p. 3) proposed that social comparison in online dating can also be made cross-gender based on "status and physical attractiveness" and argued that people try to "detect mates who match their own physical attractiveness and popularity." In the rest of this section, we present a discussion of how social comparison information will trigger different adaptation strategies of online daters across popularity levels and genders.

### *Popularity Level and Adaptation Strategies*

We argue that the favorableness of the social comparison result will lead to changes in adaptation strategies in response to popularity feedback in online dating, according to *ego utility theory* (Bénabou & Tirole, 2002; Köszegi, 2006; Kuhnen & Tymula, 2012). This theory suggests that in addition to utilitarian benefits, an agent derives "ego utility" from positive views of the self in performing tasks. Social comparisons, by conveying one's relative standing among one's peers, provide individuals with useful information for *self-evaluation* in the context of goal setting (Ederer, 2010; White et al., 1995). When feedback information is inconsistent with one's self-evaluation, individuals will update their knowledge about their ability and make adaptations to their aspirations accordingly (Mezias et al., 2002). Consistent with this argument, researchers have found that track and field athletes respond to negative feedback by revising their goals downward to make them more attainable and respond to positive feedback by raising their goals (Williams et al., 2000). Similar observations have been made in the management literature, suggesting that aspiration levels will adjust upward in response to favorable feedback and downward in response to unfavorable feedback (Lant, 1992). Research on assortative mating has also shown that people often seek romantic partners who are similar in physical attractiveness, self-worth, and popularity (Thomas et al., 2023). Therefore, we contend that in the context of online dating, the direction of selectivity calibration will similarly depend on the favorableness of one's comparison with peers, with individuals relaxing their selectivity criteria when they receive unfavorable comparison results and raising them when they receive favorable comparison results.

**H1a:** *On average, individuals who receive favorable (unfavorable) comparative popularity feedback will raise (lower) their standards in selecting partners.*

Another implication of ego utility theory is that the favorableness of comparison can also influence feedback responses through its impact on *self-esteem* (Helgeson & Mickelson, 1995; Mussweiler et al., 2000; Vogel et al., 2014). Earlier research found that exposure to upward social comparison information on social media has a detrimental impact on self-esteem (Vogel et al., 2014). More generally, when social comparison results are favorable, such comparison presents little threat to self-esteem, and the motivation for changing behavior is relatively low. However, unfavorable social comparisons often result in negative self-perceptions, and individuals are motivated to avoid experiencing them (Helgeson & Mickelson, 1995; Mussweiler et al., 2000). Relatedly, Thürmer et al. (2020, p. 266) argued that "negative affect then leads to investing more effort (pushing) and positive affect leads to investing less effort (coasting)." Therefore, when individuals receive unfavorable feedback on their standing compared to others, they will likely devote effort to improving their task performance so that they can avoid feeling inferior to their peers and gain confidence in their abilities (Gino & Staats, 2011). Applying this reasoning to online dating, we conjecture that individuals who receive feedback indicating an unfavorable comparison result will have a strong motivation to engage in remedial activities, i.e., they will likely increase their self-marketing activities. In contrast, those who receive favorable comparative popularity feedback will likely reduce their self-marketing activities.

**H1b:** *On average, individuals who receive favorable (unfavorable) comparative popularity feedback will reduce (increase) their self-marketing activities.*

## Gender and Adaptation Strategies

*Self-determination theory* (Deci & Ryan, 1985a, 1985b, 2015) assumes that individuals have innate psychological needs for autonomy, competence, and relatedness and that behavioral regulation towards an activity can be driven by either autonomous or controlled motivation (Deci et al., 2017). With autonomous motivation, individuals engage in an activity "with a full sense of willingness, volition, and choice" (Deci et al., 2017, p. 20), because the activity satisfies their basic psychological needs as they experience interest and enjoyment. In contrast, with controlled motivation, individuals engage in an activity in order to win some reward, obtain approval from others, or avoid punishment (Knee & Neighbors, 2002). While intrinsic motivation is invariably autonomous, extrinsic motivation varies in its degree of autonomy and can become autonomous through the processes of internalization and integration (Deci et al., 2017). As a result, causality orientations can be assessed by the degree to which an individual's behavior is self-determined (autonomous) or controlled by others. *Autonomy-oriented* individuals presumably carry out activities based on their awareness of needs and goals consistent with their integrated self-concept (Neighbors & Knee, 2003). In contrast, the behavior of *control-oriented* individuals tends to be motivated extrinsically, being relatively more pressure- or reward-regulated than self-regulated. Such individuals are more likely to respond strongly to performance pressures in their social environment (Knee & Neighbors, 2002).

Earlier research has documented *gender differences* in goal orientation. For example, under the context of education, empirical evidence suggests that girls are more intrinsically motivated and more self-determined than boys, whereas boys are more concerned with their social status and image than girls (Bouffard et al., 1995; Green & Foster, 1986; Vallerand et al., 1992). As a result, an extrinsic orientation toward schoolwork may influence boys' engagement and self-regulated learning more than that of girls, because "the stake of receiving (or not receiving) rewards may be perceived as higher" (Patrick et al., 1999, p. 157).

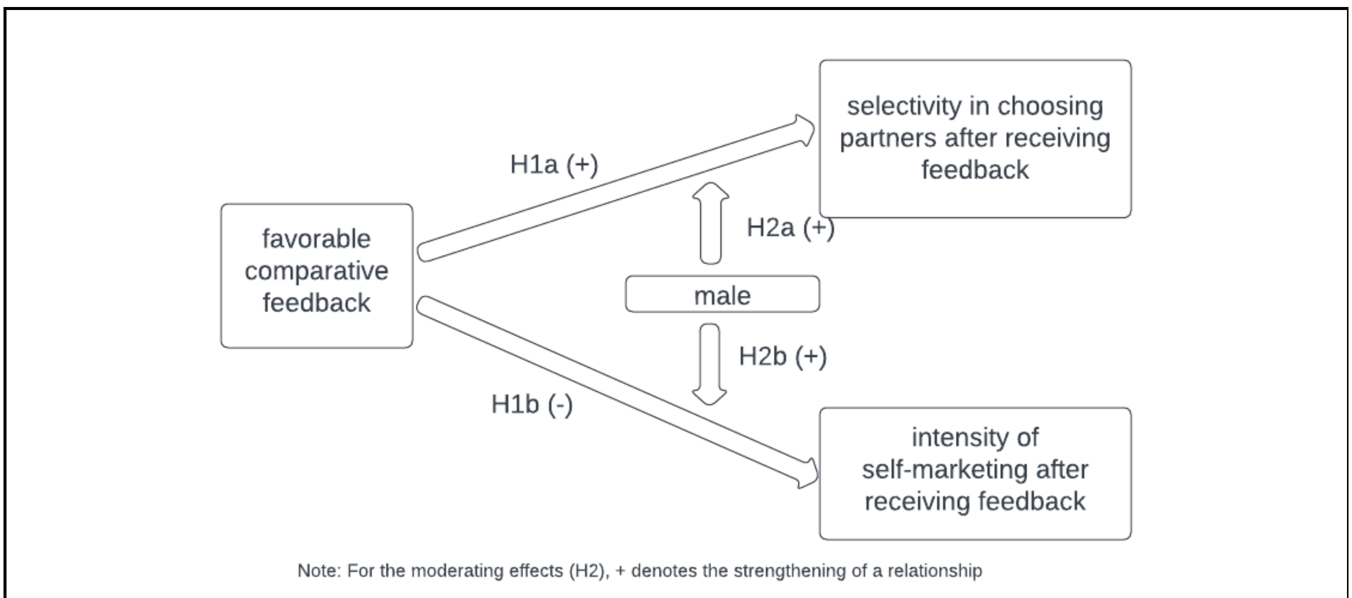



**Figure 1. Hypotheses**

In the context of online dating, user behavior is likely motivated by both controlled (such as garnering social popularity or status) and autonomous (such as building meaningful relationships or finding an ideal life partner) goal pursuit. We conjecture that, like the context of education, in online dating, women are more *autonomy oriented*, with their behavior driven by intrinsic motivations to a greater extent. In comparison, men are more *control oriented*, and their behavior is thus more impacted by extrinsic motivations. Because research has shown that a focus on extrinsic goal pursuits is likely to increase one's tendency to engage in interpersonal comparisons (Vansteenkiste et al., 2008), we expect that upon receiving comparative feedback, men will react more strongly, modifying their engagement and strategies to a greater extent than women.

**H2a:** *Upon receiving favorable (unfavorable) comparative popularity feedback, men will raise (lower) their standards in selecting partners* ***more*** *than women.*

**H2b:** *Upon receiving favorable (unfavorable) comparative popularity feedback, men will reduce (increase) their self-marketing activities* ***more*** *than women.*

We present a summary of our hypotheses in Figure 1.

## Methods

### Research Context

To investigate our research questions, we partnered with one of the leading online dating service providers in the U.S., which serves more than one million registered users as of the time of writing. Like many other online dating platforms, this platform offers a variety of features to its users to facilitate their interactions. Users of the platform typically start by creating an online profile to introduce themselves, providing information such as their age, education, hobbies, personal interests, ethnicity, religion, etc. Online profiles usually also include photos. Platform users can search and browse others' profiles without limitations and at no cost. As the primary means of building one's online identity, user profiles play an important role in online dating, particularly during early-stage screening and correspondence (Ellison et al., 2006). Users may update their profile information by editing their self-introduction text, filling out missing profile information, or uploading/removing profile pictures at any time. Moreover, the platform offers a tool wherein users can search, sort, and filter profiles by attributes such as age, height, weight, education, race, or location to find potential partners of interest. Notably, providing more complete profile information reduces search costs for others to discover the profile through searching and filtering tools, therefore improving the visibility of the profile.[4] The platform also provides a private messaging system through which a user may initiate contact with others or respond to others' messages.

An interesting feature of the platform is that users can mark other users they are interested in as "favorites" for later retrieval, a feature akin to bookmarks in web browsers that indicates a favorable impression and an interest in initiating or maintaining contact. The user's "favorites" list is private information and is not visible to others, including the person being "favorited." Someone who is "favorited" by many users receives more attention from their target audience and has a greater chance of advancing a relationship to the next stage of dating. Therefore, the number of "favorites" amounts to an objective measure of popularity in the early stages of online dating. Prior to our experiment, no information was provided to users that allowed them to infer their comparative popularity on the platform—the intervention we introduced in our experiment. We note that similar to the number of "favorites" in the context of online dating, earlier studies of two-sided digital platforms have used indicators of popularity under a variety of settings, including the number of likes, follows, and shares on social media platforms (De Vries et al., 2012; Moro et al., 2016; Oh et al., 2017), or the number of upvotes on P2P online platforms (Sarma et al., 2016; Yan & Jian, 2017).

### Experimental Design

We first designed and conducted a randomized field experiment to examine the causal impact of *comparative popularity* feedback on users' subsequent adaptation strategies, followed by a second experiment in which we used *absolute popularity* as the intervention. Because the two experiments followed very similar procedures, in this section we focus on describing the first experiment.

We designed the interventions in the first experiment following studies seeking to activate social comparison in various contexts (Burtch et al., 2017; Chen et al., 2010; Huang

[4] For example, if one's profile lacks information about age, then a search specifying an age range of between 20 and 30 would not retrieve the profile, even if the age of the profile owner is within the specified range.

et al., 2019). The popularity feedback provides the research subjects with information about their standing relative to their peers, with whom they are competing in their bid for attention from the other side of the market. In particular, the feedback that subjects received was in the form of their percentile rank within the population of their own gender on the platform, calculated based on the number of people of the opposite gender who marked the subject as a "favorite" during the week prior to the experiment. Notably, since we used percentile rankings, we were able to reveal a user's comparative popularity among their peers *without* disclosing any information regarding their absolute popularity (i.e., the number of "favorites"), consistent with prior literature (Moore & Klein, 2008). The popularity ranking was expressed in increments of 10%. The exact wording of the comparative popularity feedback is presented in Table 1.

We deployed our experiment on Tuesday, May 15, 2018. We focused on active users who had logged in at least once on that day and drew a random sample of these users ($n$ = 7,208) from the platform. Each subject was randomly assigned into one of two groups—a control group ($n$ = 3,563) with no popularity feedback and a treatment group ($n$ =3,645) with comparative popularity feedback. In randomizing, we blocked on gender to ensure that men and women were distributed evenly across the groups. To rule out the possibility of interference from other interventions, we also made sure that our experiment was the only one taking place on the platform during the experiment period and confirmed that the platform was not undergoing any other policy changes. The manipulation was a one-time message sent to research subjects, as the objective of our study was to identify the causal impact of popularity feedback on the immediate, short-term reaction in adaptation strategies.[5] The message was delivered using the messaging function in the app for better accessibility, following the platform's suggestion. To ensure that our manipulation was effective, we recorded if the message was opened by the subject, only retaining those who read the message in our sample.[6] This ensured that the subjects in the treatment group were truly exposed to our intervention. The sampling procedure resulted in 3,563 and 3,483 individuals in the control group and the treatment group, respectively.

The validity of our statistical inferences of the treatment effect depended on successful randomization and therefore required that the treatment and control groups be comparable with respect to potential confounding factors, i.e., there should be no significant initial differences between treatment and control conditions. Table 2a presents a comparison of the subjects in the treatment and control groups across several important, observable characteristics. The descriptive statistics show that the users in the two groups were not significantly different in age, gender, education, tenure on the platform, or popularity levels prior to the experiment. In addition, their profile disclosures, such as the number of photos and the percentage of profile completeness,[7] were also comparable. In Table 2b we also show that the use of the two adaptation strategies and the levels of engagement (i.e., the number of peer profiles viewed by the focal user) over the 2 days prior to the experiment were not systematically different. We mean-centered each variable to show only the differences across groups per our nondisclosure agreements with the platform. The comparison of covariates across groups indicates that our randomization was effective. We also conducted a randomization check within each *gender × popularity tier* group given that we examined heterogeneous effects across these subgroups. The balanced covariates at this finer level (Table A1 in the Appendix) further validated our effective randomization.

**Table 1. Experimental Design of Experiment I**

| | **Male users** | **Female users** |
|---|---|---|
| **Control group** | No messages | No messages |
| **Treatment group** | "Hey there! We would like to tell you your recent popularity. The number of favorites you received over the past week was above #% of all male users." | "Hey there! We would like to tell you your recent popularity. The number of favorites you received over the past week was above #% of all female users." |

**Note:** # is replaced by 0, 10, 20, … or 90 based on actual popularity. Comparative popularity is expressed in increments of 10%.

[5] There are a number of earlier studies examining the impact of feedback in a multi-phase setting, e.g., interim feedback in tournaments (Ederer, 2010; Huang et al., 2017). Designing feedback consisting of multiple rounds as a repeated game may lead to carry-over effects that are difficult to control for (Huang et al., 2017). The examination of long-term impact is beyond the scope of our study.

[6] Less than 2.5% of the subjects were removed due to this reason, which amounted to 162 subjects.

[7] Profile completeness is a score that the platform assigns to a user indicating the degree to which the user's profile provides complete information.

| **Table 2a. Randomization Check: User Characteristics** | | | | | | | |
|---|---|---|---|---|---|---|---|
| | **Gender** | **Age** | **Education** | **Popularity** | **Tenure** | **Photos** | **Profile_ completeness** |
| **Control group**: (*n* = 3563) | 0.00 (0.49) | 0.00 (10.41) | 0.00 (1.63) | 0.00 (1.82) | 0.00 (1.13) | 0.00 (4.06) | 0.00 (31.90) |
| **Treatment group**: (*n* = 3,483) | 0.01 (0.50) | 0.02 (10.50) | 0.05 (1.67) | 0.02 (1.85) | 0.00 (1.12) | -0.04 (3.90) | 0.72 (32.21) |
| ***p*-value (control = treatment)** | p=0.27 | p=0.94 | p=0.25 | p=0.60 | p=0.95 | p=0.75 | p = 0.34 |

Note: Due to our NDA, the means presented are deviations from the *control* sample mean. Standard deviations in parentheses. *Gender* and *popularity* (high/low) are categorical variables. *Education* is an ordered variable ranging from 0 to 5, with 0 indicating nondisclosure, and 1 to 5 representing middle school, high school, college, master's degree, and doctoral degree, respectively. *Tenure* is the length of time a user.

| **Table 2b. Randomization Check: Adaptation Strategies and Engagement Level *Prior to* the Experiment** | | | |
|---|---|---|---|
| | **Selectivity calibration** | **Self-marketing** | **Profile views** |
| **Control group**: No feedback (*n* = 3563) | 0.00 (3.38) | 0.00 (3.01) | 0.00 (21.22) |
| **Treatment group**: Comparative feedback (*n* = 3483) | 0.02 (3.45) | 0.08 (2.97) | 0.18 (20.52) |
| ***p*-value (control = treatment)** | p=0.87 | p=0.43 | p = 0.71 |

**Note:** Due to our NDA, the means presented are deviations from the *control* sample mean. Standard deviations in parentheses. *Selectivity calibration*, *self-marketing,* and *profile views* are outcomes measured over the 2 days immediately prior to the experiment.

| **Table 3. Variable Definition** | | |
|---|---|---|
| **Variable** | **Label** | **Definition** |
| ***Dependent variables*** | | |
| Selectivity calibration | *target_score* | The average of charm scores of the profiles a user viewed |
| | *target_score_variance* | The standard deviation of charm scores of the profiles a user viewed |
| Self-marketing | *profile_update* | The number of profile updates made by a user |
| | *profile_completeness* | The profile completeness in percentage |
| | *photo_count* | The number of photos |
| Level of engagement | *profile_views* | The number of profiles viewed by a user |
| ***Independent variables*** | | |
| Comparative feedback | *treatment_1* | Control group = 0; Treatment group (comparative popularity feedback) = 1 |
| Gender | *female* | Female = 1; Male = 0 |
| Popularity | *high_pop* | High popularity = 1; Otherwise = 0 |
| ***Follow-on experiment treatment variable*** | | |
| Absolute feedback | *treatment_2* | Control group = 0; Treatment group (absolute popularity feedback) = 1 |

## *Variables and Empirical Models*

The definitions of key variables of the experiment are provided in Table 3. Because we primarily focused on the short-term effects of comparative popularity feedback, we measured post-feedback behaviors in a two-day period after the intervention. In robustness tests, we also used slightly longer post-feedback periods (3-day and 7-day) and found no substantial differences in our results.

As explained earlier, we investigated two commonly employed adaptation strategies in online dating—the strategy of *selectivity calibration* and that of *self-marketing*. With the former strategy, platform users adjust their degree of selectiveness based on their own popularity or relative demand. With the latter strategy, they update profile information to highlight their desirable traits and increase their exposure to draw greater attention. We measured *selectivity calibration* using the *charm score* of the target profiles browsed. The *charm score* is a rating of desirability developed by the platform using its proprietary algorithms, which take a variety of factors into account including an individual's personal attributes, historical data on the viewership of the profile, the number of messages the user received, and other metrics of the user's interaction with others. Our use of a single index as the measure of vertical desirability is similar to prior research on dating and marriage markets in which matching models are often based on a one-dimensional "attractiveness" determined by a set of observable and unobservable characteristics (Bruch & Newman, 2018; Chiappori et al., 2012). Under the assumption that users apply a threshold-crossing rule (Hitsch et al., 2010) in their search for potential mates, using a higher threshold value of desirability as the standard for target selection results in a more selective consideration set, and it can be shown that the average desirability of targets in the consideration set is positively correlated with the threshold value.[8] Therefore, we calculated the average *charm score* of the user profiles viewed by each subject within 2 days after the intervention (labeled *target_score*) and used it to measure the focal subject's selectivity.[9] It should be noted that at the time of our experiment, the platform did not provide any personalized recommendations to its users; as a result, the profile browsing behavior of a user was spontaneous rather than induced.

To measure the intensity of the *self-marketing* strategy, we used the total number of profile updates made by an individual within 2 days following the intervention (named *profile_update*). Profile changes may take the form of adding or revising descriptive attributes such as educational attainment, height, weight, ethnicity, and hobbies; editing self-introduction information; or adding/deleting photos. By providing a profile with more complete information, users can increase the probability of being discovered through search and filtering tools, highlight their desirable attributes, and persuade others to spend time looking at their profile. Such a self-marketing strategy is akin to firms employing search engine optimization to drive website traffic.

We used prior popularity and gender to define subpopulations. Using the number of favorites an individual received during the week prior to the experiment, we classified subjects into low- and high-popularity groups based on the median of the population within gender. The distribution of prior popularity among research subjects is shown in Figure 2.

To test H1 regarding the heterogeneity in the effect of popularity feedback among individuals with varying levels of popularity, we evaluated the following model:

$$DV_i = \alpha + \varphi_1 * treatment_i + \varphi_2 * female_i + \varphi_3 * high\_pop_i + \varphi_4 treatment_i \times high\_pop_i + \zeta_i, \quad (1)$$

where $DV_i$ is replaced by $target\_score_i$ or $profile\_update_i$ depending on the adaptation strategy that we examined. The interaction term *treatment* × *high_pop* captures the heterogeneous effects of feedback over the popularity distribution. In particular, we expected the coefficient of *treatment* × *high_pop* to be positive for selectivity calibration, but negative for self-marketing.

Similarly, to test H2 regarding the heterogeneity between genders in treatment effects *conditional* on relative popularity standing, we specified the model as:

$$DV_i = \alpha + \varphi_1 * treatment_i + \varphi_2 * female_i + \varphi_3 * high\_pop_i + \varphi_4 * treatment_i \times high\_pop_i + \varphi_5 * treatment_i \times female_i + \varphi_6 * female_i \times high\_pop_i + \varphi_7 * treatment_i \times high\_pop_i \times female_i + \zeta_i, \quad (2)$$

in which the interaction term *treatment* × *high_pop* × *female* captures the hypothesized gender differences. Specifically, we expected the coefficient of *treatment* × *high_pop* × *female* to be negative for selectivity calibration but positive for self-marketing.

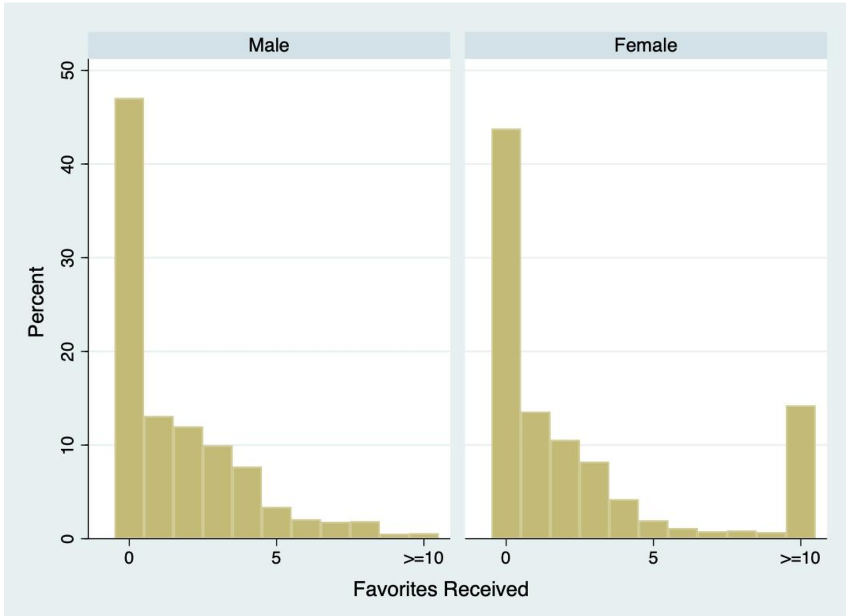
## Results

### Experiment I: Comparative Popularity as Feedback

Because the research subjects were successfully randomized across treatment conditions, we can compare outcome variables of the control group to those of the treatment group to obtain the causal effect of providing popularity feedback on subsequent changes in user behavior. We first present model-free evidence, comparing post-feedback adaptation strategies between the two groups (Figures 3a and 3b) and then formalize these results with regression analyses in the next section. Recall that beyond the average treatment effect, we were particularly interested in the heterogeneous impacts of popularity feedback among different populations. Figure 3a shows that in terms of *selectivity calibration* strategies, users exhibited different behavioral patterns across popularity tiers. Upon receiving feedback, low-popularity users lowered their selectivity significantly (Δ(treatment-control) = -0.29, *t*-statistic = -9.37), while high-popularity users raised their selectivity (Δ(treatment-control) = 0.44, *t*-statistic = 9.01). For the *self-marketing* strategies, the treatment led to significantly greater effort among low-popularity individuals (Δ(treatment-control) = 0.22, *t*-statistic = 4.07) but decreased the effort expended by high-popularity users (Δ(treatment-control) = -0.46, *t*-statistic = -4.75).

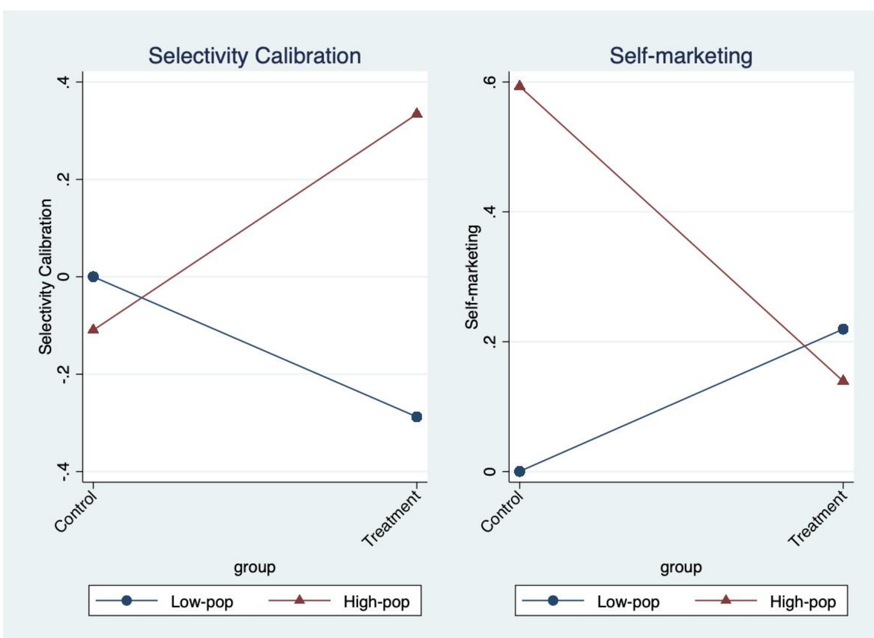
[8] Specifically, if the population desirability has a normalized range of (0,1), and an individual uses a threshold value of $a$ to define their consideration set (i.e., the individual's consideration set is $(a,1)$), then a higher value of $a$ would result in a smaller consideration set. In addition, assuming that the user uniformly samples profiles in their consideration set, the average desirability of the profiles they would view would be $(a+1)/2$, which can be used as a measure of selectivity.

[9] We used vertical quality instead of a horizontal attribute to define selectivity because there are great heterogeneities in the preferences that different people place on different horizontal attributes, such as race or height.



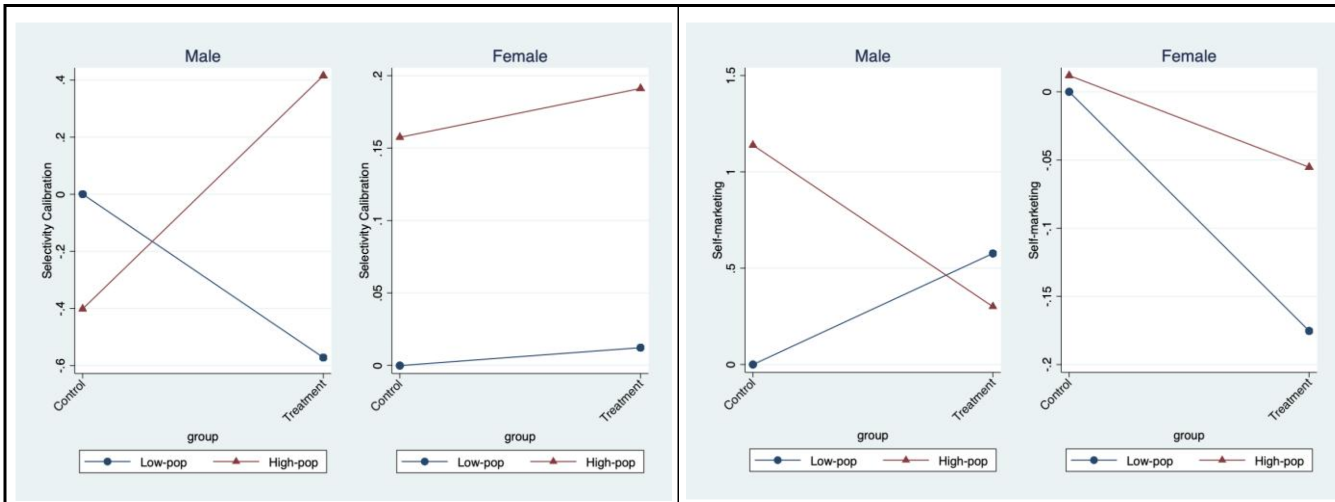

**Note:** Popularity is represented by the number of favorites received during the week prior to the experiment. The cut-off for low- and high-popularity groups is based on the medians of male users and female users, respectively. Specifically, male and female users who received 1 or less favorites are in the low-popularity group, and those who received 2 or more favorites are in the high-popularity group.

**Figure 2. Histograms of Prior Popularity**




**Note:** Numerical values represent deviations from the mean of the low-popularity tier in the control group

**Figure 3a. Model-Free Illustration of Adaptation Strategies Across Popularity Tiers**




**(1) Selectivity Calibration** | **(2) Self-marketing**

**Note:** Numerical values represent deviations from the mean of the low-popularity tier in the control group

**Figure 3b. Model-Free Illustration of Adaptation Strategies Across Popularity Tiers & Gender**

We further discovered several interesting patterns (presented in Panel 1 of Figure 3b) when taking gender into account. For the *selectivity calibration* strategy, in the male population, the treatment significantly lowered the selectivity of low-popularity individuals (Δ(treatment-control) = -0.57, *t*-statistic = -20.48), and at the same time raised the selectivity of high-popularity individuals (Δ(treatment-control) = 0.81, *t*-statistic = 13.05). Therefore, it appears that men readily adjusted their selectivity standards in response to their own desirability. Interestingly, such strategic adjustments were not observed for women, regardless of their prior popularity: the treatment effect was present for neither low-popularity individuals (Δ(treatment-control) = 0.01, *ns*) nor high-popularity individuals (Δ(treatment-control) = 0.03, *ns*), showing persistence of women's behavior, i.e., they continue to seek partners as they originally intended, without adjusting their selectiveness.

Similar heterogeneous treatment effects were observed (see Panel 2, Figure 3b) when we examined the *self-marketing* strategy, where low-popularity and high-popularity men display opposite post-feedback behavior—the former increased effort (Δ(treatment-control) = 0.57, *t*-statistic = 6.94) while the latter decreased it (Δ(treatment-control) = -0.84, *t*-statistic = -5.66). Again, women's adjustment was less strategic, with high-popularity women not changing their effort (Δ(treatment-control) = -0.07, *ns*) and low-popularity women reducing (rather than increasing) the frequency of profile updates (Δ(treatment-control) = -0.17, *t*-statistic = 2.69). With these preliminary insights,[10] we now turn to the formal evaluation of the treatment effects.

## Popularity Feedback Effects and Popularity Level

We first investigate whether the effects of popularity feedback on subsequent adaptation strategies are contingent on prior popularity. In examining selectivity calibration, we performed OLS regressions and used *target_score* as the dependent variable. For self-marketing, measured by *profile_update*, we used Poisson regressions due to the count nature of this variable.

We present the results on the role of popularity level in Table 4a, following the regression specification in Equation 1. We found that the treatment effect of popularity feedback was dependent on prior popularity, as revealed by the coefficients of *treatment* × *high_pop* ($\varphi_4$ in Equation 1) and thus supporting H1a and H1b. Specifically, upon receiving their comparative popularity feedback, those in the high-popularity tier became relatively more selective than their low-popularity counterparts ($\varphi_4 = 0.713$, $p < 0.01$) while also becoming relatively less diligent in self-marketing ($\varphi_4 = -0.936$, $p < 0.01$).

[10] We also conducted MANOVA tests to confirm if there were statistically significant differences between the control group and the treatment group in subsequent adaptation strategies within the subgroups of low-popularity men, high-popularity men, and low-popularity women, respectively, which is consistent with our model-free evidence and regression results.

**Table 4a. Regression Results: The Causal Effect of Popularity Feedback (Equation 1)**

| | Selectivity calibration<br>*target_score* | Self-marketing<br>*profile_update* |
|---|---|---|
| *treatment_1* | -0.293***<br>(0.0256) | 0.381***<br>(0.0925) |
| *female* | 1.042***<br>(0.0243) | -0.00674<br>(0.0731) |
| *high_pop* | -0.130***<br>(0.0374) | 0.813***<br>(0.100) |
| *treatment_1* × *high_pop* | 0.713***<br>(0.0525) | -0.936***<br>(0.148) |
| Constant | 6.363***<br>(0.0196) | -0.747***<br>(0.0738) |
| Observations | 7,046 | 7,046 |
| Wald test statistics<br>(Equation 1 vs. 2) | $F(1, 7041) = 184.58$<br>$p < 0.001$ | chi2(1) = 40.17<br>$p < 0.001$ |

**Note:** OLS model is used for selectivity calibration, and Poisson model is used for self-marketing. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

**Table 4b. Marginal Effects of Treatment Across Popularity Tiers**

| Popularity tier | Selectivity calibration<br>*target_score* | Self-marketing<br>*profile_update* |
|---|---|---|
| *low* | -0.293***<br>(0.026) | 0.219***<br>(0.054) |
| *high* | 0.420***<br>(0.046) | -0.454***<br>(0.096) |

**Note:** effects of Poisson models are calculated with Stata Command *margins*. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

The marginal effect (*m.e.*) calculations for the subgroups, as presented in Table 4b, reveal further insights. They show that upon receiving comparative feedback, low-popularity users selected candidates whose charm scores were 0.293 lower, on average, compared to their control group counterparts, whereas high-popularity individuals targeted candidates with charm scores 0.420 higher, on average. Meanwhile, low-popularity individuals in the treatment group also invested more in self-marketing, making 0.219 more profile updates, on average, compared to their control group counterparts in the 2 days after receiving feedback, whereas high-popularity users in the treatment group reduced their number of profile updates by 0.454. In other words, the marginal effect calculations confirmed our earlier observation that low- and high-popularity individuals made significant but divergent strategic adjustments upon receiving popularity feedback.

## Popularity Feedback Effects and Gender

We further examined whether the treatment effects across popularity levels were stronger for men than women, as stated in H2. Results from the regressions specified in Equation (2), which took the role of gender into account, are presented in Table 5a. We found evidence that gender significantly moderated the treatment effect of popularity feedback across popularity levels, as shown by the coefficients of *treatment* × *high_pop* × *female* ($\varphi_7$ in Equation 2). Specifically, the positive effect of *treatment* × *high_pop* ($\varphi_4$) on selectivity calibration became less positive for women ($\varphi_7$ = -1.367, $p < 0.01$), while the negative effect of *treatment* × *high_pop* ($\varphi_4$) on self-marketing became less negative for women ($\varphi_7$ = 2.388, $p < 0.01$), supporting both H2a and H2b.

To evaluate the patterns of individuals' responses, we again calculated the marginal effects of the treatment for different population subgroups (presented in Table 5b). Here, we observe interesting contrasts between men and women. In terms of *selectivity calibration*, men appear to be pragmatic in their post-feedback adjustments: men with low prior popularity lowered their expectations, targeting women with lower charm scores (*m.e.* = -0.572, $p < 0.01$), whereas men with high prior popularity became more selective and started targeting women with higher charm scores (*m.e.* = 0.817, $p < 0.01$). In contrast, we did not observe changes in post-feedback selectivity for female users, regardless of their popularity tier. For low-popularity women, there was no noticeable change in the desirability of the men's profiles they browsed (*m.e.* = 0.012, *ns*). High-popularity women, unlike their male counterparts, made no adjustments in their expectations for potential matches (*m.e.* = 0.034, *ns*). Overall, these findings imply that men react to comparative popularity feedback in a strategic way whereas women do not seem to respond to feedback information regarding their relative standing.

**Table 5a. The Causal Effect of Popularity Feedback (Equation 2): Regression Results**

| | **Selectivity calibration** ***target_score*** | **Self-marketing** ***profile_update*** |
|---|---|---|
| *treatment_1* | -0.572*** (0.0279) | 1.262*** (0.198) |
| *female* | 0.805*** (0.0364) | 1.184*** (0.187) |
| *high_pop* | -0.402*** (0.0505) | 1.792*** (0.198) |
| *female×high_pop* | 0.560*** (0.0743) | -1.776*** (0.241) |
| *treatment_1×high_pop* | 1.389*** (0.0684) | -2.212*** (0.260) |
| *treatment_1×female* | 0.584*** (0.0513) | -1.530*** (0.221) |
| *treatment_1×high_pop×female* | -1.367*** (0.104) | 2.388*** (0.324) |
| Constant | 6.474*** (0.0194) | -1.479*** (0.175) |
| Observations | 7,046 | 7,046 |
| Wald test statistics (Equation 2 vs. 3) | $F(3, 7038) = 70.78$ $p < 0.001$ | chi2(3) = 65.51 $p < 0.001$ |

**Note:** OLS model is used for *selectivity calibration*, and Poisson model is used for *self-marketing*. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

**Table 5b. Marginal Effects of Treatment Across Popularity Tiers and Gender**

| **Popularity tier** | **Selectivity calibration** ***target_score*** | | **Self-marketing** ***profile_update*** | |
|---|---|---|---|---|
| | **Male** | **Female** | **Male** | **Female** |
| *low* | -0.572*** (0.028) | 0.012 (0.043) | 0.577*** (0.084) | -0.175*** (0.065) |
| *high* | 0.817*** (0.062) | 0.034 (0.065) | -0.840*** (0.147) | -0.067 (0.121) |

**Note:** Marginal effects of Poisson models are calculated with Stata Command *margins*. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

The patterns of gender differences were also observed for the *self-marketing* strategy. For men, low-popularity individuals took steps to improve self-presentation and update their profiles more frequently upon receiving feedback than those in the control group (*m.e.* = 0.577, $p < 0.01$), consistent with the expectation that a threat to their self-esteem would motivate them to devote more effort (Gino & Staats, 2011). In contrast, high-popularity men, content with the status quo, updated their profiles less frequently compared to their counterparts in the control group (*m.e.* = -0.840, $p < 0.01$). The evidence further lends support to the notion that men respond readily to information regarding their comparative popularity to improve their chance of attracting attention (Azmat & Iriberri, 2010; Bandiera et al., 2015). Unlike low-popularity men who try to catch up by engaging more actively in self-marketing, low-popularity women appear discouraged and invest significantly less in self-presentation compared to their counterparts in the control group (*m.e.* = -0.175, $p < 0.01$), a finding similar to Ashraf et al.'s (2014) findings. In particular, earlier research has shown that negative and self-esteem-threatening feedback may lead individuals to engage in information avoidance or rejection of the feedback as a way of retaining a positive view of themselves, leading to "self-handicapping" at the bottom of the performance distribution (Ashraf et al., 2014; Klueger & DeNisi, 1996). In addition, high-popularity women did not alter their *self-marketing* effort in response to popularity feedback (*m.e.* = -0.067, *ns*), again appearing less strategic than their male counterparts. Our results are consistent with our conjecture that upon receiving comparative feedback, men react more strongly than women, modifying their engagement and strategies to a greater extent than women. This suggests that differing goal orientations of men (control oriented) and women (autonomy oriented) may underly differences in adaptation strategies between the genders.

**Table 6a. The Causal Effect on Selectivity Calibration Strategy: Split Sample Analyses**

| **DV:** *target_score* | **Male** | | **Female** | |
|---|---|---|---|---|
| | **Low-popularity** | **High-popularity** | **Low-popularity** | **High-popularity** |
| *treatment_1* | -0.572*** (0.0279) | 0.817** (0.0624) | 0.0124 (0.0430) | 0.0338 (0.0652) |
| Constant | 6.474*** (0.0194) | 6.072*** (0.0466) | 7.280*** (0.0308) | 7.437*** (0.0450) |
| Observations | 2,168 | 1,437 | 1,973 | 1,468 |

Note: OLS model is used for selectivity calibration. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

**Table 6b. The Causal Effect on Self-Marketing Strategy: Split Sample Analyses**

| **DV:** *profile_update* | **Male** | | **Female** | |
|---|---|---|---|---|
| | **Low-popularity** | **High-popularity** | **Low-popularity** | **High-popularity** |
| *treatment_1* | 1.262*** (0.198) | -0.950*** (0.169) | -0.269*** (0.0996) | -0.0931 (0.166) |
| Constant | -1.479*** (0.175) | 0.312*** (0.0923) | -0.296*** (0.0660) | -0.280** (0.121) |
| Observations | 2,168 | 1,437 | 1,973 | 1,468 |

**Note:** Poisson model is used for self-marketing. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

To corroborate the findings from our marginal effect calculations, we conducted split sample analyses by dividing the sample by genders and popularity tiers and running the regressions on these subpopulations separately. The results are presented in Table 6a (for the *selectivity calibration* strategy) and Table 6b (for the *self-marketing* strategy). We found that the treatment effects on different populations were highly consistent with those presented in Table 5 in both sign and magnitude. Overall, we observed that comparative popularity feedback appears to work more effectively for men in online dating, as men are generally more responsive to the popularity information conveyed. In contrast, women are far less responsive to information regarding their relative popularity standing and are likely to become demoralized when they realize that their popularity is lower than average. Such heterogeneous impacts are consistent with literature showing significant gender differences in competitive preferences (Gneezy et al., 2003; Niederle & Vesterlund, 2007) and literature demonstrating that women tend to react poorly to feedback framed in a competitive context (Huang et al., 2019), especially when the feedback is unfavorable.

## Robustness Checks

We conducted a series of robustness tests. First, although we confirmed that our randomization was successful, we performed a test that used only within-individual variations to identify the treatment effect by taking a difference-in-difference (DiD) approach to account for the possible individual-level heterogeneities. Specifically, for each subject, we included not only a post-treatment observation but also a pre-treatment observation over a 2-day period, and defined:

$$\Delta(DV_i) = post\ experiment\ DV_i - pre\ experiment\ DV_i.$$

We then ran the same regressions following Equations 1 and 2 but using $\Delta(DV_i)$ as the dependent variables. As shown in Tables 7 and 8, the marginal effects of treatment across popularity tiers and genders are consistent with Tables 4 and 5, confirming that the heterogeneous treatment effects are robust to the use of the DiD models.

We also conducted the DiD analysis with the split samples by using $\Delta(DV_i)$ as the dependent variables. As shown in Table A2 (in the Appendix), all results are consistent with those using DiD models with pooled samples.

Second, we estimated the intention-to-treat (ITT) effects of popularity feedback on adaptation strategies, using all the subjects who received the feedback message regardless of whether they opened it or not. This analysis provides practical guidance that can help platforms evaluate the average effect size for providing feedback information (see review by Gupta, 2011). In other words, we added the dropped subjects back to the treatment group and conducted ITT analyses for selectivity calibration and self-marketing strategies. As the dropped subjects ($n$ = 162) accounted for a very small fraction of the sample, the effect sizes of ITT did not differ significantly from our main findings. We present the results in Table A3.

**Table 7a. The Causal Effect of Popularity Feedback Using DiD (Equation 1): Regression Results**

| | Selectivity calibration<br>**Δ(*target_score*)** | Self-marketing<br>**Δ(*profile_update*)** |
|---|---|---|
| *treatment_1* | -0.308***<br>(0.0945) | 0.0624***<br>(0.0183) |
| *female* | -0.561***<br>(0.0831) | 0.0271*<br>(0.0149) |
| *high_pop* | -0.229*<br>(0.125) | 0.109***<br>(0.0234) |
| *treatment_1* × *high_pop* | 0.846***<br>(0.178) | -0.168***<br>(0.0313) |
| Constant | 1.151***<br>(0.142) | 0.152***<br>(0.0230) |
| Observations | 7,046 | 7,046 |
| *R*-squared | 0.010 | 0.006 |

**Note:** OLS model is used for both *selectivity calibration* and *self-marketing*. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

**Table 7b. Marginal Effects of Treatment Across Popularity Tiers**

| **Popularity tier** | Selectivity calibration<br>**Δ(*target_score*)** | Self-marketing<br>**Δ(*profile_update*)** |
|---|---|---|
| *low* | -0.308***<br>(0.094) | 0.062***<br>(0.018) |
| *high* | 0.538***<br>(0.151) | -0.105***<br>(0.026) |

**Note:** OLS model is used for both *selectivity calibration* and *self-marketing*. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

**Table 8a. The Causal Effect of Popularity Feedback Using DiD (Equation 2): Regression Results**

| | Selectivity calibration<br>**Δ(*target_score*)** | Self-marketing<br>**Δ(*profile_update*)** |
|---|---|---|
| *treatment_1* | -0.628***<br>(0.139) | 0.174***<br>(0.0248) |
| *female* | -0.507***<br>(0.130) | 0.191***<br>(0.0232) |
| *high_pop* | -0.215<br>(0.172) | 0.283***<br>(0.0337) |
| *female* × *high_pop* | -0.0308<br>(0.250) | -0.357***<br>(0.0459) |
| *treatment_1* × *high_pop* | 1.746***<br>(0.246) | -0.386***<br>(0.0449) |
| *treatment_1* × *female* | 0.669***<br>(0.187) | -0.222***<br>(0.0363) |
| *treatment_1* × *high_pop* × *female* | -1.792***<br>(0.354) | 0.447***<br>(0.0621) |
| Constant | 0.565***<br>(0.0955) | 0.0969***<br>(0.0122) |
| Observations | 7,046 | 7,046 |
| *R*-squared | 0.019 | 0.019 |

**Note:** OLS model is used for both *selectivity calibration* and *self-marketing*. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

**Table 8b. Marginal Effects of Treatment Across Popularity Tiers and Genders**

| **Popularity tier** | Selectivity calibration<br>**Δ(*target_score*)** | | Self-marketing<br>**Δ(*profile_update*)** | |
|---|---|---|---|---|
| | **Male** | **Female** | **Male** | **Female** |
| *low* | -0.628***<br>(0.139) | 0.041<br>(0.126) | 0.175***<br>(0.025) | -0.048*<br>(0.026) |
| *high* | 1.118***<br>(0.203) | -0.005<br>(0.221) | -0.212***<br>(0.037) | 0.012<br>(0.034) |

**Note:** OLS model is used for both *selectivity calibration* and *self-marketing*. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Third, in our earlier examination of the treatment effect on the *selectivity calibration* strategy, the *target_score* variable was defined as the average *charm score* over the set of profiles viewed by a subject during the post-treatment period and was undefined when the subject did not browse any profiles in the 2 days following the experiment. In the earlier analysis, we addressed this missing-value issue by replacing the missing values with the sample mean. Using an alternative approach—where we excluded the observations with missing values and examined the post-treatment behavior conditional on the set of individuals who initiated at least one profile view—we reestimated the regressions and present the split sample results in Table A4. While this approach resulted in a smaller sample, the results are highly consistent with those in Table 6.

Fourth, we tested the robustness of the treatment effects on the *selectivity calibration* strategy by using an alternative way of measuring a candidate's desirability or attractiveness. Besides charm scores, we obtained the *total* number of favorites received by a user between their platform registration and the beginning of the experiment. We normalized this number by the user's tenure on the platform to measure their attractiveness. With this alternative measure, we recalculated the average desirability of the profiles a user viewed and defined it as *target_score_favor*. As shown in Table A5, the result for the selectivity calibration strategy held with this alternative measure.

Fifth, we examined whether the observed moderation effects of gender and popularity tiers are robust to the operationalization of popularity tiers. Specifically, we replaced the binary popularity tiers (high vs. low) with the actual comparative popularity measure (in increments of 10%, e.g., 20%, 30%, etc.). In doing so, we created an ordinal measure of *popularity* that mapped 0%-90% to values 0-9 and reran the models following Equations 1 and 2. As presented in Table A6, all findings are consistent with the main results shown in Tables 4 and 5.

Sixth, we reexamined the *self-marketing* strategy employing an alternative specification—an OLS model—taking the log of *profile_update* (the outcome variable) to address its skewed distribution. The results are qualitatively very similar to those presented in Table 6 (see Table A7).

Seventh, to evaluate the degree to which our findings are sensitive to the definition of the post-feedback time window, we experimented with two longer post-feedback durations using a window of 3 days and 7 days, respectively. As shown in Table A8, the results using these two longer time windows are highly consistent with our observed effects.

Finally, we conducted some preliminary tests to account for the potential confounding effect associated with the accuracy of a user's self-evaluation.[11] Following the literature on individual-level attributes associated with self-evaluation accuracy (Brown et al., 2015; London et al., 1995; Radhakrishnan et al., 1996), we suggest that an individual's tenure on the online dating platform, though an imperfect proxy, would be correlated with the accuracy of their self-evaluation. That is, individuals would likely have a more accurate self-evaluation if they had longer tenure on the platform because they would have gathered more cues from their interactions with others on the platform. By conducting an analysis with user tenure as a moderator (shown in Table A9), we observed that our hypothesized patterns (i.e., heterogeneous treatment effects across *gender* × *popularity tiers*) still held after we accounted for these differences in the accuracy of self-evaluation.

## *Alternative Outcome Variables*

### Self-Marketing

Our primary measure for self-marketing was the count of profile changes of a focal user following the treatment. We now complement the main analyses with two additional, more granular, outcome variables to depict how users changed or updated their profiles after receiving the treatment. The first one, *photo_count*, is the number of pictures a focal user included in their profile within our window of observation (e.g., a 2-day window).[12] This analysis showed whether a focal user decided to add or remove photos from their profile as a result of the manipulation. The second outcome variable, *profile_completeness*, is the percentage of profile information completed by the focal user. It captured whether a focal user reacted to their popularity information by adding or removing profile information. Note that a profile update did not necessarily lead to increases in *photo_count* and *profile_completeness* as people could refine and update existing content and photos. Therefore, the use of these two alternative measures represents a more stringent test of the hypothesis related to self-marketing. Results for these two additional outcomes are shown in Table 9. Henceforth, split-sample results will be presented for brevity, consistently aligning with hypotheses testing using Models (1) and (2).

[11] For example, men and women may systematically differ in the accuracy of their self-evaluation.

[12] The results using a 3-day window are consistent with Table 9.

**Table 9a. Alternative Measure of Self-Marketing (Number of Photos): Split Sample Analyses**

| DV: *photo_count* | Male | | Female | |
|---|---|---|---|---|
| | Low-popularity | High-popularity | Low-popularity | High-popularity |
| *treatment_1* | 0.148** (0.0742) | -0.131** (0.0627) | 0.0931 (0.0720) | -0.0798 (0.0609) |
| Constant | 0.365*** (0.0480) | 1.103*** (0.0445) | 0.930*** (0.0464) | 1.496*** (0.0473) |
| Observations | 2,168 | 1,437 | 1,973 | 1,468 |

**Note:** Poisson model is used for *photo_count.* Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

**Table 9b. Alternative Measure of Self-Marketing (Profile Completeness): Split Sample Analyses**

| DV: *profile_completeness* | Male | | Female | |
|---|---|---|---|---|
| | Low-popularity | High-popularity | Low-popularity | High-popularity |
| *treatment_1* | 2.621** (1.132) | -4.282*** (1.314) | 0.833 (1.057) | -0.017 (1.008) |
| Constant | 51.27*** (0.783) | 66.82*** (0.873) | 63.18*** (0.742) | 70.96*** (0.726) |
| Observations | 2,168 | 1,437 | 1,973 | 1,468 |

**Note:** OLS model is used for *profile_completeness.* Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Our analysis shows that for men, low-popularity users—who we previously showed engaged in more self-marketing—also increased the number of photos in their profile and added more profile information compared to their counterparts in the control group. High-popularity male users, who we observed previously engaged in less self-marketing, added less profile information and fewer photos compared to their counterparts in the control group. These results align with the main self-marketing analysis (using profile updates). Behavior among women was also consistent with their self-marketing strategies established before, but with nuances. Specifically, low-popularity female users, who engaged less in self-marketing (using profile updates) upon receiving popularity information, showed no significant difference in terms of the photos and profile information they included between the users in the treatment group and those in the control group. For high-popularity female users—who did not alter their self-marketing strategies (using profile updates) after receiving popularity feedback—we did not observe any significant marginal effects in terms of *photo_count* and *profile_completeness* compared to their counterparts in the control group. To summarize, the heterogeneity in gender and popularity tiers consistently manifested in these two granular-level behaviors within self-marketing: while male users reacted strategically to their popularity tier, female users remained less reactive in updating their profile information and profile pictures.

Following our robustness check on running DiD models, we generated two corresponding outcome variables, which captured whether a focal user reacted to their popularity information by adding or removing profile photos and/or information. The first outcome variable, Δ(*photo_count)*, is the change in the number of pictures a focal user posted to their profile within our window of observation upon receiving the treatment. The second outcome variable, Δ(*profile_completeness)*, is the change in the percentage of profile information completed by the focal user. As shown in Table A10, we found consistent behavior patterns among both men and women.

### Selectivity Calibration

We previously measured selectivity calibration based on a change in the average desirability level of the targets a user considered. Another metric is whether the user broadened or narrowed their candidate pool, i.e., the degree of *variation* in a focal user's consideration set. Specifically, we examined the variance in charm scores of the profiles that a focal user viewed, termed *target_score_variance.*[13]

Results for this analysis are shown in Table 10. We found that low-popularity male users not only adjusted to select candidates with lower desirability, on average (as established in our main analysis), but they also expanded their selection pool, i.e., the profiles they viewed post-treatment had a larger variance in desirability. This suggests that low-popularity male users were motivated to expand their selection pool and be more open-minded in response to their popularity feedback. Moreover, these high-popularity men not only started to select those with higher desirability scores, but they also narrowed the variance of these candidates' desirability. In other words, they became more selective upon receiving popularity feedback. On the other hand, there was no

[13] Note that *target_score_variance* only applied to those who had viewed at least two profiles.

significant change in terms of *target_score_variance* among female users. Taken together with our initial findings that these women also did not adjust their selectivity calibration, we see that female users were generally more persistent in their degree of selectiveness. The results remain consistent within 3-day windows as shown in Table A11.[14]

### Level of Engagement

To facilitate a comparison between our work and earlier studies focusing primarily on post-feedback effort, we further supplement our analyses by examining focal users' overall *level of engagement,* measured by the number of peer profiles a focal user viewed (*profile_views)*. As shown in Table 11, we note that even though the way in which male users engaged strategically in self-marketing and selectivity calibration varied depending on their own popularity tier, they *all* viewed more profiles compared to their counterparts in the control group—regardless of popularity tier. This suggests that while they may have adapted their strategies differently, male users overall tended to be more motivated to engage on the platform after receiving comparative popularity information. For women, we already established that low-popularity female users engaged less in self-marketing, and the results from the *profile_views* analysis suggest that they also tended to reduce their overall level of engagement (compared to the control group). However, high-popularity women did not significantly change their level of engagement upon receiving popularity feedback. This is a markedly different reaction when compared to the male users: unlike male users who, across popularity tiers, increased their level of engagement, female users' post-treatment reactions depended on their popularity tier. In addition, comparative feedback information appeared to have a discouraging effect on women; on average, they seemed to reduce their overall level of engagement rather than increase it.

The patterns we observed in profile views were consistent across different timeframes (i.e., 2-day and 3-day) and different model specifications (i.e., Poisson and log transformation), as shown in Table A12. This exploration on focal users' level of engagement provided a more holistic view on how focal users react to popularity feedback.

**Table 10. Alternative Measure of Selectivity Calibration (Variance of Target Scores): Split Sample Analyses**

| **DV:** | **Male** | | **Female** | |
|---|---|---|---|---|
| ***target_score_variance*** | **Low-popularity** | **High-popularity** | **Low-popularity** | **High-popularity** |
| *treatment_1* | 0.395***<br>(0.0728) | -0.402***<br>(0.0744) | 0.0811<br>(0.0776) | 0.0258<br>(0.0797) |
| Constant | 1.374***<br>(0.0455) | 2.507***<br>(0.0531) | 1.970***<br>(0.0548) | 2.497***<br>(0.0576) |
| Observations | 1,343 | 1,273 | 1,359 | 1,272 |

**Note:** OLS model is used for *target_score_variance*. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

**Table 11a. Profile Views: Split Sample Analyses (Poisson Model)**

| **DV:** | **Male** | | **Female** | |
|---|---|---|---|---|
| ***profile_views*** | **Low-popularity** | **High-popularity** | **Low-popularity** | **High-popularity** |
| *treatment_1* | 0.374***<br>(0.122) | 0.498***<br>(0.101) | -0.941***<br>(0.125) | -0.190<br>(0.140) |
| Constant | 0.951***<br>(0.0836) | 2.102***<br>(0.0773) | 1.727***<br>(0.0924) | 1.997***<br>(0.101) |
| Observations | 2,168 | 1,437 | 1,973 | 1,468 |

**Note:** Poisson model is used for *profile_views*. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

**Table 11b. Profile Views: Split Sample Analyses (OLS with Log Transformation)**

| **DV:** | **Male** | | **Female** | |
|---|---|---|---|---|
| ***log(profile_views)*** | **Low-popularity** | **High-popularity** | **Low-popularity** | **High-popularity** |
| *treatment_1* | 0.120***<br>(0.0439) | 0.540***<br>(0.0653) | -0.258***<br>(0.0476) | -0.0995<br>(0.0652) |
| Constant | 0.554***<br>(0.0287) | 1.337***<br>(0.0454) | 0.796***<br>(0.0381) | 1.021***<br>(0.0479) |
| Observations | 2,168 | 1,437 | 1,973 | 1,468 |

**Note:** Model is used for *log(profile_views).* Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

[14] We also used *target_score_range* to measure the range of charm scores of the profiles a user visited as an alternative measure of selectivity and found the results to be consistent.

**Table 12a. The Causal Effect on Selectivity Calibration Strategy using *Absolute Popularity* Feedback: Split Sample Analyses**

| DV: *target_score* | Male | | Female | |
|---|---|---|---|---|
| | Low-popularity | High-popularity | Low-popularity | High-popularity |
| *treatment_2* | -0.0385<br>(0.0302) | 0.0531<br>(0.0622) | 0.0177<br>(0.0408) | 0.0201<br>(0.0709) |
| Constant | 6.122***<br>(0.0205) | 6.604***<br>(0.0446) | 7.271***<br>(0.0289) | 7.491***<br>(0.0517) |
| Observations | 2,257 | 1,467 | 2,287 | 1,139 |

**Note:** OLS model is used for selectivity calibration. Poisson model is used for *self-marketing*. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

**Table 12b. The Causal Effect on Self-Marketing Strategy using *Absolute Popularity* Feedback: Split Sample Analyses**

| **DV: *profile_update*** | **Male** | | **Female** | |
|---|---|---|---|---|
| | **Low-popularity** | **High-popularity** | **Low-popularity** | **High-popularity** |
| ***treatment_2*** | **-0.0257**<br>**(0.163)** | **-0.145**<br>**(0.176)** | **-0.0564**<br>**(0.123)** | **-0.222**<br>**(0.204)** |
| **Constant** | **-0.560*****<br>**(0.0205)** | **-0.175**<br>**(0.0446)** | **0.312*****<br>**(0.0289)** | **-0.137**<br>**(0.0517)** |
| **Observations** | **2,257** | **1,467** | **2,287** | **1,139** |

**Note:** OLS model is used for selectivity calibration. Poisson model is used for *self-marketing*. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

## *Experiment II: Absolute Popularity as Feedback*

We found that the effects of comparative popularity feedback on subsequent changes in strategies were contingent on both gender and prior popularity, and we attribute these patterns to the *social comparison* information revealed by comparative popularity rankings (Buunk & Gibbons, 2007; Gibbons et al., 1994; Huang et al., 2019). However, several alternative explanations associated with our treatment may have led to post-feedback behavioral changes as well. One possibility is the "salience effect" that causes individuals to react to *any* (even irrelevant) information that is highlighted by the platform regardless of its content (Chetty et al., 2009). Alternatively, it is possible that individuals who receive *comparative popularity* feedback may be able to infer their *absolute popularity* from the ranking information and that the observed patterns may therefore have been triggered by a "knowledge of result" intervention (Klueger & DeNisi, 1996).

To verify that our findings were indeed caused by social comparison associated with *comparative popularity* standing, rather than a "saliency effect" or a "knowledge of result" intervention, we designed and conducted a second experiment that provided the subjects in the treatment group with feedback on their *absolute popularity*. The difference between this design and our earlier experiment is that absolute popularity feedback conveyed the number of "favorites" an individual received rather than their comparative ranking among peers on the same side of the matching markets. Importantly, the absolute feedback we provided did not contain any information related to a popularity standard or a "benchmark" (such as "an average female user received three favorites over the past week"). Therefore, it cannot be used to infer a basis for social comparison.

We ran the follow-up experiment on the same platform but with a different set of randomly selected subjects. The sample size was 7,150. Consistent with our first experiment, we used active users and blocked on gender. There was no cross-contamination between the two samples because no subject was exposed to both experiments. As in the earlier experiment, we followed a between-subject design, randomly assigning users to either the control group (no feedback) or the treatment group (*absolute popularity* feedback). Subjects in the treatment group received the message: "Hey there! We would like to tell you your recent popularity. The number of favorites you received over the past week was X" (where X is a non-negative integer). Randomization checks confirmed no significant difference between the two groups prior to the experiment.

We followed the same procedures of analysis as in the first experiment. For the sake of brevity, we relegate the regression results following the specifications of Equation 1 and 2 to Tables A13 and Table A14, respectively, and present the split-sample analyses in Panel A and Panel B of Table 12, which illustrate the heterogeneous treatment effect among different populations. Interestingly, as shown in the split-sample analyses in Table 12 we found that the provision of absolute popularity feedback had no significant impact on subsequent changes in adaptation strategies regardless of prior popularity tier or gender. Our further analysis of the impact of absolute popularity information on the *level of engagement* (see Table A15), is consistent: both male and female focal users were indeed not responsive to absolute feedback. Together, these findings provide strong evidence in support of our argument that the main driver of the behavioral changes we observed in the first experiment was the social comparison information revealed by *comparative popularity*, rather than a salience or knowledge of result effect.

## Conclusion

We designed and conducted two randomized field experiments in partnership with an online dating service provider to examine how the provision of popularity feedback impacts users' subsequent adaptation behavior in a two-sided matching market. Our study differs from prior literature on peer feedback on digital platforms because, in our setting of a matching market, popularity information must be used differently from how it is used on a user-generated content (UGC) platform. We further sought to deepen the understanding of how individuals' adaptation strategies vary by gender and across popularity tiers. The hypotheses and major findings are summarized in Table 13.

In the first experiment, we found that individuals' responses to *comparative popularity feedback* depended on the feedback message, with high- vs. low-popularity individuals adopting opposite strategies: Those who received favorable feedback increased their selectivity but reduced their self-marketing efforts, while those who received unfavorable feedback revised their selectivity downward but increased their self-marketing efforts. These observed patterns are consistent with the notion that popularity feedback provides an opportunity for agents to make pragmatic adjustments based on the supply of potential partners and their own desirability in the market (Heino et al., 2010) and reflects the role of self-evaluation and self-esteem in social comparison.

Importantly, we found that post-feedback adaptation strategies also vary by gender. Our findings are consistent with the conjecture that men and women differ in the extent to which they make strategic changes in response to feedback information about their popularity ranking, as women tend to be more autonomy oriented and men tend to be more control oriented in online dating. In general, in our study men reacted to the popularity information and adjusted both their self-marketing and selectivity calibrations, exhibiting spontaneous adaptation in their subsequent strategies in a way that increased their chance of attracting attention from their target audience but also took the cost-benefit trade-off of exerting effort into account. On the other hand, the women in our study were less strategic and displayed persistence in their selectivity. In particular, comparative popularity feedback did not stimulate any adjustments to adaptation strategies for high-popularity women and decreased self-marketing for low-popularity women, a discouragement effect that echoes prior work (Ashraf et al., 2014).

Our exploration of engagement (i.e., profile views) contributes to our understanding that user adaptation strategies after popularity feedback are different from those associated with overall effort. For instance, we identified pragmatic adaptation on selectivity calibration and self-marketing for men based on their popularity level. We also found that, upon receiving comparative feedback, male users increased their level of engagement uniformly by viewing more profiles, regardless of their popularity. This highlights the importance of studying the nuanced and diverse possibilities of users' adaptation strategies rather than examining post-feedback effort alone.

In the second field experiment where we used *absolute popularity* as the feedback intervention, we observed no significant changes in adaptation strategies or levels of engagement—neither in the aggregate population nor in the subpopulations of different popularity levels or genders. Comparing the outcomes from the two, we conclude that the patterns of behavior change were driven by social comparison information revealed in the comparative feedback rather than by a salience (Chetty et al., 2009) or knowledge of result (Klueger & DeNisi, 1996) effect.

**Table 13. Summary of Findings**

| Hypothesis | | Theory | Result |
|---|---|---|---|
| **Hypothesis 1** | ***(a)*** *favorable (unfavorable) comparative feedback → more (less) selective in choosing partners* | Ego utility theory | supported |
| | ***(b)*** *favorable (unfavorable) comparative feedback → less (more) intensive self-marketing* | | supported |
| **Hypothesis 2** | ***(a)*** *favorable (unfavorable) comparative feedback → more (less) selective in choosing partners* ***to a greater extent*** *for men than for women* | Self-determination theory | supported |
| | ***(b)*** *favorable (unfavorable) comparative feedback → less (more) intensive self-marketing* ***to a greater extent*** *for men than for women* | | supported |

## Theoretical Contributions

This work makes several theoretical contributions. First, although social comparison is arguably one of the primary mechanisms behind feedback design on digital platforms (Chen et al., 2010), in empirical settings, it has been examined primarily on UGC platforms as a tool to encourage content contribution. In contrast, we show that popularity information associated with social comparison can be used as a feedback mechanism to alleviate congestion issues that can hamstring two-sided *matching markets* (Arnosti et al., 2021; Ashlagi et al., 2020). The reduced congestion can be a result of users adjusting selectivity. In online dating markets, Bruch and Newman (2018) found that both men and women pursue partners who are, on average, 25% more desirable than they are and that "the probability of receiving a response to an advance drops markedly with increasing difference in desirability between the pursuer and the pursued" (p. 1). In addition, it has been documented that matching outcomes can be greatly improved when a matching platform "redirect searchers towards listings that are more likely to accept those searchers" (Fradkin, 2017, p. 1). Following this chain of logic, it is reasonable to deduce that for low-popularity individuals, the decrease in their selectivity criteria can partially alleviate the congestion experienced by highly attractive mates. This may result in an improvement in matching outcomes by reducing the desirability difference between the pursuer and the pursued. On the other hand, for high-popularity individuals—who are experiencing congestion—the increase in their selectivity criteria will lead to lower responses from the matches they are pursuing, therefore also alleviating their own congestion.

Our findings regarding the self-marketing strategy also hint at reduced congestion because providing more complete information in one's profile will significantly increase one's visibility on a dating platform, particularly through the use of search engines. Compared with dating in the offline context, online dating "provides database-driven search queries, which affects the process by which people present themselves and assess potential partners" (Lo et al., 2013, p. 1756). In online dating, most daters start the initial screening process by attribute-based searching and filtering (Best & Delmege, 2012). Therefore, completing profile information by online daters is similar to search engine optimization by firms in their effort to attract customers through search marketing (Berman & Katona, 2013). For some individuals on dating platforms with incomplete profiles, a major reason for their low popularity may be that it is difficult for others to discover them. By providing more complete information in their profiles, these low-popularity individuals can increase their chances of appearing in search results and receiving more attention. As they become more visible and shift attention away from high-popularity individuals, congestion on the platform will likely be alleviated.

Second, the findings of this study also shed light on some plausible explanations for the inconsistent evidence presented in earlier work regarding the effect of peer feedback on agents' subsequent behavior. As explained earlier, prior research has shown that peer feedback on digital platforms has a positive effect on an individual's content contributions to online communities (Moon & Sproull, 2008; Wang et al., 2019), but it can also stifle one's creativity and reduce one's satisfaction in some other contexts (Hildebrand et al., 2013). Interestingly, in our own investigation, we also found that, *on average*, providing comparative popularity feedback does not modify the subsequent adaptation strategies in the overall population.[15] However, this lack of effect on the surface conceals the important role of moderating factors such as prior popularity or gender. By providing empirical evidence of heterogeneity in the effect of popularity feedback, we point to a promising path to reconciling the seemingly contradictory findings from earlier studies.

Finally, by examining the role of popularity feedback on subsequent behavior changes, our study also complements the recent literature on online dating (Bapna et al., 2016; Burtch & Ramaprasad, 2016; Heino et al., 2010; Jung et al., 2019), and sheds light on how to design effective feedback mechanisms to motivate user engagement on matching platforms. For example, we reveal that it is feedback information related to *comparative* popularity rather than to *absolute* popularity that significantly alters user behavior, highlighting the role of social comparison in online dating settings.

## Managerial Implications

The first takeaway of our work is that matching platforms need to utilize popularity information in a different way than UGC platforms. For example, in its effort to attract new users, an online dating platform may be tempted to promote highly attractive individuals on its website in the same way that UGC platforms promote popular content. However, due to the limited capacity of online daters, such practices are likely to backfire and exacerbate the congestion problem (Arnosti et al., 2021; Huang et al., 2022), while at the same time leaving most of the users feeling disenfranchised. Our study shows that an alternative strategy—in which popularity information is used as feedback—can be utilized to prompt changes in online daters' adaptation behaviors, and such behavioral

[15] Please refer to Table A16 for analyses of the average treatment effects on the whole population.

changes will likely lead to reduced congestion and improved matching efficiencies. Therefore, managers must carefully evaluate the benefits and downsides of the way popularity information is used on online platforms in relation to their specific business context.

Moreover, we suggest that popularity feedback design should be more flexible and tailored to the different sides of the market. In a heterosexual online dating market where the two sides of the market happen to be the two genders, we show that comparative popularity feedback works more effectively for one side (men) than the other (women). Therefore, a dating platform owner should explore other forms of popularity feedback for women, such as personalized comments or messages that are framed in a more cooperative context. Our findings also suggest that there might be benefits associated with designing differential feedback messages even for users on the same side of the market, such as those based on varying levels of prior popularity. For example, to help alleviate congestion, a dating platform might consider sending *comparative* feedback to low-popularity men but *absolute* feedback to high-popularity men. That way, low-popularity men can adjust their selectivity downward, shifting their attention away from the most popular women and marketing themselves more diligently to attract attention.

Another important implication for managers of online matching markets is that they should pay greater attention to users' adaptation strategies—particularly how they change upon receiving popularity feedback. For example, users' selectivity calibration in response to the preference of the other side and their own desirability is likely to influence the overall efficiency of matching (Jung et al., 2022); therefore, interventions that prompt such behavioral adaptation are potentially welfare enhancing. Other adaptation strategies, such as how individuals use the search function to identify potential partners or the set of personal attributes they choose to highlight or obscure in their user profiles are areas where some forms of feedback or suggestions from the platform may lead to efficiency gains. In summary, we highlight the value of delving into detailed adaptation strategies beyond a simple measure of effort, the limitations of which are becoming increasingly prominent on digital platforms such as online dating as well as other matching platforms such as employment platforms.

## Directions for Future Research

Our work paves the way for interesting future research. A natural extension to our focus on the short-term, immediate effect of popularity feedback would be to examine its long-term, dynamic impact on user behavior in a repeated setting, such as interim feedback (in various formats) provided at regular intervals. In addition, due to practical limitations, we were unable to collect data on downstream business outcomes (e.g., congestion and matching efficiencies) and therefore could not reveal how popularity feedback influences them. Exploring these downstream business outcomes could also be interesting, although we caution that most downstream outcomes would take longer to manifest and establishing causal relations between feedback and business outcomes will likely face greater identification challenges. Moreover, it would be meaningful to dive deep and explore how people perceive such information regarding popularity feedback (e.g., how it affects one's self-evaluation) in a lab setting using consumer surveys and interviews. Further, there is a scarcity of empirical research studying the impact of *unstructured* peer feedback forms such as comments that are specific to the task at hand and verbal- or text-based praises (Butler, 1987; Klueger & DeNisi, 1996), particularly in the digital platform context. Applying audio or textual analytics techniques to extract meaningful themes embedded in such peer feedback could provide greater insights into the mechanisms through which peer feedback alters agents' subsequent behavior. Finally, although our use of popularity measures resembles metrics typically adopted by two-sided digital platforms such as social media websites, the generalizability of our findings is somewhat limited due to the unique context of online dating, where men and women represent the two sides of the matching market. Follow-up studies examining these research questions on other matching platforms, such as online labor markets or rental property markets, could potentially provide additional insights.

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# Appendix

**Table A1. Randomization Checks at the Subgroup Level**

| | *p*-value (control = treatment) | | | |
|---|---|---|---|---|
| **Subgroup** | **L-popularity male** | **H-popularity male** | **L-popularity female** | **H-popularity female** |
| *age* | 0.72 | 0.28 | 0.57 | 0.18 |
| *education* | 0.14 | 0.48 | 0.65 | 0.62 |
| *popularity* | 0.76 | 0.25 | 0.56 | 0.73 |
| *tenure* | 0.51 | 0.63 | 0.94 | 0.87 |
| *photos* | 0.65 | 0.55 | 0.23 | 0.46 |
| *profile_completeness* | 0.32 | 0.37 | 0.46 | 0.64 |
| *selectivity calibration* | 0.68 | 0.47 | 0.80 | 0.86 |
| *self-marketing* | 0.30 | 0.18 | 0.80 | 0.23 |
| *profile_views* | 0.21 | 0.35 | 0.77 | 0.93 |

**Table A2. Split Sample Analyses: Using Difference-in-Difference Models**

**(a) The Causal Effect on Selectivity Calibration Strategy**

| **DV:** | **Male** | | **Female** | |
|---|---|---|---|---|
| **Δ(*target_score*)** | **Low-popularity** | **High-popularity** | **Low-popularity** | **High-popularity** |
| *treatment_1* | **-0.628*****<br>(0.138) | **1.118*****<br>(0.198) | 0.0406<br>(0.122) | -0.00480<br>(0.221) |
| Constant | 0.565***<br>(0.0955) | 0.350**<br>(0.144) | 0.0579<br>(0.0889) | -0.188<br>(0.158) |
| Observations | 2,168 | 1,437 | 1,973 | 1,468 |

**(b) The Causal Effect on Self-Marketing Strategy**

| **DV:** | **Male** | | **Female** | |
|---|---|---|---|---|
| **Δ(*profile_update*)** | **Low-popularity** | **High-popularity** | **Low-popularity** | **High-popularity** |
| *treatment_1* | **0.527*****<br>(0.0945) | **-0.598*****<br>(0.209) | **-0.284***<br>(0.165) | 0.167<br>(0.213) |
| Constant | -0.333***<br>(0.0510) | 0.0712<br>(0.166) | -0.191*<br>(0.107) | -0.848***<br>(0.156) |
| Observations | 2,168 | 1,437 | 1,973 | 1,468 |

**Note:** OLS model is used for selectivity calibration. OLS model is also used for self-marketing because the outcome variable, Δ(*profile_update*), has negative values. Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

**Table A3. Intention-to-Treat Effects Using Split Samples**

**(a) The Causal Effect on Selectivity Calibration Strategy**

| **DV:** | **Male** | | **Female** | |
|---|---|---|---|---|
| ***target_score*** | **Low-popularity** | **High-popularity** | **Low-popularity** | **High-popularity** |
| *treatment_1* | **-0.558*****<br>(0.0270) | **0.822*****<br>(0.0618) | 0.0102<br>(0.0421) | 0.0363<br>(0.0644) |
| Constant | 6.474***<br>(0.0194) | 6.072***<br>(0.0466) | 7.280***<br>(0.0308) | 7.437***<br>(0.0450) |
| Observations | 2,246 | 1,460 | 2,015 | 1,487 |

**(b) The Causal Effect on Self-Marketing Strategy**

| **DV:** | **Male** | | **Female** | |
|---|---|---|---|---|
| ***profile_update*** | **Low-popularity** | **High-popularity** | **Low-popularity** | **High-popularity** |
| *treatment_1* | **1.190***** | **-0.982***** | **-0.311***** | -0.118 |
| | (0.198) | (0.169) | (0.0998) | (0.167) |
| Constant | -1.479*** | 0.312*** | -0.296*** | -0.280** |
| | (0.175) | (0.0923) | (0.0660) | (0.121) |
| Observations | 2,246 | 1,460 | 2,015 | 1,487 |

**Note:** Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

**Table A4. Treatment Effects Conditional on the Sample with Positive Post-Feedback Profile Visits: Selectivity Calibration Strategy, Split Sample Analyses**

| DV: *target_score* | Male | | Female | |
|---|---|---|---|---|
| | **Low-popularity** | **High-popularity** | **Low-popularity** | **High-popularity** |
| *treatment_1* | -2.056***<br>(0.0798) | 1.043***<br>(0.0771) | 0.0407<br>(0.110) | 0.0645<br>(0.125) |
| Constant | 7.293***<br>(0.0323) | 5.837***<br>(0.0618) | 7.356***<br>(0.0771) | 7.376***<br>(0.0871) |
| Observations | 591 | 1,139 | 766 | 749 |

**Note:** OLS model. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

**Table A5. The Causal Effect on Selectivity Calibration Using Alternative Measure of *target_score_favor***

| DV: *target_score_favor* | Male | | Female | |
|---|---|---|---|---|
| | **Low-popularity** | **High-popularity** | **Low-popularity** | **High-popularity** |
| *treatment_1* | **-0.830*****<br>(0.0700) | **1.223*****<br>(0.0889) | -0.0509<br>(0.101) | 0.0745<br>(0.118) |
| Constant | 1.362***<br>(0.0614) | 1.728***<br>(0.0572) | 1.550***<br>(0.0705) | 1.774***<br>(0.0845) |
| Observations | 2,168 | 1,437 | 1,973 | 1,468 |

**Note:** OLS model. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

**Table A6. Robustness Check of the Treatment Effects Using Actual Popularity Feedback**

| **(a) The Causal Effect of Popularity Feedback—with Moderation Effect of Prior Performance (Eq. 1)** | | |
|---|---|---|
| | **Selectivity calibration** | **Self-marketing** |
| | ***target_score*** | ***profile_update*** |
| *treatment_1* | -0.220***<br>(0.0301) | 0.608***<br>(0.114) |
| *female* | 1.047***<br>(0.0245) | 0.00106<br>(0.0730) |
| *popularity* | 0.0114**<br>(0.00518) | 0.129***<br>(0.0133) |
| *treatment 1× popularity* | 0.0498***<br>(0.00726) | -0.132***<br>(0.0214) |
| Constant | 6.256***<br>(0.0217) | -1.017***<br>(0.0820) |
| Observations | 7,046 | 7,046 |
| **(b) The Causal Effect of Popularity Feedback – with Moderation Effects of Prior Popularity and Gender (Eq. 2)** | | |
| | **Selectivity calibration** | **Self-marketing** |
| | ***target_score*** | ***profile_update*** |
| *treatment_1* | -0.420***<br>(0.0251) | 1.732***<br>(0.171) |
| *female* | 0.897***<br>(0.0445) | 1.548***<br>(0.157) |
| *popularity* | -0.00250<br>(0.00661) | 0.260***<br>(0.0149) |
| *female × popularity* | 0.0298***<br>(0.0105) | -0.238***<br>(0.0272) |
| *treatment 1 × popularity* | 0.0909***<br>(0.00895) | -0.297***<br>(0.0282) |
| *treatment 1 × female* | 0.419***<br>(0.0622) | -2.005***<br>(0.224) |
| *treatment 1 × popularity × female* | -0.0859***<br>(0.0146) | 0.314***<br>(0.0428) |
| Constant | 6.326***<br>(0.0184) | -1.939***<br>(0.123) |
| Observations | 7,046 | 7,046 |

**Note:** OLS model is used for selectivity calibration, and Poisson model is used for self-marketing. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

**Table A7. OLS Regressions with Log Transformation of the Dependent Variable: Self-Marketing Strategy, Split Sample Analyses**

| DV: *log(profile_update)* | Male | | Female | |
|---|---|---|---|---|
| | **Low-popularity** | **High-popularity** | **Low-popularity** | **High-popularity** |
| *treatment_1* | 0.182***<br>(0.0218) | -0.232***<br>(0.0350) | -0.0894***<br>(0.0318) | -0.00464<br>(0.0325) |
| Constant | 0.0912***<br>(0.0102) | 0.410***<br>(0.0289) | 0.384***<br>(0.0250) | 0.260***<br>(0.0240) |
| Observations | 2,168 | 1,437 | 1,973 | 1,468 |

**Note:** Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

**Table A8. Alternative Post-Feedback Window (3 Days and 7 Days): Split Sample Analyses**

**(a) 3-Day Post-Feedback Window: The Causal Effect on Selectivity Calibration Strategy**

| DV: *target_score* | Male | | Female | |
|---|---|---|---|---|
| | **Low-popularity** | **High-popularity** | **Low-popularity** | **High-popularity** |
| *treatment_1* | -0.531***<br>(0.0289) | 0.757***<br>(0.0595) | 0.0006<br>(0.0427) | 0.022<br>(0.0654) |
| Constant | 6.467***<br>(0.0213) | 6.138***<br>(0.0444) | 7.285***<br>(0.0289) | 7.437***<br>(0.0525) |
| Observations | 2,168 | 1,437 | 1,973 | 1,468 |

**(b) 3-Day Post-Feedback Window: The Causal Effect on Self-Marketing Strategy**

| DV: *profile_update* | Male | | Female | |
|---|---|---|---|---|
| | **Low-popularity** | **High-popularity** | **Low-popularity** | **High-popularity** |
| *treatment_1* | 1.329***<br>(0.197) | -0.932***<br>(0.165) | -0.369***<br>(0.126) | -0.129<br>(0.158) |
| Constant | -1.411***<br>(0.167) | 0.441***<br>(0.0956) | 0.446***<br>(0.0885) | 0.0153<br>(0.118) |
| Observations | 2,168 | 1,437 | 1,973 | 1,468 |

**(c) 7-Day Post-Feedback Window: The Causal Effect on Selectivity Calibration Strategy**

| DV: *target_score* | Male | | Female | |
|---|---|---|---|---|
| | **Low-popularity** | **High-popularity** | **Low-popularity** | **High-popularity** |
| *treatment_1* | -0.321***<br>(0.0569) | 0.891***<br>(0.0616) | -0.00468<br>(0.0457) | -0.0198<br>(0.0581) |
| Constant | 6.522***<br>(0.0432) | 6.174***<br>(0.0463) | 7.365***<br>(0.0332) | 7.323***<br>(0.0386) |
| Observations | 2,168 | 1,437 | 1,973 | 1,468 |

**(d) 7-Day Post-Feedback Window: The Causal Effect on Self-Marketing Strategy**

| DV: *profile_update* | Male | | Female | |
|---|---|---|---|---|
| | **Low-popularity** | **High-popularity** | **Low-popularity** | **High-popularity** |
| *treatment_1* | 1.198***<br>(0.186) | -0.811***<br>(0.147) | -0.310***<br>(0.114) | 0.0297<br>(0.153) |
| Constant | -1.117***<br>(0.157) | 0.609***<br>(0.0879) | 0.694***<br>(0.0783) | 0.340***<br>(0.113) |
| Observations | 2,168 | 1,437 | 1,973 | 1,468 |

**Note:** OLS model is used for *selectivity calibration*. Poisson model is used for *self-marketing*. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

**Table A9. Treatment Effects of Relative Popularity Feedback Moderated by User Tenure**

| **(a) Selectivity Calibration** | | | | |
|---|---|---|---|---|
| **DV:** | **Male** | | **Female** | |
| ***target_score*** | **Low-popularity** | **High-popularity** | **Low-popularity** | **High-popularity** |
| *treatment* | **-0.498***** **(0.0391)** | **0.811***** **(0.0842)** | **0.176**** **(0.0805)** | **0.0983** **(0.0927)** |
| *long_tenure* | 0.0437 (0.0386) | -0.370*** (0.0916) | 0.247*** (0.0679) | -0.236*** (0.0889) |
| *treatment* × *long_tenure* | -0.139** (0.0556) | 0.0258 (0.120) | -0.229** (0.0951) | -0.127 (0.129) |
| Constant | 6.451*** (0.0271) | 6.294*** (0.0667) | 7.104*** (0.0575) | 7.578*** (0.0643) |
| Observations | 2,168 | 1,437 | 1,973 | 1,468 |
| **(b) Self-Marketing** | | | | |
| **DV:** | **Male** | | **Female** | |
| ***profile_update*** | **Low-popularity** | **High-popularity** | **Low-popularity** | **High-popularity** |
| *treatment* | **1.312***** **(0.102)** | **-0.839***** **(0.0835)** | **-0.196**** **(0.0883)** | **-0.104** **(0.0752)** |
| *long_tenure* | -0.0957 (0.126) | -0.464*** (0.0633) | -0.441*** (0.0751) | -0.994*** (0.0903) |
| *treatment* × *long_tenure* | -0.106 (0.143) | -0.198 (0.122) | -0.124 (0.114) | -0.0576 (0.131) |
| Constant | -1.428*** (0.0905) | 0.564*** (0.0441) | -0.00345 (0.0588) | 0.188*** (0.0535) |
| Observations | 2,168 | 1,437 | 1,973 | 1,468 |

**Note:** *long_tenure* is a binary variable that indicates a user's tenure is longer than 1 month.

**Table A10. Alternative Measure of Self-Marketing: Using Difference-in-Difference Models**

| **(a) Δ(photo_count)** | | | | |
|---|---|---|---|---|
| **DV:** | **Male** | | **Female** | |
| ***Δ(photo_count)*** | **Low-popularity** | **High-popularity** | **Low-popularity** | **High-popularity** |
| *treatment_1* | 0.115*** (0.0322) | -0.135*** (0.0384) | 0.00478 (0.0481) | 0.0711 (0.0670) |
| Constant | 0.0269 (0.0214) | 0.175*** (0.0349) | 0.132*** (0.0301) | 0.0323 (0.0496) |
| Observations | 2,168 | 1,437 | 1,973 | 1,468 |
| **(b) Δ(profile_completeness)** | | | | |
| **DV:** | **Male** | | **Female** | |
| ***Δ(profile_completeness)*** | **Low-popularity** | **High-popularity** | **Low-popularity** | **High-popularity** |
| *treatment_1* | 1.007*** (0.251) | -1.783*** (0.438) | -0.0739 (0.373) | 0.161 (0.226) |
| Constant | 0.312*** (0.100) | 2.517*** (0.391) | 1.896*** (0.258) | 0.335** (0.150) |
| Observations | 2,168 | 1,437 | 1,973 | 1,468 |

**Note:** OLS model is used for *Δ(profile_completeness)*. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

**Table A11. Alternative Measure of Selectivity Calibration: 3-Day Post-Feedback Window**

| **DV:** | **Male** | | **Female** | |
|---|---|---|---|---|
| ***target_score_variance*** | **Low-popularity** | **High-popularity** | **Low-popularity** | **High-popularity** |
| *treatment_1* | 0.362*** (0.0719) | -0.409*** (0.0740) | 0.0902 (0.0760) | 0.0101 (0.0787) |
| Constant | 1.374*** (0.0450) | 2.460*** (0.0529) | 1.914*** (0.0536) | 2.446*** (0.0570) |
| Observations | 1,343 | 1,273 | 1,359 | 1,272 |

**Note:** OLS model is used for *target_score_variance*. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

**Table A12. Profile Views: 3-day Post-Feedback Window**

| **(a) Poisson Model** | | | | |
|---|---|---|---|---|
| **DV:** | **Male** | | **Female** | |
| ***profile_views*** | **Low-popularity** | **High-popularity** | **Low-popularity** | **High-popularity** |
| *treatment_1* | 0.361***<br>(0.121) | 0.493***<br>(0.101) | -0.921***<br>(0.124) | -0.186<br>(0.139) |
| Constant | 0.966***<br>(0.0823) | 2.110***<br>(0.0766) | 1.730***<br>(0.0921) | 2.007***<br>(0.0998) |
| Observations | 2,168 | 1,437 | 1,973 | 1,468 |
| **(b) OLS with Log Transformation** | | | | |
| **DV:** | **Male** | | **Female** | |
| ***log(profile_views)*** | **Low-popularity** | **High-popularity** | **Low-popularity** | **High-popularity** |
| *treatment_1* | 0.107**<br>(0.0440) | 0.526***<br>(0.0649) | -0.245***<br>(0.0477) | -0.0812<br>(0.0650) |
| Constant | 0.570***<br>(0.0289) | 1.359***<br>(0.0450) | 0.803***<br>(0.0381) | 1.039***<br>(0.0480) |
| Observations | 2,168 | 1,437 | 1,973 | 1,468 |

**Note:** Poisson model is used for *profile_views.* OLS model is used for log(profile_views). Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

**Table A13. The Causal Effect of *Absolute Popularity* Feedback – with Moderation Effect of Prior Popularity (Equation 1)**

| | **Selectivity calibration** | **Self-marketing** |
|---|---|---|
| | ***target_score*** | ***profile_update*** |
| *treatment_2* | -0.0110<br>(0.0255) | -0.0493<br>(0.0992) |
| *female* | 1.067***<br>(0.0236) | 0.559***<br>(0.0787) |
| *high_pop* | 0.362***<br>(0.0382) | -0.0948<br>(0.113) |
| *treatment_2 × high_pop* | 0.0505<br>(0.0534) | -0.127<br>(0.167) |
| Constant | 6.164***<br>(0.0198) | -0.348***<br>(0.0814) |
| Observations | 7,150 | 7,150 |

**Note:** OLS model is used for selectivity calibration, and Poisson model is used for self-marketing. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

**Table A14. The Causal Effect of *Absolute* Popularity Feedback – with Moderation Effects of Prior Popularity and Gender (Equation 2)**

| | **Selectivity calibration** | **Self-marketing** |
|---|---|---|
| | ***target_score*** | ***profile_update*** |
| *treatment_2* | -0.0385<br>(0.0302) | -0.0257<br>(0.163) |
| *female* | 1.149***<br>(0.0354) | 0.872***<br>(0.151) |
| *high_pop* | 0.482***<br>(0.0490) | 0.384**<br>(0.167) |
| *female × high_pop* | -0.262***<br>(0.0769) | -0.833***<br>(0.235) |
| *treatment_2 × high_pop* | 0.0916<br>(0.0691) | -0.119<br>(0.240) |
| *treatment_2 × female* | 0.0563<br>(0.0508) | -0.0306<br>(0.204) |
| *treatment_2 × high_pop × female* | -0.0892<br>(0.107) | -0.0474<br>(0.338) |
| Constant | 6.122***<br>(0.0205) | -0.560***<br>(0.123) |
| Observations | 7,150 | 7,150 |

**Note:** OLS model is used for selectivity calibration, and Poisson model is used for self-marketing. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

**Table A15. The Causal Effect of *Absolute Popularity* Feedback – Level of Engagement, Split Sample Analyses**

| **(a) 2-Day Post Feedback Window Using Poisson** | | | | |
|---|---|---|---|---|
| **DV:** | **Male** | | **Female** | |
| ***profile_views*** | **Low-popularity** | **High-popularity** | **Low-popularity** | **High-popularity** |
| *treatment_2* | 0.228<br>(0.217) | 0.114<br>(0.0820) | -0.0586<br>(0.110) | -0.00640<br>(0.162) |
| Constant | -0.790***<br>(0.112) | 2.601***<br>(0.0544) | 1.727***<br>(0.0846) | 2.042***<br>(0.114) |
| Observations | 2,257 | 1,467 | 2,287 | 1,139 |
| **(b) 2-Day Post Feedback Window Using OLS with Log Transformation** | | | | |
| **DV:** | **Male** | | **Female** | |
| ***profile_views*** | **Low-popularity** | **High-popularity** | **Low-popularity** | **High-popularity** |
| *treatment_2* | 0.00353<br>(0.0202) | 0.0895<br>(0.0561) | 0.0162<br>(0.0507) | 0.00192<br>(0.0763) |
| Constant | 0.182***<br>(0.0144) | 2.073***<br>(0.0392) | 0.810***<br>(0.0359) | 1.040***<br>(0.0535) |
| Observations | 2,257 | 1,467 | 2,287 | 1,139 |

**Note:** Poisson model is used for *profile_views*. OLS model is used for *log(profile_ views)*. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

**Table A16. The Causal Effect of Popularity Feedback Regardless of Subpopulations**

| | **Selectivity calibration** | **Self-marketing** |
|---|---|---|
| | ***target_score*** | ***profile_update*** |
| *treatment_1* | 0.000680<br>(0.0245) | -0.0853<br>(0.0741) |
| *female* | 1.045***<br>(0.0246) | -0.0108<br>(0.0735) |
| *high_pop* | 0.224***<br>(0.0267) | 0.369***<br>(0.0741) |
| Constant | 6.218***<br>(0.0201) | -0.500***<br>(0.0665) |
| Observations | 7,046 | 7,046 |

**Note:** OLS model is used for selectivity calibration, and Poisson model is used for self-marketing. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$