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CONTESTANT BEHAVIOUR AND PERFORMATIVE REPUTATION: EVIDENCE FROM CROWDSOURCING OPEN INNOVATION TOURNAMENTS

[1*]Mr. Arpan Mondal, [2]Prof. Sabyasachi Sinha, [3]Dr. Anil Kumar Pandey

[1*]Ph.D. Scholar, Strategic Management Indian Institute of Management - Lucknow, Prabandh Nagar, off. Sitapur Road, Lucknow -226013, Uttar Pradesh, India.
Email: phd22032@iiml.ac.in , https://orcid.org/0000-0002-9030-9022

[2]Professor Strategic Management Group, Indian Institute of Management - Lucknow, Prabandh Nagar, Off. Sitapur Road, Lucknow -226013, Uttar Pradesh, India
Email: sabyasachi@iiml.ac.in , https://orcid.org/0000-0003-2016-032X

[3]Associate Professor ISBR Business School, 107, Behind BSNL Telephone Exchange, Near INFOSYS, Electronic City - Phase I, Bangalore - 560 100, Bengaluru, India.
Email: anil.pandey.ericsson@gmail.com

***Corresponding author:** Mr. Arpan Mondal (phd22032@iiml.ac.in)

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Abstract:

Crowdsourcing open innovation tournaments are online platforms that organizers use to expose tasks to a large number of individuals. This study examines the impact of contestants' participation behaviour dimensions on the performative reputation component in a crowdsourced innovation platform (Kaggle.com), incorporating a performance-based reputation element that allows users to track competitors unilaterally. Using Expectancy and Self-Determination Theory and empirically studying cross-sectional data from 523,797 contestants in 2015, we found that active frequency has a consistent positive impact on contestants' ratings and badges, while late submission behaviour negatively affects rating and badge performance. While more votes increase the frequency of contestants' activity and reduce late submissions, comments, in combination, have the opposite effect on contestants' rating points but a more significant impact on badges relative to followers' votes. These findings have significant implications for software developers and innovation platform managers, both in theory and in practice.

Keywords:

Crowdsourcing contests, platform, innovation tournaments, open innovation

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1. Introduction

Organisations use various approaches to obtain knowledge from external sources (Cassiman and Veugelers, 2006). One mode is through crowdsourcing innovation contests and tournaments, which are implemented on open or proprietary platforms (Schenk et al., 2019). These are specially designed by organisations and hosted on various platforms to extract valuable resources from the crowd and are adopted by companies like Netflix and General Electric (Feuerverger et al., 2012). The platforms have Performative reputation systems that recognise and validate a person's actions by peers, reflected in awards or endorsements (Deodhar and Gupta, 2023). A reputation system evaluates and reflects users' past conduct and contributions within a community or platform. Reputation systems might exhibit performative or social characteristics (Deodhar and Gupta, 2023). Studies considered Digital badges and points as a performative reputation feature (Goes et al., 2014). Performative if they directly provide reputation depending on a focal contestant's activity, such as past performance, ratings, or badges. Rating points track a particular contestant's performance and can be considered a performative feature of reputation. In contrast, digital badges are exclusively determined by the number of reviews or comments written, making them a performative reputation feature (Goes et al., 2014).

Previous research study shows that contestants who spent more time in a particular program when their point-acquisition rate was low, and their platform interactivity rate was high (Gupta et al., 2024). The rate of badge acquisition and leaderboard advancement did not correlate with increased time spent on the platform; rather, the degree of platform involvement influenced the association between leaderboard progress and time spent (Gupta et al., 2024). Studies further show that contestants who failed to earn points were more likely to obtain badges, advance on leaderboards, and engage more frequently with the platform (Gupta et al., 2024). Furthermore, earning badges, epistemic beliefs, and trust are interrelated (Schneider et al., 2022). Sociometric badges provide immediate feedback on involvement levels, leading participants in the feedback condition to perceive enhanced participative self-efficacy, which correlated with increased individual productivity (Park et al., 2022). Further, Studies show that combining early incentives with a late penalty leads to better performance outcomes (Korpusik et al., 2022). Promoting and acknowledging behaviour on a platform enhances success and growth (Singh et al., 2025). Though research talked about various behaviour elements' impacts on performance, research is silent on how contestants' behavioural characteristics –contestants' activity frequency and late submissions affect their reputations for performance on crowdsourced innovation platforms. This leads to a significant deficiency in the current understanding of how components of contestant behaviour can impact crucial outcomes in innovation tournaments. Further, studies indicate that participants voluntarily engage with an online crowdsourcing platform, contributing and providing feedback on the quality, which affects contestants' interest (Baruch et al., 2016). Studies show that feedback conditions productivity (Park et al., 2023). Moreover, peer acknowledgement and rejection positively affect the knowledge contributions of active enthusiasts, whereas reputation metrics and badges adversely affect the quantity and quality of knowledge contributions (Mustafa et al., 2023). Intangible benefits provide intrinsic motivation, influence behaviour, and promote cognitive engagement (Xiao and Hew, 2023). Previous research was silent on the impact of engaged users' or followers' characteristics, such as comments and votes, on the relationships between behaviour and performance in such innovation tournaments, leaving a lack of in-depth understanding.

Thus, building on earlier studies and considering the stated research gaps, this paper investigates the following question: How do Platform contestants' behaviours (Active frequency and late submission) affect contestants' Performative reputation (Rating Points and Badges) in an online crowdsourcing innovation tournament? How do the followers' comments and votes moderate the relationship between Platform contestants' behaviour and contestants' Performative reputation?

By using Expectancy and Self-Determination Theories, our study provides empirical evidence on the relationship between the frequency of contestants' activity and performance outcomes and further elaborates on the intricacies of the impacts of followers' comments and votes. Using a cross-sectional data of the submission dataset from Kaggle.com, a preeminent global community, and adopting the OLS regression model, we studied the impact of contestants' behaviour in 2015 on the performative reputation for 2016, a post-feature launch in May 2015. Our study makes two novel contributions. Our study makes two novel contributions. First, this research enhances the body of knowledge regarding innovation tournaments. Expanding on the established notion that contestant-centric (Jeppesen and Lakhani, 2010) and tournament-centric factors influence contestant performance (de Beer et al., 2017; Riedl and Woolley, 2017), we demonstrate that contestant behaviour, such as contestants' active frequency on the platform can lead to a notable performance enhancement, which contradicts previous studies (Gupta et al., 2024). Furthermore, the impact of late submission on performance outcomes, such as badges and rating points, has been established. Our research investigates a distinct antecedent, active frequency, which consistently positively affects contestants' ratings and badges, whereas late submission behaviour negatively affects rating and badge performance. Secondly, external factors such as followers' votes and comments have different impacts on outcomes, while more votes improve the frequency of activeness of the contestants and reduce the late submission, comments in combination have a reverse impact on rating points earned by contestants, but have a more significant impact on badges with respect to the followers' votes. The remainder of the paper is structured as follows: The next section reviews the literature followed by hypothesis development, methodology and model estimation. The results and conclusions are described next, while the final section provides directions for future studies.

2. Literature Review

Crowdsourcing contests leverage online platforms to expose tasks to a large group of individuals, who then compete to discover the optimal solution for each assignment. Various platforms exist for crowdsourcing contests, and numerous factors may influence participants' behaviour. On specific platforms, contests are accessible to everyone, and all participants can see submissions. However, only the organiser could examine the submissions on other platforms (Segev, 2020). On Kaggle, the performance of each submission in terms of the chosen evaluation metric can be viewed by participants, organisers, and the public through the public leaderboard. Contributions are concealed from public scrutiny using a private leaderboard and are exclusively accessible to the organisers.

Previous research has investigated the number of accolades received in contests (Moldovanu and Sela, 2001; Sisak, 2009) and the effects of limitations (Segev, 2020). These studies analyse a competition as a distinct event in which participants allocate efforts with irreversible costs that impact the quality of their submission. When a competitor chooses to participate in a particular crowdsourcing competition, she has already been selected from various available competitions. Frequently, they are presented with the opportunity to propose multiple options. In addition, one can receive feedback from the organiser on many platforms, which enables them to improve their contribution and acquire insights into the intended solution through comments supplied by other participants (Segev, 2020).

Prior research predominantly indicates that a more effective reward system attracts a larger number of participants and, their outcomes in turn, determines the level of excellence of the winning solution. Araujo (2013) found that increased rewards do not result in a corresponding increase in effort from individual designers, as assessed by the number of submissions they made to the same contest.

2.1 Theoretical Background

Contestants behave in a specific manner if they believe their activities will result in a favourable outcome. During a competition, players may alter their behaviour in response to their anticipation of attaining success and the perceived significance of that victory (Vroom, 1964). According to the Expectancy theory, when contestants in a situation are different from each other, their behaviour will be negative. Self-determination theory fills the gap by suggesting that Participants' behaviour in a competition can be influenced by the degree to which they feel self-directed and the extent to which they feel controlled by other forces. Self-determination theory (SDT) proposes that when individuals engage in self-directed behaviours aligned with their inherent interests, this tends to enhance overall task performance and foster the generation of innovative and valuable ideas. Therefore, although external cues may successfully encourage engagement in a specific task, conventional creativity research has generally seen them as primarily harmful to overall performance (Rigtering et al., 2019).

2.2 Background Literature

2.2.1 Online Reputation Systems:

Reputation refers to the dispersion of ideas, assessments, or evaluations of an entity, such as individuals, objects, or organisations, within a particular interest group (Cai and Zhu, 2016).

Crowdsourced innovation systems utilise the reputation function to evaluate participants' performance based on their submission history or behaviours (Namasudra and Sharma, 2023). Reputation is seen as a desirable quality in various online platforms (Liu and Munro, 2012), including two-sided marketplaces, online knowledge repositories, open-source software communities, and online labour markets (Ye et al., 2014; Luca and Zervas, 2016; Jabr et al., 2014; Cai and Zhu, 2016; Kokkodis and Ipeirotis, 2016).

2.2.2 Performative reputation features

Performative reputation is characterised by users' capacity to effectively demonstrate their skills and consistently achieve superior outcomes, as Carpenter (2010) highlighted. The ability to carry out its tasks effectively and efficiently is assessed through its performative reputation. Performative reputation refers to the user's ability to achieve their aims successfully (Carpenter, 2010).

3. Hypothesis Development

3.1 Contestant Behaviour

The participation of solvers in a contest and the submission of high-quality solutions are two interrelated activities that influence the results of an innovation contest (Hu et al., 2022). A participant is more inclined to submit a high-quality solution in a contest with numerous participants or if they have previously submitted one or more high-quality solutions; conversely, a solver is less likely to submit a high-quality solution if the contest already features many high- quality solutions from others (Hu et al., 2022). Prior research has identified multiple factors that impact the decision to exert effort and modify one's behaviour, particularly in winner-takes-all tournaments (Ke et al., 2021). The study reveals that the contestants' behaviour is positively correlated with the level of equality in their beginning endowments. Additionally, their behaviour tends to increase with the level of inequality in the awards offered in the tournament. Moreover, research indicates that those with the lowest socioeconomic status tend to exhibit competitive behaviour if the degree of status they can attain is low (Hopkins, 2018). Recent research has examined the dynamics of platforms by focusing on individuals who contribute to the platform's overall health and success. External players could collaborate, not only with the platform's owner but also among themselves, to address a specific problem (Mahony and Karp, 2020). An equally intriguing area of investigation is how members on the other side of the platform generate value, as the innovations they provide can significantly impact the platform's performance and its overall

ecosystem (Schilling, 2009). Loh and Kretschmer (2022) examined the potential of volunteer communities to offer a competitive edge and investigated how a platform's competitive standing influences contributor behaviour. They found that a platform's stronger competitive position is associated with increased activity, primarily due to more contributors. This, in turn, leads to more contributions from existing contributors. In addition, very productive individuals tend to be mainly engaged on a more robust platform. Gamber et al. (2021) identify various forms of contestants' behaviour in online contests and highlight the specific efforts competitors must make to compete effectively in ideation contests.
Studies show that online communities affect performance when participants have less experience with crowdsourcing contest platforms (Ye and Jensen, 2022). Further, studies highlighted various antecedents of Contestants' behavioural intention, including attitude, subjective norms, financial literacy, perceived risks, financial rewards, and environmental concern (Mohanty et al., 2025). Studies show that empowerment favourably affects contestants' behaviour and enhances their performance (Nanda and Nagasubramaniyan, 2025). Adaptable behavior (Nanda and Nagasubramaniyan, 2025) and Satisfaction (Singh et al., 2025) positively influence total performance. Voluntary participation enhances individual, team, and overall performance (Martina and Nagarajan, 2022). Therefore, promoting and acknowledging behaviour on a platform enhances success and growth (Singh et al., 2025). Moreover, motivational behaviour positively influences personality (Kapse et al., 2025) and Personality and self-development positively influence perceived performance (Pandey et al., 2024). In contrast, individuals with low behavioural ratings consistently achieved higher performance scores than those with high behavioural ratings (Wapnick and Darrow, 2006). Further studies suggest that intangible benefits impact intrinsic motivation, behavioural and cognitive engagement, and thereby influence performance (Xiao and Hew, 2024). Moreover, previous studies have argued that reputation systems exhibit performative characteristics (Deodhar and Gupta, 2023). Performative reputation is the recognition and validation of a person's actions by peers, reflected in awards or endorsements (Deodhar and Gupta, 2023).

3.2 Contestants' Performance Reputation

Reputation plays a crucial role in determining goal attainment and the intention to search for information (Jo and Bang, 2023). According to expectancy theory, contestants' performance affects tournament compensation systems (Gellner and Pull, 2013). An enhanced competitive position within a particular field correlates with increased overall activity, indicating that achieving success leads to further success in generating value (Loh and Kretschmer, 2022). Consequently, a larger number of participants are actively involved in creating value through collaboration. Every contributor enhances their contributions on a more robust platform. According to Loh and Kretschmer (2022), the connection between direct network effects and the relationship is likelydue to the greater social advantages of belonging to a larger group. The diversity of contributors is significant: The engagement of high-productivity contributors (HPCs), who represent the top 10% of participants in an online community, is strongly correlated with the platform's competitive standing, even when accounting for the community's size (Loh and Kretschmer, 2022). These few extremely valuable contributors play a significant role in driving platform activity, thereby enhancing value creation (Loh and Kretschmer, 2022). A larger community offers individual members enhanced social benefits (Zhang and Singh, 2016), leading to greater participation at a higher intensity level. The most valued set of contenders contributes more to platforms with a more robust relative competitive position. Several online communities use a nonmonetary compensation scheme to incentivise participation. Kaggle and other platform designers can establish a minimal benchmark for awarding badges or points to incentivise underperforming individuals, providing competitors with a tangible sense of achievement. Granting points to the top percentile on these platforms could potentially incentivise leaders and those closer to the lower norm (Dissanayake et al., 2018). Wikipedia has conducted trials with badges and other symbolic accolades to acknowledge contributions to the site (Restivo and van, 2012). Badges are employed to incentivise specific conduct. Granting badges is a way to award prizes to users at varying levels of progress and style. Badges are utilised in digital systems to leverage users' image and reputation incentives, as demonstrated by Liu et al. (2017). Badges serve as leaderboards or function as progress trackers. Badges are visual representations, typically icons or logos. The disclosure of the rules for earning badges can serve as objectives, as virtual status symbols, or as a feedback system to show user performance (Huang et al., 2018). Anderson et al. (2014) employed badges to encourage positive behaviour among participants in a massive open online course. They discovered that badge accumulation was a motivating factor for participants, leading to a tenfold increase in reading and voting activities compared to students in non-gamified settings. Badges served as a feedback system to denote users' performance. Although feedback has been extensively studied in the empirical literature, reputation systems have not received much attention (Segev, 2020). Most crowdsourcing sites have a reputation system. 99designs enables organisers to elevate their contests to a "prestigious" level by offering a substantial prize (beyond the platform's minimum value) and restricting entry to participants with a distinguished reputation. A contestant's reputation is determined by the number of contests and prizes she has won. The impact of reputation on contestants' behaviour has not been thoroughly investigated.

When contestants failed to earn points, they were more likely to obtain badges, advance on leaderboards, and engage more frequently with the platform (Gupta et al., 2024). Studies show that badges, belief, and trust are interrelated (Schneider et al., 2022). Sociometric badges provide immediate feedback on involvement levels, leading persons in the feedback condition to perceive enhanced participative self-efficacy, which correlated with increased individual productivity (Park et al., 2022). The rate of badge acquisition and leaderboard advancement exhibited no significant correlation with increased time spent on the platform; rather, the degree of involvement with the platform affected the association between leaderboard progress and time spent on the platform (Gupta et al., 2024). Further, contestants spent more time in the program when their point-acquisition rate was low and their platform interactivity rate was high (Gupta et al., 2024).

We have a limited understanding of contestants' reputations and behaviour. The dynamics of contestants on the platform in relation to other contestants have not been well investigated (Loh and Kretschmer, 2022). Contestants' behaviour in terms of remaining active on the platform if they receive a reputation and hold a stronger competitive position. Contestants with higher levels of engagement tend to be more active on platforms that offer enhanced reputations, maybe driven by their motivation for status and influence (Loh and Kretschmer, 2022). Online platform communities are voluntary systems that lack monetary incentives. However, they can create performance pressures as members strive to attain the reputations associated with these benefits (Zaggl, 2017).

Consequently, using rating scores or badges can enhance the contenders' performative reputations, directly influencing their behavioural outcomes. Performance demands can heighten individuals' proclivity to engage in cheating, deceitful actions, and excessive competition (Chambers, 2024). There is a disparity between the theoretical and empirical studies about contestants' behaviour in crowdsourcing contests (Segev, 2020). The empirical research focused on the contestants' strategies regarding the timing of their submissions, their responsiveness to self- and other- criticism, and the number of submissions they make in a tournament. Most participants in the competitions do not receive a prize, and the effects of this on their behaviour and effort have not yet been examined by theory.

In their study, Moqri et al. (2018) investigated the influence of newly acquired followers on a developer's subsequent contributions. These studies demonstrate that as users build a reputation, their behaviour improves. Studies further suggest that peer acknowledgement and rejection positively affect the knowledge contributions of active enthusiasts, whereas reputation metrics and badges adversely affect the quantity and quality of knowledge contributions (Mustafa et al., 2023). Thus, we are expanding upon and enhancing the existing research regarding antecedents and consequences.

H1a: Contestants' behaviour (Active frequency) positively improves Performative reputation (rating points)
H1b: Contestants' behaviour (Late submission) negatively impacts Performative reputation (rating points)
H1c: Contestant's behaviour (Active frequency) positively improves Performative reputation (badges).
H1d: Contestants' behaviour (Late submission) negatively impacts Performative reputation (badges).
Most of this research has focused on elements distinctive to the contest and the contestant. Only a few studies have specifically examined the elements that characterise contestants' behaviour in crowdsourcing contests, including their strategic behaviour and interaction in competitive situations (Archak, 2010; Yang et al., 2010).

3.3 Role of Follower's comments and votes

Previous studies document both internal and external factors that drive Behaviours. Intrinsic motivators encompass elements such as a personal connection to the community, the desire to give back, and the enjoyment derived from contributing (Wasko and Faraj, 2000; Hertel et al., 2003; Lakhani and Wolf, 2005; Shah, 2006; Faraj and Johnson, 2011). Extrinsic motivators are non- monetary reward systems that utilise peer recognition of outstanding performance to award points, badges, and other forms of status, thereby publicly appreciating the contributions made by members (Stewart, 2005; Zaggl, 2017; Xu et al., 2020; Burtch et al., 2022). Rewards indicate an individual's significant contribution. Prior research discusses the diverse spectrum of partiesinvolved in Crowdsourcing tournaments, including individuals and large-scale organisations. Therefore, the behaviour of these stakeholders can be influenced by several factors, including individual-level characteristics (Hutter et al., 2015) and organisational factors (Pollok et al., 2019). The impact of national culture (Chua et al., 2014) and gender diversity (Jeppesen and Lakhani, 2010) on conduct has already been examined. Timely feedback diminishes late submissions on programming assignments (Bouvier et al., 2021). Within our specific framework, we are looking at followers' comments and votes, which impact contestants' behaviour, including their activity frequency and the frequency of late submissions (See Figure 1).
H2a: Followers' Kernel's comments negatively moderate the relation between the Contestant's behaviour (Active frequency) and performative reputation (rating points).
H2b: Followers' Kernel's comments positively moderate the relation between the Contestant's behaviour (Late Submission) and performative reputation (rating points).
H2c: Followers Kernel’s comments positively moderate the relation between Contestants' Behaviour (Active frequency) and performative reputation (Badges).
H2d: Followers Kernel's comments negatively moderate the relation between the Contestant's behaviour (Late Submission) and performative reputation (Badges).
H2e: Follower's Kernel’s votes positively moderate the relation between Contestants' Behaviour (Active frequency) and performative reputation (rating points).
H2f: Follower's Kernel’s votes positively moderate the relation between the Contestant's Behaviour (Late Submission) and performative reputation (rating points).
H2g: Follower's Kernel’s votes positively moderate the relation between the Contestant's Behaviour (Active frequency) and the performative reputation (Badges).
H2h: Follower's Kernel’s votes negatively moderate the relation between the Contestant's Behaviour (Late Submission) and the performative reputation (Badges).

3.4 Model Framework

Behavioural elements influence performance (Xiao and Hew, 2023; Pandey et al., 2024; Nanda and Nagasubramaniyan, 2025; Kapse et al., 2025). Studies suggest that the degree of platform involvement affects the association between leaderboard progress and time spent on the platform (Gupta et al., 2024). Sociometric badges and involvement levels, in terms of frequency, are related and further correlated with increased individual productivity (Park et al., 2023). Intangible benefits provide intrinsic motivation, influence behaviour, and promote cognitive engagement (Xiao and Hew, 2023). Furthermore, late penalties lead to better performance outcomes (Korpusik et al., 2022). Moreover, peer acknowledgement, in the form of comments and votes, affects the contributions of active enthusiasts (Mustafa et al., 2023). Thus, we developed a framework that suggests active frequency improves performance reputation outcomes, such as badges and rating points, whereas late submission behaviour reduces them. Further followers' or peers' votes and comments have an influential effect on the relationships.

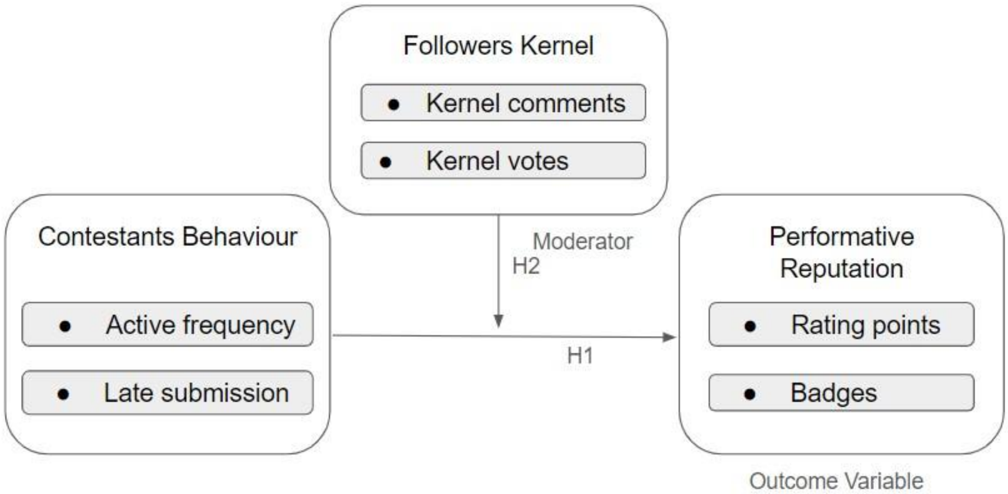

Figure 1: Theoretical representation of the relation between Contestants' behaviour (active frequency and late submission) dimensions with performance reputation (Rating points earned and badges collected) dimensions in crowdsourced online innovation tournaments. And the moderating role of while followers' comments and votes affect the relationship.

4. Methodology

4.1 Data Sources and Sample

Our study used data from Kaggle.com –an open innovation platform that was established in 2010. It is a platform and online community owned by Google LLC that focuses on data science competitions and serves as a hub for data scientists and machine learning experts. It specialises in organising and managing data science tournaments. Kaggle is utilised by notable corporations such as GE, Ford, Facebook, and other Fortune 500 companies. The platform, boasts an engaged community of members who dedicate their time and energy to creating innovative goods. The Kaggle platform operates like other crowdsourcing platforms, connecting organisers and participants, organisations that organises contests in which participants offering the most outstanding solutions are declared winners and receive a prize. As of October 2023, the platform has over 15 million registered users across approximately 200 countries. Our study is based on a natural experiment in which Kaggle implemented a performance-based reputational element on May 25, 2015 (Hammer, 2017), including information on submission activity in innovation tournaments and Kernel data for 2015. We utilised cross-sectional data from 2015 to investigate the impact of the independent variable on the dependent variable in 2016. The data used in our analysis is sourced from Kaggle's publicly accessible dataset (https://www.kaggle.com/kaggle/meta-kaggle). The dataset contains 523797 user IDs, who have earned points ranging from 0 to 10,319, and badges ranging from 0 to 1831. Each data point in the dataset corresponds to a contestant “i” submission. The dataset provides values for our model construct for contestants' behaviour and their performance outcomes. The dataset contains the frequency of participants' or contestants' activity on the platform and whether they submitted late. Moreover, the dataset includes the number of followers, votes, and comments for each ID. Finally, we analysed data on performative reputations in 2016 to assess their impact one year later using OLS regression.

5. Variable Description

5.1 Dependent Variable

Every contest-based crowdsourcing platform has distinct characteristics that appeal to specific demographics. The platform's reputation and features are the primary factors that attract participants to its competitions. To understand the performative reputation, we calculated individual ability using Kaggle's rating points (Boudreau et al., 2016) and badges (Gold, Silver, Bronze) as the total number of badges a contestant earned. The contestant's activity frequency is calculated as the frequency with which the contestant submits data. Both data sets were collected from the Kaggle database.

5.2 Independent Variables and Moderators

The contestants' behavioural outcomes were measured by the frequency of platform activity and the number of late submissions (Martinez, 2017; Moqri et al., 2018; Jain and Deodhar, 2022). The frequency of their submissions (calculated as the number of times they have submitted and are active) and late submission is calculated as if the contestant submitted after the deadline or not (which is 1 if submitted after the deadline, otherwise 0). We have accounted for a 1-year lag for both behaviour-independent variables (Martinez, 2017; Moqri et al., 2018; Jain and Deodhar, 2022). The Followers Kernel comments and votes moderate the relationship between the performative reputation feature, the contestant's behaviour and the contestant's performative reputation. The study by Bouvie et al. (2021) demonstrates that providing feedback effectively decreases the occurrence of late submissions across various online projects. Kernel comments can be calculated from the contestant's total number of comments. Kernel votes are calculated as the number of upvotes the contestant received. Both data sets are available in the Kaggle database. We have used a 1-year lag for both followers' comments and upvotes (Bouvie et al., 2021).

5.3 Control Variables

The study includes multiple time-varying control variables. Contestant behaviour may be influenced by their submission activity, which is not accounted for by the variables of the two followers' and peers' perspectives. Therefore, we create their corresponding elements: the number of contributions made by contestants, the Contestant position, the highly productive contestants, the Prior contribution made by each contestant, and the team size. Next, we explore the potential advantage a participant may gain from their previous experience participating in various Kaggle competitions. To address this phenomenon, we incorporate the contestant's prior expertise by considering the number of tournaments they had participated in before entering the current competition (Prior Compete). This is calculated as the contestant competes in t-2 or earlier (measured as 1 if previously competed; otherwise, 0) (Jain and Deodhar, 2022). Active contestants are measured using the Kaggle database, which provides data on active members (1 if active, 0 otherwise) (Loh and Kretschmer, 2022). The contestant position is measured by the tier in which the contestant is located (0 being the lowest and 4 being the highest) (Loh and Kretschmer, 2022). High-productive contestants are measured by the private leaderboard score, defined as (Private score - minimum private score)/ (Maximum private score - Minimum private score), and normalised to the range (0,1), with a 1-year lag (Jain and Deodhar, 2022). Team size is calculated as the number of team members the contestant is part of, with a 1-year lag (Loh and Kretschmer, 2022). Ultimately, we account for the possibility that a participant may be engaged in multiple tournaments concurrently. Thus, we create an indicator variable that takes a value of 1 if the player participates in at least one of the parallel tournaments before entering the focal event (Parallel), using a 1-year lag (Jain and Deodhar, 2022). Appendix Table 1 lists the variables used in the study.

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6. Estimation Model

We have estimated the model represented by Equations (1). In our estimation, we have included fixed effects for contestants, tournaments, and submission weeks.

Yi = β1 × Prior Competei + β2 × active contestanti + β3× contestant positioni + β4 × High-productive contestantsi + β5 × Team sizei + β6 × Paralleli + β7 × Kernel commentsi + β8 × kernel votesi + β9 × Active frequencyi + β10 × Late submissioni + β11 × Kernel commentsi × Active frequencyi + β12 × Kernel commentsi × Late submissioni + β13 × Kernel votesi × Active frequencyi + β14 × Kernel votesi × Late submissioni + Ei ……………………………. (1)

The equations (1) have the following components: Yi represents the Rating Score and Badges; Ei represents the error terms. Where "i" represents the contestant. The coefficients β1- β6 represent the estimated values of the time-varying control variables; β7 and β8 represent the coefficients for the moderator variables; and β9 and β10 represent the coefficients for the independent variables. β11-β14 represent the coefficients for the interaction terms between the independent variables and the moderator. We employed a basic OLS (ordinary least squares) model to analyse the influence of the contestants' conduct in 2015 on their performance reputation in 2016.

7. Analysis And Results

The descriptive and Pearson correlation matrices are presented in Tables 1 and 2, respectively. For our main study, we thoroughly evaluate all the hypotheses by gradually incorporating predictor variables into the OLS regression model. Our test results indicate a maximum VIF of 2.15, indicating the absence of multicollinearity. We tested for heteroscedasticity (p-value = 0.000 < 0.05), indicating heteroscedasticity. Thus, we used robust standard errors as a remedial measure.

*: Descriptive matrix***Table 1**

Variable	Observations	Mean	Std. Dev.	Min	Max
User id	523,797	326624.8	194259	368	660470
Points	523,797	4.088	242.624	0	100319
Badges	523,797	0.098	3.677	0	1831
Active Frequency	37,869	9.606	37.974	0	1418
Late Submission	37,869	1.238	12.270	0	887
Votes	4,220	3.669	35.967	0	1551
Comments	4,220	0.914	9.088	0	431
Prior Compete	37,869	0.701	0.458	0	1
Active Contestants	523,797	0.970	0.171	0	1
Contestant Position	508,020	0.084	0.298	0	4
High Productive Contestants	15,191	0.625	0.330	0	1
Team size	15,191	13.969	27.684	1	887
Parallel Contests	15,191	0.825	0.380	0	1

Note: The table shows the number of observations, the mean, the standard deviations, and the minimum and maximum values.

*: Pairwise correlation matrix***Table 2**

Correlation	**Points**	**Badges**	**Active Frequency**	**Late Submission**	**Votes**	**Comments**	**Prior Compete**	**Active Contestants**	**Contestant Position**	**High Productive Contestants**	**Team size**	**Parallel Contests**
Points	1											
Badges	0.2029*** (0.000)	1										
Active Frequency	0.2557*** (0.000)	0.2943*** (0.000)	1									
Late Submission	0.0197*** (0.001)	0.0295*** (0.000)	0.4222*** (0.000)	1								
Votes	0.1200*** (0.000)	0.1501*** (0.000)	0.1299*** (0.000)	0.0346 (0.143)	1							
Comments	0.0614*** (0.001)	0.1335*** (0.000)	0.1330*** (0.000)	0.0318 (0.179)	0.9380*** (0.000)	1						
Prior Compete	0.0023 (0.661)	0.0209*** (0.000)	-0.1420*** (0.000)	-0.0964*** (0.000)	0.1029*** (0.000)	0.0793*** (0.001)	1					
Active Contestants	0.0030** (0.032)	0.0047*** (0.007)	-0.0789*** (0.000)	-0.0132** (0.010)	-0.0293* (0.057)	-0.0289* (0.061)	0.1020*** (0.000)	1				
Contestant Position	0.1019*** (0.000)	0.1456*** (0.000)	0.2734*** (0.000)	-0.0218*** (0.001)	0.1666*** (0.000)	0.1513*** (0.000)	0.0336*** (0.000)		1			
High Productive Contestants	-0.014* (0.085)	-0.0322*** (0.000)	-0.0555*** (0.000)	0.0258*** (0.002)	-0.0306 (0.216)	-0.0189 (0.446)	0.0036 (0.657)	0.0440*** (0.000)	-0.1030*** (0.000)	1		
Team	0.0642	0.0740	0.5135	0.5928	0.0319	0.0648	0.0695	-	0.1764*	-	1	

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size	*** (0.000)	*** (0.000)	*** (0.000)	*** (0.000)	(0.198)	*** (0.009)	*** (0.000)	0.021** (0.011)	** (0.000)	0.0212*** (0.009)		
Parallel Contests	0.0251 *** (0.002)	0.0386 *** (0.000)	0.1854 *** (0.000)	0.0667 *** (0.000)	0.0366 (0.140)	0.0384 (0.121)	0.1078 *** (0.000)	-0.0598 *** (0.000)	0.1860*** (0.000)	-0.0139* (0.0858)	0.1975 *** (0.000)	1

Note: *** <0.01, ** < 0.05 and * <0.1 level of significance.

*OLS Regression Results (Dependent Variable is Rating Points)***Table 3:**

DV (Rating Points)	**Model 1 (Control)**	**Model 2 (Main)**	**Model 3 (Votes)**	**Model 4 (Comments)**	**Model 5 (complete)**
Prior Compete	42.215 (0.185)	-179.987 (0.257)	-80.452 (0.740)	-165.064 (0.509)	-100.673 (0.676)
Contestant Position	425.614*** (0.000)	564.507** (0.039)	634.867*** (0.000)	631.052*** (0.001)	525.523*** (0.004)
High Productive Contestants	8.745 (0.849)	445.089 (0.230)	349.836 (0.257)	442.848 (0.164)	299.853 (0.328)
Team size	2.231** (0.012)	-.565 (0.874)	2.306 (0.548)	-.633 (0.873)	2.505 (0.512)
Parallel Contests	-52.090*** (0.008)	-412.960** (0.022)	-302.492 (0.420)	-403.543 (0.297)	-314.535 (0.398)
Votes		47.745 (0.136)	16.642** (0.048)	48.903*** (0.000)	.024 (0.998)
Comments		-101.919** (0.022)	-66.248*** (0.008)	-130.9*** (0.000)	32.698 (0.340)
Active Frequency		11.028*** (0.002)	5.690*** (0.000)	9.745*** (0.000)	7.082*** (0.000)
Late Submission		-16.667*** (0.002)	-4.7 (0.405)	-11.417** (0.051)	-7.329 (0.195)
Votes*Active Frequency			.258*** (0.000)		**
Votes*Late Submission			-1.737*** (0.000)		-2.338*** (0.000)
Comments*Active Frequency				.358*** (0.009)	-.791*** (0.000)
Comments*Late Submission				-3.221*** (0.001)	4.439*** (0.001)
N	12,903	1,257	1,257	1,257	1,257
F statistics	0	0	0	0	0

R2	0.035	0.1854	0.243	0.1923	0.2555
Adjusted R2	0.0347	0.1796	0.2363	0.1852	0.2477

Note: Study modes 1-5 show the regression results with the dependent variable Rating Points.
Here, *** <0.01, ** < 0.05 and *<0.1 level of significance

*: OLS Regression Results (Dependent Variable is Badges)***Table 4**

DV (Badges)	**Model 1 (Control)**	**Model 2 (Main)**	**Model 3 (Votes)**	**Model 4(Comments)**	**Model 5(full)**
Prior Compete	3.239*** (0.000)	5.815 (0.111)	8.546** (0.017)	7.523** (0.034)	9.037** (0.010)
Contestant Position	6.215*** (0.000)	4.681* (0.086)	4.824* (0.07)	7.596*** (0.004)	7.089*** (0.007)
High Productive Contestants	1.228** (0.034)	-3.764 (0.419)	-6.333 (0.165)	-3.654 (0.418)	-5.762 (0.199)
Team size	.036*** (0.000)	-.155*** (0.007)	-.108* (0.056)	-.126** (0.026)	-.121** (0.03)
Parallel Contests	-0.298 (0.554)	-3.497 (0.537)	-1.805 (0.744)	-1.983 (0.718)	-1.829 (0.736)
Votes		.393*** (0.000)	-.33*** (0.008)	.432*** (0.000)	-0.072 (.608)
Comments		.911*** (0.010)	1.897*** (0.000)	-.964** (0.017)	.135 (0.788)
Active Frequency		.185*** (0.000)	0.12*** (0.000)	0.101*** (0.000)	.098*** (0.000)
Late Submission		-.215*** (0.009)	-0.197** (0.018)	-.085 (0.309)	-.125 (0.129)
Votes*Active Frequency			0.003*** (0.000)		.0004 (0.477)
Votes*Late Submission			0.004 (0.320)		0.023*** (0.000)
Comments*Active Frequency				.017*** (0.000)	.017*** (0.000)
Comments*Late Submission				-.084*** (0.000)	-.122*** (0.000)
N	12,903	12,903	12,903	12,903	12,903
F statistics	0	0	0	0	0
R2	0.0481	0.2227	0.2605	0.27	0.2882
Adjusted R2	0.0477	0.2171	0.2539	0.2635	0.2808

Note: Study modes 1-5 show the regression results for studies 1-5, with the dependent variable 'Badges'. Here, *** <0.01, ** < 0.05 and * <0.1 level of significance

Table 3 presents the findings for contestants' behaviour dimensions (Active frequency and late submission) on the dependent variable, Performance reputation outcome (Rating points). Table 3 presents the OLS regression results for models 1-5. Model 1 exclusively employs control variables. Model 2 shows the regression results of the main independent variables on the dependent variable (Rating points). The result of model 2 shows that the Active frequency of the contestant on the platform has a positive and significant impact on the rating points earned by the contestant (β = 11.028, p-value = 0.002), whereas if the contestant does a late submission, then it will have a negative and significant impact on the rating points earned by the contestant's (β = -16.667, p- value = 0.002). This shows that actively participating in the platform improves Rating points, while contestants possessing late submission behaviour retards it (Gupta et al., 2024; Korpusik et al., 2022).

Models 3 and 4 show the impact of peers' votes and comments on the relationship. In model 3, when peers' votes act as a moderator in the relationship, active frequency of the contestant in the platform has a positive and significant effect (β = 5.690, p-value = 0.000), which improves the rating points of the contestants, but late submission becomes negative, weaker and insignificant (β
= -4.7, p-value = 0.405) suggesting a moderating impact of peers’ votes. Thus, it is interpreted that when peers' votes are considered, participants' late submissions have a reduced effect on the rating points. Peers' Vote has a positive impact on active frequency and rating points (β = 0.258, p-value
= 0.000) because it reinforces trust and belief and enhances interest (Schneider et al., 2022). As the number of followers' votes increases, the positive effect of the contestants' active frequency on rating points becomes stronger. Whereas votes weaken the rating outcomes when participants' late submissions increase (β = -1.737, p-value = 0.000), as they enhance interest and reduce contestants' late submission behaviour (Schneider et al., 2022).

In model 4, active frequency has a positive impact on rating points (β = 9.745, p-value = 0.001), while contestants' late submission has a negative impact on rating points (β = -11.417, p-value = 0.051). Followers' comments have a positive and significant moderating effect on the relationship (β = 0.358, p-value = 0.009), as they enhance interest and the benefits of active participation (Schneider et al., 2022). Followers' comments show a negative, significant moderation effect on the relationship between late submission and contestants' rating points (β = -3.221, p-value = 0.001).

Model 5 shows the results for the full model, including both moderators' votes and followers' comments. Contestants' active frequency remains positive and significant (β = 7.082, p-value =0.000), while late submission is negative and insignificant (β = -7.329, p-value = 0.195). Voteshave a positive impact, enhancing the effect of contestants’ active participation (β = 0.364, p-value = 0.000) and substantially reducing the late submission effect (β = -2.338, p-value = 0.000). Whereas followers’ comments negatively affect the relationship between active frequency and rating points (β = -0.791, p-value = 0.001), because their effectiveness is reduced by excessive comments when followers cast more votes. The comments show a positive moderating effect (β= 4.439, p-value = 0.001) on the relationship between late submission and the rating points earned by the contestant, suggesting that it mitigates the negative effect of late submission while votes and comments work together.

Overall, the results indicate that having an active frequency among contestants enhances their rating points earning consistently, while late submission behaviour reduces it and is highly related to the impact of the moderating variables, votes and comments, which enhance as well as reverse the effects while acting independently or together to explain the impact on the final rating outcomes.

Similarly, Table 4 shows the impact of active frequency and late submission behaviour on performance-reputation outcomes (badges).

Model 1 exclusively employs control variables. Model 2 shows the regression results of the main independent variables on the dependent variable (Badges). The result of model 2 shows that the Active frequency of the contestant on the platform has a positive impact on the badges earned by the contestant (β = 0.185, p-value = 0.000), whereas if the contestant does a late submission, then it will have a negative impact on the contestant's badge earning (β = -0.215, p-value = 0.009). This shows that both the behavioural dimensions have opposite impacts on the performance outcome.

Models 3 and 4 show the impact of peers' votes and comments on the relationship. In model 3, when peers provide more votes, acting as a moderator in our study, the contestant's active frequency on the platform shows a positive and significant effect (β = 0.12, p-value = 0.000), and late submission shows a negative and significant effect (β = -0.197, p-value = 0.018). Thus, it is interpreted that when peers' votes are considered, participants' late submissions have a reduced effect on the badges. Peers' Vote has a positive impact on active frequency and badges (β = 0.003, p-value = 0.000) because it reinforces trust and belief and enhances interest (Schneider et al., 2022). As the number of followers' votes increases, the positive effect of the contestants' active frequency on badges becomes stronger. Whereas votes have an insignificant effect on badge performance outcomes when participants' late submissions increase (β = 0.004, p-value = 0.320), suggesting that there is no moderating effect of more votes on the relationship between late submissions and contestants' badge earnings.

In model 4, active frequency has a positive impact on badges earned (β = 0.101, p-value = 0.000), while contestants' late submission has a negative impact on badges (β = -0.085, p-value = 0.309). Followers' comments have a positive moderating effect on the relationship (β = 0.017, p-value = 0.000), as they enhance interest and the benefits of active participation (Schneider et al., 2022). And shows a negative moderation effect on followers' comments, indicating that comments strengthen the negative influence of the contest's late submission on badges (β = -0.084, p-value = 0.000).

Model 5 shows the results for the full model, including both moderators' votes and followers' comments. Contestants' active frequency remains positive and significant (β = 0.098, p-value = 0.000), while late submission is negative and insignificant (β = -0.125, p-value = 0.129). Votes have a positive and insignificant impact on contestants' active participation (β = 0.0004, p-value = 0.477) and a substantially positive impact on reducing the late submission effect on badge performance outcomes (β = 0.023, p-value = 0.000). Whereas followers' comments positively affect the relationship between active frequency and badges (β = 0.017, p-value = 0.000), because their effectiveness is enhanced by excessive comments when followers cast more votes. And with more votes, the comments show a negative moderating effect (β = -0.122, p-value = 0.000) on the relationship between late submission and the badges earned by the contestant, due to the negative sentiments created by more comments indicating a penalty. This is explained by strong collinearity between increased votes and increased comments from followers (β = 0.938, p-value = 0.000), thereby increasing the likelihood of late submissions by contestants.

Overall, the impact on earning badges: the active frequency of the contestant has a consistent positive effect, while late submission has an undermining effect. Followers' comments play an important moderating role by increasing the frequency of contestants' activity and reducing the drawbacks of late submissions, whereas the moderating impact of votes is weaker when considered jointly for improving badge earnings.

8. Conclusion

In contrast to the previous studies, which show that ownership, empowerment, initiative, and self- development behaviour have a positive impact (Xiao and Hew, 2023; Pandey et al., 2024; Nanda and Nagasubramaniyan, 2025; Kapse et al., 2025) and inertness has a negative impact (Meeus and Oerlemans, 2000) on performance. Our study shows that the different dimensions of behaviour – submission time (late submission) and platform activity (active frequency)- have distinct impacts on contestants' performance outcomes in a crowdsourced innovation tournament. Participants' active frequency consistently has a positive impact on rating and badge-earning performance,

while more followers' votes indicate that active participation frequency increases as more followers vote, but it can also lead to later submissions by contestants. In line with Bouvier et al. (2021), timely feedback, in the form of comments, reduces late submissions on programming assignments. Comments can't improve participants' active frequency behaviour in the presence of more votes; rather, they can reduce it. Moreover, followers' comments negatively affect the relationship between active frequency and rating points, and reduce the negative impact of late submission on contestants' rating points. While participants' active frequency positively affects their earning badges on the platform, more followers' votes indicate a decrease in active participation frequency. Late submissions have no effect on badge performance metrics, and votes further reduce participants' late-submission behaviour, but have a minimal effect when considered with comments. Here, followers’ comments play an important moderating role by increasing the frequency of contestants' activity and reducing the drawbacks of late submissions. While peer comments enhance late submissions and negatively affect the relationship, votes also factor in, but have no significant impact on the frequency of contestants or badge performance metrics.

8.1 Theoretical contribution

Innovation crowdsourcing may be executed via open or proprietary platforms (Schenk et al., 2019). Research indicates that volunteer engagement on an online crowdsourcing platform, along with feedback regarding the quality and impact of contributions, is essential for sustaining interest (Baruch et al., 2016). The ambiguity and the nature of the problem must be explicitly addressed in the design of innovation tournaments (Boudreau et al., 2011). Systematically incorporating competitors enhances overall contest performance (Boudreau et al., 2011).

The individual circumstances of participants are emphasised as a significant factor influencing engagement in campaigns (Baruch et al., 2016). Their engagement is closely associated with the extent of interaction they maintain with campaign coordinators, both in the platform's design and in offering feedback regarding the effects of their contributions (Baruch et al., 2016). Creators who dedicate themselves to others' concepts on the crowdsourcing platform garner greater commitments from others for their own ideas (Deichmann et al., 2021). Our study addresses the previous gap by investigating how late submissions and contestants' activity frequency affect their performative reputation in online innovation tournaments. And highlights the significance of performative reputation features in open contest platforms where crowdsourcing occurs, enabling participants to compete in solving various problems.

This research enhances the body of knowledge regarding innovation tournaments. Expanding on the established notion that contestant-centric (Jeppesen and Lakhani, 2010) and tournament-centric factors influence contestant performance (de Beer et al., 2017; Riedl and Woolley, 2017), we demonstrate that contestant behaviour can lead to a notable performance enhancement. Our research examined the behavioural components as precursors to performance outcomes, so expanding the social mechanisms that elucidate the principal behavioural consequences of searchers and solvers (Jain and Deodhar, 2021). Our focus on participant behaviour diverges markedly from previous research on innovation tournaments, which has treated platforms as static and ambient (Jain and Deodhar, 2021).

Additionally, we contribute to the literature on behavioural consequences. Previous research has investigated the influence of contestants' cumulative reputation on their subsequent behaviour (Goes et al., 2014; Moqri et al., 2018); we demonstrate that behavioural components may have substantial implications for performance. Consequently, our research investigates a quantitatively distinct antecedent (i.e., frequency and submission behaviour versus rating and badge performance outcomes) and a significantly different consequent, i.e., the moderating influence of follower comments and votes on the relationship between behaviour and performance, rather than behaviour alone (Beal et al., 2003).

Secondly, our study considered external factors that can affect relationships, which may have different effects on contestants' outcomes in an open innovation tournament. While considering the factors together, they have different impacts on outcomes, while more votes improve the frequency of activeness of the contestants and reduce the late submission, comments in combination have a reverse impact on rating points earned by contestants, but have a more significant impact on badges with respect to the followers' votes.
Thus, our study extends previous discussions by looking at a different dimension of the participants behaviour that can impact in the presence of external factors on their outcomes, which indirectly impacts the organising platforms and the contest organisers.

8.2 Managerial Implications

Our research possesses considerable practical implications. Since contestants are the important players for the survival of the platforms that provide solutions to various contest organisers. Both platform organisers and crowdsourcing agents should consider the factors that impact contestants' outcomes. We urge that tournament platform organisers closely consider contestants' behaviour and strive to enhance it, as it is directly linked to their performance. An improvement in performance will have a direct effect on platform crowdsourcing event organisers, enabling better outcomes and solving problems more effectively. Moreover, external factors need to be considered, including followers' characteristics, both independently and in combination, which may impact the final outcomes.

8.3 Limitations and Future Research Directions

While we emphasise contestants' behaviour as a precursor to performance, we do not assert that such impacts are entirely independent of the naturally occurring circumstances. Future research should investigate potential relationships among numerous antecedents, including distinct platform features, contestant behaviour, and performance outcomes. Research indicates that performance ratings influence both individual (Archak, 2010) and competitor behaviour (Boudreau et al., 2016). Future researchers can investigate reverse causality and examine additional moderating and mediating variables, including the salient traits that significantly alter the underlying reputation system. Secondly, we do not investigate the potential contingencies associated with socio-psychological variables, such as contestants' personality (Zhang and Singh 2016) and efficacy (Mihm and Schlapp, 2019), in influencing the link between contestants' behaviour and performance. Moreover, future studies may demonstrate that firms conducting crowdsourcing contests can enhance performance outcomes by employing early incentives alongside late penalties (Korpusik et al., 2022).

Appendix:

*: Lists of all the variables used in the study.***Table 1**

Variables	Variable Name	Variable unit	Measures	Citation
IV	Behaviour	(Active frequency) t-1	Number of times they have submitted and are active	(Martinez, 2017; Moqri et al., 2018; Jain and Deodhar, 2022)
	outcomes	(Late submission) t-1	Contestant submitted after the deadline or not (which is 1 if submitted after the deadline, otherwise, 0)	(Martinez, 2017; Moqri et al., 2018; Jain and Deodhar, 2022)
	Performative	(Points) t	Rating points	(Boudreau et al., 2016)

DV	reputation feature	(Badges) t	Badges = sum of (Gold, Silver, Bronze)	(Huang et al., 2018)
Moderator	Followers	(Kernel comments) t-1	Number of Kernel comments	(Bouvie et al., 2021)
Kernel		(Kernel upvotes) t-1	Number of Kernel upvotes	(Bouvie et al., 2021)
		(Prior Compete) t-2,6	The contestant competes during the time period from t-2 to t-6. (It is measured as 1 if previously completed, otherwise, 0)	(Jain and Deodhar, 2022)
Control		(Active contestants) t	Active members (1 if active, otherwise 0)	(Loh and Kretschmer, 2022)
		(Contestant position) t	Tier in which the contestant is present (0 being the lowest and 4 being the highest position)	(Loh and Kretschmer, 2022)
		(High-productive contestants) t-1	(Private score - minimum private score)/ (Maximum private score - Minimum private score) Normalizing the score results in a value range between (0,1)	(Jain and Deodhar, 2022)
		(Team size) t-1	Number of members in the team of which the contestant is part	(Loh and Kretschmer, 2022)
		(Parallel) t-1	Participation in parallel tournament (1 if the player participates in at least 1 of the parallel tournaments before entering the focal event (1 if at least one parallel tournament, 0 otherwise)	(Jain and Deodhar, 2022)

Declaration

All authors hereby declare that they have no conflicts of interest.

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