Employee Well-being Program: Designing the Digital Nudge

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This is to certify that to the best of my knowledge; the content of this thesis is my own work. This thesis has not been submitted for any degree or other purposes.

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Signature

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ABSTRACT

Many organisations have adopted employee well-being into their HR strategies and have implemented ongoing well-being management programs. With the ongoing pandemic and work-from-home arrangements, numerous well-being campaigns are delivered digitally. The thesis aims to investigate employees' engagement in digital employee well-being programs (EWPs) and how they are affected by the design and delivery of the campaigns. Built upon the Task Technology Fit (TTF) theory, the thesis conducted an analysis of employee participation data at a company's digital well-being platform. The results of this study indicate that employees' engagement levels are affected by notification intrusiveness and notifications schedules. In addition, time constraints can also play an important role in employee engagement as the findings show that employees typically delay taking action until the campaign deadline comes. The potential contribution and future study are finally discussed.

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1. Introduction

Employee well-being programs (EWPs) have become increasingly popular in recent years as companies recognize the benefits of promoting employee health and well-being. An EWP is also called well-being management program, employee wellness training etc. EWPs are shown to reduce employees stress, improve their physical health, reduce absenteeism and boosting productivity and organization's performance. (Baicker et al., 2010; Parks & Steelman, 2008; Gubler et al., 2018). Additionally, research has found that nearly 53% of organizations want to create a culture that promotes health and wellness[1].

EWPs consist of a variety of activities in the workplace designed to improve and support the health and fitness of employees. They can take the form of fitness programs, health workshops or seminars to raise the employees' awareness of health and help them make healthier choices in daily life. During the ongoing pandemic, the importance of supporting employee well-being has become even more crucial.

With the advancement of information and communication technologies and trends toward remote work, many EWPs are now being delivered online or through digital applications. This allow employees to access well-being contents anywhere at their own convinience, rather than setting their time to attend a number of health workshops. Moreover, many useful aspects (i.e., friendly user interface, real-time activities tracking, and data process based on data analytics results, fast

[1] *https://www.shrm.org/hr-today/trends-and-forecasting/research-and-surveys/pages/2017-employee-benefits.aspx*

insight, and customized feedback on health and individual behaviour) equip users' well-being awareness.

One key feature of the digital program is that users can be nudged by notifications or reminders to engage with online well-being management content and activities. For example, companies may send emails reminders to employees to participate in EWPs, or employees can be nudged by the push notification from a digital application. Prior studies revealed that notifications are effective ways to increase user engagement and they are effective in terms of bringing users awareness and immediate actions (Bidargaddi et al., 2018a; Schneider et al., 2018; Oakley-Girvan et al., 2021; and Freyne et al., 2013).

However, the effectiveness of notifications also varies by the time and format of the nudges. For example, users of a digital health app were found to respond differently to a notification sent over weekdays and weekends (Bidargaddi et al., 2018a). Notifications are also considered to be disruptive to people's current tasks (Morrison et al., 2017; Bidargaddi et al., 2018b; Iqbal et al., 2010). Additionally, Morrison suggests that notifications may have little effect on users' enaction, but only encourage them to engage with intervention content. However, we believe that sending the right type of notifications at the right time can attract user attention.

Thus, it is imperative to investigate what design works better to engage participation for digital EWPs. The main research question of the study is: *What are the design factors that impact employee engagement in digital well-being management programs?*

The Task Technology Fit model (TTF) is chosen to provide the theoretical foundation to investigate the research question. TTF is a theoretical framework to explain the effectiveness of technology by examining the fit of technology to users' task characteristics (Goodhue and Thompson, 1995). TTF has been widely studied in the field of information systems and human-computer interaction as a mean to understand and improve the effectiveness and efficiency of technology use. Studies have shown that a good TTF can lead to higher user satisfaction, increased productivity, and improved task performance. On the other hand, a poor TTF can result in low adoption rates, frustration, and decreased performance. Several studies have explored the impact of TTF on various aspects of technology use, including user satisfaction, acceptance, adoption, and performance. These studies have found that TTF has a significant impact on the success of technology adoption and usage.

In this study, I consider participation in EWPs as an organizational task for employees, as it shares more common characteristics with organizational tasks than personal activities. Traditional EWPs are usually held during office hours, and there is a limited time for employees to complete the training and activities. In the context of digital EWPs, where employees can join remotely at their own convenient time, they still see the notifications from the companies to remind them to complete the task assigned by the management team.

With this contextualization of digital EWPs as organizational tasks, the design of digital notifications will be assessed from three perspectives, including (i) the intrusiveness of the notifications, (ii) the scheduling of notifications, and (iii) the time constraints – deadline effect. A field experiment will be conducted to answer the research question. In collaboration with an organization offering digital EWPs to employees, we will capture users' log data to assess the online well-being management materials.

The study will advance the understanding of designing digital nudges for EWPs. The study will identify and evaluate specific factors that impact employees' engagement with the EWPs. The study will also reveal the contextual factors that influence employees' engagement with digital EWPs. The study will also contribute to the literature on EWPs and explain how employees perceive EWPs as organizational tasks. The study will also provide several practical guidelines to organizations running EWPs digitally.

The research is organized as follows: Firstly, it provides an overview of EWPs, notification triggers in EWPs, and a literature review on Task Technology Fit (TTF). Following, it presents the theory and hypothesis derived from the literature review. Next, the research describes a field experiment using a digital well-being application called Springday to collect data from financial organization employees. Detailed information is provided about the data collected from financial organization employees during a predefined campaign period. The data collection was done during a predefined campaign period. Finally, the report concludes by discussing future work related to the study, providing an opportunity for future research and advancements in the field.

2. Background

2.1 Employee Well-being Programs (EWPs)

Employee well-being programs (EWPs) are provided by many organizations to improve the lifestyle choices and health of their employees (Baiker et al., 2010). It takes the form of different names such as workplace well-being management, organizational wellness programs (Parks & Steelman, 2008) and employee health management (Wolfe & Parker, 1994). These programs may offer a wide range of contents, including improving physical activities, reducing sleep disorders, managing stress, and coping with chronic diseases (Redeker et al., 2011; Mattke et al., 2013). Some key literature in the EWPs research is summarized in Table 1 below.

Table 1. A summary of key literature on EWPs

Reference	Context	*Theoretical Foundation*	Predictors/ design	Outcomes	Methodology	Major finding
Gubler et al., 2018	A private industrial laundry service company. Design to encourage		Participation of the program (Compilers vs.	The health and emotional well-being of the employees.	A quasi-experimental setting	Demonstrated how participation in the EWP improves employees' productivity, reduces absenteeism, increases job motivation and

	employees to take health screening, improve self-awareness of health		Noncompliers)	Insurance cost saving; absenteeism. Productivity; job satisfaction		capabilities, and reduces insurance costs.
Solnet et al., 2020	EWP program to improve the well-being of front-line services worker.	classical and contemporary management theories	EWP Participation	Wellness program effectiveness	Theory development; No empirical study	Emphasized the importance of orientation session that provide benefits information and user guides. Drawbacks: Employees must set aside time to attend these types of sessions. Applied on the Front-line service worker only
Song et al., 2019	A multicomponent workplace wellness program resembling programs offered by US employers Program consists of total 8 modules (Each module lasted 4 to 8 weeks) and focused on key elements of health and wellness, including nutrition, physical activity, stress reduction, and prevention.		EWP Participation	health behaviour changes) Healthcare insurance Organization outcome)	Experiment Individuals were assigned to treatment or control status based on their worksite at the time of randomization or initial employment	Confirmed the effectiveness of a workplace wellness program in promoting physical activities, weight control, and healthy behaviours. Drawbacks: Within a short-term period of less than 18 months, the effectiveness of this program is substantiated in terms of healthcare spending/utilization or employee outcomes.
Melzner et al., 2014	Mobile health application in workplace	*Theory of planned behaviour*	Employees' Motivation	App usage	Model development based on technology	Developed a model to assist organization managers and application developers in achieving successful implementation and

					acceptant model (TAM), health belief model No empirical data	enhancing the attractiveness of apps by emphasizing content and ease of use. The model is based on research on health behavior and the Technology Acceptance Model (TAM).
Yassaee et al., 2018	Design principle Main objective is to help senior employees on their jobs effectively without putting their health at risk	Socio-technical IS design theory	Physical and psychology issues	Program effectiveness Productivity	Focus group and literature review Proposed a framework	Provided employees with corporate health and well-being programs, such as raising their self-awareness and preventing potential health risks. Drawback: Privacy concerns and work-related pressure need to be considered when using this affordable method.
Dailey et al., 2018	Workplace health promotion Employer offered 30 mins every day in working hours for employee to improve their health through exercise class, concealing		Working hours	Employee narrative on WWP	Qualitative research based on semi-structure interview	Showed positive outcome of Wellness Program during work time. Drawback: Study shown the concerns on how to balance the wellness time and work demand
Baicker et al., 2010	Workplace Wellness Program can generate savings		WWP characteristics	Absenteeism rate, Saving	Systematic review	Demonstrated the benefits of a WWP in terms of budget improvements, reduced absenteeism, and enhanced productivity and health outcomes.

The literature reveals that participation in the well-being program is shown to reduce absenteeism costs (Baicker et al., 2010, Harmar et al., 2015) and improve employees' productivity (Gubler et al., 2008). An effective well-being program can improve both the physical and mental health of the employees (Proper et al., 2019; Song et al., 2019). A workplace wellness program is also shown to increase employees' self-awareness of their health (Yassaee et al., 2018), encourage more physical activities and better weight control, and lead to health behaviour change (Song et al., 2019).

However, there are also some concerns and drawbacks of the EWPs reported in the literature. As most EWPs, such as yoga sessions/consulting sessions, are offered during working hours, employees have difficulty balancing the demands of work with wellness time (Dailey et al., 2018). One study reported that employees expressed their desire to participate, but their work schedules interfered with the wellness activity schedule (Kohll, 2017). However, if the EWPs are held out of working hours, employees are also less willing to sacrifice their personal time to attend such programs, resulting in low employee engagement (Farrell & Geist-Martin, 2005).

To provide employees more flexibility in attending the training and educational content on well-being management, many EWPs programs have moved online, especially during the pandemic as employees also find it difficult to attend the programs physically.

Although there are not many studies on digital EWPs, we could leverage the extensive research on digital health applications (Milošević et al., 2011; Melzner et al., 2014). The huge interest in using these apps is that they can continuously monitor, perform real-time data processing based on the data collected, and provide customized feedback on health and behaviour. A recent thematic analysis by Monge and Russis (2019) found that digital well-being apps come up with huge advantages in many specific situations, for example: (i) supporting self-monitoring, i.e., tracking user's behaviour and receiving feedback; (ii) strengthening user motivation by showing the overall result and improvement.

Because of the great benefits of digital health applications, combined with the advantages of the EWPs, we then focus on the approach that can increase user engagement with the digital application which represents an EWP. The typical digital EWP which has more options to measure employee engagement, such as how long they remain enrolled, how many times users enter the program, and when is the best time for them to engage with the EWP application/website is under-considered.

In addition, leveraging digital applications within the context of EWPs offers a convenient method to remind users to participate in the programs through a variety of designs of reminders and notifications. Effective notifications can significantly improve employee participation and engagement in the programs, even when they are participating remotely. This indicate that digital EWPs should prioritize the design and implementation of effective notifications to boost user engagement.

2.2 Nudge theory

Nudge theory, rooted in behavioural economics, decision-making, behavioural policy, social psychology, consumer behaviour, and related sciences, suggests modifying the decision environment to influence the behaviour and decision-making of individuals or groups (adapted from Wikipedia). Introduced by Richard H. Thaler and Cass R. Sunstein in their 2008 book "Nudge: Improving Decisions About Health, Wealth, and Happiness," this theory interprets how choices affect behavioural changes in both groups and individuals.

In the realm of information systems (IS), nudge theory finds widespread applications, aligning with the principles of digital nudge theory. Numerous successful papers have employed this theory to implement digital nudges within IS research (Weinmann et al. 2016, Dennis et al. 2020). Weinmann confirmed that digital nudge can influence users' behaviour in online environment, by specifying various types of digital nudge, such as visual cues, default setting, personalize messages etc. in steering users toward desired decision. Similarly, Dennis explored and summarised how digital nudge, especially numeric and sematic priming, can impact customer behaviour on online shopping environment. Furthermore, Mirsch et al. 2018, exemplifies how this theory is utilized to predict group and individual behaviours based on contextual conditions.

In the context of well-being apps designs, nudging techniques were initially explored in the researched by Auf et al. 2021. Auf's study integrated nudging techniques with gamification to enhance user engagement in well-being applications. However, the nudge techniques in this research were primarily evaluated in term of ranking the nudge techniques, not applying it in predicting the method to increase user engagement. Additionally, it mainly focused on the mental health and well-being application. In contrast, our research extends the concept of digital nudge specially for employee well-being applications, which are primarily used to improve users' health, in turn, improving user productivity and overall organizational outcomes.

2.3 Notification triggers in EWPs

With more well-being management programs moved online, digital notifications are widely used to remind users of engagement and nudge their immediate actions. A notification is "a visual cue, auditory signal, or haptic alert generated by an application or service to capture the user's attention" (Iqbal and Horvitz, 2010; Kanjo, Kuss, & Ang, 2017). A notification can be either an email prompt or a push notification. Prior studies have shown that notifications have been long viewed as not only an effective way of proactively helping users maintain information awareness but also an effective way to increase engagement (Bidargaddi et al., 2018a; Bidargaddi et al., 2018b; Schneider et al., 2013; Hernández-Reyes et al., 2020 and Freyne et al., 2017). For example, an experimental approach was conducted by Bidargaddi et al., 2018a with a "micro-randomized" study on the effect of push notifications on user's engagement in mobile health shown that participants made almost 9% more use of the app if they were received tailored health messages at 12:30 pm on any given day or 7:30 pm on weekends.

However, notifications have also been found to be a source of disruption on focal tasks, despite their great benefits (Cutrell et al., 2001; Czerwinski et al., 2004, and Iqbal and Horvitz, 2010). Oftentimes, notifications are received at inconvenient times, luring users to process and respond to them. (Czerwinski et al., 2004; Iqbal et al., 2010). In the context of well-being management programs, employees may also be distracted from their focal jobs by notifications. Studies have shown that responding to notifications slows down task resumption and negatively affects performance on interrupted tasks (Bailey et al., 2007). However, the level of distraction varies with different types of notifications. Email notifications can be viewed as a mechanism to provide passive awareness rather than a trigger to switch tasks (Iqbal et al., 2010). This kind of passive awareness can be considered as the option not to reply to messages or defer responses and is widely regarded as a valuable feature of email notifications. Although users believe (email) notifications are disruptive, they persist with them since they perceive them as helpful in providing information. (Iqbal et al., 2010).

Similarly, from a technology perspective, push notifications, usually sent from digital applications, taking the form of pop-up messages (Weber et al., 2015), can pressure a user to reply or respond. They are viewed as more disruptive by the receivers (Pielot, M., & Rello, 2017; Yoon et al. 2021). People have been found to "attend to notifications quickly, if not immediately, which arrive at random times, making mobile phones particularly disruptive" (Kanjo et al., 2017).

Knowing how different designs of notifications work will reduce distractions, help users stay focused, and will improve employee engagement with the well-being management program at their own convenience.

A proper notification should allow users to choose to switch attention from ongoing tasks at moments that are more suitable for them, rather than allowing notification to divert their attention unexpectedly during less opportune moments. A prior study also found that notification time plays an important role in nudging users' immediate actions (Bidargaddi et al, 2018a). Thus, it is also important to understand the scheduling of the notification.

A summary of key literature research is summarized in Table 2 below.

Table 2. A summary of key literature on notification

Reference	Context	Predictors	Outcome	Methodology	Major finding
Bidargaddi et al., 2018a	An experiment approach by measuring the usage of a Happy Mind app - a smartphone-bas ed stress management intervention app.	Push notification scheduling	User engagement	Micro randomized trial (MRT) design different level of notification schedule.	Pushing notifications with tailored health messages appears to affect near time, proximal engagement with self-monitoring activity High rate of engagement if push notifications are sent during weekend and according to time at mid-day.
Iqbal et al., 2010	A review on email notification and awareness Investigate the effect and drawback of email notification	Email notification in workplace	Task focus interruption	A two-week in situ field study Recording users' interactions with software applications for two weeks and studied how notifications or their forced absence influenced users' quest for awareness of new email arrival, as well as the impact of notifications on their overall task focus	Giving the best understanding on how users perceive the email notification: as a passive awareness of information/ or as a source of disruption.

Bidargaddi et al., 2018b	A self-monitoring in JOOL Health smartphone app was used to send the customized message to 1414 users	Push notification's contents and frequency	Self-monitoring capability	Mixed method and a self-monitoring in JOOL Health smartphone app	- Developed a framework to identify two interrelated sets of consequences of health and well-being in the workplace - Offerred a summary - informal model for organization's knowledge - effectiveness of notification
Morrison et al, 2017	Push notification is used to test with 3 groups: ○ intelligent notifications: when the algorithm predicted that a user was most likely to notice and respond based on phone-based sensors. Up to 3 notifications a day. ○ daily notifications within 24 hours. ○ occasional notifications within 72 hours Notification was randomly triggered from 17:00 ~ 20:00 with daily and occasional notification; and 8:00~22:00 with intelligent notification. Notification contents embedded some information, ie: tool announcement, tool suggestion, general reminder	Push notification response and intervention usage Push notification frequency	The effectiveness of the notification in app usage	Experiment method using an app called Healthy Mind Evaluated the effect of notification scheduling based on notification response and Healthy Mind usage Phone interview was conducted to the app users (user perception, user experience)	Frequent notifications may encourage greater exposure to intervention content without deterring engagement, but adaptive tailoring of notification timing does not always enhance their use.
Mehrotra et al.,2017	Investigate relationship between notification acceptance and place and current activities	Current user place Current activities	users' attention towards new notifications and user acceptance	in-situ study	To assist app/program designers in identifying the factors that increase users' acceptance of notifications. New notifications are strongly influenced by the location of the user and in a minor way by their current activity.

Pielot et al., 2014	Different types of notification studies	Email/push notification	Response time Emotional effect	in-situ study with 15 users in one week	To have better understanding on the users responded time (longer responded time for email comparing to push)

2.4 Task Technology Fit Model

TTF is "the correspondence between task requirements, individual abilities, and the functionality of the technology" (Goodhue and Thompson, 1995, p.218). In general, Fit means how well a certain technology matches a given task while technology refers to the tool used by a user to complete a task (Fuller and Dennis, 2009). The TTF theory is widely applied in many other research areas, including consumer research (Klopping et al., 2004), the health care sector (Chen et al., 2015), and mobile information system (Gebauer et al., 2010). With the technology improvement, e-commerce is the common way for businesses to contact potential customers, therefore, the importance of having an effective TTF can help in interpreting how and why people perform online shopping tasks. Similarly, the TTF model was used in the health care sector to find the match between technologies characteristic and performance task, which is clearly defined as patient care tasks (Chen et al., 2015).

TTF was expanded by Gebauer et al., 2010 in the design of the effective mobile IS to gain a better balance of managerial tasks, mobile IS, and the mobile use context, therefore, providing better support to managerial tasks. It can be also combined with TAM (Technology Acceptance model) to change behaviour, and achieve high satisfaction on education goals, by using social media. However, there are few studies on applying this TTF model in workplace wellness programs.

Based on technology adoption theories, potential users will be more motivated to adopt an information technology if it fits the task environment (TTF) (Dishaw et al., 2018; Goodhue and Thompson, 1995). Yet the challenge is conceptualizing a task environment that reflects the user's goals and identifies the causal mechanisms for adoption (Davis et al., 1989).

In IS research stream, (Goodhue and Thompson, 1995) discuss how the fit between people, tasks, and technologies predicts IS-enabled task performance. Furthermore, they argue that the task-technology fit (TTF) approach should be renamed task–individual–technological fit as based on "a better name would be task–individual–technology fit" (p. 218), rather than TTF due to its simplicity, as users play a vital role in controlling task performance. Within this research stream, numerous studies have examined technology, user characteristics, and task characteristics in relation to task performance outcomes. A recent study by Burton-Jones and Grange (2012) elaborates on the concept of effective system use. This concept includes three elements: the competencies and motivations of users, the nature and purpose of systems, and the characteristics of tasks" (p. 634). The nature of the task also plays an important role in a group's interaction process and performance (Hackman and Morris, 1975; Goodman, 1986), as important as individual performance.

In our research, we focus on individual performance. Task characteristics are believed to affect individual performance; thus, we focus on the task characteristic to investigate its effect on user engagement when using digital well-being apps.

3. Theory and Hypothesis

3.1 Intrusiveness of notification

Czerwinski et al., 2004 and Iqbal and Horvitz, 2010 have found that while notifications offer a great deal of value, they can also distract from main tasks. These studies have shown that responding to notifications impedes the efficient resumption of interrupted tasks and negatively impacts task performance, therefore, users may refuse to respond or take an action when notifications are received at inconvenient times. Thus, users miss out on the opportunity to interact with the well-being application. However, if a user is passively aware of the notification, they may return and engage with the app when they finish their main task (Iqbal et al., 2010). As a result, determining the effectiveness of notification by understanding its intrusiveness is of great importance.

Based on the literature review of push/email notifications summarised in section 2.2, users view email notifications as a mechanism to provide passive awareness rather than a trigger to switch tasks. Push notification can be considered as a strong/more stressful way to trigger the user's awareness to start engaging with the EWPs. It can be clearly explained in Pielot et al., 2014 study, where users' response time is different based on the type of notification, for example, 3.5 mins/ push notification vs 27.7 mins/ email notification on weekends. Some other important features such as frequency, content, and importance level of the notification will increase/delay or disable the notification, thus directly affecting users' engagement with the app (Bidargaddi et al., 2018a; Bidargaddi et al., 2018b; Morrison et al., 2017).

In this hypothesis, the intrusiveness of notifications is seen as a key factor in determining user engagement with employee well-being programs (EWPs). The intrusiveness of the notification is considered based on the finding of Pielot et al., in the context that "notifications can also pressure a user to reply, as taking a long time to respond to an unread message may result in a negative evaluation of the receiver by the sender". It is proposed that low intrusive notifications, such as emails, provide passive awareness of the EWP and allow employees more flexibility in participating in the program. On the other hand, high intrusive notifications in the form of push notifications from a digital app are seen as more urgent and may lead to task switching, but if the employees do not respond immediately, they may overlook the task of participating in the program.

Based on TTF theory, the technology characteristic can be modified/selected to create a good fit with the task, thus increasing the individual performance. We focus on the benefit of notification and mitigate the negative disruption effect; therefore, we hypothesize that notification with low intrusiveness will bring a better way to remind employees to engage in the well-being program. Low intrusiveness notifications are used to remind employees to participate in well-being management tasks, in addition to their primary tasks, so they shouldn't disrupt primary tasks. Thus, we hypothesize that:

H1: Passive notification will lead to more user engagement in EWPs.

3.2 Time constraints on engagement in EWP

The majority of studies focused on the user's behaviour after receiving the notification. Users tend to use the app after 24 hours of receiving a notification according to Bidargaddi et al., 2018. More than 3.9% of users entered the app compared to users who did not receive the notification. In a better way, notification features can be described as enhancing connectivity and up-to-datedness via user alerts when a user interacts with services (Dawot et al., 2014) but it also brings the side effect of distracting them while they are working on a particular task (Iqbal et al., 2010). Users tend to access the content quickly if it's very attractive and interesting at a convenient time, or they may refuse to connect and trigger the procrastination directly, until the deadline. Therefore, procrastination may occur depending on the type of notification and characteristics of the program.

Alblwi et al., 2019 found that procrastination occurred based on the task characteristic. In the workplace well-being context, employees may treat the wellness program as their organizational task, therefore, tend to procrastinate because of the nature of the task. It may be only when a deadline is looming that they first consider the specifics of a task, including what will be required to complete it, the context in which it will take place, and other details (McCrea, et al., 2008). In relation to task characteristics, the time effect needs to be carefully considered as the constraints on engagement to the well-being app. Within the organization, if the well-being task is set to a deadline, we believe that people tend to quickly make the action soon before the deadline, especially well-being tasks can be decided as non-urgent/critical tasks. Therefore, we hypothesize:

H2: Employees engage in the EWPs closer to the deadlines.

3.3 Scheduling of notifications

Prior studies also found that notification time plays an important role in nudging user participation (Farrell & Geist-Martin, 2005; Kohll et al.,2014; Dailey et al., 2018). For example, a fitness app is designed to send an excise reminder during the users' regular lunchtime or sleep time. An experimental approach by Bidargaddi et al., 2018a with a "micro-randomized" study on the effect of push notifications on user engagement, showed that participants made almost 9% more use of the app if they were received tailored health messages at 12:30 pm on any given day or 7:30 pm on weekends. In a separate study conducted by Okoshi et al. (2018), it was found that users tended to respond to notifications at noontime rather than at other times of the day such as 8 AM, 6 PM, and 9 PM. Conversely, in Morrison's study, sending numerous notifications daily between 5 PM and 8 PM did not result in increased engagement with the EWP.

In the context of the employee well-being program, the notifications can be sent either on weekdays or weekends. The advantage of an employee well-being management program is employees can complete it during working hours, thus not interfering with their personal life. Therefore, there will be more usage if the notifications are sent during the workdays.

As a result of the literature review, we derive this hypothesis based on the Fit of the technology, i.e., the notification characteristic. Instead of sending the notifications after hours, we will schedule/fit them into the workday, and we believe it will encourage employees to use the EWPs during office hours, because they see it as a task assigned by their managers.

Thus, we hypothesis that:

H3: The mode of notification will influence user engagement in EWPs.

3.4 Notification intrusiveness and notification time

Morrison et al. (2018) found that users who access the application after receiving a push notification enter twice as many as those who access the website after receiving an email notification. However, they only spent half as much time on the intervention as web users. It depends on the timing when they receive the notification. Most users consider email notifications “are usually from exchange server, so they are work-related” (Pielot et al., 2014), which meant users need more time to read and take an action. As a result, they refuse to do it at the weekend when they would like to reserve most of their time for family/private activities. Okoshi et al., 2018 study concluded that the number of users’ clicks during the weekend is 1% lower than during weekdays, and this behaviour was assumed to be true based on the breakpoint when users perform physical activities (i.e., daily commuting for work during weekdays and taking breaks at home on the weekend).

Thus, we need to determine when the best/easiest time is to interact with the application/web portal so that we can send out the right type of notification. For instance, people tend to use mobile phones more frequently on the weekend as they are free from computers and company tasks. In this case, the push notification is the most applicable way to remind them to interact with the mobile well-being app at weekend, whereas most of the time email notification is more effective when people use computers, during working hours.

Therefore, we hypothesize:

H4: The interaction effect of notification intrusiveness and notification scheduling influences user engagement in EWPs.

4. Research Method

4.1 Field experimental study

A quasi-field experience will be conducted to answer the research question and test the hypotheses, as it allows us to observe participants' genuine behaviours under experimental conditions without direct interventions (Hergueux and Jacquemet 2015). In this research, we use a field experimental study conducted online and capture employee engagement to a customized EWP through the use of the SpringDay application.

4.2 The SpringDay App

SpringDay is an app that can be downloaded and used on both iOS and Android phones, or as a website. It was created by Springday, a well-being management company that provides effective EWPs for many large companies in Australia. Springday provides 5 well-being services – Physical Well-being, Emotional Well-being, Career Well-being, Financial Well-being, and Social Well-being. Springday focus on technology and design, it provides customized campaigns designed based on importance to increase the level of engagement of current users as well as gain the interest of future users.

4.3 Data description

We use data from an online employment well-being management program offered to a consulting firm over a month starting from June 2020 to July 2020. Employees' clickthrough data at the online well-being management portal/application were captured by Google

Analytics. The usage data were downloaded from Google Analytics using Google Analytics API v4. It contains the information about the number of sessions users browsed once entering the web portal, the accessed time, the page links and the page titles.

The additional data such as campaign email information was received directly from the Human Resource department that manages the program, which includes campaign start time, end time, the contents, and the texts of the email and app push notifications. The description of the raw data is shown in Table 3.

Table 3. Raw data resource

Data source	***Data description***	***Data category***
Google Analytics	*System usage data* The user explorer data recorded every time users interact with the well-being management app	o UserID, o Access time o Number of sessions o Total duration o Page link o Page title
Campaign data	The campaign information sent out by the organizational email, or by app notification.	o Campaign content o Campaign start time o Number of users received the email

We then combined all the campaign data with the system usage data to have a clean dataset that includes the user ID, campaign title, the percentage of employees who attended the campaign, accessed time, and accessed duration they spent on the campaign.

4.1 Data processing

The Google Analytics data were cleaned and processed using Python to create the dataset about individual employees' usage patterns, particularly, we have calculated the session counts and session durations for sessions that are triggered by emails and push notifications. A total of 500 participants have led to a total of 3131 sessions for analysis.

We define the following terminologies and use them during the research. **A *session*** refers to a period a user is actively engaged with the website, app, etc (Google Analytic, Leidl et al., 2017). **Session counts** were calculated based on the total number of sessions that a user browsed during a campaign period. **Session duration** is calculated, based on the time user stayed on that web page before switching to another. If the user clicked on only one web page and did not move to another page, then the duration time is set to zero. These two terminologies are applied in both email and push notifications as described in Table 4.

As mentioned in section 2.1, we used the literature review result which best describes how to evaluate the user engagement to EWP, such as how long they remain enrolled, how many times users enter the program, etc. Table 5 describes the data that reflects each employee engagement with the online well-being application at the individual level based on the system usage variables listed in Table 4.

Table 4. System Usage Variables

Variable	*Explanation*
$SessionCountDay_i$ (*)	*Number of sessions in which a user engaged per day*
$EmailSessionCountDay_i$ (*)	*The number of sessions directed by email notifications on day i*
$PushSessionDay_i$ (*)	*The number of sessions directed by push notifications on day i*
SessionDuration	*Total duration of all sessions in a day (in second).*

$EmailDurationDay_i$ (*)	*The total time/duration that user interacted with the app by clicking on the email notification.*
$PushDurationDay_i$ (*)	*The total time/duration that user interacted with the app by clicking on the email notification.*
(*) ***i = 1,2,3,4,5,6,7*** – stands for 7 days of the week (Monday to Sunday).	

Table 5. Individual system usage data

Variable	**Fomula** (with n is number of records in the dataset)	***Explanation***
Total session counts for all types of notification (Descriptive result)	$\sum_{i-1}^{28}(PushSessionDay_i + EmailSessionDay_i)$	Aggregated over all days for email and push notifications for each participant
Total session counts for email	$\sum_{i=1}^{k} EmailSessionDay_i$	Aggregated over all days for email notifications for each participant
Total session counts for push	$\sum_{i=1}^{k} PushSessionDay_i$	Aggregated over all days for push notifications for each participant
Mean session count for email	$= \text{Mean}(EmailSessionDay_i)$	Mean of email session for each participant
Mean session count for push	$= \text{Mean}(PushSessionDay_i)$	Mean of push session for each participant
Average session duration for email (in second)	$= \frac{\sum_{i=1}^{k} EmailDurationDay_i}{\sum_{i-1}^{28} EmailSessionDay_i}$	Aggregated duration over all days per aggregated session counts for email sessions for each participant
Average session duration for push (in second)	$= \frac{\sum_{i=1}^{k} PushDurationDay_i}{\sum_{i=1}^{k} PushSessionDay_i}$	Aggregated duration over all days per aggregated session counts for push sessions for each participant
Average session duration for email (in second) (Time Constraint = 1)	$= \frac{\sum_{i=1}^{k} EmailDurationDay_i}{\sum_{i=1}^{k} EmailSessionDay_i}$	Aggregated duration over all Mondays and Tuesday per aggregated session counts for email session for each participant

Average duration for email (in second) (Time Constraint = 0)	$= \frac{\sum_{i=1}^{k} EmailDurationDay_i}{\sum_{i=1}^{k} EmailSessionDay_i}$	Aggregated duration over all Thursday and Friday per aggregated session counts for email sessions for each participant
Average session duration for push (in second) (Time Constraint = 1)	$= \frac{\sum_{i=1}^{k} PushDurationDay_i}{\sum_{i=1}^{k} PushSessionDay_i}$	Aggregated duration over all Mondays and Tuesday per aggregated session counts for push sessions for each participant
Average session duration for push (in second) (Time Constraint = 0)	$= \frac{\sum_{i=1}^{k} PushDurationDay_i}{\sum_{i=1}^{k} PushSessionDay_i}$	Aggregated duration over all Thursday and Friday per aggregated session counts for push sessions for each participant

4.2 Operationalization of the constructs

This research evaluates employee engagement with a digital employee well-being program (EWP) using two main independent variables: Average session duration and Total session count, described in Table 5. The data was collected from 500 participants over a 28-day campaign, with Monday and Tuesday being considered "far from the deadline" and Thursday and Friday being considered "close to the deadline." Wednesday was eliminated to ensure equal calculation opportunities over two consecutive dates.

Table 6 summarizes the key independent and dependent variables in the study, which are based on the hypothesis. The literature suggests that email notifications are less intrusive compared to push notifications. The scheduling of notifications is based on office hours and can be divided into weekdays and weekends. The study focuses on employee engagement and finds a strong correlation between it and other dependent variables such as intrusiveness, scheduling, and time constraints.

Table 6. Important independent/dependent variables

Construct	**Definition**	**Operationalization**

Intrusiveness of notification	The notification type is used the campaign	• 1 = Low intrusiveness [Email notification] • 0 =High intrusiveness [Push notification]
Scheduling of notification	The campaign delivery time; usually on weekday or weekend	• 1 = weekday • 0 = weekend
Time constraint on engagement	Time constraint can be defined as close the deadline (0) and far from the deadline (1)	• 1 = Mon and Tue • 0= Thurs and Fri (close to deadline)
User engagement	The high frequency and the longer time user spend on the app/ web portal	• Individual system variables shown in Table 5

5. Analysis

5.1 Descriptive Analysis

The descriptive analysis is based on the data collected during a campaign. Over the course of 4 weeks, a total of 15,091 notifications were sent out, comprising of 7,717 emails and 7,314 push notifications. The majority of these notifications were dispatched in the first two weeks, making up two-thirds of the total count. Moreover, a significant proportion of the notifications were sent on Mondays and Tuesdays, with concurrent weekly counts of 3,330, 3,823, 1,298, and 2,080, respectively. In contrast, Thursdays and Fridays saw considerably fewer notifications sent, with weekly counts of 900, 900, 0, and 940, respectively.

We have also plotted the average session durations and session counts in Figure 1 and Figure 2. Figure 1 shows that the average session duration, which measures the length of time users stay on the website before moving on to other content, is longer for email notifications than for push notifications.

Figure 2 shows that the distribution of total session counts for email notifications and push notifications is different. The total session count, which was calculated based on the total number of sessions that a user browsed during a campaign period, for email notifications is almost twice that of push notifications, indicating that users tend to visit the web portal more frequently when notified via email.

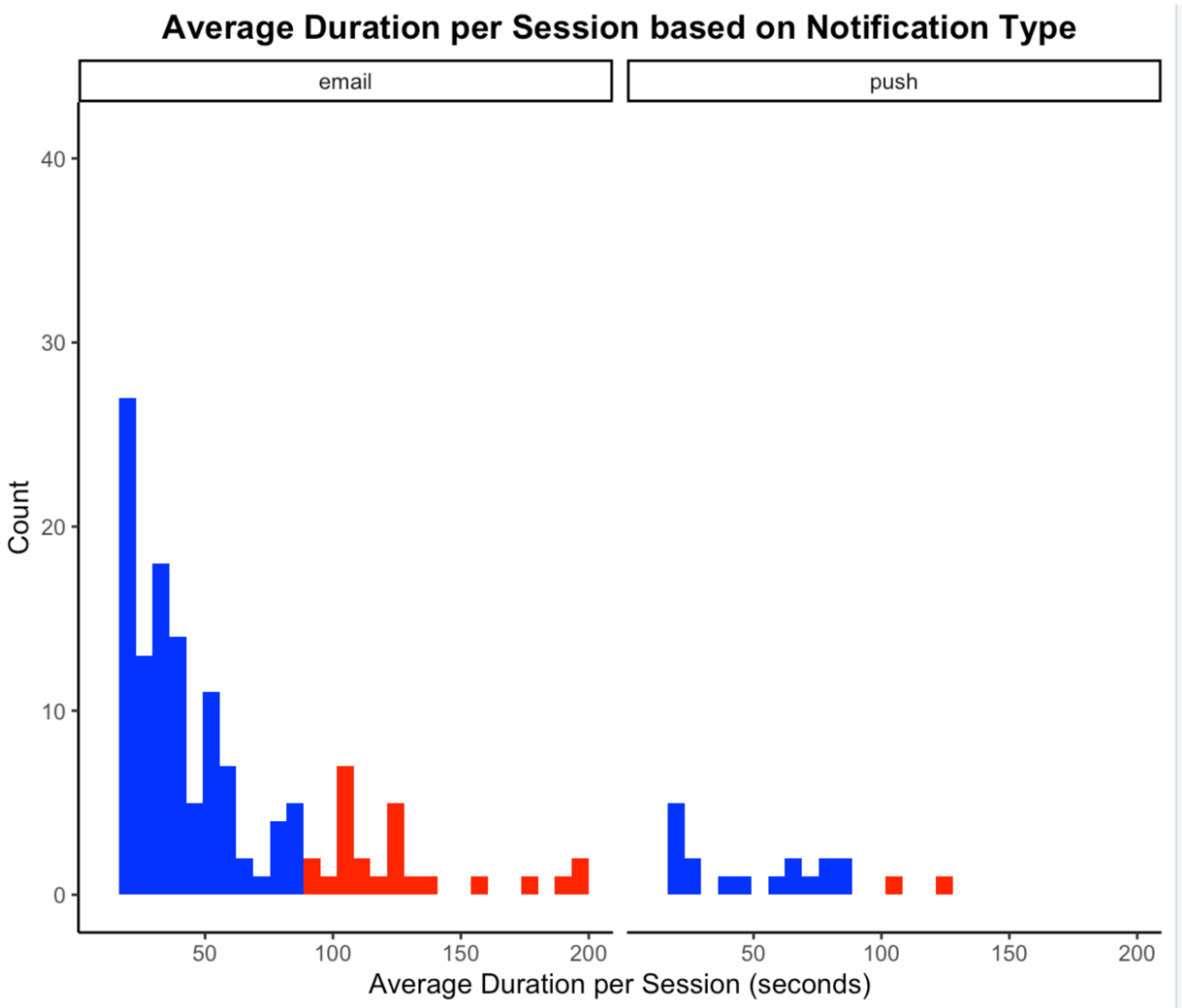

Figure 1 The average duration per session for each individual user based on notification type

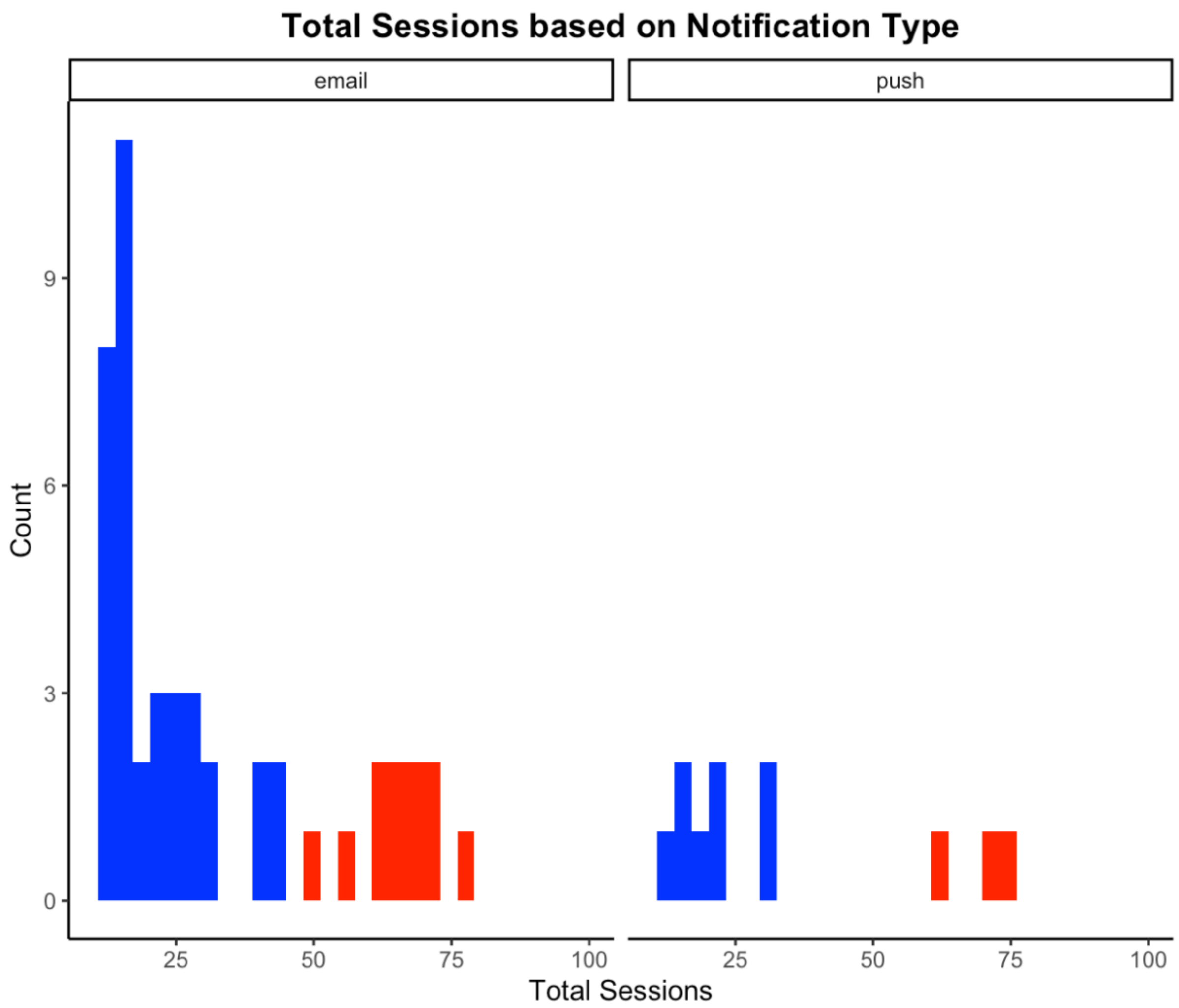

Figure 2 Total sessions for both email and push notification over the 4 weeks calculated per individual.

5.2 Hypotheses Testing

A zero-inflated Poisson regression was applied to test the individual predictors' effect on employee engagement because there is a high proportion of zero values in the dependent variables (average session count and average session duration). The zero-inflated Poisson model is appropriate for this data analysis as it takes into account the excess zeroes in the data set.

The function zeroinfl() was used to fit a model for both the non-zero and zero counts in the data set during the statistical analysis. As a result, the analysis contains two parts: a Poisson count model and a zero-inflated model for predicting excess zeroes. Although this method is useful, it is acknowledged that the model has limitations when applied to duration data.

H1: Passive notification will lead to more user engagement in EWPs.

Based on the literature review and conclusion in Section 3.1, we defined email as a passive notification, whereas push notification can be considered as a strong way to deliver notification. To test the effect of notification type on engagement, we focused on the average session duration and the mean session counts for emails vs push for each individual user and run the regression models on the selected data. The independent variables are the type of notification used. The incident rate ratio values for each independent variable describes the effect of that variable relative to the intercept in a multiplicative way. In the models below, the intercept represents email as an independent variable.

Table 7. Zero inflated Poisson regression for average duration and mean session count based on the notification type.

			Incidence Rate Ratios	CI	P	R2 / R2 adjusted
Average Session duration	Count Model	Intercept [Email]	54.96	54.00 – 55.94	<0.001	
		Notification [Push]	0.74	0.70 – 0.79	<0.001	
	Zero-inflated Model	Intercept [Email]	1.23	1.03 – 1.47	0.02	
		Notification [Push]	13.18	8.71 – 19.95	<0.001	0.974 / 0.974
Mean Session count	Count Model	Intercept [Email]	9.41	9.04 – 9.80	<0.001	0.304 / 0.302
		Notification [Push]	2.73	2.52 – 2.96	<0.001	
	Zero-inflated Model	Intercept [Email]	1.02	0.85 – 1.21	0.859	
		Notification [Push]			<0.001	

			14.89	9.95 – 22.29		

The count model of the zero-inflated Poisson model shows that the average session duration spent for each individual user is significantly longer when the individual interacts with emails in comparison to push notifications (ratio < 1 & p-value < 0.001 in count model) in Table 7.

In addition, it is noted from the zero-inflated model component of the model summary that the proportion of zeroes in the average duration for push notifications is significantly larger than the proportion of zeroes in the average duration for emails (ratio > 1 & p-value < 0.001 in zero-inflated model).

With the mean session counts, although the number of mean session count when users enter the app with push notification is higher than ones enter app using email (ratio > 1 & p-value < 0.001 in zero-inflated model)., the proportion of zeroes in mean session count for push notification is significantly larger than that of the proportion of zeroes for emails.

To summary, the notification types have effect on the user engagement which can be induced from the two variable, average duration, and number of session count in Table 5. As the intercept is email notification, it can be easily seen that users are likely staying longer with the web portal/app when dealing with the email notification, while users tent to click more on the push notification to enter the web portal/app.

Hence, it is inferred from this model that participants generally are more likely to spend time and spend a longer duration of time on the web portal if they access it through email. This result supported the **H1** that predicted the intrusiveness of the email have impact on the users' engagement, which reflected on the average duration.

<u>H2</u>: Employees engage in the EWPs closer to the deadlines.

Table 8. Zero inflated Poisson regression for average duration and mean session count based on deadline target on email/push notification

Average Session Duration			*Incidence Rate Ratios*	CI	P	R2 / R2 adjusted
	Count Model	Intercept [Mon/Tue]	53.58	52.48 – 54.70	<0.001	0.662 / 0.660
		Deadline [Thurs/Fri]	1.22	1.18 – 1.27	<0.001	
	Zero-inflated Model	Intercept [Mon/Tue]	0.15	0.10 – 0.23	<0.001	
		Deadline [Thurs/Fri]	0.5	0.18 – 1.36	0.177	
Mean Session count	Count Model	Intercept [Mon/Tue]	1.14	0.90 – 1.43	<0.001	0.001 / 0.001
		Deadline [Thurs/Fri]	5.4	4.22 – 6.90	<0.001	
	Zero-inflated Model	Intercept [Mon/Tue]	20.44	16.01 – 26.10	<0.001	
		Deadline [Thurs/Fri]	1.9	1.36 – 2.66	<0.001	

In Table 8, for both types of notifications, both average session duration and mean session count had significant p-values (< 0.001) and the ratios (or odds) are all greater than 1. This means that the average session durations/mean session count during deadline [Thurs/Friday] is greater than that of beginning of the campaign – which can be considered as not closer to deadline period (1.22 and 5.4 respectively). The chance of an individual not responding (> 0.5 since ratio or odds > 1) is also higher than the chance of them responding when deadline period comes.

H3: The mode of notification will influence user engagement in EWPs.

The results in Table 9 show that for both types of notifications (push and email), both weekdays and weekends have significant p-values (< 0.001) and odds ratios greater than 1. This means that the average duration and mean session counts are higher on weekends compared to weekdays (in count model, ratio > 0 and p-value < 0.001). The mean session count for weekends is 6.59 times higher than on weekdays. However, the chances of an individual not responding are also higher during weekdays and weekends for both push and email notifications. The chance of not responding is highest during weekends (odds > 1 relative to weekdays).

In addition, the results show that the mean session count indicates that users access the app more frequently on weekends when they receive notifications, compared to weekdays (ratio > 1 and p-value < 0.001 in the zero-inflated model). This supports the hypothesis based on the data and analysis presented.

Table 9. Zero inflated Poisson regression for average duration and mean session count on weekday/weekend.

			Incidence Rate Ratios	CI	P	R2 / R2 adjusted
Average Duration	Count Model	Intercept [weekdays]	53.29	52.36 – 54.24	**<0.001**	0.971 / 0.971
		Schedule [weekend]	1.94	1.84 – 2.04	**<0.001**	
	Zero-inflated Model	Intercept [weekdays]	1.16	0.98 – 1.39	0.09	
		Schedule [weekend]	27.77	16.13 – 47.79	**<0.001**	
	Count Model	Intercept [weekdays]	7.52	7.10 – 7.97	**<0.001**	0.304 / 0.302

Mean Session counts		Schedule [weekend]	6.59	6.04 – 7.19	**<0.001**	
	Zero-inflated Model	Intercept [weekdays]	2.2	1.82 – 2.66	**<0.001**	
		Schedule [weekend]	12.14	7.31 – 20.16	**<0.001**	

<u>H4</u>: The interaction effect of notification intrusiveness and notification scheduling influences user engagement in EWPs.

In Table 10 & 11, it is easy to see that for both types of notifications, both weekdays and weekends had significant p-values (< 0.001) and the ratios (or odds) are all greater than 1. This means that the mean session count/average duration during weekend is greater than weekdays (2.33 and 1.47 respectively). The chance of an individual not responding (> 0.5 since ratio or odds > 1) is also higher than the chance of them responding during weekdays as it can be seen that the chance of not responding for push is nearly 1 during weekdays. The chance of not responding is even higher during the weekend (odds > 1 relative to weekdays).

Table 10. Zero inflated Poisson regression for mean session count on weekday/weekend on email/push notification

Mean session count							
Zero-Inflated Poisson Regression output for **Email**				Zero-Inflated Poisson Regression output for **Push**			
Predictors	*Incidence Rate Ratios*	*CI*	*p*	*Predictors*	*Incidence Rate Ratios*	*CI*	*p*
Count Model				**Count Model**			
(Intercept)	2.85	2.58 – 3.15	<0.001	(Intercept)	6.59	5.65 – 7.68	<0.001
day_cat [Weekend]	2.33	1.85 – 2.92	<0.001	day_cat [Weekend]	1.47	0.99 – 2.18	0.057
Zero-Inflated Model				**Zero-Inflated Model**			
(Intercept)	14.5	12.28 – 17.11	<0.001	(Intercept)	98.86		<0.001

						66.67 – 146.60	
day_cat [Weekend]	4.85	2.79 – 8.43	<0.001	day_cat [Weekend]	3.36	1.01 – 11.16	0.048
Observations	3500			Observations	3500		
R^2 / R^2 adjusted	0.001 / 0.000			R^2 / R^2 adjusted	0.001 / 0.000		

Table 11. Zero inflated Poisson regression for mean session count on weekday/weekend on email/push notification

Average duration

Zero-Inflated Poisson Regression output for **Email**				Zero-Inflated Poisson Regression output for **Push**			
Predictors	*Incidence Rate Ratios*	*CI*	*p*	*Predictors*	*Incidence Rate Ratios*	*CI*	*p*
Count Model				**Count Model**			
(Intercept)	53.95	52.99 – 54.94	**<0.001**	(Intercept)	42.5	40.15 – 44.98	**<0.001**
day_cat [Weekend]	2.02	1.92 – 2.14	**<0.001**	day_cat [Weekend]	1.21	1.02 – 1.43	**0.027**
Zero-Inflated Model				**Zero-Inflated Model**			
(Intercept)	1.29	1.08 – 1.54	**0.004**	(Intercept)	16.86	11.51 – 24.68	**<0.001**
day_cat [Weekend]	28.96	16.24 – 51.64	**<0.001**	day_cat [Weekend]	9.83	2.97 – 32.54	**<0.001**
Observations	1000			Observations	1000		
R^2 / R^2 adjusted	0.968 / 0.968			R^2 / R^2 adjusted	0.424 / 0.423		

6. Discussion

In this study, we give 4 hypotheses and proved them using our data analysis result.

Our hypothesis (H1) is that passive notification, such as email, will result in greater user engagement with EWPs. This is supported by our literature review and data analysis. Email is considered a low intrusiveness notification that allows employees to enter the EWP at their convenience, providing passive awareness without disrupting their work. In contrast, push notifications are more intrusive. Our study, which analysed the usage patterns of 500 users over a four-week period, found that email notifications led to more frequent and longer sessions on the web portal compared to push notifications. Therefore, our results support the hypothesis that passive notification leads to increased engagement in EWPs.

After conducting a literature review, we found that employees tend to interact with EWPs through an application when approaching deadlines due to busy work schedules. This behaviour reflects employee procrastination, which may be exacerbated by frequent notifications that can distract them from their current tasks. Therefore, we hypothesize (H2) that employees engage with EWPs closer to deadlines. Our data analytics results support this hypothesis.

We also explored whether a specific usage pattern emerged during the week. Our analysis revealed that users were more responsive to notifications on Thursdays and Fridays, which aligns with the deadline-based behaviour described in H2.

Our hypothesis (H3) is that the mode of notification influences user engagement in EWPs. Previous studies have shown that scheduling notifications during appropriate times can increase user interaction. Our hypothesis is based on the Technology Fit Framework (TTF), thus we emphasize notification characteristics. We suggest scheduling notifications during work hours to encourage employees to use the EWPs as a task assigned by their managers.

Our data analytics results revealed that people are more likely to respond to email or push notifications on weekdays rather than weekends, which supports both H2 and H3. However, upon further examination, we found that people tend to interact with the EWPs more during weekends than weekdays. This suggests that employees treat employee management programs more as an organizational task than for personal benefits.

Therefore, digital nudge designs should take this into consideration to achieve maximum engagement and benefits, based on the main elements we analysed in Section 3, Theory and Hypothesis. Our hypothesis (H4) is that the interaction effect of notification intrusiveness and notification scheduling influences user engagement in EWPs. This hypothesis suggests that the best way to determine the appropriate time for interaction with the application/web portal is to combine notification intrusiveness and scheduling. This allows us to send out the most effective type of notification to increase user engagement.

6.1. Theoretical Contribution

Our research has made substantial contributions to both academic literature and practical aspects of workplace well-being management. Through our investigations, we have uncovered valuable insights that shed light on the current state of well-being management programs and offer guidance for their enhancement.

Firstly, our research has highlighted a critical issue concerning the lack of attention given to effectively influencing user engagement in existing well-being management programs. Despite the well-established benefits of improved engagement, such as increased productivity, reduced absenteeism, and lower insurance costs, many programs fall short in this regard. This finding underscores the need for improvements in how these programs are designed and implemented.

Building upon this discovery, we have taken a significant step forward by applying the Task-Technology Fit (TTF) theory to the design and intervention strategies of technology-based well-being programs, specifically health apps. By leveraging this framework, we propose a more effective approach to enhancing user engagement in well-being programs. For instance, our research suggests that incorporating stress management tools into office-hour-focused apps can assist employees in better managing their stress levels. Additionally, these apps can provide valuable resources to expand employees' knowledge, enabling them to develop professionally, while also facilitating the building of stronger relationships with their colleagues.

Furthermore, our study's findings hold substantial promise in providing a comprehensive understanding of the intricate relationship between technology, notifications, and user engagement within well-being management programs. By unravelling this connection, we aim to equip organizations with the knowledge and insights needed to prioritize Workplace Well-being Programs (WWP) as a crucial aspect of their overall development strategies. This understanding will enable organizations to design and implement interventions that effectively engage employees, leading to improved individual well-being and organizational outcomes.

In conclusion, our research serves as a significant milestone in the field of workplace well-being management. Through our exploration of the gaps in existing programs and the application of the TTF theory, we offer practical recommendations to enhance user engagement and maximize the benefits of well-being interventions. We hope that our findings will inspire organizations to invest in comprehensive WWP initiatives that prioritize employee well-being, fostering

6.2. Practical contribution

Our research findings carry substantial practical implications for both workplace wellness program designers and application developers. By delving into the intricacies of user engagement, technology design, and notification strategies, we offer valuable insights that can inform the development of effective workplace wellness initiatives.

Firstly, our research emphasizes the pivotal role of good technology and notification design in driving employee engagement with digital workplace wellness programs. We have observed that well-designed technology platforms and thoughtful notification systems can significantly enhance user engagement, thereby leading to improved productivity and reduced insurance costs for organizations. This insight provides program designers and app developers with a tangible and practical method to attract a larger user base and maintain their engagement over an extended period. By investing in user-friendly interfaces, intuitive features, and personalized notifications, organizations can optimize the effectiveness of their workplace wellness programs.

Secondly, our research highlights the importance of considering the type and timing of notifications in order to maximize user engagement. We have discovered that the strategic combination of different notification types, such as reminders, progress updates, and personalized messages, when delivered at appropriate intervals, can have a profound impact on user engagement levels. By understanding the preferences and needs of their target audience, program designers and developers can tailor notification schedules to increase the likelihood of positive outcomes in typical employee wellness programs (EWPs). This insight serves as a valuable guideline for organizations seeking to create effective notification strategies that resonate with their employees and foster sustained engagement.

Lastly, the findings of our research carry significant implications for organizations aiming to design technology and notification strategies that drive employee engagement with workplace wellness programs and, ultimately, achieve positive business outcomes. By considering our research insights, organizations can develop comprehensive and targeted approaches to workplace wellness, leveraging technology and notification systems as powerful tools. These strategies can lead to increased employee participation, improved overall well-being, and enhanced business performance.

In summary, our research offers practical guidance to workplace wellness program designers and application developers. By emphasizing the importance of technology design, thoughtful notification strategies, and user engagement, we enable organizations to create impactful initiatives that benefit both employees and the business as a whole. By implementing our research findings, organizations can build an environment where workplace wellness is prioritized, resulting in healthier, more engaged employees and positive outcomes for the organization.

7. Limitation and Future research.

This research has limitations in terms of the methodology used and the scope of its implications. Firstly, the zero-inflated Poisson model used to investigate the effect of email and push notifications on the average duration spent per session has limitations due to the large number of 0 values present in the data set. Secondly, the research's implications for employee well-being programs are limited to one organizational context and more research is needed to understand when and how to apply the TTF scale to notifications in a more general context. Thirdly, the hypothesis is based on data from one large organization, and a wider range of data sources would be needed to prove it. Lastly, the limited amount of time to combine the analytic results with real-world scenarios such as interviews with both users and program administrators limited the comprehensiveness of the study

Future work should aim to address these limitations by: (1) understanding non-participants' perceptions of EWPs, (2) creating better notifications to increase user engagement, and (3) incorporating a wider range of data sources and perspectives.

Due to the high number of users who entered the webpage but did not engage with the EWP, it is important to understand non-participants' perceptions. We need to determine whether non-participants enter the webpage because they consider the EWP as part of their organization task or due to other factors preventing them from interacting with the app efficiently. Increasing the app's interesting features has been shown in some studies to improve user engagement. Additionally, some users may not engage with the EWP because doing so would interrupt their current tasks, causing them to leave the webpage soon after entering it. Understanding these reasons can help program administrators or app designers improve the

EWP and increase user engagement. Conducting interviews with non-participants can provide ideas on how to improve the EWP.

Creating better and more interesting notifications can increase user engagement. Studies have shown that notifications with full information or including images can stimulate app users and encourage them to explore and interact with the contents of the app. In addition, with this study, we have a theory that users are more likely to use the app near the deadline and on weekends rather than on weekdays. We can combine this finding with other studies (Bidargaddi et al., 2018a; Okoshi et al., 2018) to determine if there is a better time frame for sending out an attractive/interesting notification.

Furthermore, our study was conducted on a single large organization, so the results may not be applicable on a global scale. Gathering data from a wider range of sources and perspectives could provide a more comprehensive understanding of the effectiveness of EWPs.

8. Conclusion

There are a lot of concerns on health and well-being for the organization employees' recent years. The need of having an effective EWPs is proved over a decade. There are numeral researches on well-being program, but less studies focus on the relationship of EWPs with TTF theory, which can help the managers, executive members, program designers to better understand the concept, and all the features that take effect on the employees' engagement to the application.

This research aimed to explore the impact of notification intrusiveness, scheduling, and time constraints on employee engagement in digital well-being management programs. The study used the TTF theory to support the hypothesis and conducted a literature review to summarize the importance of well-being programs in organizational context. The zero-inflated Poisson model was used to analyse the data and test the hypothesis. The findings showed that all employees' engagement levels are affected by notification intrusiveness, notifications schedules and time constraints factors.

However, this study also highlighted the limitations of using a single data source, the need for diverse data sources, and the need for a better understanding of the nonparticipants' perspectives and concerns. The purpose of this research is to provide a better understanding of the factors that impact employee engagement in EWPs and to support program administrators and application designers in creating better programs and applications.

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