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RESEARCH PAPER

Does the Framing of Progress Towards Virtual Rewards Matter?

Empirical Evidence from an Online Community

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Abstract A natural experiment on a popular German Question & Answer community is used to find out whether the small-area hypothesis applies to user activation by means of a virtual reward in the form of badges. Koo and Fishbach's small-area hypothesis posits that individuals in pursuit of a goal are more highly motivated when focusing on the smaller percentage of progress towards their goal, irrespective of whether this figure represents the actions already completed or those still remaining. Consistent with the authors' theoretical predictions, the study finds empirical evidence for the small-area effect and its activating power, translated here into increased online user contributions. Besides contributing to the literature with an empirical study anchored in theory, the findings have direct practical implications for designers of online virtual reward systems by suggesting more effective (and motivating) ways of framing user progress towards virtual rewards.

Keywords Small-area hypothesis · Gamification · Virtual rewards · Badges · Question & Answer community · Motivation · User effort

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This paper is an extended version of Mutter and Kundisch (2015).

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1 Introduction

Over the last few years, gamification has experienced a rise in popularity and become a trending topic among practitioners and academics (e.g., Gartner 2011; Blohm and Leimeister 2013; Hamari et al. 2014). Gamification refers to the application of game design elements in a non-gaming context (Deterding et al. 2011), and is used by all types of organizations for a variety of purposes: to improve user engagement, to motivate employees, to facilitate innovations, to promote personal development, to improve learning, and to encourage people to make healthy choices (e.g., Kumar 2013; Penenberg 2013; Burke 2014). Popular game elements include badges, points, levels, progress bars, or leaderboards (e.g., Hamari et al. 2014; Cheong et al. 2013). The popular question and answer site StackOverflow, for example, uses badges dubbed 'Guru' and 'Altruist' to activate its members (Fig. 2 shows examples of badges from a range of sites).

While research suggests that gamification can exert a positive effect on user motivation and engagement, its impact depends on both the context and the precise manner in which game elements are implemented (e.g., Hamari et al. 2014; Kankanhalli et al. 2012). For an effective implementation, more research using rigorous methodologies (e.g., Hamari et al. 2014) is needed to better understand the behavioral mechanisms associated with gamification (Kankanhalli et al. 2012). Such insights would, amongst others, enable gamification designers to integrate game elements into applications more successfully. With our research we aim at improving the understanding of the key drivers behind the effectiveness of gamification by specifically analyzing the so-called *small-area hypothesis* in the context of online-communities. In the broad field of goal-performance research (e.g., Heath et al. 1999; Locke and Latham 2002; Mento et al. 1987), the small-area hypothesis states that individuals in pursuit of a goal exhibit stronger motivation when they focus on whichever is smaller in size: the share of completed actions or the share of actions still needed to reach a goal (Koo and Fishbach 2012). Put differently, the way recorded progress is framed is likely to affect motivation. In practical terms, users who are in the early stages of goal-pursuit show greater motivation when presented with their accumulated progress (e.g., 10 % achieved) rather than with the progress still to be made (e.g., 90 % remaining), whereas with greater proximity to the goal, it is more effective to focus users on their remaining progress (e.g., 10 %) rather than on their accumulated progress (e.g., 90 %).

The small-area hypothesis has been researched experimentally in the context of customer loyalty programs (Koo and Fishbach 2012). However, given the substantive differences between loyalty programs and non-monetary virtual reward systems (such as badges), it is by no means evident whether this finding can be transposed from one setting to the other. Leaving aside the absence of monetary incentives or quasi-monetary benefits (e.g., lounge access or priority booking at frequent flyer programs), another main difference is that customer loyalty programs aim to influence individual decision making, notably buying behavior, while virtual reward systems in the context of online communities are designed to address motivational phenomena such as user effort. By answering the following research question, we investigate the generalizability of the small-area hypothesis to those aspects: *Does the small-area effect activate the contribution behavior of users in online communities?*

To address our research question we exploit a natural experiment using a unique and rich dataset provided by a German Question & Answer (Q&A) community. This exclusive dataset includes detailed information about all user activity on the platform between February 2006 and May 2008. To activate its members, the platform has set up a virtual reward system. On performing certain activities, users are rewarded with points, the accumulation of which earns them badges. Thus, in our research environment goals are represented by badges. The natural experiment took place in February 2007, in the middle of our observation period, when the operator of the platform fundamentally restructured the virtual reward system. As a consequence users were exogenously set back from their next goal and the average distance towards their next badge was increased. This natural experiment provides a unique research environment for the identification of the small-area effect. In an empirical analysis, we compare the contribution behavior of 650 users in the 7 days before and after the event. We find that the users who were set right back to the beginning increase their post-event contribution levels, whereas users who were set back only half-way decrease their contribution levels. Since in both situations progress towards the next badge is framed in terms of accumulated actions we are able to explain this seemingly contradictory behavior with the small-area effect.

Our results have important practical implications for designers and managers of online communities. In particular, the design of virtual reward systems should explicitly consider the framing of the distance or proximity towards a virtual reward. With this paper we also make novel and significant contributions to research in two ways: (1) we contribute to the literature of gamification by providing empirical evidence that user contribution levels are affected by the framing of progress towards their virtual rewards; (2) we contribute to the research on the small-area hypothesis by being the first to provide empirical field evidence of the presence of this effect on goals in form of non-monetary rewards, and by showing that the small-area effect also applies to motivational phenomena such as user effort.

2 Theoretical Background

Two streams of research are relevant to our study. The first examines goal pursuit and framing. The second stream analyzes gamification, and badges in particular, as game design elements. In the following paragraphs we discuss relevant work from both of these streams.

2.1 Goal Pursuit and Framing

It is well established in the literature that individuals perform better when given more specific and challenging goals compared with being told to ‘do your best’ (e.g., Heath et al. 1999; Latham and Locke 1991; Locke and Latham 1990, 2002, 2013; Mento et al. 1987). Mitchell and Daniels (2003, p. 231) state that it is “[…] the single most dominant theory in the field, with over a thousand articles and reviews published on the topic in a little over 30 years.” Goal setting theory (Locke and Latham 1990, 2002) proposes three key mechanisms for this behavior: goals (1) activate individuals into increasing their effort, (2) induce greater persistence, and (3) direct attention toward goal-relevant activities (Heath et al. 1999; Locke and Latham 2002).

The literature distinguishes between two main types of goals: extrinsic rewards and ‘mere’ goals (Heath et al. 1999). Extrinsic rewards are associated with external objects and have a direct bearing on physiological well-being, while ‘mere’ goals represent “specific levels of performance (e.g., finishing a manuscript in 3 days as opposed to 5)", without discrete pay-offs (Heath et al. 1999, p. 80). While the effectiveness of extrinsic rewards may be explained with economic calculus – at least under certain conditions – 'mere' goals require a psychological explanation (Heath et al. 1999).

According to Locke and Latham (2002) the goal-performance relationship is strengthened by several moderators. Goals are effective when, for example, people are committed to them, when the complexity of a task is commensurate with their ability to adopt appropriate strategies to accomplish the task, and when they receive feedback on their progress towards the goal. In the following we will focus on a specific type of this last moderator: quantitative feedback on the progress towards a goal and its framing.

It is well established in the literature on motivation that persistence increases with proximity towards a goal's end state (Koo and Fishbach 2012). Research explains this phenomenon with the *goal-gradient hypothesis* (e.g., Hull 1932; Kivetz et al. 2006; Kopalle et al. 2012; Mutter and Kundisch 2014b; Nunes and Drèze 2006). For example, in a field study conducted at a university café in which participating customers have to buy ten cups of coffee to get one for free, Kivetz et al. (2006) found that participants purchase coffee more frequently the closer they get to the reward. A widespread explanation for this phenomenon is based on the perceived contribution of each consecutive action towards goal achievement which increases with proximity towards the goal's end state (Brendl and Higgins 1996; Förster et al. 1998). For example, buying the first of ten cups of coffee at the café reduces the distance to the goal by 10 % (1 out of 10 outstanding cups), whereas purchasing the last cup reduces the distance by 100 % (1 out of 1 outstanding cups). Mutter and Kundisch (2014b) show that the goal-gradient hypothesis also holds in environments with 'mere' goals, such as an online Q&A community with virtual rewards in the form of badges.

Based on the view that the perceived impact of actions affects the motivation to perform the action, Koo and Fishbach (2012) propose the *small-area hypothesis*. The small-area hypothesis states that apart from the actual level of progress, motivation is also affected "by the perception that the action has greater impact because the person is comparing it to a smaller set of other actions (e.g., stronger motivation for 20 % completed vs. 80 % remaining)" (Koo and Fishbach 2012, p. 507). This implies that – given the proper framing (Wiebenga and Fennis 2014) – motivation can be positively affected by being either far from or close to goal completion, because in both situations people are able to focus on whichever is the smaller area and hence, the one in which their action is perceived to have the greater impact (Bonezzi et al. 2011). However, this does not apply to the mid-point in a goal pursuit, regardless of

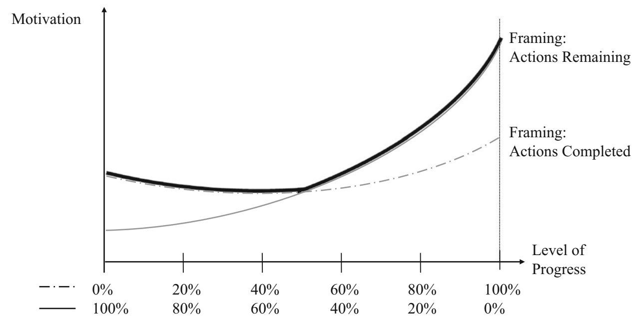

Fig. 1 Framing of actions (modified version from Bonezzi et al. (2011))

how progress is framed. "The small-area effect is orthogonal to the goal-gradient effect, such that both proximity to goal attainment and attention to small areas independently increase the perceived impact of an action and thereby increase motivation" (Koo and Fishbach 2012, p. 494). The small-area hypothesis is proposed, in particular, for "goals with a clear end state" (Fishbach et al. 2014). Figure 1 shows the level of motivation and progress towards a goal for alternative framings (solid grey line for the framing "Actions Remaining" dotted grey line for the framing "Actions Completed", and thicker black line for an ideal framing depending on the level of progress). We notice two things: First, with proximity towards a goal's end state the goal-gradient effect is present regardless of the framing (focus on actions remaining or completed). Thus, the goal-gradient and the small-area effect are coterminous there. Second, at the beginning of progress the activated small-area effect (framing: "Actions Completed") causes a downward sloping motivation function – in contrast to the motivation function when the framing expresses the actions remaining.

In the field of marketing research, Koo and Fishbach (2012) provide empirical evidence for the small-area and the goal-gradient hypothesis in the context of customer reward programs (with external rewards), having run one field experiment (context: sushi restaurant), and two lab experiments (context: coffee shop and bagel store).[1] Their findings are consistent with the results from Bonezzi et al. (2011) in the field of psychology, who present evidence from the lab for a non-monotonic motivational pattern which consists of the classical increasing goal-gradient with proximity to the goal and a decreasing goal-gradient from the early stages of goal-pursuit. Further, in the domain of weight maintenance McKee et al. (2013) report anecdotal evidence in support of the small-area hypothesis.

[1] With an additional study in the lab (Koo and Fishbach 2012) rule out "the possibility that attention to remaining actions solely drives the small-area effect." This study is not performed in a real-life context (e.g., coffee shop) but uses lexical and numerical tasks.

Table 1 Search results for "gamification" – number of hits (data retrieved on 01-02-2016)

Year	Database		
	Google scholar (excluding patents and citations)	Scopus (search in: article title, abstract, keywords)	Web of science (search in: topic)
2010	74	0	0
2011	365	24	7
2012	1310	97	37
2013	2870	266	115
2014	4610	424	188
2015	5040	350	200

Fig. 2 Examples of badges in different online platforms. Taken from the following Websites: Foursquare: http://allesfoursquare.de/swarm-sticker/; Wikipedia: https://en.wikipedia.org/wiki/Wikipedia:Barnstars; Khan Academy: https://www.khanacademy.org/badges; Stack Overflow: http://stackoverflow.com/help/badges. Accessed 2 May 2015

We contribute to this literature by empirically testing whether the small-area hypothesis also applies to 'mere' goals represented by a virtual rewards system with non-monetary incentives and to motivational phenomena such as user effort.

2.2 Gamification and Badges

Gamification refers to "using game design elements in non-gaming contexts" (Deterding et al. 2011). Recently, gamification has received considerable attention in the literature. Table 1 shows search results with the keyword "gamification" in different databases. The Google Scholar service, for example, returns 45 articles dated from 2010 and a staggering 4300 articles dated from 2014. In the IS discipline, gamification research is still in its infancy, though (Bui and Veit 2015). For extensive literature reviews about studies on gamification see Hamari et al. (2014) (with a focus on empirical studies), Schlagenhaufer and Amberg (2015) (with a focus on IS outlets), Seaborn and Fels (2015), Thiebes et al. (2014) (with a focus on empirical studies in a workplace context).

In the context of online communities or social media sites, gamification is used in order to activate user contribution behavior and encourage the social interaction between users (Hamari 2013).[2] One popular game element are so-called *badges* (Hamari et al. 2014). "Badges are given to users for particular contributions to a site, such as performing a certain number of actions of a given type" (Anderson et al. 2013). They have been implemented in a variety of online contexts, including education (e.g., Khan Academy), social news (e.g., Huffington Post), knowledge-creation (e.g., Wikipedia), location-based social networking tools (e.g., Foursquare), and many others (e.g., Anderson et al. 2013; Denny 2013; see also Fig. 2).

Beyond their application in online communities we would like to mention two recent trends that emphasize the relevance of research on gamification.

First, fueled, amongst others, by the Mozilla-led Open Badge initiative (http://openbadges.org/) that defined an open standard to display skills, interests and achievements gained from different issues, gamification using badges gained traction in the education market in 2011 (Hickey et al. 2015). MIT's Michael Schrage even predicted at the end of 2012 that "course content, quality and participation

[2] Undercontribution is a common problem in online communities – even if the community would be classified as being highly successful (Kraut and Resnick 2011). An overview about how to encourage contribution to online communities can be found in Kraut and Resnick (2011).

won't ultimately determine the triumph of the online educational revolution. The ability to measure and assess real learning and skills acquisition in virtual environments will. Badges – not digital diplomas – seem to be the best and likeliest bet on accreditation's future." (Schrage 2012) This is in line with results of a survey conducted by Extreme Networks in 2014 with over 1900 respondents that revealed that over 60 % of the respondents believe that digital badges will either entirely replace diplomas and course certificates or be used in combination with them (Extreme Networks 2014). Two-thirds (65 %) of respondents further stated that they believe that digital badging will grow in the future. IBM just recently took up this trend and introduced an Open Badge program for skills earned at IBM (e.g., industry certification, passing an online course) (Leaser 2015). However, the educational badge market is still in its infancy and there is a long way to go for badges to become an accepted standard by admissions or hiring officials (Hickey et al. 2015).

Second, the market for health and fitness apps and related products and services (such as wearables) has strongly developed in the last 2 years. At the end of 2014 there were more than 100,000 apps available for Android or iOS and was the fastest growing app category in 2014 in Google's Play Store (Boxall 2014). Many of the popular apps not only facilitate the user to track and measure health related activities but also integrate badge systems as a means of motivating users.

Depending on the application domain (i.e., whether leisure or job related) badges might represent either 'mere' goals or extrinsic rewards. Consequently, either an explanation rooted in psychology (for 'mere' goals) or based on economic calculus (for extrinsic rewards) might be more appropriate to model the impact of badges on user behavior.

The literature has theorized several reasons why users might value badges and, thus, perceive them as valuable goals.

> Badges carry information about a user's past engagement, level of experience and expertise. This information can be used by other users to assess a contributor's reputation (e.g., Kollock 1999; Wasko and Faraj 2005). In this way badges function as a valuable indicator for the trustworthiness of users and the reliability of the content they produce (Antin and Churchill 2011).
>
> Badges may represent status symbols. Here, the virtual reward system exploits the power of status reflected in users' awareness that others will look upon them more favorably if they have accomplished the activities represented by a specific badge (e.g., Festinger 1954; Drèze and Nunes 2009; Mutter and Kundisch 2014a; Roberts et al. 2006).
>
> Badges may also constitute a set of activities that bind a group of users together around a common experience. Consequently, achieving badges might foster a sense of solidarity and group identification through the perception of similarity between an individual and the group (e.g., Ren et al. 2012).

Whilst a body of literature has recently emerged which analyzes the impact of badges on user contribution levels more generally (e.g., Li et al. 2012; Hamari 2013; Denny 2013), and the goal-gradient hypothesis more specifically (Mutter and Kundisch 2014b), the literature is silent about the effects of different alternatives for framing the level of progress towards achieving a badge. Further, despite the increase in the number of scholarly contributions about gamification (see, e.g., Table 1), Seaborn and Feld (2015) conclude in their literature review that the "majority of applied research on gamification is not grounded in theory". We add to the existing empirical literature on badges by addressing both aspects. First, our work is an empirical investigation of how the achievement of badges representing 'mere' goals affects user contribution behavior, grounded in theory (i.e., the small-area hypothesis). Using data from a leisure related Q&A community we can rule out potential spillovers to the labor market or confounding effects caused by any other type of external reward. Second, our work contributes to the literature on gamification by providing empirical evidence that the framing of progress towards virtual rewards affects user contribution levels.

3 Research Environment[3]

The website at the center of our analysis was launched in January 2006 and has requested to stay anonymous. The platform offers registered and non-registered users the opportunity to ask questions to the community on everyday topics (e.g., beauty, computers, gardening). This means that the platform deals exclusively with leisure rather than labor-market related topics. All registered users automatically participate in the virtual reward system of the platform that features both task-contingent as well as performance-contingent rewards (Kraut and Resnick 2011). For almost all of the activities performed, registered users receive an incentive in the form of status points. Each time users earn status points, their total number of status points increases. Users need to accumulate a predetermined

[3] Four related papers (Mutter and Kundisch 2014a, b; von Rechenberg et al. 2016; von Rechenberg and Gutt 2016) are drawing on the same research environment. Despite some overlap in the underlying dataset, the related studies differ in their scope, each addressing different research questions.

Table 2 Status point scheme (before the event)

Main activities	Status points per activity
Answering questions	0–25
Asking questions	0–4
Adding friends	5–20
Adding and copying links	1–2

number of status points to earn badges. In Table 2, we present a list of the main activities and their corresponding status points. Almost all – 99 % – of the status points earned by users were acquired through taking part in the listed activities.[4]

The core activity on the platform is answering questions. Depending on the quality of their answer, users can earn between 0 and 25 status points for a given answer. The quality of the answer is rated by both the questioner and by other members of the community, but only the questioner can tag an answer as 'top' answer whereas the members of the community can tag it as 'helpful'. Apart from the activity *answering questions*, registered users can also get status points by *asking questions* to the community. If a question receives at least one answer or is rated as a *helpful* question by at least one other user, the questioner receives between 1 and 4 status points. No status points are earned, however, if the question remains unanswered. Registered users also have the opportunity to add friends to their network of friends. If a friend request is accepted by another user, both earn a set number of status points. Furthermore, each user has a personal link catalogue. Whenever a user adds a new link to the catalogue, or copies a link from another user, she earns status points.

In Table 3, we provide a detailed list of all the available badges and the total number of status points required for each badge. The badge 'Bachelor', for example, requires an accumulation of at least 120 status points. By earning an average of 4 status points per answer users would have to answer more than 30 questions to earn this badge. In comparison, the next 'Master' badge requires a total of 720 points (or an additional 600 after having acquired the Bachelor badge), equivalent to 180 questions answered. And so on.

The list with the badges and the status points required for each badge are displayed on the platform, as are the personal profiles of every user, showing which badges and how many status points they have earned. This information is also publicly visible to any other platform user or guest whenever they pose or answer a question.

[4] There are further activities which play only a very minor role and account for less than 1 % of the total accumulated status points (e.g., *inviting new members* to the platform or *following other users*).

On this platform the level of progress towards the next badge is framed in terms of completed actions because users' total number of status points is represented as an increasing number. It is important to note that the total number of status points is not reset to zero after users have earned a badge. This means that the small-area effect can activate user contribution behavior only shortly after users register on the platform, because only then do they start to possess a small total number of status points. However, it is more challenging to isolate the impact of the small-area effect directly after their registration from observational data alone, because there might be other factors at play that could affect user behavior. For example, users might be more passive in the earlier phases of their membership until they get to know the community better before starting to focus on goal attainment and adding their own contributions. Fortunately, a natural experiment that took place on the platform allowed us to isolate the impact of the small-area effect.

4 Natural Experiment[5]

In February 2007, the operator of the Q&A community fundamentally restructured the virtual reward system.[6] According to the operator, the objective of the restructuring was to simplify and enhance the reward system. The provider changed the status point scheme for the activities on the platform, retrospectively recalculated the total number of status points of each user and modified the badge system. As a result of this restructuration, the number of status points that could be earned for certain activities listed in Table 4 were either reduced or abolished. These activities included adding and copying links, and adding friends. The activities *asking* and *answering questions* were not affected by the restructuring. The new status point scheme is illustrated in Table 4.

In addition, the community provider recalculated the total number of status points that each user had earned since the first day of registration, based on the new point scheme. For example, by adding a new friend to their network users were rewarded with up to 20 status points before restructuration but none at all after the event – the

[5] Natural experiments – caused by policy changes, for example – are empirical studies that are characterized by a transparent exogenous source of variation in the explanatory variable that determines treatment assignment. The exogenous source of variation strengthens the claim of a causal interpretation of the results. Natural experiments are most helpful when controlled experiments are too difficult to implement or unethical. More details on natural experiments as a method in social sciences can be found, e.g., in Dunning (2012).

[6] It is noteworthy that the badge systems as well as the framing towards goal achievement on the analyzed as well as other popular platforms (such as Stack Overflow) has not changed much since then – underscoring that our work and its implications are still valid.

Table 3 List of badges (before event)

Label of badge	Required status points	Label of badge	Required status points
Student	0	Archimedes	4790
Bachelor	120	Ts'ai Lun	4890
Master	720	Johannes Gutenberg	4990
Research assistant	1130	Alexander G. Bell	5090
Doctor	1640	Gottfried W. Leibniz	5190
Assistant professor	2250	Max Planck	5290
Professor	3050	Johannes Kepler	5390
Nobel Laureates	3780	Leonardo da Vinci	5490
James Watt	4690	Albert Einstein	>6490

Table 4 Status point scheme (after the event)

Main activities	Status points per activity		Status points reduced or abolished?
	Before event	After event	
Answering questions	0–25	0–25	(Unchanged)
Asking questions	0–4	0–4	(Unchanged)
Adding friends	5–20	0	✔
Adding and copying links	1–2	1	✔

Table 5 List of badges (after the event)

Label of badge after event	Required status points after event	Label and order of badge unchanged by event?	Label of badge after event	Required status points after event	Label and order of badge unchanged by event?
Beginner	0	No	Robert Koch	8240	No
Student	210	Yes	Immanuel Kant	8740	No
Bachelor	530	Yes	Archimedes	9240	No
Master	1030	Yes	Max Planck	9740	No
Research assistant	1630	Yes	Isaac Newton	10,240	No
Doctor	2430	Yes	T. A. Edison	10,740	No
Assistant Professor	3330	Yes	Pythagoras	11,240	No
Professor	4240	Yes	Galileo Galilei	11,740	No
Nobel Laureates	5240	Yes	Leonardo da Vinci	12,240	Yes
Albert Schweitzer	7740	No	Albert Einstein	>12,740	Yes

reward for this activity had been abolished. Not only this, but if a user had earned 40 status points by adding new friends before the event, she lost these 40 status points after the event.

The new badge system is illustrated in Table 5.

The provider added two new badges, changed the labels of the badges between 'James Watt' and 'Leonardo da Vinci' (see also Table 3), and increased the number of required status points for each badge. The labels and the order of badges from 'Student' to 'Nobel Laureates' and for 'Leonardo da Vinci' and 'Albert Einstein' stayed the same. Users who held a badge between 'Student' and 'Nobel Laureates' before the event could easily compare their new position in the badge system based on the label of the new badge. Subsequently, these users could assess precisely how many badges they had lost. For example, a user with 200 status points held the badge 'Bachelor' before the event, while after the event, and holding the total number of status points constant, this user now holds the badge 'Beginner' and thus lost two badges.

The plan to restructure the virtual reward system was repeatedly announced prior to its implementation. The first announcement was made 5 months before the event. However, it is important for the analysis that follows to realize that users had no advance knowledge of the details of the modifications to come – the recalculation and the deduction of status points – and hence, the changes to the badge system had taken them by surprise.

As a consequence of the restructuring users were exogenously set back from their goal and the average distance towards their next badge was increased. This enables us to focus our analysis on two groups. The first comprises users who were set back to the beginning (and hence lost almost all of their status points) and the second, those who were only set back half-way towards earning the next badge (and hence lost fewer status points). As the positioning of the users after the event was for the most part determined exogenously, we have the opportunity to properly identify the small-area effect.

5 Hypothesis Development

The small area hypothesis states that for "goals with a clear end state, individuals exhibit greater motivation when they focus on their completed progress at the beginning and their lack of progress toward the end" (Fishbach et al. 2014). In our context, the badges serve as valuable goals with clear end states as the number of required status points for each badge is publicly available. The online community informs its registered users about the level of progress in terms of completed actions (number of already accumulated status points). Hence, according to the theory, we would expect to see an increase in the contribution levels of users who, as a result of the event (see section "Natural Experiment"), were set back to the beginning (with status points close to zero). This is because progress towards the next badge is framed in terms of completed actions. So when these users compare their recently earned status points to the lower (post-event) cumulative total of, say 10, compared with a pre-event total of 100, their post-event contribution is perceived as more effective (e.g. 4 points from one action added to 10, compared with 4 points added to 100, with the next badge requiring 210 points). However, the impact of the small-area effect decreases as users accumulate status points (see also Fig. 1). While the goal-gradient hypothesis has virtually no effect in the early stages towards goal achievement, the closer a user gets towards the goal, the more pronounced is the goal-gradient effect. Thus, an isolated measurement of the small-area effect – without potential confounding goal-gradient effects – ideally focuses on the first half of the level of progress towards goal achievement. Therefore, we derive the following research hypothesis:

> Hypothesis: The online community users who are set back to the beginning are activated by the small-area effect and therefore increase their post-event contributions compared with users who are set back only half-way towards their next badge.

6 Dataset, Sample and Descriptive Statistics

6.1 Dataset

We are very fortunate in having been provided with this unique dataset by the community's operator as this allows us to analyze this natural experiment. The whole dataset covers all user activities on the platform between February 2006 and May 2008. The number of newly registered users was 12,901 in 2006, 54,404 in 2007, and 25,909 up to the beginning of May 2008. During the observation period, we observe how these users collect 14,132,466 status points on the platform and, in the process, earn badges. To earn status points, users replied to 1,000,542 posted questions with 2,996,446 answers, built 32,696 friendships with other users, and added 87,872 links to the link catalogue of the platform. Our data is at the level of each individual user. Thus, we know exactly when a user registers on the platform, when and how often she performs a certain activity, when and how many status points she earns for her actions, and when she earns a badge. This allows us to establish a detailed profile for each user based on her activity history on the platform.

6.2 Sample

For our empirical analysis we select the 650 users who hold the badge 'Student' on the day prior to the event and who, at the time of the event, were still actively participating. We regard users as inactive if they permanently stopped performing any of the platform's activities. All users in our sample lost one badge and hold the badge 'Beginner' after the restructuring. In addition, these users lost status points and thereby were exogenously set back to an interval ranging from the beginning to half-way towards the next badge after the event. We choose this group of users because all users in this group receive the same treatment except for the positioning towards the next badge.

In our empirical analysis, we compare the user contribution behavior of these users in the 7 days before and after the event. The main reason is that the small-area effect is expected to be evident only in the days directly after the event, because with an increasing number of status points the impact of the small-area effect weakens. Therefore, we chose a small time window covering 7 days before and after the event. Moreover, the bigger the time frame encompassing the event, the higher the risk of potential confounding effects (e.g., users earning another badge). This is especially true for very active users who are likely to achieve the next badge quickly and would have been excluded from our sample, had we taken a broader time frame.

Table 6 Users' activity history

Variables	Mean	Min	Q25	Median	Q75	Max	Sum
Length of Membership	99.6	1	14	52	155	392	–
Sum of Answers	4	0	0	1	6	47	2612
Sum of Questions	3.2	0	0	1	3	49	2089
Sum of Friends	0.2	0	0	0	0	3	126
Sum of Links	0.4	0	0	0	0	22	260

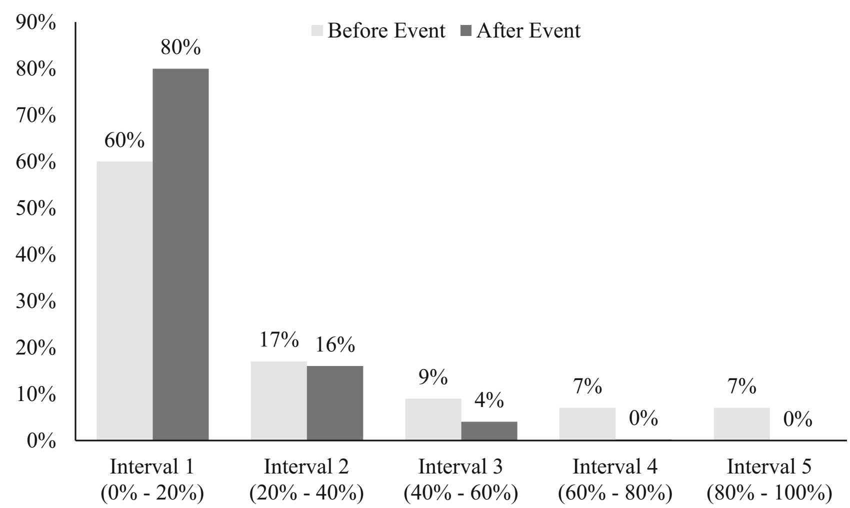

Fig. 3 Proximity to the next badge

This leaves us with an unbalanced panel of 650 users and 8650 observations on a daily level over a period of 14 days. The overall number of observations is 8650 and not 9100 (650 users times 14 days) because there are some users who registered in the week before the event. Therefore, we do not have seven observations for each user in the week preceding the event. We account for differences in the length of membership by including the control variable *Length of Membership* (measured in days) in absolute and squared terms in our model (see subsection "Extended Model").

6.3 Descriptive Statistics

6.3.1 Activity History of Users

In Table 6 we present a short summary of the activity history for the 650 users in our sample from the foundation of the platform up to the day of the event. At the time of restructuration, users are registered on the platform for 99.6 days (*Length of Membership*) on average, while 50 % of users are registered for 52 days or more. During the entire period of their membership users contributed on average 4 answers (*Sum of Answers*), asked 3.2 questions (*Sum of Questions*), had 0.2 friends (*Sum of Friends*), and added 0.4 links (*Sum of Links*).

6.3.2 Proximity to the Next Badge

In Fig. 3, we present the distribution of users in our sample across five intervals which track their distance from the next badge before and after the event.

Each interval covers 20 % of the required status points (e.g., *Interval 1* covers 0–20 % which is equal to the 0–24 status points before the event and 0–42 status points after the event). Before the event, 60 % of users had earned less than 20 % of the required points, 17 % were positioned in *Interval 2*, and the remaining 23 % of users were almost equally distributed across *Interval 3, Interval 4* and *Interval 5*. After the event, the distance towards the next badge increased substantially for those users. The proportion of users who possess less than 20 % of the required points increased from 60 to 80 %, and the remaining 20 % are placed into *Interval 2* or *Interval 3*. After the event, no more users remain in *Interval 4* or *Interval 5*. We use this exogenous variation in the positioning of users in our empirical analysis to identify the small-area effect.

6.3.3 Quantity Measures

In Table 7 we illustrate the number of *Answers* and the number of *Main Activities* per user per day in the week before and after the event. The number of *Main Activities*

Table 7 Quantity of users' contributions

Variables	Before event					After event				
	Mean	Std.	Median	Max	Sum	Mean	Std.	Median	Max	Sum
Answers	0.13	0.74	0.0	15	522	0.14	0.84	0.0	21	628
Main Activities	0.33	1.54	0.0	26	1364	0.34	1.58	0.0	32	1541

represents the sum over the four main activities illustrated in Table 2. We provide mean, standard deviation, median, maximum value and the total sum for both variables. Naturally, we have a large number of zeros in our sample as we work with user activity data on a daily level. The average of *Answers* increases slightly from 0.13 per day before, to 0.14 after the event. The average daily user activity for *Main Activities* increases also slightly from 0.33 to 0.34 from before to after the event.

7 Empirical Analysis

7.1 Main Variables

We use the number of *Answers* per user per day to measure user contribution levels. In addition, we use the number of *Main Activities* as second quantity measure to rule out potential reallocation effects of effort (e.g., users adding fewer links while increasing the number of their answers). To test our research hypothesis, we create a dummy variable (*Small-Area Dummy*) which takes the value zero for users who are in *Interval 2* or *Interval 3* after the event (control group), and one for users who are in *Interval 1* after the event (treatment group), respectively.[7] Finally, we create another dummy variable separating the days before and after the event (*Event Dummy*).

7.2 Model

We use a differences-in-differences (DD) approach to analyze the data from the natural experiment. With the DD framework we explicitly estimate how each group responds to the restructuring and how each group's response differs. To consider the distribution properties of both quantity measures (i.e., only non-negative integer values and large number of zeros) we estimate a Poisson model (Cameron and Trivedi 2013). The model is illustrated in Eq. (1):

$$Y_{it} = \alpha + \gamma D_S + \theta D_E + \rho(D_S * D_E) + \varepsilon_{it}. \tag{1}$$

The variable Y_{it} represents the dependent variables. Each observation in the sample is identified exactly by the index *it* where *i* represents the individual and *t* the day in our observation period. The variable D_S is the *Small-Area Dummy*. The estimator for the coefficient γ reveals potential differences between treatment and control group in average activity levels before the event. D_E is the *Event Dummy* and the estimator for θ represents the difference in average activity levels of the control group between the seven days before and after the event. The coefficient ρ of the interaction term between the *Small-Area Dummy* and the *Event Dummy* measures the difference between the differences in average activity levels between treatment and control group. Hence, the estimator reveals the difference in how each group is affected differently by the restructuring. The variable e_{it} is the error term. We cluster the standard errors on the user level to account for heteroscedasticity and autocorrelation in the data (Wooldridge 2010).

7.3 Identification

In the underlying research environment the level of progress towards the next badge is framed in terms of completed actions because the user's total number of status points is represented as an increasing number (see Sect. 3). This implies that the small-area effect is most pronounced when users are closer to zero status points and gradually weakens with an increasing number of points. This allows us to separate users into two groups, those who are set back to *Interval 1* (treatment group) and those set back to *Interval 2* or *Interval 3* (control group) (see Sect. 6.3.2). Crucial to our analysis is the difference in each group's responses. Due to the small-area effect, users who are set back to *Interval 1* (treatment group) are expected to respond more positively to the event compared to users who are set back to *Interval 2* or *Interval 3* (control group).

In Eq. (1), the estimator ρ for the interaction term between the *Small-Area Dummy* and the *Event Dummy* reveals how the responses between groups differ. There are two scenarios which can explain how the interaction term relates to the small-area effect. In the first, or *base case scenario*, both groups respond equally to the restructuring, were it not for the small-area effect. In this scenario the estimator for the *Event Dummy* θ is representative for both

[7] Please note that our 'control group' is not a control group in the strict sense of the term, given that both groups receive the treatment. However, as their treatment differs in terms of level of intensity, we consider the users who after the event are in Interval 2 or 3 as a control group. This helps us present our analysis in a differences-in-differences framework.

Table 8 Empirical results main model

Variables	Answers	Main Activities
Constant	−1.446** (0.230)	−0.684** (0.193)
Small-Area Dummy	−0.893** (0.269)	−0.577* (0.229)
Event Dummy	−0.348° (0.183)	−0.390* (0.159)
Small-Area Dummy * Event Dummy	0.642** (0.235)	0.560** (0.200)
Number of Users	650	650
Observations	8650	8650
-Log Likelihood	−4267	−8943

Cluster robust standard errors in parentheses, ** $p < 0.01$, * $p < 0.05$, ° $p < 0.1$

groups and the estimator for the interaction term ρ equals the small-area effect. In the second, or the *pessimistic scenario*, only users who are set back to *Interval 2* or *Interval 3* (control group) are negatively affected by the restructuring and the estimator for the *Event Dummy* θ is not representative for either group. In this scenario the estimator for the interaction term ρ has to be substantially larger than the *Event Dummy* θ if it is able to identify the small-area effect. Otherwise the estimator for the interaction term ρ might only artificially mirror the estimator of the *Event Dummy* θ (e.g., $\theta \approx -20$ % and $\rho \approx +20$ %).

In general, the base case scenario appears to be more likely than the pessimistic scenario. Both groups are expected to be negatively affected by the event because the distance towards the next goal is increased after the event and thus the activating power of the goal-gradient effect is less pronounced (see Sect. 2). However, as we cannot be absolutely certain of the presence of the base case scenario, we require the estimator for the interaction term ρ to be substantially larger in magnitude than the estimator for the *Event Dummy* θ, to enable us to identify the small-area effect in the subsequent analysis with confidence.

7.4 Results

In Table 8 we present the results of our empirical analysis. The first column shows the independent variables, the second column the results for the number of *Answers*, and the third column the number of *Main Activities*. For the dependent variable number of *Answers* all estimators are significant on a one percent level except for the *Event Dummy*.

The estimator for the *Event Dummy* is significant on a ten percent level. The estimator for the *Small-Area Dummy* is −0.893 or −60 % and reveals that users in the treatment group were less active before the event than users in the control group. The estimator for the *Event Dummy* is −0.348 or −29 %. This represents a decrease in the activity levels of users in the control group. The estimator for the interaction term between the *Small-Area Dummy* and the *Event Dummy* is 0.642 or 90 %.

We find a similar pattern for the second measure of the contribution quantity. All estimators are significant on a 1 or 5 % level. The estimator for the *Small-Area Dummy* is −0.577 or −44 %, for the *Event Dummy* −0.390 or −32 %, and the estimator for the interaction term is 0.560 or 75 %.

7.5 Discussion

The negative estimators for the *Event Dummy* indicate that users who are set back to *Interval 2* or *Interval 3* (control group) decrease their activity levels after the restructuring. The positive estimators for the interaction term between the *Small-Area Dummy* and the *Event Dummy* indicate that users who are set back to *Interval 1* (treatment group) increase their activity levels after the event compared to users in the control group. Even more importantly, the estimators for the interaction term are substantially larger in size than the estimators for the both *Event Dummy* variables, which means that our results are valid for both the *base case scenario* and the *pessimistic scenario*. Thus, these results support the theoretical predictions which suggest that the activity levels of users who were set back to Interval 1 are positively affected by the small-area effect. Hence, we derive the following result:

> Result: The online community users who are set back to the beginning are activated by the small-area effect and substantially increase their post-event contribution levels compared with users who are set back only half-way towards the next badge.

This result provides support for our research hypothesis. If the framing of the progress towards the next badge had no impact on user activity levels, we would expect the activity levels of both groups to be negatively affected by the event. However, as the users who are set back to *Interval 1* are positively affected by the restructuring, we attribute this positive effect to the small-area effect.

7.6 Robustness Checks

Although we find support for our research hypothesis, we have examined a number of competing explanations for the effects observed. In the following, we demonstrate that our results withstand a wide range of robustness checks.

Table 9 Robustness check – length of membership

Variables	Answers	Main Activities
Constant	−0.181 (0.354)	0.456° (0.271)
Small-area dummy	−1.319** (0.286)	−0.959** (0.228)
Event dummy	−0.348° (0.183)	−0.390* (0.159)
Small-area dummy * event dummy	0.502* (0.231)	0.437* (0.199)
Length of membership	−0.0230** (0.005)	−0.0195** (0.0036)
Length of membership^2	0.00005** (0.00001)	0.00004** (0.00001)
Number of users	650	650
Observations	8650	8650
-Log Likelihood	−4018	−8420

Cluster robust standard errors in parentheses, ** $p < 0.01$, * $p < 0.05$, ° $p < 0.1$

Table 10 Robustness check – adjusted sample

Variables	Answers	Main activities
Constant	−1.446** (0.230)	−0.684** (0.193)
Small-area dummy	−0.585° (0.327)	−0.286 (0.277)
Event dummy	−0.348° (0.183)	−0.390* (0.159)
Small-area dummy * event dummy	0.687* (0.322)	0.579* (0.269)
Number of users	256	256
Observations	3572	3572
-Log Likelihood	−2230	−4352

Cluster robust standard errors in parentheses, ** $p < 0.01$, * $p < 0.05$, °$p < 0.1$

7.6.1 Extended Model

We include the *Length of Membership* on the day before the event in absolute and squared terms in our model in Eq. (1) to account for negative effects of time (e.g., an increase in the probability to become inactive with increasing length of membership). The estimation results are illustrated in Table 9. The structure of the table is identical to Table 8. The estimator for the interaction term between the *Small-Area Dummy* and the *Event Dummy* is positive and significant for both dependent variables, that is, 0.502 or 65 % for the number of *Answers*, and 0.437 or 55 % for the number of *Main Activities*. Both estimators are lower compared to the estimators in Table 8. However, they are still reasonable in size and support the predictions from theory that the activity levels of users who were set back to *Interval 1* are positively affected by the small-area effect after the event.

7.6.2 Adjusted Sample

We restrict our sample to rule out that our findings are driven by users who were not (substantially) set back after the event or who newly registered on the platform shortly before the event. Hence, we exclude the 394 users (60 %) from our sample who were already positioned in *Interval 1* before the event (see Fig. 3) and estimate the model in Eq. (1) for both dependent variables again. The results are illustrated in Table 10 and structured in the same way as in the previous tables.

For both dependent variables the estimator for the interaction term between the *Small-Area Dummy* and the *Event Dummy* is both positive and significant. The estimator for the number of *Answers* is 0.687 or 99 %, and for the number of *Main Activities* it is 0.579 or 78 %. Both estimators are higher compared to the estimators in our main model, and thus provide another support for our main results.

7.6.3 Individual-Specific Fixed Effects

Although we use a natural experiment to identify the small-area effect, we recognize that there might be other factors (e.g., gender, age) that we have not accounted for but that might also be playing a role in our research environment. Therefore, we include individual-specific fixed effects in the model in Eq. (1) to account for time constant heterogeneity on the user level (Wooldridge 2010). The results are illustrated in Table 11. For both dependent variables the estimator for the interaction term between the *Small-Area Dummy* and the *Event Dummy* is both positive and significant on a five or ten percent level. The estimator for the number of *Answers* is 0.467 or 59 %, and for the number of *Main Activities* it is 0.41 or 51 %. Although the estimators are slightly smaller than in our main model (see Table 8), they are still economically significant. This again supports the results from our main model.

Table 11 Robustness check – individual-specific fixed effects

Variables	Answers	Main activities
Event dummy	−0.348° (0.183)	−0.390* (0.159)
Small-area dummy * event dummy	0.467° (0.241)	0.410* (0.202)
Number of users	238	415
Observations	3162	5531
-Log Likelihood	−1986	−4795

Cluster robust standard errors in parentheses, ** $p < 0.01$, * $p < 0.05$, ° $p < 0.1$

7.6.4 Adjusted Event Window

Although there are other special functionalities offered to discuss changes on the platform among users, one might speculate that those users who were set back to *Interval 1* are likely to be particularly engaged in discussing this event on the platform's question and answer mechanisms soon after the time of the event. To address this concern, we exclude the day of the event itself, and extend the end of the event window by another day to account for potential special effects on the day of the event. We estimate the model in Eq. (1) with the adjusted sample. The results are illustrated in Table 12. For both dependent variables the estimator for the interaction term between the *Small-Area Dummy* and the *Event Dummy* is both positive and significant on a one or five percent level. The estimator for the number of *Answers* is 0.720 or 105 %, and for the number of *Main Activities* it is 0.486 or 62 %. This too corroborates our main findings.

7.6.5 Adjusted Treatment Group

Our final robustness check deals with the concern that our results might be driven by the definition of the intervals and thereby the definition of the treatment group (see Fig. 3). We ensure the robustness of our results by both reducing and raising the size of *Interval 1* from 0–20 to 0–15, 0–25, and 0–30 %, redefine the variable *Small-Area Dummy*, and run the model in Eq. (1) for each specification again. The results are illustrated in Tables 13, 14, and 15. In each scenario the estimators for the interaction term between the *Small-Area Dummy* and the *Event Dummy* are positive. Further, except for the dependent variable *Main Activities* in the model with the interval size 0–15 % (see Table 13), all the estimators for the interaction term between the *Small-Area Dummy* and the *Event Dummy* are significant on a five or ten percent level. This again supports the results from our main model.

Table 12 Robustness check – adjusted observation period

Variables	Answers	Main activities
Constant	−1.446** (0.230)	−0.684** (0.193)
Small-area dummy	−0.893** (0.269)	−0.577* (0.229)
Event dummy	−0.321 (0.196)	−0.318 (0.172)
Small-area dummy * event dummy	0.720** (0.242)	0.486* (0.218)
Number of users	650	650
Observations	8650	8650
-Log Likelihood	−4471	−9025

Cluster robust standard errors in parentheses, ** $p < 0.01$, * $p < 0.05$, ° $p < 0.1$

Table 13 Robustness check – interval 1 (0–15 %)

Variables	Answers	Main activities
Constant	−1.488** (0.194)	−0.696** (0.166)
Small-area dummy	−0.964** (0.247)	−0.639** (0.212)
Event dummy	−0.144 (0.203)	−0.135 (0.178)
Small-area dummy * event dummy	0.440° (0.255)	0.273 (0.219)
Number of users	650	650
Observations	8650	8650
-Log Likelihood	−4239	−8092

Cluster robust standard errors in parentheses, ** $p < 0.01$, * $p < 0.05$, ° $p < 0.1$

Table 14 Robustness check – interval 1 (0–25 %)

Variables	Answers	Main Activities
Constant	−1.484** (0.277)	−0.699** (0.229)
Small-area dummy	−0.740* (0.309)	−0.502 (0.257)
Event dummy	−0.359 (0.188)	−0.366* (0.152)
Small-area dummy * event dummy	0.566* (0.239)	0.475* (0.193)
Number of users	650	650
Observations	8650	8650
-Log Likelihood	−4290	−8962

Cluster robust standard errors in parentheses, ** $p < 0.01$, * $p < 0.05$, ° $p < 0.1$

Table 15 Robustness check – interval 1 (0–30 %)

Variables	Answers	Main Activities
Constant	−1.309** (0.326)	−0.521 (0.270)
Small-area dummy	−0.905* (0.351)	−0.684* (0.292)
Event dummy	−0.414* (0.208)	−0.379* (0.168)
Small-area dummy * event dummy	0.604* (0.251)	0.474* (0.204)
Number of users	650	650
Observations	8650	8650
-Log Likelihood	−4282	−8943

Cluster robust standard errors in parentheses, ** $p < 0.01$, * $p < 0.05$, ° $p < 0.1$

8 Conclusion

With this paper we enhance the understanding of the underlying behavioral mechanisms prompted by virtual rewards (badges) in online communities, drawing on the small-area hypothesis as an explanatory framework. We test the applicability of the small-area effect in a natural experiment which allows us to investigate whether the framing of the progress towards virtual rewards has any impact on user effort. We find an increase in user contribution levels in the core activity 'answering questions' when users are in the early stages of their goal pursuit and when their progress was framed in terms of accumulated actions (highlighting the 10 % achieved instead of the 90 % remaining). We further find evidence that the activating power of this effect weakens with increasing progress to the next badge. By providing empirical evidence for the small-area effect on user contribution levels in the context of virtual rewards, our results make a distinct contribution to the body of literature investigating gamification (e.g., Hamari 2014). In addition, we contribute to the research on the small-area hypothesis (Koo and Fishbach 2012) by extending its applicability to non-monetary goals and to motivational phenomena such as user effort.

Although we use a natural experiment to identify the small-area effect and thereby control for potential alternative explanations, we recognize that our results are not as robust as results from a randomized experiment. For example, it might be that some users increase their post-event activity levels because they are eager to regain their lost points. Although users in the treatment as well as in the control group lose points it might be that those users are unequally distributed across both groups. Future research could strengthen and refine our results by performing a randomized experiment with a two (progress: low vs. high) by two (framing: accumulated vs. remaining) between-subject design. Such an experiment would also provide the opportunity to investigate the interplay between the goal-gradient and the small-area effect in more detail. Another interesting approach for future research might be to analyze whether the framing of progress in large numbers is more effective in activating user contribution levels than framing in small numbers. Indeed, research suggests that the contribution of an action is perceived as higher when it is rewarded with a large number (e.g., 4000 points) compared with a small number (e.g. 4 points) (Cantor and Kihlstrom 1987; Carver and Scheier 1998).

While the results from the Q&A community under study may not be directly transferable to other domains, our findings are nevertheless suggestive. Previous research in the domain of knowledge contribution has emphasized that user contribution behavior is influenced by both idealistic and altruistic factors (e.g., Kankanhalli et al. 2005; Jeppesen and Frederiksen 2006). We expect the small-area effect to be more pronounced in an environment where individuals are more extrinsically motivated and therefore more focused on virtual rewards and on their progress towards their reward goal. Thus, we have reason to believe that the activating power of the small-area effect could apply to various other domains including business and education.

Our results also have important managerial implications. Gamification designers should be aware that the framing of progress towards virtual rewards influences user effort. Our findings suggests that it would be more beneficial to frame progress in terms of accumulated actions in the beginning of goal pursuit up to a half-way point, and after this point is reached, to switch the framing to the number of actions remaining. For example, if a user needs 100 points to get a badge and has achieved 10 % of the points, progress should be highlighted as ‘10 % achieved’ and not as ‘90 % remaining’. By contrast, when a user has earned 90 % of the points, the progress should be presented as ‘10 % remaining’ instead of ‘90 % achieved’. The same reasoning also applies to any graphics illustrating progress (e.g., progress bar) which should highlight whichever is the smaller area of a user’s progress (accumulated progress or remaining progress). For example, if a user’s progress is represented by a solid blue line on a white background, the line should increase in length from 0 to 50 %. When the midpoint is reached the colors of the progress bar should be inverted which means that the interval 0–50 % is white and the interval 50–100 % is blue. Beyond that point the solid blue line should decrease with increasing progress. This mechanism would ensure that a user focuses on whichever is smaller in size, regardless of whether this is the accumulated or the remaining progress. Finally, since the small-area effect appears to be effective in activating user contribution behavior shortly before and after users attain their goal, this would suggest that a virtual reward system with multiple goals and medium achievement levels would be more effective at activating users than one with fewer goals and higher achievement levels.

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