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Zero is hero: Round number effects on knowledge-sharing platforms

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A R T I C L E I N F O

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A B S T R A C T

With the inherent public goods problem embedded in knowledge-sharing platforms, various incentive mechanisms have been implemented, most of which are in the form of gamified elements. Among those motivating elements, reputation points are the most direct feedback about individuals' contribution effort, which use numerical units indicating progress. Although some research has found that points can incentivize users to contribute, empirical evidence regarding the influential patterns of such numerical units remains limited. Drawing on numerical cognition literature that an individual's evaluation and judgments may be influenced by certain numerical cues, we particularly focus on the round number bias on knowledge-sharing platforms. Several hypotheses regarding users' behavioral changes when their accumulated points approach round numbers have been proposed, including their contribution level, contribution quality, and writing style. By analyzing data collected from StackOverflow.com, we find that users perceive round numbers as category boundaries or endpoints and crossing such boundaries can motivate aspirational behaviors. Concretely, users significantly increase their post frequency and length, and write answers with more function words and second-person pronouns. Meanwhile, their posts will be more likely to be accepted as the best answers and gain more votes. We also explore the moderating effects of advanced explicit incentives and numbers' magnitude. Theoretically, our research contributes to a body of literature on knowledge-sharing platform incentive mechanisms to motivate users' contributions and sheds light on the utilization of numerical cues to guide individuals' behaviors in user-generated-content (UGC) provision context.

1. Introduction

Knowledge-sharing websites such as StackOverflow, Zhihu, and Quora have been widely recognized as effective and favorable platforms that facilitate knowledge seeking, creative content providing, and social bonding [1,2]. In most cases, the generated contents are freely available to all users—they do not need to exert much effort to enjoy the contributions of others. Hence, the knowledge-sharing platforms share some inherent public goods problems such as free-riding and undersupply [3]. In addition, such platforms heavily rely on users' voluntary contributions, further exacerbating the impact of these problems. Without proper incentive or intervention, voluntary contributions may begin relatively high but tend to gradually decay thereafter [4,5].

To mitigate the natural decay phenomenon, various incentive mechanisms have been designed on these platforms, mostly through gamified elements such as points, badges, ranks, status, and leaderboards [1,6]. All these elements provide timely feedback about where the individual stands and how he or she is doing [7], which not only provide external incentives but also play an important role in users' self-evaluation processes [8]. It is well-established that these simple feedback-based interventions are of great value in facilitating effort across various settings including our context (i.e., user-generated-content) [7,9–11]. Nevertheless, there is still a lack of clarity around what the influential patterns are on individuals' behaviors across various dimensions, as well as the underlying mechanisms driving these patterns.

Among those motivating elements, reputation points, which use numerical units to indicate progress, are the most straightforward feedback about individuals' contribution effort. The majority of the other gamified elements are designed on the basis of points. For example, once the individuals accumulated a sufficient number of points, their ranks/status on the site will be elevated from "regular member" to higher levels such as "master"; leaderboards display the ranks of points for comparison [12]. Extant research mostly focuses on the more advanced incentive elements with explicit benefits for users, such as badge systems [1,6,12], peer awards [13], and hierarchical

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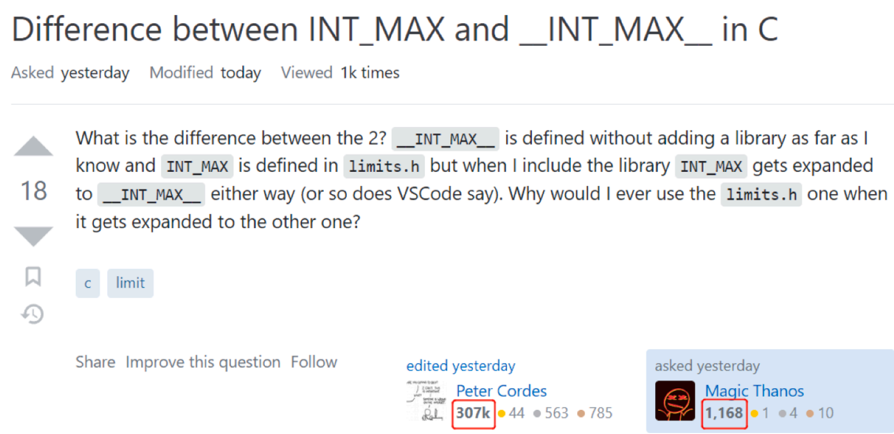

Fig. 1. An Example of Q&A Page on StackOverflow.com.

ranks [3], paying little attention to the intermediate agent: points. Though it may be obvious that the presence of points, as a simple feedback information, can increase users' contribution motivation (i.e., with points information vs. without points information), it remains unexplored how the numerical values of points influence users' behavior. The literature has revealed that different numerical cues may affect people's judgments and evaluations in different ways [8]. In our context, this raises an array of important research questions—for instance, what are the influential patterns with the accumulation of points? Are there any special numbers that have prominent motivating effects?

Fig. 1 presents a typical Q&A page on StackOverflow.com where a brief profile of the questioner is displayed on the bottom right corner. We can see that the reputation point is one of the most prominent information in the presented profile, which uses numerical units to indicate progress. In this research, we focus on a hitherto unexplored aspect (i.e., the impact of round numbers in the process of gaining reputation points). Round numbers refer to digital values ending with zero or more zeros in a given base [8], and to deem a value as a round number, the length of trailing zeros usually depends on the context and value range. For example, an integer (e.g., 2) is sometimes considered a round number when compared with decimals; numbers that are powers of 10 (i.e., 1000) are better round number options when the data allow integers only and span a wide range. In our research context, we use the multiple of 1000 points as our definition of round numbers. Round number bias generally exists—we tend to aim for a score of 90 out of 100 on examinations, donate 50 or 100 dollars to a crowdfunding project, and try to complete 10 or 20 laps while running. On a numerical scale, round numbers have long been recognized as cognitive reference points [14]. They can also be used as goals in subjective judgments, thereby affecting human behavior. Psychologists believe that people with certain evaluative metrics just below the round number are more likely to exert more effort than the case just above the round number [15]. With very few studies in Information Systems (IS) literature investigating the effect of numerical cues on knowledge-sharing platforms, we are particularly interested in the following research questions:

(1) How do users change their contribution behaviors when their reputation points are close to a round number, including contribution level, contribution quality, and writing style?
(2) If the round number effects exist, how do the more advanced explicit gamified incentives built upon points interact with the round number to influence user behaviors?
(3) What's the role of round-number magnitude?

Compared with the well-explored gamified incentive elements such as badges [1,3,6,12], round number effect induced by points possesses several unique features that make it a worthwhile endeavor to study the round number effect on users' content contribution behavior, despite some apparent similarities. First, the non-point elements (e.g., badges or rewards) have well-defined goals that are clearly specified in terms of what tasks need to be done to achieve the badges or rewards [16]. However, there is no clear goal for accumulating points. Round numbers may serve as invisible goals guiding users' behaviors, but they are not pre-defined and can only be internalized by users themselves. Second, the non-point elements generally measure users' efforts over a period of time (e.g., users' rank will be elevated to a higher status once a sufficient level of content is contributed) or award them for certain types of behaviors (e.g., users can obtain an "Adventurer" badge in Foursquare for checking into 10 different venues), whereas points capture the very granular information and enable precise measurement of user actions and performance [7]. Third, the badges/rewards/status/ranks are designed with limited quantities (e.g., 10 different types of badges), whereas the number of points that a user can accumulate is infinite. Fourth, it will be progressively more difficult to achieve a higher rank or status [3,12], for example, the thresholds of points for higher ranks increase exponentially [12]. On the contrary, the round numbers of points can be achieved in a linear process (e.g., 1000, 2000, and 3000 points). Finally, the non-point elements endow users with explicit benefits such as glory, honor, privilege, visual tokens, and tangible items [3,6]. But the points are just simple feedback for an individual's progress, and users are not entitled to any benefits unless the value coincidentally reaches a threshold for obtaining a higher status or a badge.

Given these distinctions, we believe it is essential and necessary to fill the research gap that how the numerical values of accumulated points, particularly round numbers, affect users' contribution behaviors on knowledge-sharing platforms. To systematically answer the proposed questions, we construct a panel dataset with 1873 users and 99,269 weekly observations on StackOverflow.com to analyze users' behavioral changes as they approach the round numbers from below. To measure the three types of behaviors, we use two indicators for each of them: post frequency and average post length are for contribution level; the ratio of best answers and average votes received for contribution quality; mean values of function words ratio and post attentional focus for writing style. Then, we develop three hypotheses to explore the round number effect, its interaction with explicit incentive, and the marginal effect. A two-way fixed effects model is then applied to empirically test these hypotheses with a one-year panel dataset. Our investigation yields several interesting findings. First, when users' reputation points approach a round number from below, they significantly increase their post frequency and length, and write answers with more function words and second-person pronouns. Meanwhile, their posts will be more likely to be accepted as the best answers and gain more votes; Second, the effect of round numbers will be strengthened when it overlaps with some explicit benefits such as reaching a round number can unlock a certain privilege; Third, the marginal effect of round numbers will decrease as a consequence of the smaller perceived extent of an improvement given the same level of effort.

The rest of the paper proceeds as follows. We first review related literature and develop our research hypotheses in Sections 2 and 3, respectively. Then, we introduce the data collection details, measurements of the main variables, and the model specifications in Section 4. Section 5 describes the estimation results, several robustness checks, and a post hoc experimental study. Section 6 concludes the paper.

2. Literature review

2.1. Knowledge-sharing platforms

The round number effect on knowledge-sharing platforms we study is an exploration about how the numerical cues can motivate users to voluntarily contribute more and better contents. Thus, our work largely builds on and contributes to the research of user motivations and incentive mechanisms on knowledge-sharing platforms.

2.1.1. User motivations on knowledge-sharing platforms

Users voluntarily participate in activities on knowledge-sharing platforms to derive social value or personal fulfillment [17]. Based on the social exchange theory, by helping other members of the community, users can gain social value [18]. The reason for users' contribution may also be the pursuit of a good self-image, such as being perceived as a knowledgeable and helpful person [17]. Garnefeld et al. [18] suggest that the contribution behaviors may be driven by the passion and enjoyment that the activity provokes for users, or it may also be out of users' desire to gain recognition from others [19]. Chen et al. [1] argue that reciprocity is only effective in transiting users from low to medium motivation states, whereas peer recognition can promote all users to higher states. And self-image helps users in low and medium states move to higher states but shows no effect on users already with high motivation. Li et al. [20] put forward the concept of ex-ante and ex-post reciprocity, showing that helping others in anticipation of others' future help can be regarded as an investment, whereas helping others in the future to reciprocate the help received before is a kind of indebtedness.

2.1.2. Incentive mechanisms on knowledge-sharing platforms

Research has shown that platforms focusing on utilitarian knowledge-sharing are more difficult to sustainably survive than those focusing on hedonic knowledge-sharing [21]. To increase users' motivation to contribute more content, knowledge-sharing platforms have launched a variety of incentive mechanisms, such as free products [22], rebates [23], and gamified incentives including reputation points, badges, and levels [3,12,16,24,25]. Generally, these incentives can be divided into financial incentives and non-financial incentives. Financial incentives include monetary rewards, rebates, coupons, and so on [17]. Short-term financial incentives can increase the members' participation [18,26]. However, because of the crowding-out effect, these incentives will undermine active users' intrinsic motivation for goals in the long run [17,18]. Through research on Amazon.com, Qiao et al. [22] find that financial incentives will reduce users' effort, including the usefulness of reviews and lexical richness. Cabral and Li [23] carry out a series of experiments on eBay, which suggests that offering rebates in exchange for feedback will increase the valence of feedback and reduce the possibility of getting negative yet useful feedback from buyers.

In contrast with financial incentives, explicit normative incentives will reinforce rather than undermine the users' motivation [18]. The introduction of gamified elements has reduced the utilitarianism triggered by financial incentives to a certain extent. It not only ensures that active users contribute based on their intrinsic motivation but also encourages some inactive users. Gamification incentives use elements drawn from game designs to increase motivation and participation in everyday tasks [7]. On knowledge-sharing platforms, gamified elements such as reputation points, badges, rankings, status, and votes are used to represent users' prior experience on platforms [6]. Voting is believed to directly influence users' willingness to contribute [21], which is an effective way to gain points. Badges are visual icons signifying achievements and commonly in the form of a hierarchy system. They are often perceived as good signals for the contributor's ability and usefulness of the content, thus leading to their behavioral changes [3,6]. Similarly, a user's rank on the platform will be elevated to a higher level once a sufficient number of points are accumulated [3,12]. The thresholds of points for higher ranks or badges generally increase exponentially [12], making it progressively more difficult to level up.

In summary, most of the gamified incentives are either intermediaries to gain points (such as votes) or designed on the basis of point accumulation (such as badges, status, and ranks), suggesting that reputation points are the most direct and precise feedback about individuals' progress and achievements. In particular, the point-based system uses numerical values to keep a record of individuals' progress. Although it has been acknowledged that the presence of points, as simple feedback information, can increase users' contribution motivation, it remains unexplored how the numerical patterns of points influence users' behavior. Actually, there is little research investigating the role of numerical cues in incentivizing users' voluntary contribution behaviors on knowledge-sharing platforms.

2.2. Use of round-number and its effects on individual behaviors

Much research on psychology literature has long recognized that the properties of numerical information can affect an individual's evaluation and judgments [8], such as financial decision making [27] and product evaluations [28]. An uncontroversial finding is that people perceive and react differently to round vs. precise numbers. In a given context, round numbers end with more zeros, compared with precise numbers that end with fewer zeros or no zeros [29,30].

People tend to adopt round numbers as reference points to reduce cognitive efforts in decision making, especially under uncertainty [31]. This is usually referred to "round-number bias" or "round-number heuristic" [32,33]. For example, Johnson et al. [34] collect data from the CRSP[1] dataset for clustering exploration and find that stock prices cluster on prices ending with 0, and to less prominent round numbers such as prices ending with 5. Hervé and Schwienbacher [31] find that when facing uncertainty, investors are more likely to invest with the amount being round numbers in equity crowdfunding campaigns, and the greater the uncertainty, the higher the round degree. In addition, the use of round numbers as anchors or reference points can sometimes motivate goal-directed behavior. For example, school students are more likely to retake the SAT examination when their score is just below a round number than if their score is a round one [35]. This indicates that round numbers may be perceived as boundaries of a desired level of performance [30]. However, the overuse of round numbers may represent a lack of information and a limitation of cognition. For instance, Lin and Pursiainen [36] suggest that a round campaign goal leads to a lower likelihood of success in entrepreneur crowdfunding. Similarly, Kuo et al. [33] find that investors with lower cognitive abilities, defined as higher limit order submission ratios at round numbers, suffer greater losses in their limit orders. More generally, when making numerical forecasts, researchers believe that people with low IQ tend to report round numbers [37].

Another stream of research tries to investigate what signals the round number represents to better understand why it may affect an individual's perception and behavior (e.g., [29,38]). Shoham et al. (2018) [29] indicate that round numbers are usually perceived as category boundaries or endpoints. Crossing such round-number category

[1] The Center for Research in Security Prices (CRSP) is a provider of historical stock market data.

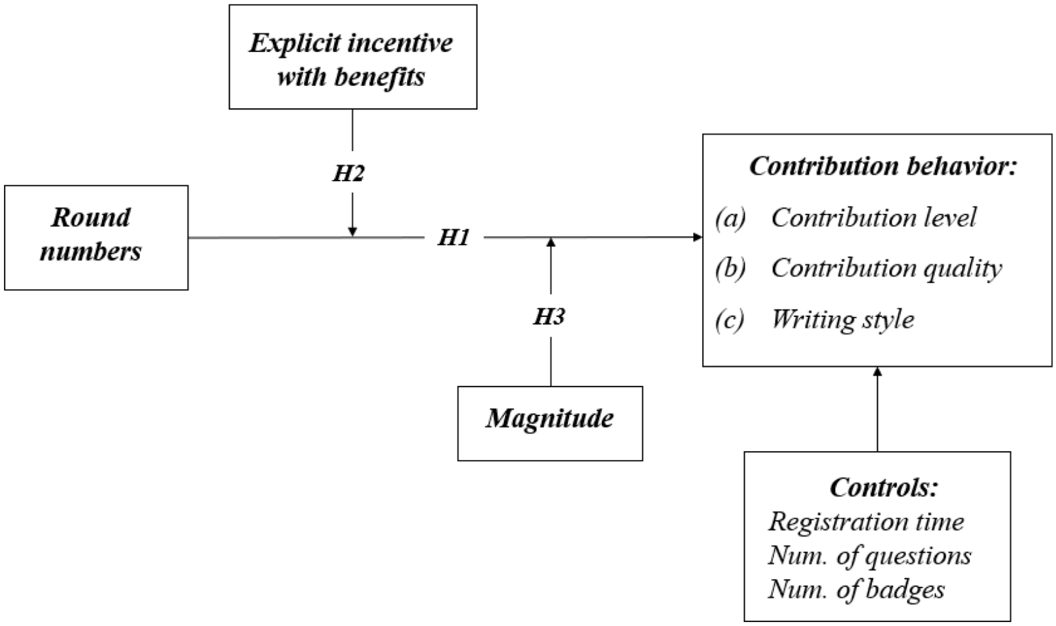

Fig. 2. Research Model.

boundaries can enhance the perceived magnitude of a change [29,30], thus motivating aspirational behavior [38,39]. This phenomenon is also explained by the "left-digit-effect" [30,32], that is, individuals process numerical values in left-to-right digit order, causing a biasing effect toward the leftmost digits. Thus, there is a major discontinuity in the evaluation of 0-ending numbers and 9-ending numbers next to it [8,40]. Some researchers argue that round numbers deliver a sense of stability [29,30], completion [41], or cognitive accessibility [42]. Specifically, Pena-Marin and Bhargave (2016) [43] find that consumers perceive energy drinks and pills with round-number doses as more effective than those with a more precise volume, as the round numbers tend to be perceived as more stable and beneficial. In rating systems of e-commerce, the thresholds for summary symbols assigned to sellers are often round numbers, and different symbols have significant effects on consumers' perception of sellers' performance because of their limited attention [44]. Yan and Pena-Marin [41] suggest that when negotiators subscribe to the association between round numbers and the feeling of completion, they are more willing to accept round offers. Pena-Marin and Bhargave [43] demonstrate that product characteristics described in round numbers (versus precise numbers) are perceived as performing for a longer time. One interesting finding is that when products or attributes are defined as feminine, marketing communications using round numbers lead to more favorable evaluations [45]. Wieseke et al. [42] challenge the traditional marketing belief that just-below prices are advantageous through four field experiments. They verify the superiority of round prices because round prices bring consumers high cognitive accessibility and convenience during transactions.

In summary, prior research about round-number bias largely focuses on marketing or finance. Individuals have the propensity to use round numbers as reference points when there is uncertainty associated with decision making, such as accepting or declining offers, evaluating a seller/product's performance, selecting between two options, and making investment decisions. The consequences of using round numbers are mixed, depending on the context. Our context (i.e., knowledge-sharing platform) is a public goods setting where individuals voluntarily contribute content without any uncertainty. It is still unclear and hence worth investigating whether the voluntary contribution behaviors (rather than decision making) would be driven by round number anchors. In addition, most numbers in existing research are clear and explicit goals. For example, consumers who are shopping will seek a cheaper price, and students taking an examination will strive for higher grades. But in our scenario, the essential goal of users on knowledge-sharing platforms is not to achieve certain reputation points; instead, their participation in the contribution is entirely voluntary. Considering that reputation points are not what they explicitly pursue, we aim to explore whether the implicit cues of round numbers will also affect users' behaviors.

2.3. Numerical cues in UGC provision

There have been a few studies examining the impact of numerical cues on individuals' perception in the UGC provision context. In online review sites, the most relevant research question is how the numerical cues affect review helpfulness [46–49]. Researchers classify the numerical cues of reviews into two categories (i.e., central route and peripheral route) based on the dual-process model and elaboration likelihood model [47,49]. Specifically, numerical cues in central route are those revealed by the review itself such as review ratings [50], word counts [48], and quantitative information about product attributes [46], whereas peripheral numerical cues refer to the context of reviews such as the number of friends and number of badges from the writer [47]. For instance, Zhu et al. (2014) [47] find that reviewer expertise (measured by number of "Elite" badges) and reviewer online attractiveness (measured by number of friends) both help a review receive helpfulness votes. Zhang et al. (2014) [49] discuss two types of review numerical indicators, that is, the quantity of reviews and the number of "medals" that the review contributor received. Empirical evidence shows that these numerical cues reflect the source credibility of reviews and hence positively affect argument quality, leading to higher purchase intentions of consumers. Li et al. (2022) [46] argue that reviews containing quantitative information (i.e., numbers) are efficient in eliciting more precise, persuasive, and unequivocal meanings, and as a consequence, are perceived as more helpful than those that are purely qualitative. Another related research is from Pötzsch et al. (2010) [51] that uses cues-filtered-out theory to study online forum users' privacy-awareness behavior. A socially connected forum is also a typical voluntary contribution context in which personal data is mainly implicitly displayed in the user-generated content. This study finds that showing privacy-awareness information in the form of numerical values is more effective compared with the form of text in promoting users' privacy awareness, and as a result, affecting their self-disclosing behavior.

In summary, most of the research investigates the effect of numerical cues on UGC *readers'* perception (e.g., perceived review helpfulness), with only very few studies from the perspective of UGC *contributors* [51]. More specifically, there is a significant gap in understanding how the round numbers embedded in feedback information impact contributors' behavior.

3. Hypotheses development

Fig. 2 presents the proposed research model. "Round numbers" is one type of numerical cues embedded in the accumulated points. The explicit incentive with benefits is the non-point gamified elements on the platforms that generally endow users with explicit benefits such as glory, tangible items, or privilege. This paper aims to study how users' contribution behavior changes in response to a round number. Particularly, we assess users' contribution behavior changes in terms of contribution level, contribution quality, and writing style, each of which functions as an essential part and has been explored in prior studies [11,13,20,25,52]. First, contribution level measures the user engagement that explains users' contribution intentions to promote communities [53]. It is a straightforward dimension to quantify the users' contributions from the knowledge *creators'* perspective. Second, contribution quality examines how knowledge seekers evaluate and adopt knowledge [54]. In this sense, it quantifies users' contributions from the knowledge *seekers'* perspective. Third, in the context of knowledge-sharing platforms, textual features are essential complements to numeric ones. They offer intrinsic information about the posts provided by users and are more granular than their numeric counterparts. Consequently, we take the third dimension (i.e., writing style) to extract the embedded information of textual contents in posts.

In this section, we will develop research hypotheses from three aspects: (1) the effect of round numbers on users' contribution behaviors; (2) the role of explicit incentives with benefits; and (3) the marginal effect of round numbers (i.e., magnitude).

3.1. Round number effect and users' contribution behavior

Humans heavily rely on cognitive convenience when making decisions or processing information [55]. Reliance on round numbers is a common cognitive limitation [14] because of their prevalent use in everyday communication [30]. Specifically, round numbers are very important cognitive reference points, which will bring consumers the cognitive bias of stability and lasting performance [43]. For example, investors in financial markets have a tendency to over-buy or over-sell at specific round-number prices [32]. People strive to reach round thresholds such as a round SAT score [35]. This so-called "round-number bias" [32] or "round-number heuristics" [33] is considered to be induced by the "left-digit-effect," that is, individuals tend to evaluate numbers sequentially starting from the left-most digits first. This causes a major discontinuity in the evaluation of the 0-ending numbers and the 9-ending numbers next to it [30,40]. For instance, when facing a value of 2999 points, people tend to be anchored by the leading 2 and pay less attention to the ending 999; as a result, 2999 is perceived as significantly smaller than 3000. This can largely explain the common use of retail prices ending with 9 [8].

In this regard, round numbers are usually perceived as category boundaries or endpoints [29]. Crossing such round-number category boundaries can enhance the perceived magnitude of a change [29,30,56], thus motivating aspirational behavior [38,39]. For example, Pope and Simonsohn (2011) [35] carry out an experiment and find that people will exert more effort when their performance is just below a round number rather than just above or far below a round number. This indicates that round numbers may be perceived as boundaries of a desired level of performance [30]. On knowledge-sharing platforms, users gain points by actively contributing more and higher quality content, in which case points serve as the most direct feedback about their efforts and performance. A round-number performance may therefore be seen as personally meaningful and encourage users to reflect on their own progress and achievements [8,38]. Thus, when the accumulated points approach round numbers from below, users on knowledge-sharing platforms experience enhanced motivation to initiate goal-pursuit behavior—they exert more effort to gain additional reputation points to reach the nearest round number (e.g., 100/1000/10,000) as soon as possible. Hence, we hypothesize:

H1: When users' reputation points approach a round number from below, the users will change their contribution behaviors.
H1a: When users' reputation points approach a round number from below, the users will increase their contribution level. Specifically, their post frequency will be higher, and the post length will be longer.

By using the nearest round-number level as an anchor, users change their contribution behaviors to accumulate more points and cross the round-number category boundary. Compared with the quantity of contents, the quality of contents is usually deemed as more determinant in obtaining points [57], and more important to the sustainable development of a platform. Chen et al. [1] find that low-quality contents are far more harmful to the platform than free-riding. The point is, if answerers pursue quantity only and ignore quality, they will not only fail to meet the needs of questioners but also bring serious information-overloading problems. Fang et al. [58] find that after the release of the reward program, the quality of user-generated content on Lvmama.com improves. Motivated by specific goals, users should contribute higher quality content [59]. In this sense, their answers are more likely to be accepted as the best answers by the questioner or favored by other users, earning them more points to reach the round goal as quickly as possible. Therefore, we propose the hypothesis:

H1b: When users' reputation points approach a round number from below, the users will improve their contribution quality. Specifically, their answers will be more likely to be accepted as the best answers and get more votes.[2]

Users' linguistic style of writing online textual contents serves as a signal to reflect their personalities [60] and intentions [61]. For instance, on product review websites, as users become more popular, the reviews written by them tend to be more objective in reducing the use of emotional words and stabilizing the readability, which will make them look like an authority [52]. When users have an urge to earn reputation points to reach a round number, they may change their writing style. Users tend to polish their words to make their answers more competitive among those homogeneous ones. To gain more reputation points, some users may even respond to questions that they are not sure about the real answers. Eager to be recognized by others, they may feel a decreased sense of autonomy [22] and may be compelled to write answers that lead to desirable consequences, such as receiving more positive votes or being accepted as the best answer. In our research context, we explore how users aim to enhance the comprehensibility of their post texts by considering the density of function words and the level of attentional focus. However, it is pertinent to note that we do not imply that writing style is confined solely to these two dimensions. Rather, we contend that users strive to improve their reputation points to reach a round number by modifying their linguistic style along these two aspects.

Prior research suggests that humans are highly attentive to the way how people organize words [62], with no exception for knowledge seekers on online knowledge-sharing platforms. Given the crucial role of function words in sentence structure [63], answerers may use a greater number of these words to refine their sentences and ensure clearer

[2] The votes here refer to the net value of upvotes minus downvotes.

communication. Doing this also reflects users' sophisticated social skills [62], which may arouse the questioner's intimacy and finally increase the possibility of earning reputation points. Hence, we hypothesize that users will post contents which contain more function words as their accumulated reputation points approach a round number from below.

Moreover, Lei et al. [64] argue that one's focus of attention on oneself or others plays a key role in social interactions. Prior research has shown that being considerate of others can increase an individual's willingness to help others [65] and facilitate prosocial behavior [66], which means shifting attention to others is beneficial for oneself [67]. In our context, when users post contents (i.e., answers) with their attention shifting from themselves to others, the questioner perceives strong empathy from the answerers, which will, in turn, make them regard the answers as more helpful. Thus, the possibility of being selected as the best answer will increase, leading to a higher chance to gain reputation points. Hence, we put forward the hypothesis:

H1c: When users' reputation points approach a round number from below, the users will change their writing style. Specifically, users tend to use more function words and their attentional focus will shift to others.

3.2. The role of explicit incentives with benefits

The round number effect that we focus on is induced in the process of accumulating reputation points. Because knowledge-sharing platforms generally design some non-point gamified elements on the basis of points [3], we are also interested in how these more advanced explicit incentive elements interact with the round number of points in influencing users' contributing behaviors. We refer to these non-point gamified elements as explicit incentives because they usually endow users with explicit benefits such as glory, honor, privilege, visual tokens, or tangible items [3,6]. On the contrary, the points are just simple feedback for an individual's progress, and users are not entitled to any benefit unless the value coincidentally reaches a threshold for obtaining a higher status or a badge. In addition, the non-point elements (e.g., privileges or rewards) have well-defined goals that are clearly specified in terms of what tasks need to be done to achieve the privileges or rewards [16], whereas there is no clear goal for accumulating points. Round numbers may serve as invisible goals guiding users' behaviors, but they are not pre-defined and can only be internalized by users themselves.

The explicit incentives with benefits are generally designed by requiring users to accumulate a sufficient number of points [12]. For example, after reaching specified points, users on StackOverflow.com can unlock a corresponding privilege (e.g., reaching 2000 points allows users to edit questions and answers). A similar mechanism also exists in Dianping.com,[3] where users can upgrade after accumulating a certain contribution value (e.g., 1000 points to upgrade to LV4). Coincidentally, the target points are often set as round numbers, resulting in the coexistence of explicit incentives and round numbers. Prior research has found that explicit non-financial incentives are effective in enhancing users' intrinsic motivation and improving their contribution performance [6,18,68]. According to the motivational intensive theory [69], individuals' goal commitment (i.e., the willingness to invest effort into the task) is positively correlated with the likelihood that successful performance on the task will achieve the desired motive (e.g., monetary incentives, prowess, "feeling good," or privilege) [9]. Thus, when crossing a round number of points is also accompanied by some explicit benefits, users' goal commitment will be strengthened because they can achieve both the desired level of performance [30] and the explicit benefit. Therefore, we propose the following hypothesis:

H2: The explicit incentives with benefits that are built on reputation points will positively moderate the effect of round numbers. When reaching the nearest round number can unlock a privilege, the effect of this round number will be stronger.

3.3. The marginal effect of round number

In numerical cognition literature, studies have demonstrated that the same unit difference is perceived as smaller when the numbers involved go larger [70]. Thus, when individuals' points approach round numbers from below, the perceived differences between the current values and the nearest round numbers depend on the order of magnitudes of the round numbers. For instance, the difference between 9990 and 10,000 will be perceived as smaller compared with the difference between 990 and 1000, even though the remaining distance to the objective (i.e., 10) is the same. This phenomenon can be largely explained by the psychological model of proportion judgment [71], which was originally developed for tasks involving judgments of perceptual magnitude. There is generally an estimation bias when individuals are required to estimate a smaller magnitude (the value presented) relative to a larger one (the value given at the upper endpoint)—that is, individuals tend to make a judgment of a numerical proportion rather than unbounded numerical magnitude [72]. In the example presented previously, the subjective proportional difference of (10,000–9990)/10,000 is much smaller than (1000–990)/1000 (i.e., 0.001 vs. 0.01). Similarly, Pandelaere et al. [70] use the logarithmic mental number account to explain the subjective proportional difference, that is, the logarithmic relation between numbers is $(\log(10{,}000)-\log(9990))/\log(10{,}000) \approx 0.0001 < (\log(1000)-\log(990))/\log(1000) \approx 0.001$.

On knowledge-sharing platforms, because the round number of reputation points represents a category boundary or endpoints [29], it is natural for users to make a proportional judgment when estimating their performance relative to the nearest round number. In this regard, crossing such category boundary becomes less attractive when the magnitude of the nearest round number progressively increases (e.g., from 1000 to 2000). This is because the perceived extent of an improvement is smaller and less meaningful, given the same level of effort (e.g., "from 1990 to 2000" vs. "from 990 to 1000"). Thus, the marginal effect of the round number decreases. It is expected that users will be less motivated by the round number with the accumulation of reputation points. Hence, we hypothesize that:

H3: The marginal effect of the round number is decreasing, that is, the larger the magnitude of a nearest round number, the weaker the incentive effect of this round number.

4. Research design

4.1. Data collection

Our research context is StackOverflow.com, one of the most popular community-based question and answer (Q&A) sites for programmers. StackOverflow.com was launched in 2008. It has attracted about 16 million users and accumulated more than 50 million posts, including about 20 million questions and more than 30 million answers with an answered rate of over 85% by November 2021. The platform built a reputation system in which its users can earn reputation points through active participation such as posting questions and answers and voting. By earning more reputation points, users are eligible to unlock advanced privileges. For example, reaching 1000 points will grant the user privilege of "creating gallery chat rooms."

Our data were collected in February 2021. We downloaded data about users' activities on StackOverflow.com, including all posts, votes, badges, and user public information, between December 23, 2019, and January 1, 2021, from https://data.stackexchange.com/. To ensure the sample of users is active and familiar with the rules of StackOverflow.

[3] Dianping.com is one of the largest urban life consumption guide websites in China. It is an information-sharing platform based on the model of tripartite reviews.

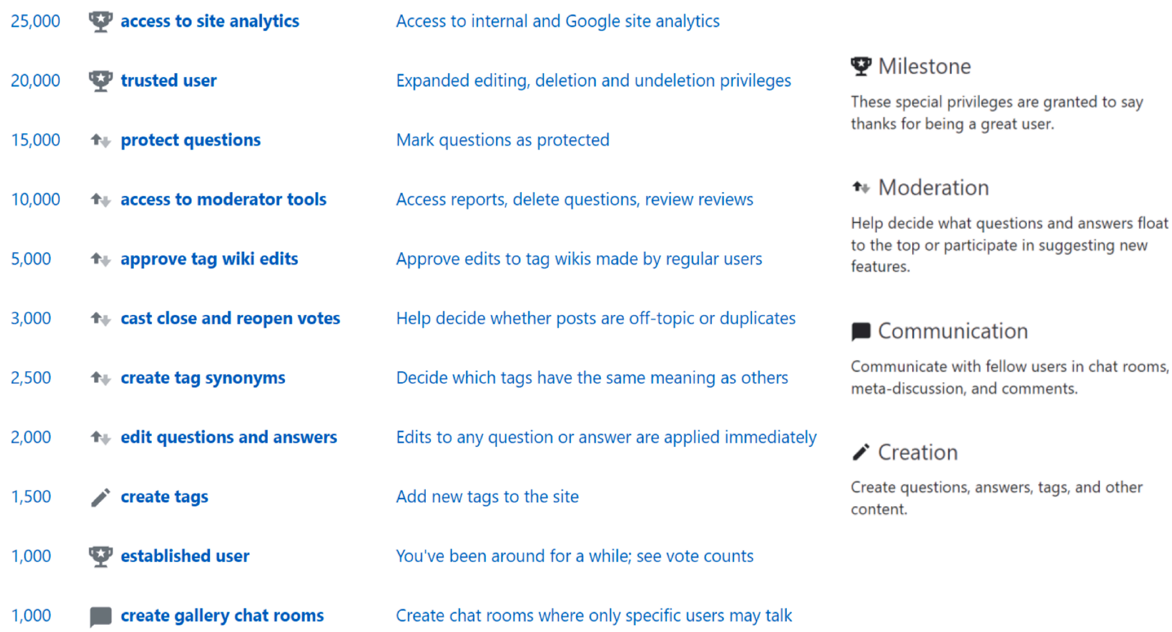

Fig. 3. The Co-existence of Round Number Cue and Explicit Privilege on StackOverflow.com.

com, we focus on the users who registered their accounts before January 1, 2019, and who have posted more than 10 times from January 4, 2021, to February 3, 2021.

Because the Stack Exchange database does not include the time series data of users' reputation history, we have to reconstruct such data. We crawled the total reputation and daily reputation changes from each user's homepage on StackOverflow.com. By adding and subtracting users' loss and gain over a time, we can reconstruct their reputation points on any given day.

Finally, we constructed a panel dataset in which each unit of observation is a user, and each period is one week. The dataset, therefore, contains weekly observations about each user over a total of 53 calendar weeks in 2020. It is worth noting that daily aggregation (e.g., [24]) and weekly aggregation (e.g., [3,20]) have been widely used in prior research. Because not all users contribute every day, we aggregated their contribution within one week to rule out the "day of the week" effect [20]. If we use each day as the data point, the panel dataset will be highly unbalanced [57]; a longer period may lead to excessive time loss between periods [20]. Hence, a week is a fairly reasonable time frame, and the resulting sample has 1873 users, with each user's activity grouped weekly over 53 weeks.

4.2. Main variables and summary statistics

4.2.1. Dependent variables

As mentioned previously, what we are interested in is the users' behavioral changes when their points approach the round numbers from below. Based on the proposed hypotheses, we measure users' behavioral changes in the following aspects: contribution level, contribution quality, and writing style. Accordingly, six dependent variables are developed: (a) post frequency, (b) average post length, (c) ratio of best answers, (d) average votes received, (e) mean value of function words ratio, and (f) mean value of post attentional focus.

(1) Contribution level. In our study, contribution level is defined as the users' effort to post [3]. To explore the level of effort that users exert, we develop two measurements by following prior studies [3,25], that is, post frequency and average post length. Specifically, we only consider *answers* posted by users, as this is the most common way to get reputation points.[4] Post frequency is defined as the number of answers that a user posts in each period (denoted as *Frequency*), no matter whether the answers are correct or not. And the average post length is calculated by dividing the total number of words by the number of posts in a week (denoted as *Avg_length*).

(2) Contribution quality. Contribution quality assesses the usefulness and helpfulness of the answers. The question's asker-based best answer and the audience-based most popular answer are the most frequently used measurements for content quality assessment [54]. Inspired by this, we adopt the ratio of best answers and average votes received to assess the contribution quality. Specifically, we measure the ratio of best answers by calculating the percentage of the total answers accepted as the best answer each week (denoted as *Bestanswer_ratio*). Referring to the rules of StackOverflow.com, the net value of votes received for a post is counted by subtracting the number of downvotes from the number of upvotes, which is then averaged on a weekly basis (denoted as *Avg_votes*). Further, we also calculate the answers' readability as an alternative measurement for contribution quality [73], and the results remain consistent. For conciseness, the details are presented in Appendix A.

(3) Writing style. Writing style describes the users' tendency of polishing words to make their answers more competitive. As mentioned previously, we consider two measurements for this construct, namely the average function words ratio (denoted as *Avg_function*) [74] and post attentional focus (denoted as *Avg_focus*) [64]. First, we use Linguistic Inquiry and Word Count (LIWC-22), a reputable dictionary that has been extensively adopted for linguistic analysis [74,75], to compute the density of

[4] In our sample, a total of 447,118 posts are made by users during the selected time window. Only 7,014 of these posts (1.57%) are "questions," and 439,629 of them (98.33%) are "answers."

Table 1
Description of Main Variables.

Variable type	Variable	Description	Mean	S.D.	Min	Max
Dependent variables	$Frequency_{i,t}$	Number of answers posted by user i during week t	4.306	10.914	0.000	307.000
	$Avg\_length_{i,t}$	Average number of words per post written by user i during week t	43.838	71.267	0.000	1806.500
	$Bestanswer\_ratio_{i,t}$	Ratio of answers accepted as best answers by user i during week t	0.247	0.329	0.000	1.000
	$Avg\_votes_{i,t}$	Average votes per post written by user i during week t	0.703	1.832	−4.000	347.000
	$Avg\_function_{i,t}$	Average ratio of function words per post used by user i during week t	0.283	0.274	0.000	1.000
	$Avg\_focus_{i,t}$	Average ratio of second-person pronouns per post used by user i during week t	0.372	0.403	0.000	1.000
Independent variables	$Round_{i,t}$	An indicator that equals to 1 if user i's reputation points are close to a round number during week t	0.069	0.254	0.000	1.000
	$Privilege_{i,t}$	An indicator that equals to 1 if user i reaches the round number can unlock a privilege during week t	0.477	0.499	0.000	1.000
	$Magnitude_{i,t}$	The value of the round number pursued by user i during week t	37,330.390	91,741.240	1000.000	1232,000.000
Control variables	$Tenure_{i,t}$	Number of days user i has been in the platforms until week t since registration	2225.967	1036.095	365.000	4527.000
	$Questions_{i,t\text{-}1}$	Number of questions posted by user i during week t-1	0.066	0.382	0.000	17.000
	$Badges_{i,t\text{-}1}$	Number of badges user i obtained during week t-1	0.462	1.218	0.000	45.000

function words. We begin by quantifying the ratios of nine categories of function words in each post, including personal pronouns, impersonal pronouns, articles, prepositions, auxiliary verbs, high-frequency adverbs, conjunction, negations, and quantifiers. The value of each category is then summed up to obtain a total percentage of function words in each post. Subsequently, these values are averaged across all the posts in a week for a given user. Second, referring to [64], we operationalize users' attentional focus based on their use of personal pronouns. Personal pronouns are a kind of common function words that do not convey substantive meanings [76]. Much research has revealed that the use of personal pronouns can reflect one's mental or social status [62,77]. Specifically, the use of these words indicates one's focus of attention [64]. More frequent use of first personal pronouns (e.g., "I," "me," "my") is related to an increased self-focus [78], and more frequent use of second personal pronouns (e.g., "you," "your") has been interpreted as indicants of other focus [79]. We quantify the appearance of first-person and second-person pronouns and calculate the ratio of second-person pronouns by the sum of first-person and second-person pronouns in each post that contains either type of personal pronouns [64]. Hereafter, the ratios of second-person pronouns are averaged for all the posts in a week to construct the measurement.

4.2.2. Independent variables and control variables

The main explanatory variable we are interested in is whether the user's reputation is close to a round number. We measure this using a dummy variable (denoted as *Round*). We choose the multiple of 1000 as the criteria of a round number, and the dummy variable *Round* equals 1 if the distance of a user's reputation points from its next closest round number is less than or equal to 100 points. Further, we also consider another measurement of the "round number," which is the actual difference between the user's current points and the nearest round number target (denoted as *Distance*). We will explore this alternative explanatory variable in our robustness checks.

To test our hypotheses H2 and H3, we construct another two explanatory variables, i.e., *Privilege* and *Magnitude*. The privilege mechanism is the most important explicit incentive on StackOverflow.com. Users with different privileges can engage in different activities on the platform, such as creating new chatting rooms, adding new tags to the site, marking questions as protected, and so on. Only by increasing the reputation points can users gain more privileges. The screenshot shown in Fig. 3 presents some of the rules to gain a privilege based on accumulative points, which illustrates the co-existence of round number cue and explicit privilege incentive. So, we develop a dummy variable, *Privilege*, to represent explicit incentives, which equals 1 if reaching a current round number can unlock a privilege. Another variable, *Magnitude*, indicates the magnitude of a round number. We will explore the interaction effects between *Round* and these two variables in the following sections.

We also include some users' characteristics as control variables, such as *Tenure* (number of days since registration), *Questions* (number of questions posted last week), and *Badges* (number of badges obtained last week). Table 1 summarizes the descriptive statistics of the main variables as well as the control variables.

4.3. Model specification

We use hierarchical ordinary least squares (OLS) regression analysis to test our hypotheses. To control for other potential factors that may have an impact on users' contribution behaviors, we build a fixed-effects model on our dataset. In Model (1), we test the main effect of the independent variable, *Round*. As the primary focus of this study, we further estimate the interaction effects between the independent variable and other two variables in Model (2) and Model (3), shown as follows:

$$\begin{gathered} DV_{i,t} = \alpha_0 + \alpha_1 Round_{i,t} + \alpha_2 Privilege_{i,t} + \alpha_3 \ln\left(Magnitude_{i,t} + 1\right) \\ + \alpha_4 \ln Tenure_{i,t} + \alpha_5 \ln\left(Questions_{i,t-1} + 1\right) + \alpha_6 \ln\left(Badges_{i,t-1} + 1\right) \\ + \mu_i + \varphi_t + \varepsilon_{i,t} \end{gathered} \tag{1}$$

$$\begin{gathered} DV_{i,t} = \beta_0 + \beta_1 Round_{i,t} + \beta_2 Round_{i,t} \times Privilege_{i,t} + \beta_3 Privilege_{i,t} \\ + \beta_4 \ln\left(Magnitude_{i,t} + 1\right) + \beta_5 \ln Tenure_{i,t} + \beta_6 \ln\left(Questions_{i,t-1} + 1\right) \\ + \beta_7 \ln\left(Badges_{i,t-1} + 1\right) + \mu_i + \varphi_t + \varepsilon_{i,t} \end{gathered} \tag{2}$$

$$\begin{gathered} DV_{i,t} = \gamma_0 + \gamma_1 Round_{i,t} + \gamma_2 Round_{i,t} \times \ln\left(Magnitude_{i,t} + 1\right) + \gamma_3 Privilege_{i,t} \\ + \gamma_4 \ln\left(Magnitude_{i,t} + 1\right) + \gamma_5 \ln Tenure_{i,t} + \gamma_6 \ln\left(Questions_{i,t-1} + 1\right) \\ + \gamma_7 \ln\left(Badges_{i,t-1} + 1\right) + \mu_i + \varphi_t + \varepsilon_{i,t} \end{gathered} \tag{3}$$

where i indexes the user and t indexes the week, and the left-hand side of the model refers to the six dependent variables introduced previously. μ_i denotes user-level fixed effect that controls the effect of all time-invariant individual heterogeneity of user i. φ_t denotes week-level fixed effect that accounts for any potential temporal shocks at the weekly level. $\varepsilon_{i,t}$ is the error term. α, β, and γ are the coefficients we try to estimate. Based on these formulas, we can estimate the effect of "round number" on contribution behaviors by examining the coefficients α_1. We are also interested in the coefficients β_2 and γ_2, which capture the interaction effects between "round number" and other variables.

Table 2
Estimation Results of Model (1).

Variable	Contribution level		Contribution quality		Writing style	
	Frequency	*Avg_length*	*Bestanswer_ratio*	*Avg_votes*	*Avg_function*	*Avg_focus*
Round	0.062***	0.123***	0.015***	0.008***	0.012***	0.017***
	(0.012)	(0.025)	(0.003)	(0.002)	(0.003)	(0.004)
Privilege	0.063***	0.069	0.010**	0.008**	0.008*	0.008
	(0.023)	(0.042)	(0.004)	(0.003)	(0.004)	(0.006)
Magnitude	0.309***	0.392***	0.065***	0.026***	0.043***	0.063***
	(0.049)	(0.069)	(0.008)	(0.006)	(0.007)	(0.010)
Tenure	−0.015	−0.307	−0.023	0.035*	−0.019	−0.030
	(0.135)	(0.232)	(0.024)	(0.019)	(0.025)	(0.032)
Questions	0.219***	0.494***	0.038***	0.023***	0.052***	0.052***
	(0.022)	(0.042)	(0.005)	(0.005)	(0.004)	(0.005)
Badges	0.227***	0.365***	0.033***	0.023***	0.039***	0.048***
	(0.012)	(0.019)	(0.002)	(0.002)	(0.002)	(0.003)
Constant	−1.991*	0.494	−0.262	1.046***	−0.073	−0.125
	(1.094)	(1.804)	(0.190)	(0.147)	(0.196)	(0.251)
User FE	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Num. of users	1873	1873	1873	1873	1873	1873
Num. of obs.	99,269	99,269	99,269	99,269	99,269	99,269
Adjusted R^2	0.346	0.319	0.253	0.206	0.323	0.274

*** $p<0.01$.
** $p<0.05$.
* $p<0.1$
Robust standard errors are in parentheses. FE, fixed effect.

Table 3
Estimation Results of Model (2).

Variable	Contribution level		Contribution quality		Writing style	
	Frequency	*Avg_length*	*Bestanswer_ratio*	*Avg_votes*	*Avg_function*	*Avg_focus*
Round	0.026**	0.051**	0.008**	0.003	0.004	0.008**
	(0.012)	(0.026)	(0.003)	(0.003)	(0.003)	(0.004)
Round × *Privilege*	0.136***	0.265***	0.025***	0.016***	0.031***	0.034***
	(0.032)	(0.070)	(0.007)	(0.006)	(0.008)	(0.010)
Privilege	0.050**	0.044	0.008	0.007*	0.005	0.005
	(0.023)	(0.042)	(0.005)	(0.004)	(0.005)	(0.006)
Magnitude	0.317***	0.406***	0.066***	0.027***	0.045***	0.064***
	(0.049)	(0.069)	(0.008)	(0.006)	(0.007)	(0.010)
Tenure	−0.022	−0.322	−0.024	0.034*	−0.021	−0.032
	(0.134)	(0.231)	(0.024)	(0.019)	(0.025)	(0.032)
Questions	0.219***	0.493***	0.038***	0.023***	0.052***	0.051***
	(0.022)	(0.042)	(0.005)	(0.005)	(0.004)	(0.005)
Badges	0.227***	0.364***	0.033***	0.023***	0.039***	0.048***
	(0.012)	(0.019)	(0.002)	(0.002)	(0.002)	(0.003)
Constant	−1.992*	0.492	−0.262	1.045***	−0.073	−0.125
	(1.090)	(1.798)	(0.190)	(0.147)	(0.196)	(0.250)
User FE	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Num. of users	1873	1873	1873	1873	1873	1873
Num. of obs.	99,269	99,269	99,269	99,269	99,269	99,269
Adjusted R^2	0.348	0.322	0.254	0.208	0.326	0.276

*** $p<0.01$.
** $p<0.05$.
* $p<0.1$
Standard errors are in parentheses.

5. Empirical results

5.1. *The round number effect on users' contribution behavior*

To test H1, we conduct OLS regression based on Model (1). Table 2 presents the regression coefficients and the standard errors in parentheses for six different dependent variables (i.e., *Frequency, Avg_length, Bestanswer_ratio, Avg_votes, Avg_function*, and *Avg_focus*). As presented in the first row, all the coefficients of the key independent variable *Round* are significant and consistent with our hypotheses, suggesting users' contribution behavior changes when their reputation points are approaching a round number.

Particularly, as shown in columns (1) and (2) of Table 2, the post frequency and average post length significantly increase when the "round number effect" occurs, thus supporting H1 (a). The coefficients of *Round* are 0.062 and 0.123, respectively, both of which are positive and significant at the 0.01 level. This indicates that when users' reputation points are close to a round number, their contribution levels will increase such that they will make efforts to answer more questions as well as write longer answers. Regarding the contribution quality, we can see the coefficients in columns (3) and (4) are 0.015 and 0.008, respectively (p value < 0.01). This indicates round numbers will motivate users to contribute higher quality contents. Thus, H1 (b) is supported, suggesting answers contributed by users closer to the round number will be more likely to be accepted as the best answers and receive more votes. Regarding writing style, the results are shown in

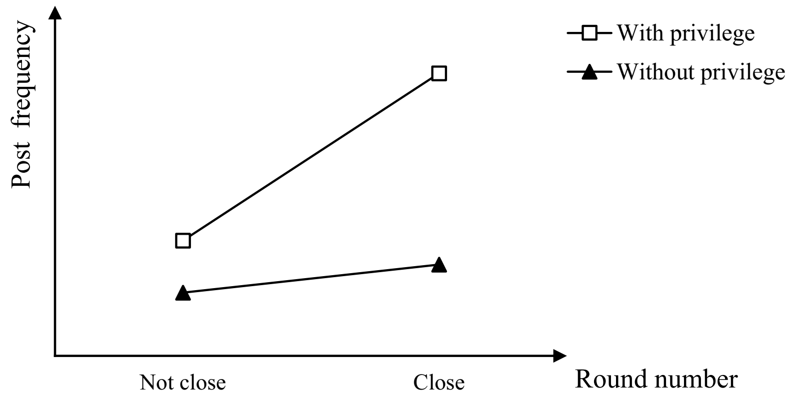

Fig. 4. The Moderating Effect of Explicit Incentives with Benefits.

Table 4
Estimation Results of Model (3).

Variable	Contribution level *Frequency*	*Avg_length*	Contribution quality *Bestanswer_ratio*	*Avg_votes*	Writing style *Avg_function*	*Avg_focus*
Round	0.095***	0.179***	0.021***	0.011***	0.019***	0.025***
	(0.015)	(0.034)	(0.004)	(0.003)	(0.004)	(0.005)
Round × *Magnitude*	−0.044***	−0.074***	−0.009***	−0.004***	−0.009***	−0.010***
	(0.008)	(0.016)	(0.002)	(0.001)	(0.002)	(0.002)
Privilege	0.063***	0.070*	0.010**	0.008**	0.008*	0.008
	(0.023)	(0.042)	(0.005)	(0.003)	(0.004)	(0.006)
Magnitude	0.324***	0.416***	0.067***	0.027***	0.046***	0.066***
	(0.049)	(0.069)	(0.008)	(0.006)	(0.007)	(0.010)
Tenure	−0.022	−0.320	−0.024	0.034*	−0.020	−0.031
	(0.134)	(0.231)	(0.024)	(0.019)	(0.025)	(0.032)
Questions	0.219***	0.493***	0.038***	0.023***	0.052***	0.051***
	(0.022)	(0.042)	(0.005)	(0.005)	(0.004)	(0.005)
Badges	0.226***	0.364***	0.033***	0.023***	0.039***	0.048***
	(0.012)	(0.019)	(0.002)	(0.002)	(0.002)	(0.003)
Constant	−2.060*	0.378	−0.275	1.039***	−0.086	−0.140
	(1.091)	(1.799)	(0.190)	(0.147)	(0.196)	(0.251)
User FE	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Num. of users	1873	1873	1873	1873	1873	1873
Num. of obs.	99,269	99,269	99,269	99,269	99,269	99,269
Adjusted R^2	0.348	0.322	0.254	0.208	0.326	0.276

*** $p<0.01$.
** $p<0.05$.
* $p<0.1$
Robust standard errors are in parentheses. FE, fixed effect.

columns (5) and (6), and the coefficients of the key independent variable are 0.012 and 0.017, respectively (p value < 0.01), which provide evidence that users' writing style significantly changes. Specifically, as users' accumulated reputation points approach a round number, they tend to use more second-person pronouns and function words in their answers, which makes them appear more friendly and their answers easier to process. Hence, H1 (c) is supported.

The regression results of the three control variables are also presented in Table 2. The estimated coefficients of control variables such as *Questions* and *Badges* also offer some interesting insights. With all else being equal, users who asked more questions in the last period are likely to increase their contribution level (or quality) and change their writing style. Also, users who received more badges in the last period are more likely to exhibit these behavioral changes.

5.2. The role of explicit incentives with benefits

We present the estimation results of Model (2) in Table 3, which aims at testing our hypotheses about the interaction between the numerical cue (i.e., the round number) and the explicit incentive with benefits (i.e., the privilege). From Table 3, we can see the coefficients of interaction terms *Round* × *Privilege* on six dependent variables are all positive and statistically significant, which supports H2. Generally, this result suggests when the round number of accumulated points overlaps with an explicit benefit (e.g., privilege), its positive effects on users' behavior will be strengthened.[5] We also conduct further analyses to see whether different forms of privilege exert different degrees of influence on users' behaviors, and the results are presented in Appendix B.

In Fig. 4, we take *Frequency* as an example of the dependent variables to visualize the interaction between round numbers and explicit incentives with benefits (i.e., privilege). The slope of the line for users motivated by explicit privilege is steeper than the line for users not being motivated by explicit privilege. This illustrates that round numbers have a greater impact on users being motivated by explicit privilege at the same time than those not in terms of post frequency.

[5] Note that we should not interpret the p value of the main effects (i.e., coefficients of *Privilege*) if the interaction has a significant p value [82].

Table 5
Robustness I: Results of Model (4).

Variable	Contribution level		Contribution quality		Writing style	
	Frequency	*Avg_length*	*Bestanswer_ratio*	*Avg_votes*	*Avg_function*	*Avg_focus*
Distance	−0.032***	−0.051***	−0.006***	−0.003***	−0.006***	−0.007***
	(0.005)	(0.009)	(0.001)	(0.001)	(0.001)	(0.001)
Privilege	0.064***	0.070*	0.010**	0.008**	0.008*	0.009
	(0.023)	(0.042)	(0.005)	(0.003)	(0.004)	(0.006)
Magnitude	0.327***	0.417***	0.067***	0.027***	0.046***	0.066***
	(0.050)	(0.069)	(0.008)	(0.006)	(0.007)	(0.010)
Tenure	−0.031	−0.332	−0.025	0.034*	−0.022	−0.033
	(0.134)	(0.231)	(0.023)	(0.019)	(0.025)	(0.032)
Questions	0.219***	0.493***	0.038***	0.023***	0.052***	0.051***
	(0.022)	(0.042)	(0.005)	(0.005)	(0.004)	(0.005)
Badges	0.226***	0.364***	0.033***	0.023***	0.039***	0.048***
	(0.012)	(0.019)	(0.002)	(0.002)	(0.002)	(0.003)
Constant	−1.824*	0.775	−0.230	1.061***	−0.042	−0.084
	(1.083)	(1.793)	(0.189)	(0.146)	(0.195)	(0.249)
User FE	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Num. of users	1873	1873	1873	1873	1873	1873
Num. of obs.	99,269	99,269	99,269	99,269	99,269	99,269
Adjusted R^2	0.349	0.324	0.254	0.209	0.323	0.277

*** $p<0.01$.
** $p<0.05$.
* $p<0.1$
Robust standard errors are in parentheses. FE, fixed effect.

Table 6
Estimation Results of Model (5).

Variable	Contribution level		Contribution quality		Writing style	
	Frequency	*Avg_length*	*Bestanswer_ratio*	*Avg_votes*	*Avg_function*	*Avg_focus*
After	−0.098***	−0.204***	−0.016***	−0.012***	−0.023***	−0.027***
	(0.015)	(0.030)	(0.003)	(0.002)	(0.003)	(0.004)
Privilege_after	−0.048**	−0.034	−0.011**	−0.006*	−0.004	−0.005
	(0.024)	(0.038)	(0.005)	(0.004)	(0.004)	(0.005)
Magnitude_after	0.072***	0.109***	0.014***	0.007***	0.012***	0.016***
	(0.009)	(0.014)	(0.001)	(0.001)	(0.001)	(0.002)
Tenure	−0.092	−0.485**	−0.033	0.022	−0.038	−0.051*
	(0.130)	(0.221)	(0.023)	(0.018)	(0.024)	(0.030)
Questions	0.215***	0.486***	0.037***	0.023***	0.051***	0.050***
	(0.021)	(0.041)	(0.005)	(0.005)	(0.004)	(0.005)
Badges	0.224***	0.360***	0.033***	0.023***	0.038***	0.047***
	(0.012)	(0.019)	(0.002)	(0.002)	(0.002)	(0.003)
Constant	0.918	4.679***	0.305*	1.327***	0.390**	0.500**
	(0.973)	(1.644)	(0.172)	(0.135)	(0.177)	(0.227)
User FE	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Num. of users	1873	1873	1873	1873	1873	1873
Num. of obs.	99,269	99,269	99,269	99,269	99,269	99,269
Adjusted R^2	0.344	0.296	0.253	0.204	0.328	0.277

*** $p<0.01$.
** $p<0.05$.
* $p<0.1$.
Robust standard errors are in parentheses. FE, fixed effect.

Table 7
Mean (SD) Answer Length in Each Group.

	Treated group	Control group	*p* value
All	118.850 (111.680)	84.550 (49.703)	0.002***
Round 1	108.120 (101.869)	76.430 (40.004)	0.064*
Round 2	147.670 (132.141)	104.520 (66.075)	0.061*
Round 3	100.770 (94.178)	72.690 (30.743)	0.070*

Notes: "All" denotes the aggregated data; "Round 1," "Round 2," and "Round 3″ denote the observations for each round of the task. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

5.3. The marginal effect of round number

In line with H3, there is a significant interaction effect between the round number and its magnitude, which can be supported by the coefficients of the interaction term in Table 4. As reported in Table 4, the coefficients of the interaction term are all negative. Considering the positive main effect of round numbers, this suggests that the influence of round numbers decreases with the increase of magnitude. That is to say, the marginal effect of round numbers is decreasing. For users with a smaller magnitude of round-number goal, when they approach a round number from below, they are relatively more likely to change their contribution behaviors (i.e., contribution level, contribution quality, and writing style). However, as the magnitude enlarges, the round number effects on users will decrease accordingly.

Table A1
Results of Contribution Quality Analysis: Readability.

Variable	Readability GFI	SMOG
Round	0.202**	0.220***
	(0.083)	(0.050)
Privilege	0.187	0.041
	(0.138)	(0.070)
Magnitude	1.133***	0.442***
	(0.233)	(0.115)
Tenure	−0.570	−1.060***
	(0.768)	(0.369)
Questions	1.335***	0.654***
	(0.140)	(0.080)
Badges	1.036***	0.444***
	(0.063)	(0.036)
Constant	−0.514	6.363**
	(6.084)	(2.882)
User FE	Yes	Yes
Week FE	Yes	Yes
Num. of users	1873	1873
Num. of obs.	99,269	99,269
Adjusted R^2	0.259	0.105

Robust standard errors are in parentheses. FE, fixed effect. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

This can be explained that users' subjective proportional difference of large round numbers is much smaller than that of small round numbers. Compared with approaching round numbers of small magnitude, the perceived extent of an improvement becomes smaller when users attain a larger round-number goal, which in turn weakens users' motivation to contribute. As discussed previously, we can see in the second row of Table 4 that the coefficients of *Round* × *Magnitude* are all statistically significant. Hence, H3 is supported.

5.4. Robustness checks and additional analyses

Our main analyses thus far have consistently shown the effects of incentives with round numbers on a series of contribution behaviors such as contribution level, contribution quality, and writing style. To validate our results and dig deeper into the patterns of round number effect, we next conduct several additional data analyses.

5.4.1. Alternative independent variable: distance

In our main analysis, we measure the key independent variable using the status of whether the user's reputation points are close to a round number or not, which is a binary indicator. Because it only tells the difference between the two states of a user, a more precise measurement is taken into consideration in this subsection; this is defined as the distance between their current reputation points and the nearest upcoming round-number goal. This allows us to quantify the changes in users' behavior as the distance to goals shortens. To test whether our main results are robust under this alternative measure, we modify Model (1) in the following way:

$$\begin{aligned} DV_{i,t} = {} & \alpha_0 + \alpha_1 \ln\left(Distance_{i,t}+1\right) + \alpha_2 Privilege_{i,t} + \alpha_3 \ln\left(Magnitude_{i,t}+1\right) \\ & + \alpha_4 \ln Tenure_{i,t} + \alpha_5 \ln\left(Questions_{i,t-1}+1\right) + \alpha_6 \ln\left(Badges_{i,t-1}+1\right) \\ & + \mu_i + \varphi_t + \varepsilon_{i,t} \end{aligned} \tag{4}$$

The result of Model (4) is shown in Table 5. The coefficients of the new independent variable *Distance* on all dependent variables are negative and statistically significant at the 0.01 level, which suggests that users will change their behaviors when they are approaching the nearest round number. Taking contribution level as an example, as the distance from the users' current points to the round-number goal shortens, they will increase their post frequency in the next week, and the average post length will also be increased. Similarly, contribution quality will be improved and writing style will be changed. In addition, the results for interaction effects (i.e., H2 and H3) are also consistent with the main findings, which are reported in Appendix C. Hence, the estimation results lend support to the robustness of our main findings.

Table B1
Moderating Effects of Different Privileges.

Variable	Contribution level *Frequency*	*Avg_length*	Contribution quality *Bestanswer_ratio*	*Avg_votes*	Writing style *Avg_function*	*Avg_focus*
Round	0.023*	0.046*	0.007**	0.003	0.003	0.007*
	(0.012)	(0.026)	(0.003)	(0.003)	(0.003)	(0.004)
Round × *Moderation*	0.089**	0.203**	0.019**	0.016**	0.024***	0.024**
	(0.039)	(0.085)	(0.009)	(0.007)	(0.009)	(0.012)
Round × *Milestone*	0.239***	0.419***	0.039***	0.020***	0.050***	0.057***
	(0.052)	(0.113)	(0.011)	(0.008)	(0.012)	(0.016)
Moderation	0.076***	0.098**	0.012**	0.009**	0.011***	0.013**
	(0.026)	(0.047)	(0.005)	(0.004)	(0.005)	(0.006)
Milestone	−0.094**	−0.271***	−0.018**	−0.011*	−0.031**	−0.039***
	(0.044)	(0.074)	(0.008)	(0.006)	(0.008)	(0.010)
Magnitude	0.243***	0.241***	0.053***	0.017**	0.026***	0.041***
	(0.057)	(0.073)	(0.009)	(0.007)	(0.008)	(0.011)
Tenure	−0.032	−0.342	−0.026	0.033*	−0.023	−0.034
	(0.133)	(0.226)	(0.023)	(0.018)	(0.024)	(0.031)
Questions	0.217***	0.490***	0.038***	0.023***	0.051***	0.051***
	(0.022)	(0.041)	(0.005)	(0.005)	(0.004)	(0.005)
Badges	0.226***	0.363***	0.033***	0.023***	0.039***	0.048***
	(0.012)	(0.019)	(0.002)	(0.002)	(0.002)	(0.003)
Constant	−1.225	2.187	−0.124	1.140***	0.119	0.113
	(1.076)	(1.734)	(0.187)	(0.147)	(0.189)	(0.242)
User FE	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Num. of users	1873	1873	1873	1873	1873	1873
Num. of obs.	99,269	99,269	99,269	99,269	99,269	99,269
Adjusted R^2	0.354	0.317	0.260	0.200	0.333	0.285

*** $p<0.01$.
** $p<0.05$.
* $p<0.1$.
Robust standard errors are in parentheses. FE, fixed effect.

Table C1
Robustness I: Results of Model (2) by using Alternative Independent variable *Distance*.

Variable	Contribution level		Contribution quality		Writing style	
	Frequency	*Avg_length*	*Bestanswer_ratio*	*Avg_votes*	*Avg_function*	*Avg_focus*
Distance	−0.008*	−0.009	−0.001	8.91e-05	−0.001	−0.002*
	(0.004)	(0.009)	(0.001)	(0.001)	(0.001)	(0.001)
Distance × *Privilege*	−0.093***	−0.161***	−0.017***	−0.011***	−0.019***	−0.021***
	(0.014)	(0.026)	(0.003)	(0.002)	(0.003)	(0.004)
Privilege	0.050**	0.046	0.007	0.007*	0.005	0.005
	(0.023)	(0.042)	(0.005)	(0.003)	(0.004)	(0.006)
Magnitude	0.358***	0.470***	0.073***	0.030***	0.053***	0.073***
	(0.050)	(0.069)	(0.008)	(0.006)	(0.007)	(0.010)
Tenure	−0.072	−0.402*	−0.033	0.029	−0.030	−0.042
	(0.132)	(0.227)	(0.023)	(0.018)	(0.025)	(0.031)
Questions	0.217***	0.491***	0.038***	0.023***	0.051***	0.051***
	(0.022)	(0.042)	(0.005)	(0.005)	(0.004)	(0.005)
Badges	0.224***	0.360***	0.033***	0.023***	0.039***	0.048***
	(0.012)	(0.019)	(0.002)	(0.002)	(0.002)	(0.003)
Constant	−1.916*	0.616	−0.247	1.050***	−0.061	−0.104
	(1.070)	(1.770)	(0.186)	(0.145)	(0.192)	(0.247)
User FE	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Num. of users	1873	1873	1873	1873	1873	1873
Num. of obs.	99,269	99,269	99,269	99,269	99,269	99,269
Adjusted R^2	0.356	0.333	0.258	0.218	0.338	0.284

*** $p<0.01$.
** $p<0.05$.
* $p<0.1$
Robust standard errors are in parentheses. FE, fixed effect.

Table C2
Robustness I: Results of Model (3) by using Alternative Independent variable *Distance*.

Variable	Contribution level		Contribution quality		Writing style	
	Frequency	*Avg_length*	*Bestanswer_ratio*	*Avg_votes*	*Avg_function*	*Avg_focus*
Distance	−0.055***	−0.090***	−0.010***	−0.005***	−0.010***	−0.013***
	(0.006)	(0.013)	(0.001)	(0.001)	(0.001)	(0.002)
Distance × *Magnitude*	0.028***	0.047***	0.005***	0.003***	0.005***	0.006***
	(0.003)	(0.006)	(0.001)	(0.001)	(0.001)	(0.001)
Privilege	0.065***	0.073*	0.010**	0.008**	0.008*	0.009
	(0.023)	(0.042)	(0.005)	(0.003)	(0.004)	(0.006)
Magnitude	0.370***	0.489***	0.075***	0.031***	0.055***	0.076***
	(0.050)	(0.070)	(0.008)	(0.006)	(0.008)	(0.010)
Tenure	−0.074	−0.404*	−0.033	0.030	−0.030	−0.043
	(0.132)	(0.227)	(0.023)	(0.018)	(0.024)	(0.031)
Questions	0.217***	0.491***	0.038***	0.023***	0.052***	0.051***
	(0.022)	(0.042)	(0.005)	(0.005)	(0.004)	(0.005)
Badges	0.224***	0.360***	0.032***	0.023***	0.038***	0.047***
	(0.012)	(0.019)	(0.002)	(0.002)	(0.002)	(0.003)
Constant	−1.721	0.949	−0.210	1.071***	−0.022	−0.062
	(1.061)	(1.762)	(0.185)	(0.144)	(0.191)	(0.245)
User FE	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Num. of users	1873	1873	1873	1873	1873	1873
Num. of obs.	99,269	99,269	99,269	99,269	99,269	99,269
Adjusted R^2	0.357	0.335	0.259	0.217	0.340	0.284

*** $p<0.01$.
** $p<0.05$.
* $p<0.1$
Robust standard errors are in parentheses. FE, fixed effect.

5.4.2. *Alternative measurement for magnitude: reputation*

In our main specification, we use *Magnitude* as the moderating variable to test the marginal effect of round numbers. Alternatively, we could measure user level by their current reputation instead of the round number's magnitude. We replicate the analysis of marginal effect with this alternative measurement, and the results are highly consistent (see Appendix D).

5.4.3. *Additional analysis: the patterns of round number effect*

To dig deeper into the patterns of round number effect, we first define a new dummy variable (denoted as *After*) to explore whether users' performance will drop once they have passed a round number. Second, a heterogeneity analysis is conducted to see whether users with different reputation levels are equally sensitive to the next nearest round number.

To remain consistent with the definition of *Round*, we select the multiple of 1000 as the criteria of a round number. *After* equals 1 if the distance of a user's reputation points from an adjacent previous round number is less than or equal to 100 points; otherwise, *After* equals 0. It is worth noting that when *After* equals 1, the anchored round number should not be the next one, but the previous one which is lower than the users' current reputation points. Thus, the definitions of *Privilege* and

Table D1
Robustness II: Results of Model (3) by using Alternative Measurement for *Magnitude*.

Variable	Contribution level *Frequency*	*Avg_length*	Contribution quality *Bestanswer_ratio*	*Avg_votes*	Writing style *Avg_function*	*Avg_focus*
Round	0.067***	0.148***	0.015***	0.008**	0.016***	0.019***
	(0.019)	(0.043)	(0.004)	(0.003)	(0.005)	(0.006)
Round × *Reputation*	−0.021***	−0.042***	−0.004**	−0.002*	−0.005***	−0.005**
	(0.007)	(0.016)	(0.002)	(0.001)	(0.002)	(0.002)
Privilege	0.051**	0.072*	0.006	0.008**	0.008*	0.008
	(0.024)	(0.042)	(0.005)	(0.003)	(0.004)	(0.006)
Reputation	0.237***	0.413***	0.042***	0.024***	0.047***	0.057***
	(0.019)	(0.030)	(0.003)	(0.002)	(0.003)	(0.004)
Tenure	−0.415***	−1.085***	−0.087***	−0.009	−0.107***	−0.133***
	(0.131)	(0.215)	(0.023)	(0.017)	(0.023)	(0.030)
Questions	0.203***	0.466***	0.035***	0.021***	0.049***	0.048***
	(0.021)	(0.040)	(0.005)	(0.005)	(0.004)	(0.005)
Badges	0.205***	0.326***	0.029***	0.021***	0.035***	0.043***
	(0.011)	(0.018)	(0.002)	(0.002)	(0.002)	(0.002)
Constant	1.882*	6.537***	0.466***	1.411***	0.213***	0.754***
	(0.963)	(1.587)	(0.169)	(0.129)	(0.042)	(0.218)
User FE	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Num. of users	1873	1873	1873	1873	1873	1873
Num. of obs.	99,269	99,269	99,269	99,269	99,269	99,269
Adjusted R^2	0.345	0.305	0.243	0.215	0.327	0.272

*** $p<0.01$.
** $p<0.05$.
* $p<0.1$
Robust standard errors are in parentheses. FE, fixed effect.

Table E1
Results of Model (5) by using Alternative Measurement for *After*.

Variable	Contribution level *Frequency*	*Avg_length*	Contribution quality *Bestanswer_ratio*	*Avg_votes*	Writing style *Avg_function*	*Avg_focus*
Distance_after	0.041***	0.079***	0.007***	0.005***	0.009***	0.010***
	(0.005)	(0.010)	(0.001)	(0.001)	(0.001)	(0.001)
Privilege_after	−0.053**	−0.043	−0.012***	−0.006*	−0.005	−0.007
	(0.024)	(0.038)	(0.005)	(0.004)	(0.004)	(0.005)
Magnitude_after	0.075***	0.114***	0.014***	0.008***	0.013***	0.017***
	(0.009)	(0.014)	(0.001)	(0.001)	(0.001)	(0.002)
Tenure	−0.131	−0.555**	−0.039*	0.018	−0.046**	−0.060**
	(0.129)	(0.219)	(0.023)	(0.018)	(0.024)	(0.030)
Questions	0.214***	0.484***	0.037***	0.023***	0.051***	0.050***
	(0.021)	(0.041)	(0.005)	(0.005)	(0.004)	(0.005)
Badges	0.223***	0.357***	0.032***	0.023***	0.038***	0.047***
	(0.012)	(0.019)	(0.002)	(0.002)	(0.002)	(0.003)
Constant	0.951	4.697***	0.311*	1.327***	0.393**	0.502**
	(0.968)	(1.631)	(0.171)	(0.134)	(0.176)	(0.225)
User FE	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Num. of users	1873	1873	1873	1873	1873	1873
Num. of obs.	99,269	99,269	99,269	99,269	99,269	99,269
Adjusted R^2	0.346	0.296	0.253	0.207	0.329	0.277

*** $p<0.01$.
** $p<0.05$.
* $p<0.1$
Robust standard errors are in parentheses. FE, fixed effect.

Magnitude need corresponding adjustments. We denote the new variables as *Privilege_after* and *Magnitude_after* respectively. The new model is defined as:

$$DV_{i,t} = \alpha_0 + \alpha_1 After_{i,t} + \alpha_2 Privilege\_after_{i,t} + \alpha_3 \ln\left(Magnitude\_after_{i,t} + 1\right) + \alpha_4 \ln Tenure_{i,t} + \alpha_5 \ln\left(Questions_{i,t-1} + 1\right) + \alpha_6 \ln\left(Badges_{i,t-1} + 1\right) + \mu_i + \varphi_t + \varepsilon_{i,t} \tag{5}$$

The results are reported in Table 6. The coefficients of *After* on all the dependent variables are negative and statistically significant at the 0.01 level, which indicates that once users' accumulated reputation points have passed a round number, their contribution behaviors will significantly change in the opposite way. Taking contribution level as an example, as soon as users have passed a round number, they will slack off instantaneously and their contribution levels drop. More specifically, their post frequency will decrease, and they will be less likely to write longer, more detailed answers.

Further, we also consider an alternative explanatory variable to capture the effect of "passing a round number," which is the actual difference between the user's current points and the adjacent previous round number (denoted as *Distance_after*). We substitute *After* with *Distance_after* to run regressions and the results are highly consistent (see Appendix E).

As to the heterogeneity analysis, we divide the users into two groups to investigate whether users with different reputation levels are equally sensitive to 1000-multipled round numbers. In particular, we first draw

Table F1
Results of Heterogeneity Analysis: Low-reputation Group.

Variable	Contribution level		Contribution quality		Writing style	
	Frequency	*Avg_length*	*Bestanswer_ratio*	*Avg_votes*	*Avg_function*	*Avg_focus*
Round	0.129***	0.256***	0.029***	0.014***	0.027***	0.034***
	(0.027)	(0.063)	(0.006)	(0.005)	(0.007)	(0.009)
Privilege	0.107***	0.142*	0.017**	0.014***	0.019**	0.019*
	(0.038)	(0.076)	(0.007)	(0.005)	(0.008)	(0.011)
Magnitude	0.284***	0.449***	0.063***	0.022***	0.049***	0.068***
	(0.057)	(0.093)	(0.010)	(0.007)	(0.010)	(0.013)
Tenure	−0.233	−0.784**	−0.037	−0.032	−0.071**	−0.092**
	(0.160)	(0.304)	(0.029)	(0.021)	(0.033)	(0.042)
Questions	0.217***	0.595***	0.048***	0.022***	0.063***	0.068***
	(0.028)	(0.064)	(0.007)	(0.005)	(0.007)	(0.008)
Badges	0.499***	0.896***	0.074***	0.046***	0.099***	0.120***
	(0.025)	(0.039)	(0.004)	(0.003)	(0.004)	(0.005)
Constant	−0.311	2.842	−0.169	1.50***	0.197	0.221
	(1.283)	(2.293)	(0.227)	(0.162)	(0.251)	(0.318)
User FE	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Num. of users	937	937	937	937	937	937
Num. of obs.	49,661	49,661	49,661	49,661	49,661	49,661
Adjusted R^2	0.195	0.115	0.126	0.054	0.137	0.125

*** $p<0.01$.
** $p<0.05$.
* $p<0.1$.
Robust standard errors are in parentheses. FE, fixed effect.

Table F2
Results of Heterogeneity Analysis: High-reputation Group.

Variable	Contribution level		Contribution quality		Writing style	
	Frequency	*Avg_length*	*Bestanswer_ratio*	*Avg_votes*	*Avg_function*	*Avg_focus*
Round	0.010	0.043*	0.003	0.002	0.003	0.006
	(0.013)	(0.026)	(0.004)	(0.003)	(0.003)	(0.004)
Privilege	0.118***	0.174***	0.016**	0.022***	0.016**	0.020**
	(0.031)	(0.059)	(0.007)	(0.005)	(0.006)	(0.008)
Magnitude	−0.076	−0.636**	−0.012	−0.106***	−0.058**	−0.065*
	(0.225)	(0.251)	(0.034)	(0.027)	(0.027)	(0.039)
Tenure	−1.386***	−1.360**	−0.190**	0.029	−0.163***	−0.188**
	(0.433)	(0.576)	(0.076)	(0.068)	(0.061)	(0.083)
Questions	0.170***	0.319***	0.026***	0.016*	0.032***	0.023***
	(0.030)	(0.059)	(0.007)	(0.009)	(0.005)	(0.008)
Badges	0.077***	0.110***	0.012***	0.013***	0.011***	0.014***
	(0.009)	(0.016)	(0.002)	(0.002)	(0.002)	(0.002)
Constant	12.788***	20.264***	1.859***	2.544***	2.186***	2.517***
	(2.631)	(3.566)	(0.450)	(0.439)	(0.374)	(0.505)
User FE	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Num. of users	769	769	769	769	769	769
Num. of obs.	40,757	40,757	40,757	40,757	40,757	40,757
Adjusted R^2	0.015	0.018	0.004	0.070	0.008	0.008

*** $p<0.01$.
** $p<0.05$.
* $p<0.1$.
Robust standard errors are in parentheses. FE, fixed effect.

the cumulative distribution of all users' reputation points at the last week to get the median value (i.e., 7914) as the threshold, then define "high-reputation" users as the top 50% in terms of their reputation points and "low-reputation" users as the bottom 50%.[6] We then analyze each segment to distinguish the effects of round numbers at the segment level by using our model (1).

According to the reported results, the main coefficients in the low-reputation group are significant, whereas it turns out to be insignificant for almost all coefficients in the high-reputation group (see Appendix F). Thus, we can conclude that users with lower reputation levels are more sensitive to 1000-multipled round numbers than users with higher reputation levels. That is possibly because high-reputation users are strongly self-driven to participate in the platform and they will be willing to contribute even if their accumulated points are not close to a round number. This segment-level analysis helps us manifest the boundary of our research findings.

5.5. *Post hoc experimental study*

5.5.1. *Design and participants*

The "privilege" perks are usually set at round numbers, which suggests that there could be an alternative mechanism of round numbers being effective in incentivizing users to contribute. For instance, the round numbers could be treated as milestones to the privilege, and the

[6] Note that 8,851 observations of 167 users were dropped because their reputation points are not always above or below the threshold throughout the whole time series.

ultimate goal for users is to achieve a certain privilege. Thus, to rule out the potential impact posed by "privilege," we conducted a randomized experiment to further test the validity of our findings. Particularly, we would like to see whether the round number still has an incentive effect on users without any explicit perks (e.g., unlocking privilege at certain round numbers). Thus, we designed a between-subject experiment with two groups to mimic a knowledge-sharing platform where participants were able to accumulate points by voluntarily answering questions. The manipulated factor is *accumulative points*, either approaching a round number (i.e., the treatment group) or just passing a round number (i.e., the control group). No other incentive elements were available in our experimental setting.

We recruited 100 participants from an online platform.[7] To ascertain that most participants are familiar with knowledge-sharing platforms, we restricted to only users aged between 18 and 35 years could participate in this online experiment. We dropped observations of 15 participants because they either did not pass the attention check or the manipulation check questions. As a result, we had 85 valid observations, among which 43 were assigned to the treatment group and 42 were in the control group.

5.5.2. Stimuli and procedures

Experiment participants were put in the scenario of answering several subjective questions in a hypothetical Q&A platform. Before the main task of the experiment, participants were first asked to answer a set of choice questions in various domains such as geography and grammar. Participants were told that they could earn points by actively and correctly answering questions on this platform and the correctness of their answers would determine their initial points in next stage. Though their initial points were actually manipulated (i.e., approaching or passing a round number), this pre-experiment task was used to eliminate their doubts about where the initial points come from.

After this pre-experiment task, participants were randomly assigned to one the two groups. In the treatment group, participants were endowed with 914 points as their initial points and reminded with a banner saying "Based on your performance from previous task, your initial points are 914. Congratulations! You are only 86 points away from 1000 points." In the control group, they were given 1017[8] initial points and the banner presents information with "Based on your performance from previous task, your initial points are 1017. Congratulations! Your points have just passed 1000 points." Then they were directed to answer a subjective question which is the same across two groups. Although there was no correct answer, participants were told that the quality of their answers would determine how many points they can earn, that is, the more detailed of an answer, the more points would be endowed.

To eliminate the potential bias toward a specific question, participants were instructed to go through three rounds of this task, that is, first being assigned with an initial point based on his/her previous performance (i.e., just below or just above 1000, 2000, 3000 respectively) and then writing an answer to a subjective question. We used the length of answers as an indicator of their contribution efforts.

5.5.3. Results analyses

To test whether approaching round-number points can incentivize participants to write longer answers, we first calculated the mean and standard deviation of answers' length in both the treated group and control group by aggregating all observations. Because each participant experienced three rounds of Q&A tasks, we also separately compared the results for each round as complementary evidence for the overall results, which are shown in Table 7. Participants endowed with an initial point approaching a round number (i.e., treated group) wrote answers much longer than those endowed with points that are just passing a round number (i.e., control group), indicating their higher contribution efforts (e.g., $Mean_{treated} = 118.850$ vs. $Mean_{control} = 84.550$ for integrated results). Further, we also conducted one-way analysis of variance for each round as well as the overall observations to test the significance of differences. The p values for each pair of comparison are also shown in Table 7, lending support to the effectiveness of round number. Thus, in a well-controlled experimental setting where no other explicit perks are available, individuals are still prone to increase their contribution levels when their accumulative points approach a round number, supporting the effectiveness of a simple numerical cue.

6. Conclusion and implications

With the inherent public goods problem embedded in knowledge-sharing platform, various incentive mechanisms have been implemented, most of which are built on the basis of reputation points. Although some research has found points can incentivize users to contribute, empirical evidence regarding the influential patterns of such numerical units remains limited. Drawing on numerical cognition literature that individual's evaluation and judgments may be influenced by certain numerical cues, we propose several hypotheses regarding users' behavioral changes when their accumulated points approach round numbers. By analyzing data collected from StackOverflow.com, we find that users perceive round numbers as category boundaries or endpoints and crossing such boundaries can motivate aspirational behaviors. In particular, users significantly increase their post frequency and length and write answers with more function words and second-person pronouns. Meanwhile, their posts will be more likely to be accepted as the best answers and gain more votes. Besides, by exploring the interaction effects of round numbers and other gamified elements that built on points, we find that with the existence of explicit privilege incentives, the effect of round numbers will be strengthened. Meanwhile, the marginal effect of round numbers will decrease. This is because the perceived extent of an improvement to reach the next round number is smaller and less meaningful, given the same level of effort. This also indicates that as users become more experienced (i.e., earn more points by active participation) or have a higher reputation on the platform, they are less prone to behavioral bias and less incentivized by the round-number cue as a consequence.

6.1. Theoretical contribution

This research offers two main theoretical contributions. First, our work adds to the growing literature on knowledge-sharing platform incentives by investigating the role of numerical cue, which have previously received little attention. Extant research primarily focuses on the more advanced incentive elements (e.g., badges, ranks, status, peer awards) with explicit benefits for users (e.g., glory, honor, privilege, visual tokens, tangible items) [3,6], but pays little attention to the simple feedback information: points. Our results reveal that the roundness of numerical values in the process of accumulating points have significant effects on users' behavioral changes. The interesting findings with respect to users' dynamic behavioral changes on their contribution level, contribution quality, and writing style constitute an important complement to the incentive mechanism literature. In sum, our research highlights the integral role of numerical cues embedded in the accumulative reputation points, suggesting that users on knowledge-sharing platforms are not only motivated by explicit rewards or benefits, but also under the influence of numerical cues.

Second, our research contributes to the literature on numerical cognition by showing that round numbers denote a sense of completion and stability and can guide individuals to change their content contribution behaviors in public goods settings. Though the round-number bias has been recognized in various decision-making contexts such as

[7] www.credamo.com

[8] A pilot experiment had been used to determine the manipulation of initial points.

product pricing [28] and financial investment [31], these contexts generally involve uncertainty where users rely on round numbers to reduce cognitive efforts. For example, investors are more likely to invest a round number when facing greater uncertainty. In contrast, online knowledge sharing is a typical public goods setting where users voluntarily make content contribution without uncertainty or any clear pre-defined goal. We use the left-digit effect to explain that individuals pursue round numbers because the same relative differences can be perceptually greater when the left digit changes. Thus, crossing such round numbers can enhance the perceived progress that they have achieved. Our findings show that people are still prone to round-number bias even when the numerical values do not represent clear goals such as scores in examinations (i.e., users contribute contents on knowledge-sharing platforms because of their intrinsic motivation, not for purposely gaining points).

6.2. Practical implications

Our work offers significant implications and actionable insights for knowledge-sharing platforms as well as other business models that rely on voluntary contributions. First, our reported study shows the effectiveness of simple numerical cues induced by accumulated points. The round numbers have the potential to tap into people's motivation to cross the category boundary and therefore yield greater contributions and potential overcome the natural decay phenomenon and free-riding problems inherent in UGC provision context. Developers of knowledge-sharing platforms can consider designing a reminder system that sends messages to users about their current progress (e.g., accumulated points) and the distance to the next round number, enabling users to initiate active behaviors. An alternative way is to design relevant recommendation algorithms to push more questions to users who are about to reach a round number, thus increasing users' possibility of contributing. At the same time, it also meets the needs of these users, saving the energy and time spent searching for open questions.

Second, the positive interaction effect between round number and explicit privilege incentive also demonstrates possible ways to improve the design of gamification module in such platforms. Liu et al. [7] has proposed a set of elements and principles for designing gamified information systems. Our findings may supplement this framework with numerical cues. Specifically, the platforms could likely wish to adapt to users' behavioral patterns at the round number to design effective gamification strategy, thus enhancing users' interaction with these gamification modules. For instance, platforms can use quantitative metrics and emphasize round numbers in the process that users pursuing gamified elements such as badge, status, and virtual awards. Among existing gamified incentives, the thresholds of points for higher badges or status usually increase exponentially [12]. It will be progressively more difficult to level up, which may discourage users from continuously contributing contents. In contrast, our study shows that each round number of points has a significant positive effect on users' contribution behavior though the marginal effect is diminishing. Thus, future design of upgrading principles in such platform can consider using round numbers in a linear mode rather than in a mere exponential mode.

6.3. Limitations and future work

The current study can be extended in several directions. First, individual differences such as cultural background and psychological characteristics might also impact the way they perceive round numbers and subsequent contribution behaviors. Given the limitation of observational data, it is not feasible to get users' race information or personal traits from StackOverflow.com. We leave this as a future research direction to consider more human factors, thus further improving the interpretability of the model. Second, the interaction of round number cues and explicit incentive elements is also worth further investigation. We preliminarily find that the incentivizing effect is strengthened when realizing a round-number point can unlock a privilege. Other forms of gamified incentive elements may have different degrees of interaction effects with the round number cues. For example, can rising to a round-number ranking in a leaderboard (e.g., Top 10 ranking) have a stronger incentivizing effect? Third, in addition to numbers, many other elements in the inherent design of website that are not specifically designed for motivating contribution behaviors may also serve as implicit cues to influence users' behavior, such as icons of milestones, avatars of users, and layouts of pages, which is worth a separate study. Fourth, it would be interesting to investigate other types of knowledge-sharing platforms and consider the non-textual factors, such as images or videos, to measure the richness of content.

CRediT authorship contribution statement

Mingyue Zhang: Conceptualization, Methodology, Formal analysis, Supervision, Writing – review & editing. **Tiancheng Zhu:** Data curation, Writing – original draft, Formal analysis. **Yu Xu:** Formal analysis, Writing – review & editing. **Baojun Ma:** Conceptualization, Writing – review & editing, Project administration.

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Appendix A. Alternative measurements for contribution quality

To assess the readability of the texts, we adopt Gunning Fog Index (GFI) [52,73,80] and Simplified Measure of Gobbledygoop (SMOG) [81]. Previous literature has established that higher GF index values (i.e., more complex text) are usually associated with higher content quality as perceived by individuals [73]. The formulas used to calculate the two indexes are as follows:

$$GFI = 0.4 \times \left[\frac{Number\ of\ Words}{Number\ of\ Sentences} + \left(100 \times \frac{Number\ of\ Complex\ Words}{Number\ of\ Words}\right)\right]$$

$$SMOG = 3 + \sqrt{Number\ of\ Polysyllabic\ Words\ in\ a\ 30 - Sentence\ Sample}$$

We regress GFI and SMOG on the independent variables based on our model (1), respectively. The results are reported in Table A1. The coefficients of *Round* are all positive and significant, suggesting that users tend to post answers of higher complexity and professionality (i.e., higher quality) when their accumulative points approach a round number.

Appendix B. Different forms of privilege

According to the privilege hierarchy of StackOverflow.com (see Fig. 3), there are four types of privileges: *Milestone, Moderation, Communication*, and *Creation*. We would like to see whether different forms of privilege have different degrees of influence on users' behaviors. In our research context, we use the multiple of 1000 points as our definition of round numbers. In this regard, *Communication* and *Creation* privileges are excluded because the thresholds for unlocking these two privileges are not overlapped with the defined round numbers (i.e., there is no interaction). Thus, constrained by the data, only two types of privileges can be included for further discussion, namely *Milestone* and *Moderation*.

We introduce a dummy variable for each type of privilege into the regression model, and the results of moderating effects of *Milestone* and *Moderation* privileges are presented in Table B1. It is quite exciting to see that different forms of privileges indeed exert different degrees of influence on users' behaviors. Specifically, the coefficients of *Round* × *Moderation* and *Round* × *Milestone* are all positively significant, suggesting both forms of privileges can strengthen the round number effect. Moreover, the coefficients of *Round* × *Milestone* are all larger than that of *Round* × *Moderation*, indicating that *Milestone* has a stronger moderating effect on round number than *Moderation*. This is consistent with our intuitive perception that *Milestone* privileges endow users with higher recognition and more benefits than *Moderation* privileges, thus having a stronger effect.[9]

Appendix C. Alternative independent variable: *Distance*

Table C1, Table C2

Appendix D. Alternative measurement for *magnitude: Reputation*

Table D1

Appendix E. Alternative measurement for *After:Distance_after*

Table E1

Appendix F. Results of the heterogeneity analysis

Table F1, Table F2

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