Stimulating Feedback Contributions Using Digital Nudges: A Field Experiment in a Real-time Mobile Feedback Platform

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Abstract

In the contemporary remote work environment, the demand for effective and timely feedback has significantly grown. Despite the adoption of feedback systems, many employees still find these platforms lacking in delivering meaningful insights. This study delves into the potential of digital nudges—reminder notifications sent to users—as a strategy to enhance feedback contributions on mobile platforms. A randomized field experiment was conducted in collaboration with a prominent organization, exploring variations in nudge send times and the emphasis on task significance. Spanning five weeks, the experiment evaluated the efficacy of these nudges in fostering feedback engagement among employees. Our findings indicate that the timing, content of nudges (i.e., task significance message), and a combination of these two, can significantly influence feedback behavior. The study's findings have potential implications for organizations aiming to bolster their feedback systems, making them more responsive and effective in the digital age.

Keywords: digital nudges, feedback engagement, timing, task significance, feedback systems, randomized field experiment

Introduction

In this era of remote work, employees are more eager for quality feedback than ever. One report found a 100% increase in the number of employees seeking feedback from performance reviews in 2020 compared with 2018 (Reflektive, 2020). However, employee feedback is not always present or helpful, even in companies that have adopted feedback systems. For example, one study found that only 38% of employees at companies that use feedback systems believe their feedback will benefit others in their development (AllVoices, 2021). These findings illustrate a growing disconnect between firms and employees who both acknowledge the necessity of exchanging quality feedback between employees and management and recognize that implementation practices are often ineffective.

While many companies rely on an annual review process to provide performance feedback to employees,

employees often report dissatisfaction with this process, instead preferring to receive more frequent feedback to give them time to correct and modify behaviors (Reflektive, 2020; St-Aubin, 2021). An overwhelming 90% of employees do not believe the traditional performance review process provides timely and accurate information to help them pivot to behaviors that improve outcomes (St-Aubin, 2021). Hence, there is a growing understanding that employees should receive feedback more frequently.

One strategy to help managers deliver more valuable and frequent feedback involves sending digital nudges (reminder notifications sent to application users) to encourage them to take action. Nudges are an application feature designed for many industries, including health, finance, wellness, and business. Earlier studies have shown the importance of digital nudge timing to influence user behavior (Purohit & Holzer, 2019). Companies can target more feedback by sending these prompts when users are most likely to be engaged. In addition to optimizing nudge timing, companies may ensure higher quality feedback by optimizing notification messaging to ensure that it compellingly communicates task significance. Specifically, messaging that speaks to employees' internal sense of altruism by emphasizing the value of giving feedback may improve the real-time feedback process. In other words, altruistic messaging may communicate the task significance of feedback giving in a culturally compelling way, ensuring that more nudge recipients react to the nudges by providing quality feedback. Leveraging the factors of time and message together may yield better results, ensuring that feedback is frequent and valuable.

Our paper attempts to expand on existing research by investigating optimal nudge timing with a focus on nudge content. We utilize a novel data set from a randomized field experiment in collaboration with the real-time feedback platform DevelapMe. Our analysis helps establish that combining optimal digital nudge timing with altruistic message framing can lead to more impactful feedback that translates into positive outcomes for employees and the overall organization.

Motivation

Implementing a convenient digital platform for real-time feedback between employees and supervisors may improve communication, increase employee engagement, and improve organizational outcomes. Two essential factors play a critical role in employee engagement on feedback platforms: (i) a strategic approach that accounts for the timing of shared feedback and (ii) relating feedback to task significance, which can significantly enhance the positive impact of feedback. Petty and Wegener (1999) posit that there are two cognitive processing routes—peripheral and central—through which attitudes are formed and behaviors enacted. The central route requires high cognitive effort, enabling people to form, change, and act on their attitudes through high-effort processes. In contrast, the peripheral route consists of lower-effort mental shortcuts that can be utilized when users have already expended their cognitive energy on previous tasks. When users are low on energy and mental attention, they are less able to focus. Thus, it is essential to time nudges appropriately to encourage the most valuable responses.

In addition to timing digital nudges appropriately, organizations must ensure that users understand the task significance of giving, receiving, or responding to feedback. How a person perceives the task significance of a digital nudge will impact how they react to it. Altruistic significance, such as the belief that giving or responding to feedback will directly benefit others, may emerge with higher intensity due to a properly timed digital nudge. Firms facilitating quality feedback exchanges between employees and managers see positive employee retention, engagement, and performance (Jenkins, 2019). These findings demonstrate that organizations' understanding of feedback is essential for employees at all hierarchy levels.

Research Questions and Contributions

Employees' engagement and feedback responses on digital platforms are generally suboptimal. Even when individuals provide reviews, they are more likely to provide quantitative rating scores, which give almost no information to the recipient, instead of detailed textual reviews that may lead to more insights into improving performance. Hence, our study examines ways to stimulate feedback frequency and qualitative details. Specifically, we focus on two perspectives: timing and task significance.

First, we explore the effect of timing in stimulating feedback contribution by sending digital nudges at different times of the day. According to the elaboration likelihood model (Petty & Wegener, 1999), timing may correspond to different cognitive loads and, in turn, influence individuals' cognitive processing patterns (e.g., Sweller, 2011). Different processing routes may affect individuals' tendency to provide feedback. Hence, exploring the appropriate timing of a digital nudge could offer insight into how to optimize feedback contributions. Accordingly, we ask the following research question:

RQ1: How does a digital nudge's timing (i.e., morning vs. evening) influence the resulting feedback contribution (i.e., number of ratings and textual feedback provided)?

Next, we use a task significance model to encourage feedback contribution by providing digital nudges that emphasize its importance and advantages. By doing so, we leverage the belief that feedback benefits others to provide users with intrinsic motivation to provide more feedback. Studies have shown that emphasizing the importance of tasks may promote altruism (Crawford et al., 1991) and increase social connections (Grant, 2008). Both may help individuals privilege others above themselves, stimulating a more significant number of responses and more detailed feedback to their colleagues. Accordingly, we ask the following research question:

RQ2: How does the task significance communicated in the messaging of a digital nudge influence the resulting feedback contribution (i.e., the number of ratings and textual feedback provided)?

Finally, we explore how the combination of timing and task significance influences feedback contribution behaviors. Specifically, we want to know if digital nudges emphasizing or not emphasizing task significance sent at different times of day will affect feedback contribution behavior. In other words, whether the effects of timing (cognitive load) and task significance complement or substitute each other in simulating feedback. By doing this, we seek to explore how the impact of task significance on promoting feedback contributions varies according to the cognitive loads implied by sending time. Accordingly, we ask the following question:

RQ3: How do time and task significance, in combination, influence feedback contribution (i.e., number of ratings and textual feedback provided)?

To answer these research questions, we conducted a randomized field experiment in collaboration with one large organization and its employees across various departments and roles (i.e., managers and staff) participating. Our experiment utilized two treatments involving digital nudges: send times (morning vs. evening) and task significance (with task significance vs. without task significance). We also created a control group that did not receive any digital nudges. Participants were randomly assigned to one of the five groups. We collected feedback data over a period of five weeks, from March 1, 2021, to March 31, 2021.

Our study provides rich theoretical contributions to the emerging literature on digital nudges (Burtch et al., 2018; Ghose et al., 2020; Blaufus & Milde, 2021) by exploring the effects of timing on feedback contribution behavior in organizations. The majority of the prior literature focuses on how message frames (e.g., social norms and task significance) impact individuals' engagement behaviors (e.g., providing online reviews) (Gu et al., 2022). Our study goes beyond this by adding the dimension of timing. Specifically, we time digital nudges to take advantage of individuals' cognitive processes (i.e., high- versus low-effort processes), which may motivate different levels of feedback engagement. Our study explores how this method influences employee engagement and whether it substitutes or complements the message-framing method. In addition, our study contributes to decision-making literature by examining the interplay of cognitive loads and intrusive motivations on feedback contributions in a real-world organizational setting. While most prior literature examining this question relies on lab experiments and has not reached an agreement (Subramoney, 2016), our study provides solid empirical evidence using a randomized field experiment.

Literature Review

This study builds upon multiple research streams. We highlight the importance of each of these streams and explain how our study contributes to each one.

Feedback Dynamics in Organizations

In this section, we explore feedback dynamics within performance management systems as they relate to organizational nuances. Prior work on feedback dynamics considers how positive and constructive feedback impacts performance and the various stages of performance appraisal. For example, Coens and Jenkins (2002) describe typical formal performance appraisals or reviews a supervisor gives to a direct report. During these sessions, supervisors provide feedback regarding what employees are doing well while highlighting ways to improve work performance (DeNisi et al., 2017). Notably, this process leaves out much information about an employee because it comes strictly from the reviewer's viewpoint. Even if a reviewer seeks more details by asking others about the ratee's performance, the reviewer still analyzes the employee through a very specific and individualized lens about what makes an employee "good" or "bad." Our research mitigates this shortcoming by merging several feedback sources for each assessment instead of relying on a single source of information from one supervisor to evaluate an employee.

Recognizing that this review system is inadequate for providing a well-rounded assessment of an individual employee, organizations often use 360-degree feedback, wherein all stakeholders give and receive feedback, including peers, direct reports, and supervisors. Although well-meaning, the practice of giving and receiving 360-degree feedback can cause employees, supervisors, peers, and direct reports to change their behavior preemptively to receive better feedback. Therefore, organizations need to take care when deploying 360-degree feedback to ensure authentic feedback. This can be a challenge; in some cases, candid 360-degree feedback can undermine collegial relationships and damage the authority of supervisors who receive constructive feedback from their direct reports (Shi et al., 2021). One study explored a particular organization's use of 360-degree feedback over 12 months, finding that when direct reports gave their supervisors higher ratings, supervisors' reciprocal reports showed more engagement and satisfaction.

Organizations across industries are embracing technology to streamline all aspects of business, including feedback. Real-time, app-based feedback systems enable supervisors, direct reports, and peers to deliver real-time feedback on performance, competency, and goals (Huang et al., 2015; Gutt et al., 2019). Because of their real-time nature and ease of use, these systems allow employees to adjust performance iteratively. The widespread adoption of real-time feedback applications underscores their potential significance among today's management teams (Chappelow & McCauley, 2019).

As remote work becomes more common and employees seek timely and high-quality feedback, understanding how to encourage feedback contributions effectively is crucial. Recent studies have shown that many employees in organizations with feedback systems doubt the effectiveness of the feedback they receive (AllVoices, 2021), highlighting a disconnect between the need for quality feedback and its implementation. To address this issue, our study examines how organizations use digital feedback apps and nudges to improve employee performance and promote a culture of constructive feedback.

Our research also enriches the information systems (IS) literature around real-time employee feedback. Literature has investigated the impact of the dynamics of organizations on the feedback rating (Rivera et al., 2021), network structure (Petryk et al., 2022), way of getting feedback (Rivera et al., 2023), devices used for generating feedback (Shan et al., 2023), feedback types (Shan & Rivera, 2022), and the social norm nudges (Guo et al., 2022) on the feedback contribution quantity and quality. However, the missing gap is to understand the impact of task significance and timing used in digital nudges on real-time feedback.

Timing of Digital Nudges

Earlier studies demonstrate how a digital nudge's timing affects whether or not employees offer feedback in a performance feedback application (e.g., Egelman et al., 2009). Mehrotra et al. (2016) conducted a study on how people respond to mobile notifications and discovered that the effectiveness of notifications is greatly influenced by the time they are sent. Furthermore, Purohit & Holzer (2019) emphasized the significance of determining the best times for digital nudges to encourage behavior modification. The Elaboration Likelihood Model (Petty & Wegener, 1999) posits that employees can take two processing routes after getting nudged—the central and peripheral routes—which can form attitudes and behaviors. Those who follow the central route use a high-effort, elaborate, consciously determined, and explainable process to form, change, or act on their attitudes. In contrast, the peripheral route requires less conscious awareness and effort. Using the peripheral route, employees do not rely on high-effort cognitive processing to form, change, or act on their attitudes (Petty & Cacioppo, 1981). So, the question is, what determines whether an employee takes a central or peripheral route when forming their attitudes or behaviors? Prior research suggests that individuals' cognitive load plays a prominent role in influencing a user's thinking process (e.g., Sweller, 2011). According to Kahneman (2011), users have a finite amount of effort and attention available to dedicate to a particular task. For example, people have a lower level of attention after doing an activity that requires intense cognitive effort. Therefore, they have fewer cognitive resources to dedicate to elaborate information. As a result, they use low-effort processing (Petty & Wegener, 1999; Li et al., 2017). On the flip side, people who are mentally energized (such as after getting a good night's sleep) are more likely to take the additional effort to scrutinize information using high-effort processing.

There is a lack of research on how engagement with digital feedback systems changes over time. While it is known that people's cognitive processes vary throughout the day, it is not clear how this affects feedback engagement, especially when it comes to digital nudges. Our study uses data on individuals' cognitive load at different times to show that the timing of digital nudges can greatly affect user interaction with a feedback platform. For example, people are more likely to engage in detailed evaluative thinking in the morning when their cognitive resources are heightened. In contrast, nudges later in the day could lead to more superficial processing due to potential cognitive fatigue. These temporal variations could result in differences in feedback quality, with morning nudges potentially producing more detailed and actionable insights. Our research helps fill this knowledge gap and provides new insights into optimizing digital feedback engagement. Recognizing and using these temporal dynamics is important for organizations, as properly timed nudges can improve feedback quality and lead to a more effective feedback culture.

Task Significance Message Framing

Another factor that can influence feedback platform engagement is task significance or the extent to which employees feel their work is meaningful to their organization and community (Allan et al., 2016). Task significance describes "the degree to which the job provides opportunities to positively impact the well-being of others" inside or separate from the organization. Task significance has been shown to motivate user engagement, thereby improving task performance (Grant, 2008; Wang et al. 2016). The altruistic aspect of task significance can make employees more likely to participate in feedback. This is because many people in our cultural milieu put more emphasis on helping others than themselves (Crawford et al., 1991; Allen et al., 2016). Research shows that employees want to do meaningful work and are more productive when they feel their work adds value to someone (or something) outside of themselves (Grant, 2014).

In the context of how digital nudges influence real-time feedback applications, providing employees with information about how their feedback will positively impact their colleagues, organization, or community may be intrinsically motivating. Employees may be more likely to deliver helpful feedback on the platform when they believe it will benefit someone else. Since receiving valuable feedback from colleagues and supervisors can improve employee retention and lead to improved performance, we propose that digital nudges with messaging emphasizing how the feedback will positively impact the receiver and other stakeholders will encourage users to deliver more frequent and useful feedback.

Task significance is a critical factor that may impact the quality and efficacy of feedback. Reviewers need to feel that the task of seeking or giving feedback will significantly impact others in their work environment before they will take steps to pursue or deliver it (Park et al., 2014). Task significance can also encompass the degree to which employees feel their feedback contribution will impact themselves or their organization. Organizations need to communicate the significance of feedback to encourage employees to participate in real-time feedback applications. Creating an environment that encourages helping others through frequent feedback from all members of the organization may demonstrate the importance of feedback. Digital nudges targeting employees within a strategic window of time are essential to creating a culture of feedback.

Although the value of prompt feedback is increasingly acknowledged, there remains a significant gap in research regarding how framing feedback messages, particularly those that highlight the significance of tasks, interacts with timing to affect engagement. Many feedback systems within organizations overlook the nuanced motivators that underlie providing feedback. Our study is important in its investigation of this intersection, exploring how the combination of timing and task-focused message framing can improve the effectiveness of digital performance feedback. By emphasizing the importance of tasks in feedback messaging, organizations have an opportunity to communicate the concrete effects of feedback better, making it more applicable and actionable for the recipient. This approach can elicit more precise and contextually appropriate responses, even during periods typically marked by low-effort cognitive processing. In this way, organizations can foster a culture of collective commitment to task excellence and community engagement.

Interaction Between Timing and Task Significance

Our study also explores the interaction effect between digital nudges with timing and task significance on feedback-contributing behaviors. Prior literature has provided mixed evidence of the impact of cognitive loads (manipulated by timing) on the effectiveness of digital nudges. On the one hand, cognitive load can weaken the effectiveness of a digital nudge on decision-making by limiting one's expended mental effort (Eagly & Chaiken, 1993; Killeya & Johnson, 1998). Digital nudges can only be effective if recipients actually focus on the nudges' messages, which is more likely to happen when the recipients have sufficient cognitive resources. For instance, Alashoor et al. (2022) found that people may not prioritize privacy concerns when they are mentally exhausted or happy. Similarly, cognitive depletion can affect consumer preferences, with Hildebrand et al. (2021) noting that people may not enjoy complex flavors when they are mentally drained. Zabel et al. (2015) highlighted that the content of conversations can exacerbate cognitive depletion during interracial interactions.

On the other hand, cognitive loads may not hinder the effectiveness of digital nudges. Studies have found that message framing is more salient for individuals with intuitive and low-effort processing (Petty & Wegener, 1998; Dinev et al., 2015). In terms of altruistic behavior, the dual-process theory of moral judgment (Greene, 2012) suggests that subjects are less utilitarian when making moral judgments under a heavy cognitive load. The rationale is that altruistic behavior is typically encouraged by cultural norms and social expectations and thus is the "default" reaction in inter-personal exchanges, while deliberate thinking adjusts behaviors towards the payoff maximum and allows an individual to rationalize behavior that may not seem kind or fair (Chen et al., 2021). For example, Paxton et al. (2011) found that participants became more utilitarian when they engaged in reflective thinking before making moral judgments.

These findings highlight the importance of considering the timing and context of digital interactions. Given the lack of consensus in the literature, our study seeks to provide further empirical results using a field experiment from a real-world organization. Our study is among the first to look closely at the combination of timing and task significance of digital performance feedback to drive engagement.

Organizational Dynamics and DevelapMe Implementation

Our study examines the above-proposed effects using data from a real-time feedback application called DevelapMe. This application was initially designed to assess feedback within student teams in an educational setting (Petrucci et al., 2016; Santos, 2017). Since its development, DevelapMe has expanded into business use and is currently commercially available. Businesses of all sizes have adopted this tool to streamline internal real-time feedback, including Fortune 500 organizations and smaller operations. Its inclusion in industry magazines such as *Chief Officer Learning* (Santos, 2017) and *Training* (Freifeld, 2017) underscores its recognition as a leading example of real-time feedback technology. Users particularly appreciate its user-friendly design and secure platform, which allows employees and supervisors to easily give and receive constructive feedback in a safe setting.

Employees can access DevelapMe at any time from any compatible device, including their smartphone, tablet, or laptop. To provide feedback without prompting, a user opens the application and clicks the "Give Feedback" icon (see Figure 1). From there, the user scrolls through the drop-down menu to select an employee and then goes through the process of rating that employee with both one-to-five scales and textual feedback. Users may submit feedback anonymously or include their name so the ratee knows who wrote the feedback. After a user submits feedback, the recipient receives a popup notification on their device, letting them know they have new feedback to review inside the application. After receiving the notification, feedback recipients can go into the app to read and review their feedback.

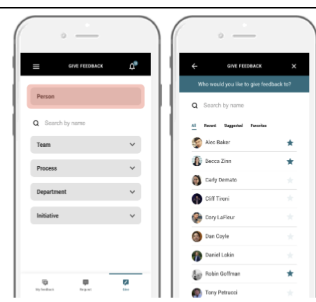


Figure 1. Feedback-giving

Methodology and Data Description

Experimental Design

To test our hypotheses, we conducted a randomized field experiment with a large global financial services company utilizing the DevelapMe tool. Due to a signed non-disclosure agreement (NDA), we are unable to disclose specific details about the company, but we are permitted to share some general information. This organization has approximately 44,000 employees, processes $3 trillion in transactions annually, and generates over $14 billion in annual revenue. It offers various financial technology services, such as banking, global commerce, and merchant acquisition. Additionally, its point-of-sale systems are highly regarded by retailers. From banks to broker-dealers, this corporation's impact is significant in the financial industry. Its leadership's ongoing efforts towards improvement and customer service, like using a real-time mobile feedback application, further confirm its respected position in the financial technology sector.

We designed a 2 × 2 experiment to explore the effects of treatments on participants' feedback contributions. The two treatments were timing (morning vs. evening) and message framing (without task significance vs. with task significance). For the timing treatment, we sent a push notification message at two different times: (1) morning (i.e., 10:00 a.m.) and (2) evening (i.e., 6:00 p.m.). We anticipated that a morning message would trigger the central route of information processing and motivate participants to provide more detailed reviews. In contrast, we hypothesized that an evening message would lead to the peripheral route of information processing, and participants would be less likely to provide reviews to their colleagues. For the message framing condition, we created two versions of the message, with and without task significance (shown in Table 1). The message with task significance emphasized the impact of providers' feedback on colleagues' performance to trigger participants' sense of altruism and willingness to help others and, in turn, influence the feedback contribution. We also included one control group that did not receive any messages during the experimental period.

Regular Message	Please provide a review for your colleagues in the DevelapMe platform.
Task Significance Message	Feedback is an important way to improve employees' performance and promote efficient human resources management in organizations. Please provide a review for your colleagues in the DevelapMe platform.

Table 1. Message Framing – Task Significance

To ensure the validity of the treatment, we conducted pre- and post-experiment interviews with some experiment participants. Before the experiment, we interviewed seven application users to validate the design of our treatment stimuli. We presented each interviewee with the task significance treatments at two different times (e.g., 10 a.m. and 6 p.m.). They were then asked to evaluate a series of statements on a five-point Likert scale. For instance, in the timing condition, interviewees were asked to indicate the extent to which they agreed with the statement, "*I feel tired and exhausted now.*" In the message framing condition, interviewees were asked to evaluate the statement, "*I feel that my feedback would help others*." Our interview results revealed that our designed treatments were valid in manipulating cognitive load via timing and altruism via task-significant message framing. After the experiment, we further explored the different cognitive loads in the morning and afternoon through a post-experiment survey. The results further bolster the validity of the timing measure implemented in our study.

In our experiment, all treatments were delivered via mobile push notifications sent to the home screens of users' smartphones. Push notifications have some advantages over other digital treatment delivery methods (e.g., email or short messaging service). First, because of the number of junk emails related to promotions, users tend to ignore such emails. Second, push notifications are integrated with the mobile application, avoiding the concern that recipients may ignore SMS text messages they believe to be spam. The platform did not run any other experiments in parallel.

Participants

Our participants included employees from our corporate partner across various departments and roles (e.g., manager, staff, etc.). Each participant was randomly selected to enter one of five conditions (i.e., the four treatment conditions in Table 2 and one control condition). To ensure the randomization of the treatments, we collected several participants' demographic information such as gender and role and conducted pairwise t-tests to compare the demographic characteristics in each pair of groups. We found that the four treatment (1/2/3/4) and one control (5) groups had statistically indistinguishable demographic properties before manipulation (see Table 3). The variable definitions can be found in Table 4.

Timing / Message Framing	High-effort Processing (10:00 a.m.)	Low-effort Processing (6:00 p.m.)
Without Task Significance	Treatment Condition 1 (1) (Morning + Regular Message)	Treatment Condition 2 (2) (Evening + Regular Message)
With Task Significance	Treatment Condition 3 (3) (Morning + Task Significance Message)	Treatment Condition 4 (4) (Evening + Task Significance Message)

Table 2. Two-by-Two Experimental Design

Treatment	Female		Team—Marketing		Team—Operation		Role—Manager	
	T-stat	P value	T-stat	P value	T-stat	P value	T-stat	P value
2 vs 1	-0.40	0.691	0.62	0.536	-0.22	0.826	-0.00	1.000
3 vs 1	-0.00	1.000	1.03	0.303	-0.44	0.661	-0.64	0.524
4 vs 1	-0.80	0.427	-0.41	0.680	-0.44	0.661	0.43	0.671
5 vs 1	-1.19	0.234	-0.62	0.536	0.22	0.826	1.06	0.288
3 vs 2	0.40	0.691	0.41	0.680	-0.22	0.826	-0.64	0.524
4 vs 2	-0.40	0.691	-1.03	0.303	-0.22	0.826	0.43	0.671
5 vs 2	-0.80	0.427	-1.24	0.217	0.44	0.661	1.06	0.288
4 vs 3	-0.80	0.427	-1.44	0.150	0.00	1.000	1.06	0.288
5 vs 3	-1.19	0.234	-1.65	0.100	0.66	0.510	1.70	0.090
5 vs 4	-0.40	0.691	-0.21	0.837	0.66	0.510	0.64	0.524

Table 3. Randomization for the Field Experiment

Procedures

Our push notifications were designed as an A/B test of the corporate partner's weekly notification systems. Users were randomly assigned to one of the five conditions. For users receiving push notifications, the notifications would appear on their device's home or lock screen. Once they clicked or swiped the notification, the user was taken into the mobile application, where the same short message would appear as a pop-up. Within the mobile feedback app, users could provide feedback to colleagues. They would first view several multiple-choice questions and then offer textual feedback. If participants chose to provide feedback, they could provide rating scores alone or rating scores with textual reviews. We observed each user's contributing behaviors (i.e., number and scores of rating feedback, number, and characteristics of textual comments) weekly throughout the five-week study period.

Participants in the control group received no push notifications. In the first treatment group, participants received a generic push notification from the mobile app at 10:00 a.m. each Monday asking them to provide feedback for their colleagues. In the second group, participants received the same baseline message via push notifications at 6:00 p.m. on Monday. In the third group, participants received push notifications at 10:00 a.m. each Monday with a message emphasizing the importance of their message to their colleagues' performance. Finally, participants in the fourth group received the task significant message at 6:00 p.m. each Monday. Among all groups (5 groups of 50 participants each), we collected 2,533 comments from 216 employees across three departments.

Empirical Analysis and Results

Dependent variables. Our analyses focus on two main dependent variables: the number of rating feedback reviews and textual comments provided by the participants in the experimental period. We use the natural log to address the potential problem of non-normal distributions in the dependent variables. Besides the quantity of feedback, we also consider the quality of the textual comments, such as length and readability, as additional dependent variables in the latter of the study.

Independent variables. Our analysis focuses on four treatment groups as outlined in Table 2. To further investigate the individual impacts of timing and task significance on feedback contribution, we examine two additional independent variables: *Timing* and *Task Significance*. The *Timing* variable is set to one when the digital nudge is dispatched at 10 am, and zero when sent at 6 pm. On the other hand, *Task Significance* equals one when participants receive the digital nudge containing the Task Significance message, and zero otherwise."

Controls. Our control variables include gender, role in the firm (i.e., managers vs. staff), and team (i.e., marketing, strategic operations, and IT). The detailed summary statistics for the key variables are presented in Table 4.

Variables	Definition	Mean	Std	Min	Max
Feedback	Number of feedback reviews provided	2.03	14.29	0	257
Comment	Number of textual feedback reviews provided	0.68	3.97	0	75
Length	Number of words in the textual review	39.06	34.01	1	209
Readability	Readability of textual reviews	16.36	14.14	-4.20	91.48
Task Process	Percentage of words related to detailed task process in textual review	0.56	0.32	0.00	1.00
Feedback Verification	Percentage of words related to feedback verification in textual review	0.17	0.15	0.01	0.74
Female	Indicator in which 1/0 indicates female/male	0.49	0.50	0	1
Manager	Indicator in which 1/0 equals manager/associate	0.67	0.47	0	1
Marketing	Indicator in which 1/0 equals marketing/otherwise	0.34	0.48	0	1
Operation	Indicator in which 1/0 equals operation team/otherwise	0.28	0.45	0	1
Team—IT	Indicator in which 1/0 equals IT team/otherwise	0.34	0.48	0	1

Table 4. Summary Statistics

Model-Free Evidence

Our empirical analysis starts with model-free evidence for average differences between experimental conditions on the number of rating feedback and comments. We first consider the impact of each treatment group on the probability that a participant agrees to provide rating feedback and textual comments.

Manipulation	Variable	Mean	StdErr	T-value	P-value
Control	No. Feedback	0.15	0.06		
Treatment 1	No. Feedback	0.60	0.16	2.51	0.012
Treatment 2	No. Feedback	0.48	0.12	2.48	0.014
Treatment 3	No. Feedback	8.53	2.26	3.62	0.000
Treatment 4	No. Feedback	1.96	0.35	4.91	0.000

Table 5. The Effect of Treatment on the Number of Rating Feedback

Tables 5 and 6 present the detailed two-sample t-test analyses. As shown, all the treated groups received a significantly higher number of ratings and textual comments than the control group, suggesting that push notifications play a significant role in encouraging participants to provide more feedback. Specifically, the higher effects of treatment 3 than the other four groups in terms of ratings and textual reviews are statistically significant, indicating that sending push notifications emphasizing task significance in the morning is the most effective treatment. Regarding the effect of task significance, compared with Treatments 1 and 2, Treatments 3 and 4 receive a significantly greater number of rating feedback and textual comments, respectively, suggesting that the task significance message encourages participants to provide more feedback to their colleagues at different times. In terms of timing, the effect differs for the different notification messages (i.e., regular vs. task significance message). Treatment 4 generates significantly fewer ratings and textual comments than Treatment 3, which suggests that participants are less likely to contribute in the evening than in the morning when given the task significance message. However, compared with Treatment 1, the number of rating feedback and textual reviews received by Treatment 2 is not significant, which may indicate that the effect of timing is not significant without the task significance message. Also, the above results suggest the interaction effects of the two treatments.

Manipulation	Variable	Mean	StdErr	t-value	p-value
Control	No. Comment	1.42	0.34		
Treatment 1	No. Comment	2.58	0.36	2.09	0.044
Treatment 2	No. Comment	2.77	0.38	2.35	0.025
Treatment 3	No. Comment	9.33	2.05	1.74	0.086
Treatment 4	No. Comment	3.98	0.24	5.26	0.000

Table 6. The Effect of Treatment on the Number of Textual Comments

Regression Analysis and Results

Next, we estimate the average treatment effects using regression analyses, which could produce estimates with higher precision than pairwise t-tests (Duflo et al., 2007). Specifically, we use the natural log to address the potential problem of non-normal distributions in the dependent variables and interpret coefficients as a percentage change. The detailed model is outlined in Equation 1.

$$\ln(Y)_{it} = \beta_0 + \beta_1 Treatment_i + \beta_2 Controls_i + \lambda_t + \varepsilon_{it} \quad (1)$$

$ln(Y)_{it}$ represents the log-transformed number of rating feedback or textual comments provided for participant i in week t. Our main independent variables are the four treatment conditions (four dummies). Specifically, the Treatment 1 dummy represents sending generic digital nudges in the morning (i.e., 10 a.m.), whereas the Treatment 2 dummy signifies sending the digital nudges in the evening (i.e., 6 p.m.) Treatment 3 dummy denotes that participants receive task significance digital nudges in the morning (i.e., 10 a.m.), while the Treatment 4 dummy represents that participants receive the task significant digital nudges in the evening (i.e., 6 p.m.). The omitted dummy is for the control group, which receives no notifications during the experimental period. λ_t refers to the week fixed effect to account for unobserved week heterogeneity. We use robust standard errors clustered by participants and week.

Table 7 presents the estimation results from Equation (1). Compared with the control group, all the treatment groups are positive and significant, suggesting the positive effects of sending a push notification on participants' feedback contribution in terms of the number of feedback reviews and the textual comments provided. Compared with Treatment 2, Treatment 1 has stronger effects on the volume of feedback and textual comments stimulated. This supports our position that individuals are more likely to provide feedback and textual comments when experiencing a low cognitive load than a high one. In addition, Treatment 3 has a stronger effect on the volume of feedback and textual comments stimulated than Treatment 4, suggesting the effectiveness of the task significance message. Given the same sending time, the message with task significance can contribute to more feedback contributions (i.e., providing feedback). Furthermore, Treatment 3 has the highest magnitude in coefficients, which suggests that the effects are strongest when we combine the timing and task significance treatment, i.e., sending the task significance message in the morning will stimulate the most significant number of reviews.

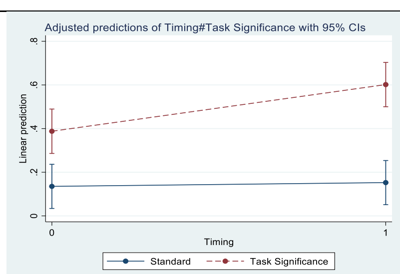
Dependent Variables	Log (number of Feedback)	Log (number of Comments)
Treatment 1—10 a.m.	0.102***	0.065***
	(0.034)	(0.021)
Treatment 2—6 p.m.	0.087**	0.062***
	(0.034)	(0.023)
Treatment 3—10 a.m.+ts	0.545***	0.342***
	(0.081)	(0.054)
Treatment 4—6 p.m.+ts	0.348***	0.212***
	(0.052)	(0.032)
Constant	-0.045	-0.064**
	(0.046)	(0.032)
Controls	Yes	Yes
Week FE	Yes	Yes
Observations	1,250	1,250
R-squared	0.121	0.128

Notes: Controls include employee gender, team, and role. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05. Control: No Message.

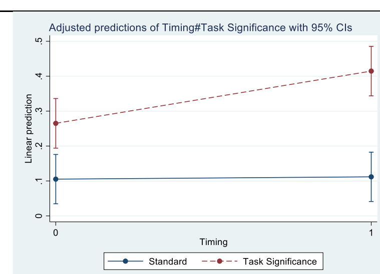
Table 7. Effects of Digital Nudges on Feedback Quantity

To explore the interaction effects of the two treatments, we included the additional interaction terms of timing and task significance in the model. Specifically, we generated one dummy variable for each of the treatments. $Timing$ equals one if the push notification is sent in the morning; otherwise, it equals zero. $Task\,Significance$ equals one if the message emphasizes the importance of the message to colleagues; otherwise, it equals zero. The interaction term $Timing_i * TaskSignificance_i$ equals one if the task importance message is sent in the morning. We also include the week-fixed effect to control for the week-specific heterogeneity. The detailed model is shown in Equation 2.

$$\ln(Y)_{it} = \beta_0 + \beta_1 Timing_i + \beta_2 TaskSignificance_i + \beta_3\, Timing_i * TaskSignificance_i + \beta_4 Controls_i + \lambda_t + \varepsilon_{it} \quad (2)$$



(a) Log (#ratings)



(b) Log (#comments)

Figure 2. Interaction Effects of Timing and Social Norms

Figure 2 and Table 8 present the estimation results from Equation (2). As seen, the interaction term (Time × Task Significance) is positive and significant for both dependent variables, which shows a complementary effect between timing and task significance—the impact of task significance on feedback contribution is stronger when sending the message in the morning than in the evening. This result suggests that a low cognitive load (i.e., in the morning) can help people focus more on altruistic motivations and lead to a higher level of feedback contributions (e.g., helping others improve their performance). Our study provides empirical evidence of the synthesis of timing and task significance treatments in a real organization setting.

Dependent Variables	Log (number of Feedback)	Log (number of Comments)
Time	0.015	0.002
	(0.042)	(0.027)
Task Significance	0.260***	0.150***
	(0.056)	(0.036)
Time × Task Significance	0.183*	0.128**
	(0.100)	(0.065)
Constant	0.038	-0.016
	(0.063)	(0.045)
Controls	Yes	Yes
Week FE	Yes	Yes
Observations	1,000	1,000
R-squared	0.118	0.131

Note: Controls include employee gender, and role. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. The baseline group is Treatment 2.

Table 8. Interaction — Effects of Digital Nudges on Feedback Quantity

Additional Analysis

So far, we have empirically examined the effects of the two treatments on the quantity of feedback. Next, we explore the effect of timing and task significance digital nudges on the quality of textual comments provided by participants. Higher-quality textual comments contain more detailed instructions and guidelines that can be more helpful in improving employees' performance than lower-quality comments. Specifically, we focus on four quality dimensions of textual comments—length, readability, task process, and feedback verification. The length of textual comments is measured by the number of words. Lengthier comments may demonstrate that raters put more effort into writing the textual comments (e.g., Burtch et al., 2018; Huang et al., 2019). Readability is measured by the Flesch Reading Ease (ranging from 1 to 100), i.e., the higher the score, the easier it is to read (McClure, 1987). This readability measure has been widely used in prior IS literature (e.g., Huang et al., 2015; Khurana et al., 2019).

Next, we generate two textual characteristics to further capture the detailed level of feedback using content analysis (Krippendorff, 2018). Textual characteristic measures were generated by creating and applying two Spacy (https://spacy.io) text-classification models. To support the creation of these text classification models, we utilized a tool called Prodigy (https://prodi.gy) to annotate, train, and evaluate these measures. Prodigy's workflows involve generating a seed word list for the textual measure, annotating a training set of industry feedback comments, training the model with a subset of comments using its machine-learning algorithm, and evaluating for model validity with the remaining subset of comments. These valid models are then applied against our dataset to determine the probability of language presence for each feedback comment. First, we focus on the Task Process, which refers to the detailed and specific process information to fulfill a task (Hattie & Timperley, 2007). The task process is measured by the percentage of words related to the detailed task process (such as procedures the comment receiver did not execute well) and provides detailed procedures for improvement. A high percentage of task processes represents a very detailed and specific review in terms of describing detailed task procedures. Second, we explore the feedback verification dimension, which refers to whether feedback provides a simple "yes" or "no" statement (Kulhavy et al., 1989). Prior literature has shown that feedback with the direct judgment of right and wrong is effective in motivating desired behaviors (e.g., Marsh et al., 2011). This dimension is measured as the percentage of words related to the right or wrong features of the feedback. We anticipate that following the task significance push message, participants would contribute lengthier and more detailed reviews since they would have higher motivation to help others. In addition, we anticipate that people will be more likely to contribute textual comments with a greater level of detail in the morning, since they tend to use the central route to make more high-effort and deliberate decisions during that time of day.

Dependent Variables	Length	Readability	Task Process	Feedback verification
Treatment 1-10 a.m.	0.180**	-0.218	0.102	0.057
	(0.082)	(1.239)	(0.120)	(0.088)
Treatment 2-6 p.m.	0.113	1.676	0.106	0.041
	(0.075)	(1.157)	(0.111)	(0.087)
Treatment 3-10 a.m.+ts	0.687***	1.532	0.231**	0.282***
	(0.110)	(1.495)	(0.107)	(0.098)
Treatment 4-6 p.m.+ts	0.381***	2.584*	0.178	0.054
	(0.087)	(1.402)	(0.114)	(0.004)
Constant	0.029	2.460**	-0.008	0.001
	(0.082)	(1.178)	(0.008)	(0.004)
Controls	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes
Observations	1,250	1,250	1,250	1,250
R-squared	0.082	0.549	0.794	0.589

Notes: Controls include employee gender, team, and role. Robust standard errors in parentheses *** $p<0.01$, ** $p<0.05$.

Table 9. Effects of Digital Nudges on Length and Other Textual Characteristics

The results are presented in Table 9, which shows that all treatments except Treatment 2 are positive and statistically significant compared with the control group, which suggests that either sending the digital nudge in the morning or with the task significant message can motivate participants to provide lengthier textual comments. Also, for textual comments' readability, only Treatment 4 (6 p.m. + ts) is statistically significant, which suggests people tend to write easier to read textual feedback when proving the task significant digital nudges in the evening. A possible explanation is that people may tend to use shorter and easier sentences when their cognitive load is high. Furthermore, for task process and feedback verification, we found that compared with the control group, only Treatment 3—sending the task significance message in the morning—significantly increased the detailed level of textual comments. The results suggest that individuals are more likely to provide detailed reviews when providing the task significance message with a low cognitive load, which further supports the effectiveness of combining both treatments.

Discussion and Conclusion

A central problem confronting organizations centers on hiring employees who expect and desire more and better feedback from their employers and peers (Modo, 2016; Newman, 2017). However, given that most employees respond negatively to available feedback systems (AllVoices, 2021), there may be a problem with perceived reciprocity between supervisors, peers, and employees. As such, organizations are aware that they may not be fostering an environment that promotes social norms for participation in feedback applications nor communicates the significance of feedback. This study aims to address this gap in the literature by focusing on more effective models to include the timing of stimulating feedback through digital nudges within the task significance model. In elucidating these individual factors and their interactions, organizations may learn strategies to elicit real-time feedback with rich, qualitative significance. Theoretically, this study seeks to go beyond the message framing of digital nudges and explore how different cognitive loads (influenced by timing) affect the impact of digital nudges.

Managerial Implications

The results of RQ1 provide insight into the extent to which the timing of digital nudges improves employee response, in accordance with the elaboration likelihood model (Petty & Wegener, 1999). Our results show that employees who received digital nudges in the form of push notifications in the morning provided a greater number of ratings and textual comments than employees who received nudges in the evening. Specifically, users who received a push notification at 10:00 a.m. each Monday were more engaged than users who received push notifications at 6:00 p.m. This is possible because employees have fewer tasks to juggle in their immediate setting in the morning, resulting in a lower cognitive load. In contrast, at the end of the workday, employees receiving a digital nudge may put off the task until later, which may result in a rushed, last-minute scenario. On the other hand, using digital nudges in the morning may take advantage of a more relaxed task schedule, enabling the user to complete the responses diligently with more contextual and valid information. Given the results of this study, managers should time nudges in the morning when employees have the greater mental capacity to devote to writing helpful feedback.

The findings related to RQ2 established that employees who received digital nudges with task significance showed more feedback contribution than employees who received generic messages. This indicates that employees may volunteer more feedback when they are reminded of the altruistic implications of feedback-giving to their peers. Therefore, managers should remind employees about the positive impact their feedback may have on their co-workers' performance and overall well-being to encourage a more robust culture of feedback giving. It is possible that optimal task significance messaging may vary with workplace culture, and managers should consider this when scripting feedback nudges for their employees.

Moreover, findings related to RQ3 demonstrate that, among the treatments tested, the combination of morning timing and task significance messaging produced the greatest amount of feedback contributions in terms of the number of feedback instances and the number of textual comments left in feedback. Given this information, we recommend that managers time nudges in the morning to take advantage of the reduced cognitive load. They should customize the nudge to incorporate a message reiterating task significance. Based on our results, this is the most effective way to encourage employees to contribute beneficial feedback for others.

Real-time feedback applications allow managers to easily manipulate nudge timing and messaging to adapt to these findings. Additionally, real-time feedback apps allow managers to modify target employee competencies according to the unique needs of their organizations and enable employees and supervisors to give feedback in their immediate setting. Based on our results, managers should take advantage of the widespread use of smartphones and other digital devices that promote the likelihood that the employee will make deliberate and rational decisions with relative immediacy. Without an application that can vary both the timing and messaging of digital nudges, managers may sacrifice valuable time and resources by soliciting feedback during inopportune times. By utilizing an app-based, real-time feedback platform, managers may begin to overcome the cyclical nature of negatively perceived feedback systems.

Theoretical Implications

Our study provides rich theoretical contributions to digital nudges, decision-making, and performance feedback scholarship. First, we contribute to the emerging digital nudges literature (e.g., Burtch et al., 2018; Ghose et al., 2020; Blaufus & Milde, 2021) by exploring the effects of cognitive loads (manipulated by timing) on the effectiveness of digital nudges. Much of the prior literature focuses on how message framing (e.g., social norms) impacts individuals' engagement behaviors (e.g., providing online reviews) (e.g., Huang et al., 2019; Gu et al., 2022). Our study goes beyond this by adding a new dimension of people's information processing systems with high and low cognitive loads. Our study shows that digital nudges substantially impact quantitative and qualitative feedback contributions when receivers have low cognitive loads.

Second, our study demonstrates the positive effects of the task significance digital nudge, a prosocial motivation, on both the quantity and quality of the feedback. While most current studies in the digital nudge literature focus on intrinsic and extrinsic motivations, our study explores a new message framing to stimulate feedback. Prior studies have shown that using one type of digital nudge is challenging to stimulate the quantity and quality simultaneously (e.g., Burtch et al., 2018). Our study finds that digital nudges that include task significance result in a greater number of reviews and lengthier and more detailed textual feedback than regular message digital nudges. Our study complements the existing literature by providing a prosocial motivation method to stimulate more and higher quality feedback.

Third, our study contributes to the decision-making and performance feedback literature by exploring the interaction between cognitive loads and the effectiveness of persuasion in altruistic behaviors. Prior studies have shown mixed results and have not reached an agreement. Our study shows that people are more likely to perform altruistic behaviors when they have low cognitive loads and can exert more effort to perform the task. Furthermore, while most prior literature examining this question relies on small-scaled lab experiments or hypothetical scenarios (e.g., prisoner's dilemma) (e.g., Hiraoka & Nomura, 2016; Subramoney, 2016), our study examines this question using a randomized field experiment in an organizational setting to provide more concrete and credible empirical evidence.

Future Research Directions and Limitations

Future studies should focus on manipulating the contents of task significance prompts to optimize responses with greater employee engagement. For example, the salience of varying altruistic motivations might be highlighted in different prompts that appear on an application. Future work should also explore whether specific prompt wordings are more effective depending on the industry, culture, or other differences. Additionally, more research is needed to better understand whether demographic factors beyond timing and task significance impact the quality and validity of ratings, such as age and seniority. In exploring these questions, researchers may better understand how to use this technology to best communicate with different types of employees and produce better performance outcomes. Additionally, it is worth noting that our results are based on a single platform implemented within one organization. Future research could employ similar digital nudges in organizations across different industries to further validate our findings. Moreover, by exploring its temporal patterns, future research could explore whether the digital nudge impact persists over time.

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