UNIVERSITY OF AMSTERDAM

# Unpacking Environmental Concern in Digital Green Nudging: Insights from a Large-Scale Field Study on a Sustainability Oriented App

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**Master Thesis**

**Msc. Business Administration - Digital Marketing Track**


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**Date:** June 27, 2025

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**Statement of originality**

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**Acknowledgements**

This thesis was written as part of the Master Business Administration at the University of Amsterdam. I would like to thank Vikas Garg, CEO of Abillion, for granting me access to their platform and providing the data that made this research possible. I also really appreciate the help and support of Dorra Sayadi and Ravi Gopalan, working in the data team of Abillon, during the data collection and preparation process. Furthermore, a big thanks goes to my supervisor Dr. Dale Rickert for his guidance, helpful feedback and close involvement throughout the entire process. Finally, thanks to everyone who supported me along the way, your help and encouragement were much appreciated.

## Abstract

How do we get people to act more sustainably in the digital age? Digital green nudges may hold the key, but their effectiveness depends on who you're nudging. This thesis explores how individual differences in environmental concern influence the effectiveness of two green digital nudging strategies, social norm nudges and impact nudges. While environmental concern is known to influence responses to impact nudging, little is known about its effect on social norm nudges. To address this gap, a two-phase mixed-method study was conducted. In Phase 1, a large-scale field experiment (N > 490,000) tested the impact of both nudges on click-through rate, time spent on the app and conversion. In Phase 2, a follow-up survey (N = 179) assessed environmental concern and examined its moderating role. Results demonstrate that both nudging strategies led to significantly higher engagement across all engagement metrics. Moreover, environmental concern positively moderated the effect of the impact nudge but had no significant effect on the social norm nudge. These findings contribute to the literature by demonstrating that nudging is a heterogenous approach. Practically, these findings highlight the importance of tailoring digital nudges to user characteristics. By aligning nudging strategies with individual motivations, this study highlights how digital platforms can meaningfully influence user behaviour and can play an active role in driving positive change in the fight against climate change.


**Keywords**; digital nudging, environmental concern, green nudging, engagement, social norms, push notifications, impact, sustainability app.

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# 1. Introduction

Do you remember the last time you clicked on a notification? Maybe it was a quick reaction, a moment of curiosity or just simply habit. These small digital messages are everywhere, on our phones, laptops, watches and are designed to guide our attention and behaviour. These notifications have become a common part of online platforms and can be called digital nudging. Nudging refers to subtly guiding individuals toward a desired decision without restricting their freedom of choice, often by altering the way choices are presented or structured (Thaler & Sunstein, 2021). Digital nudging applies these behavioural principles within online environments for example by using interface design elements such as scarcity signals like “only a few items left” to influence user behaviour (Hmurovic et al., 2022). But can such simple messages do more than just remind or distract? As billions of people use digital apps and platforms every day, businesses are increasingly leveraging insights from behavioural science to optimise user experience and enhance conversion rates. Although often used for commercial purposes, nudging hold much greater potential; it can be a powerful tool in addressing urgent global issues like climate change.

The Intergovernmental Panel on Climate Change (IPCC, 2022), the United Nations body for assessing the science related to climate change, warns that the world is on track to exceed 1.5°C of global warming as early as 2030 if current trends continue, with far-reaching consequences for people and the planet. To limit global warming to below this level, the IPCC states that not only policy and innovation are needed, but also fundamental changes in everyday consumption behaviour. Green nudges, which are designed to promote environmentally friendly choices, are often used to subtly guide users toward sustainable behaviours (Berger et al., 2022). Whether prompting users to reduce their carbon footprint, donate to climate-related causes or support ethical consumption, these nudges aim to activate pro-environmental values and translate them into actions. As much of today’s consumption and decision-making takes place online, digital nudges offer a powerful opportunity to influence sustainable behaviour at scale. Understanding how such digital green nudges function and for whom they are most effective can offer a valuable contribution to promoting more climate-conscious behaviour.

Among the wide range of green nudging strategies used in digital environments to promote sustainable behaviour, social norm nudges and impact-based nudges illustrate two approaches. Social norm nudges draw on the principle of social proof, where individuals use the behaviour of others as a guide, particularly in uncertain situations (Nolan et al., 2008; Cialdini, 2001). An example is that most users chose a particular option or complete a specific action, which can encourage others to adopt the same behaviour (Asch, 1956; Gonçalves et al., 2021). In contrast, impact nudges appeal to intrinsic values by highlighting the broader social or environmental consequences of an action (Schubert, 2016). This can be in the form of highlighting that you can supporting charities or reducing carbon emissions. Such nudges reinforce the user's identity as someone who acts in accordance with sustainable values (van der Werff et al., 2013).

Numerous studies have examined the effectiveness of nudging strategies in digital environments, demonstrating their potential to influence user behaviour across various domains such as user registration, e-commerce (Weinmann et al., 2016; Dennis et al., 2020), rating platforms (Schneider et al., 2020) and software development (Haki et al., 2022). However, research suggests that the impact of nudges can vary significantly across different contexts and individuals, underscoring the need to identify the conditions under which they are most effective (Hummel & Maedche, 2019). For instance, social norm nudges that provide feedback on household energy consumption, have been shown to reduce energy use among high-consumption households (Allcott, 2011). Yet, the same intervention can lead to a so-called "boomerang effect" among already efficient users, who may increase their energy use upon realizing they are performing better than average (Ruokamo et al., 2021). Also, socio-economic background (De León Solís, 2025), digital literacy, cultural values and even personality traits can mediate the effectiveness of nudges (De Ridder et al., 2021). Additionally, several studies warn against the uncritical adoption of nudging techniques, raising concerns about their broader applicability and scalability (Merrick, 2022). According to Szaszi et al. (2018), limited attention has been given to personal traits or values that may moderate the effectiveness of nudges, contributing to the so-called "black box" problem in which the underlying mechanisms of behavioural change remain unclear.

One illustration is environmental concern (EC) which has received growing attention in nudging research (Schultz & Oskamp, 1996; Wee et al., 2021). While it is often assumed to enhance receptiveness to impact-based nudges (Taufik et al., 2014), its role in shaping responses to social norm nudges remains less well understood. For instance, studies by Moons and de Pelsmacker (2012, 2015) show no consistent relationship between EC and sensitivity to social norms and Wee and colleagues (2021) found that individuals with higher EC may be less influenced by social norm nudges, as their behaviour is more likely driven by internal values than by external cues. In contrast, findings by Ek and Söderholm (2008) suggest that individuals with higher levels of EC may be more receptive to social norm nudges, particularly in contexts such as green electricity purchasing. Yet, individuals with strong EC often hold pro-social values and may therefore logically more motivated by that reflect collective behavioural norms aligned with sustainability goals (de Groot & Steg, 2007). But in general, the literature contains few studies that specifically examine how individuals' level of EC influences their receptiveness to social norm nudges especially in digital environments, even though such a relationship may well exist and could have important implications for the design of more effective nudges tailored to specific target groups. This raises an important question: Does EC make people more responsive to both impact-driven and social norm-based nudges?

Understanding this difference is not only important for academic theory, but also for designing digital marketing strategies that effectively promote sustainable behaviour.

This study examines the two commonly used green nudging strategies; impact-based and social norm nudges, within a real-world digital sustainability app with more than a million users. The goal of this first step is to confirm the effectiveness of these nudges in a applied digital setting to replicate findings from previous studies under realistic conditions (Staudt et al., 2021). Thereafter this study contributes to existing research by examining whether EC increases the effectiveness of social norm nudges, which is an open question in the literature that has so far received limited attention.

The remainder of this thesis is structured as follows; first, extant literature on digital nudging, engagement and EC will be reviewed to develop the theoretical framework. Based on this, key hypotheses will be formulated. Next, the methodology and results of two consecutive phases will be presented. This two-phase design was chosen to combine large-scale behavioural data with psychological self-report measures, enabling a more comprehensive understanding of both what users do and why, including a self reflection method. Phase 1 analyzes behavioural data to assess the effectiveness of green nudges, in the form of push notifications, across three engagement metrics: click-through rate, time spent on the platform and conversion. Phase 2 focuses on EC as a moderating trait, using survey data from a subset of users to explore how individual differences in EC influence responses to impact-based and particularly social norm nudges. The findings will then be discussed in light of theoretical and practical implications. Finally, limitations and future research directions will be addressed, followed by a conclusion summarizing the key contributions of this study.

# 2. Theoretical Framework & Literature Review

## 2.1 Bounded Rationality and the Dual-Process Theory

A fundamental psychological basis for the concept of nudging comes from Simon's (1997) theory of bounded rationality, which challenges the classical notion of fully rational decision-making. Simon argues that individuals operate within cognitive and informational constraints, leading them to seek satisfactory rather than optimal outcomes. These cognitive limitations also help explain why people often rely on mental shortcuts and automatic thinking, an idea further elaborated in the dual-process theory of cognition. Originally conceptualized by Schneider and Shiffrin (1977) and later popularized by Daniel Kahneman (2011). The theory explains that people make decisions using two types of thinking: System 1 and System 2. System 1 works quickly and automatically, using gut feelings and habits, often without us being aware of it. In contrast, System 2 operates more slowly and deliberately, requiring cognitive effort and reflective reasoning.

Nudging strategies are mainly aimed at influencing System 1, the type of thinking we use most often in daily life, because it relies on mental shortcuts that help us process information quickly and allows nudges to guide behaviour without the need for deep reasoning (Thaler & Sunstein, 2021). Moreover, nudges are especially effective in low-stakes and repetitive decision contexts, which are increasingly found in digital environments. When scrolling through a social media feed, users constantly make small, routine choices often without much conscious thought. In these moments, digital nudges like push notifications are designed to capture attention and trigger quick, automatic responses. (Schneider et al., 2018; Weinmann et al., 2016).

## 2.2 Digital Nudging

Weinmann et al. (2016) define digital nudging as the practice of using interface design elements to subtly guide user behaviour in online decision-making. Unlike traditional nudges, digital nudges operate in a virtual environment and examples include the use of default settings, pop-up notifications and pre-filled forms that exploit cognitive heuristics (Gigerenzer & Gaissmaier, 2011; Tversky & Kahneman, 1981). More advanced digital nudges include visual salience (highlighting certain buttons or options to draw attention and the timing of messages) and sending reminders at moments of high receptivity (Meske & Potthoff, 2017).

Building on these examples, a growing area of interest is green nudging, which aims to promote environmentally friendly behaviour through nudging techniques (Schubert, 2016). In digital environments, these nudges can take the form of interface elements that guide users toward more conscious decisions, such as emphasizing environmentally friendly options or using social comparison feedback to encourage sustainable behaviour (Staudt et al., 2021).

A particularly prominent form for digital (green) nudging used by companies is the use of notifications and push notifications; short, attention-grabbing messages that are delivered directly to a user's device (Nations, 2021). These notifications can act as behavioural cues that align with System 1 processing by interrupting routines and prompting immediate, intuitive actions (Stawarz et al., 2015; Schneider et al., 2018). Over time, the design and implementation of such nudges have become more advances and have involved from simple reminders to context-aware, personalized tools (Mehrotra et al., 2016).

Studies show that push notifications can create behavioural change in domains such as health (Morrison et al., 2017) and education (Pham et al., 2016). But mainly, push notifications have become an essential feature within social media platforms. They are strategically deployed not only to inform users about new content or interactions but also to foster sustained engagement (Gavilan & Martinez-Navarro, 2022). Platforms such as Facebook, Instagram and

X (formerly Twitter) utilize push notifications all the time to maximize engagement (Fahlman et al., 2018). Studies indicate that personalized push notifications significantly enhance user response rates compared to generic alerts (Heinisch et al., 2022). So it offers a powerful tool to increase engagement.

### 2.3 User Engagement

However, user engagement is not a monolithic concept. Work by Muntinga et al. (2011) shows that engagement can be broken down into specific engagement levels based on the COBRA model (Consumers' Online Brand-Related Activities). This framework distinguishes between three hierarchical levels of consumer engagement with brand-related content on social media: consumption**,** contribution and creation**.**

Consumption refers to passive behaviours such as viewing posts, watching videos, or reading brand-related messages, indicating low levels of engagement. For instance, nudges aimed at increasing passive exposure, such as placing brand-related content in visually prominent areas or embedding it in frequently browsed sections, are particularly effective in stimulating consumption-level engagement. As shown by Simonetti and Bigné (2023), even the placement of a simple banner can attract user attention through visual salience, particularly during low-involvement browsing.

Contribution involves more active forms of interaction, including liking, sharing, or commenting on content and reflects a deeper level of engagement. Simple interactive features, like a comment box that opens after reading, can encourage users to do more than just passively browse.

Creation represents the highest level of engagement and entails producing and publishing original content related to the brand, such as posting reviews, uploading branded photos, or creating posts. This form of participation is could be encouraged through customization tools, interactive formats or gamification elements which have been found to help motivate people to create new original content. This is proved by Sundar et al. (2017) who argued that giving users control over how they express themselves, through creative tools like branded filters, templates, or interactive challenges, can trigger intrinsic motivation and lead to increased user-generated content.

An overview of the different engagement levels retrieved from the paper of Muntinga, et al., (2011) is displayed in table 1.

**Table 1**

*COBRA Typology*

| COBRA Type | Examples of Brand-Related Social Media Use |
|---|---|
| **Consuming** | • Viewing brand-related video<br>• Listening to brand-related audio<br>• Watching brand-related pictures<br>• Clicking on notifications<br>• Reading comments on brand profiles on social network sites |
| **Contributing** | • Rating products and/or brands<br>• Joining a brand profile on a social network site<br>• Engaging in branded conversations, e.g. on online brand community forums or social network sites<br>• Commenting on brand-related weblogs, video, audio, pictures, etc. |
| **Creating** | • Publishing a brand-related weblog<br>• Uploading brand-related video, audio, pictures or images<br>• Writing brand-related articles<br>• Writing product reviews |

*Note.* Adapted from Li & Bernoff (2008), as cited in Muntinga, et al., (2011). COBRAs come in countless forms. Thereby the examples from the table are generated by literature and by the author.

This categorization helps researchers to capture different levels of user engagement and makes it easier to distinguish which specific nudging strategies target which type of engagement. By aligning digital nudging strategies with the COBRA levels, platform owners and researchers gain insight into whether a nudge is likely to stimulate low-effort, (consumption-level) behaviour or encourage more active forms of the creation level such as posting a photo.

### 2.4 Social Norm Nudging

Social proof theory posits that people tend to look at others' behaviour to determine their own, particularly in contexts of uncertainty or limited information. When individuals see that a large number of others have engaged with a product, service, or feature, they are more likely to follow suit (Cialdini, 2001).

Social proof can be effectively applied in the context of digital green nudging. By showing individuals how others behave, for example, indicating that “most people in your neighborhood recycle” or “your energy use is higher than 80% of similar households”, could trigger people to also promote more sustainable behaviour (Allcott, 2011). This approach is particularly effective when individuals experience uncertainty or lack strong preferences, as they tend to rely on the behaviour of others to guide their own decisions (Venema et al., 2020). A well-known example is the study by Goldstein et al., (2008), which showed that hotel guests were more likely to reuse towels when told that the majority of previous guests had done so, demonstrating the power of social proof as a green nudge. Further also in digital environments a large-scale study by Salganik et al. (2006) demonstrated that merely displaying download counts in a digital music marketplace significantly influenced user behaviour, with users disproportionately selecting highly rated or downloaded items. Similarly, empirical work by Klumpe et al. (2020) found that real-time display of peer activity significantly increased conversion and engagement rates in e-commerce settings. A growing body of research shows that users rely heavily on social signals in digital environments and that social proof nudges can effectively steer behaviour toward desired outcomes with minimal cognitive effort

Based on the reviewed literature, social norm nudges delivered via push notifications are expected to positively influence user engagement across both passive and active levels of the CORBA model (Muntinga et al., 2011). At the consumption level users engage in low-effort actions like viewing or clicking on content, which is expected to be the easiest triggered by those nudges. Research by Bakshy et al. (2012) found that even minimal social cues, like showing a peer's name, significantly increased click-through rates in social ads. It is expected that because people are triggered by the notification, they will be more likely to click on it. It is reasonable to assume that when users feel more socially engaged, they are not only more likely to interact, but also to stay active within the app environment. Greater engagement typically translates into a stronger willingness to explore content further, resulting in longer session durations. At the creation level, users engage in higher-effort behaviours like posting reviews. When push notifications communicate that many others are also writing reviews, this activates perceived social norms that can lower hesitation and increase users' willingness to contribute as well. As prior research has shown that social norm cues can effectively motivate participation through mechanisms such as social validation and conformity (Cialdini et al., 1990; Venema et al., 2020; Goldstein et al., 2008; Asch, 1956), a social norm nudge is expected to elicit stronger motivation and higher response rates compared to a neutral nudge. Taken together, these expectations form the basis for the following hypotheses:

**H1:** The social norm nudge will have a significant positive effect on click-through rate compared to a neutral nudge.

**H2:** The social norm nudge will have a significant positive effect on time spent on app compared to a neutral nudge.

**H3:** The social norm nudge will have a significant positive effect on conversion rate (posting review) compared to a neutral nudge.

Since increased engagement on the sustainability-focused app used in this study directly contributes to positive impact, the social norm nudge is expected to function effectively as a green nudge by motivating users to take meaningful action.

**2.5 Impact Nudging**

In addition to social norm nudge, green nudges can also appeal to users' values and intrinsic motivations by highlighting the broader consequences of their behaviour. One such approach is the impact-based nudge, which communicates the positive environmental outcomes of an action, for example, indicating how much $CO_2$ has been saved or how a behaviour contributes to waste reduction or biodiversity protection. These messages aim to trigger people's personal values and align with their environmental self-image (Taufik et al., 2015). Recent experimental work by Collet et al. (2023) further supports this approach, demonstrating that $CO_2$-framed nudges significantly increase pro-environmental behaviour.
The psychological foundation for this approach lies in Environmental Self-Identity Theory, which holds that individuals are more likely to engage in sustainable behaviour when they perceive themselves as someone who cares about the environment (van der Werff et al., 2013). Making the environmental impact of a behaviour salient reinforces this identity and makes them more likely to act in line with it. For example, Fanghella et al. (2019) found that reminding individuals of their past eco-friendly behaviour strengthened their environmental self-identity and that his was positively linked to higher donations to an environmental charity, especially among those who already frequently acted pro-environmentally. Other research continues to support the efficacy of impact nudges in both analog and digital settings. In e-commerce contexts, Hummel and Maedche (2019) demonstrated that sustainability-framed labels

increased preference for eco-friendly products. Also, Hoffmann and colleagues, (2023) demonstrates that providing users with real-time, quantified $CO_2$ impact data through a sustainable consumption app significantly reduced their carbon emissions. The findings suggest that this form of feedback enhances users' environmental awareness and can support decisions that align with their sustainability values also in mobile environments (Schneider et al., 2018).

The strength of the impact nudge's effect may vary depending on the level of user engagement At the consumption level (Muntinga et al., 2011) impact nudges are expected to function similarly to social norm nudges by appealing to intuitive, automatic responses. Just as users are more likely to engage with content perceived as popular (Bakshy et al., 2012), they may also be prompted to click when their action is framed as making impact for the world. In addition to driving immediate actions, impact nudges may foster deeper engagement by activating intrinsic motivation. When individuals perceive their actions as meaningful and aligned with personal values, they are more likely to continue engaging over time (Deci & Ryan, 2000; van der Werff et al., 2014). Nudges that highlight ecological impact can encourage users to explore more content and stay longer. Lastly, at the creation level the influence of impact nudging may be more limited but still meaningful because this requires a high effort action. Research indicates that when pro-environmental actions are framed in a way that aligns with users' social or moral values, people may feel more compelled to contribute, even when the effort is greater (Song et al., 2022). Based on this, the following hypotheses are proposed:

**H4:** The impact nudge will have a significant positive effect on click-through rate compared to a neutral nudge.

**H5:** The impact nudge will have a significant positive effect on time spent on app compared to a neutral nudge.

**H6:** The impact nudge will have a significant positive effect on conversion rate compared to a neutral nudge.

## 2.6 Environmental Concern

While impact nudges rely primarily on personal values and identity alignment, their effectiveness is likely moderated by individual differences in Environmental Concern (EC). Nudges are not universally effective; rather, their impact often depends on how well the psychological mechanism underlying the nudge is in line with the person's individual values and motivations (Weber & Johnson, 2009). For example, a nudge that frames energy use in terms of moral responsibility may be particularly effective for individuals with a strong sense of environmental self-identity, while others may respond more to other types of nudges. This heterogeneity in nudge responsiveness underscores the importance of understanding which traits best predict receptivity to different types of nudges (Bolderdijk et al., 2013; Van der Linden, 2014).

EC is generally defined as the degree to which individuals are cognitively aware of, emotionally engaged with and behaviourally motivated by environmental issues (Dunlap & Jones, 2002). This refers to a general attitude toward environmental protection, often rooted in broad ecological worldviews such as belief in human responsibility for environmental degradation (Bamberg, 2003; Whitmarsh & O'Neill, 2010). This is in line with other research that has shown that individuals with high EC are more likely to view environmental issues as morally significant, to feel a personal obligation to act and to make choices consistent with pro-environmental values (Stern, 2000; Fransson & Gärling, 1999; Fielding & Hornsey, 2016). According, to cognitive dissonance theory (Festinger, 1957), inconsistencies between one's internal beliefs and outward behaviour lead to psychological discomfort, which individuals seek to reduce by aligning actions with values. For individuals high in EC, failing to act sustainably can trigger such dissonance, creating a strong motivational force to behave in environmentally responsible ways. For example by supporting environmental policies, demonstrate a willingness to reduce personal consumption and intend to recycle or use public transport.

In the context of digital platforms, this means that users with high EC may be more receptive to impact-framed nudges, because they perceive them as relevant and consistent with their identity (van der Werff et al., 2013). Prior studies for example showed that individuals with high EC are more likely to respond positively to green advertisements, especially when these evoke negative emotions such as fear, guilt, or disgust and when they align with personal values or identity-related motivations (Balaskas et al., 2023). Research shows that people with high EC are more likely to respond positively to pro-environmental nudges at first. However, this effect often fades over time, especially if the motivation comes from outside or if people feel they've already "done their part." (Clot et al., 2021). Long-term engagement is more likely when people are driven by their own internal motivation. This means that nudges are more effective over time for people who already care deeply about the environment, while people with low EC are less likely to stay engaged in the long run.

In sum, individuals with high EC are more likely to engage with the impact nudges that because it affirm their identity as environmentally responsible (van der Werff et al., 2013; Fielding & Hornsey, 2016). This perceived relevance can increase user engagement, as supported by findings that show stronger reactions to sustainability-related nudges among environmentally concerned individuals. Based on this, the following hypothesis is proposed:

**H7**: The effect of the impact nudge on user engagement will be positively moderated by EC, meaning that increased EC will enhance engagement with the impact nudge.

While EC aligns most intuitively with impact-based nudging, it is suggested that it may also strengthen responsiveness to green social norm nudges. Individuals with high EC often have strong altruistic and biospheric values (de Groot & Steg, 2007). These values are linked to the belief that protecting the environment is important and that everyone has a personal responsibility to contribute. As a result, they not only act from their own convictions, but also care deeply about how others behave. They are more likely to be influenced by others' actions when it comes to making a positive impact and may feel encouraged to act when they see others doing the same. In digital environments, social proof nudges, can serve as signals of group consensus and shared moral commitment (Blay et al., 2016). When individuals perceive that a normative message is widely followed and socially expected, they are more likely to align their behaviour with it, especially if they think others expect it of them too. As Bicchieri (2008) shows, social norms exert stronger influence when people have clear empirical and normative expectations which means that norm-based messages can encourage people to join in by showing what is common and socially accepted. In the context of sustainability, such normative cues may be particularly persuasive for environmentally concerned users, as they align personal values with perceived social expectations. Additionally, Individuals with higher levels of EC are generally more motivated to act in ways that reflect their broader values around sustainability and social responsibility (Stern, 2000). In digital environments focused on impact and sustainability, social norm nudges play an important role in highlighting collective expectations and signaling shared goals and values (Goldstein et al, 2008; Bicchieri, 2006).

This makes users with high EC are likely more receptive to such normative nudges because they are already attuned to the significance of collective behaviour in making impact. Being part of a community that visibly upholds values they themselves endorse reinforces their motivation to participate actively. This increased receptiveness can result in higher engagement with content or features that emphasize what others in a sustainability platform are doing.

Therefore, it is likely that EC not only influences the effect of the impact nudge but also affects how effective green social norm nudges are in digital environments. Users with higher EC are more sensitive to what others are doing on the platform and feel more motivated to take action themselves. When they perceive their behaviour as part of a shared goal, they are more likely to engage actively. Based on this, the following is hypothesized:

**H8**: The effect of the social norm nudge on user engagement will be positively moderated by EC, meaning that increased EC will enhance engagement with the social norm nudge.

Together, these hypotheses suggest that EC may serve as a key moderating variable in the effectiveness of both impact- and social norm nudges, as it appears to heighten users' sensitivity to each, despite their reliance on different psychological mechanisms.

## 3. Conceptual Framework

This study is structured around a two-phase conceptual framework through which all hypotheses will be tested. The conceptual framework (Figure 1) is visually divided into two sections to reflect methodological differences. Phase 1 (straight line) examines the direct effects of a social norm nudge, an impact nudge and a neutral nudge, as control, on user engagement. Engagement is measured through click-through rate (CTR), time spent on app and conversion rate (CR), using large-scale real-life data from Abillion which is an impact and sustainability focused social media app. Phase 2 (dashed line) builds on these findings by investigating how EC, moderate the effects of the nudges. This phase is based on self-reported data from a sub-sample. Table 2 provides an overview of all hypotheses.

**Figure 1**

*Conceptual Framework*

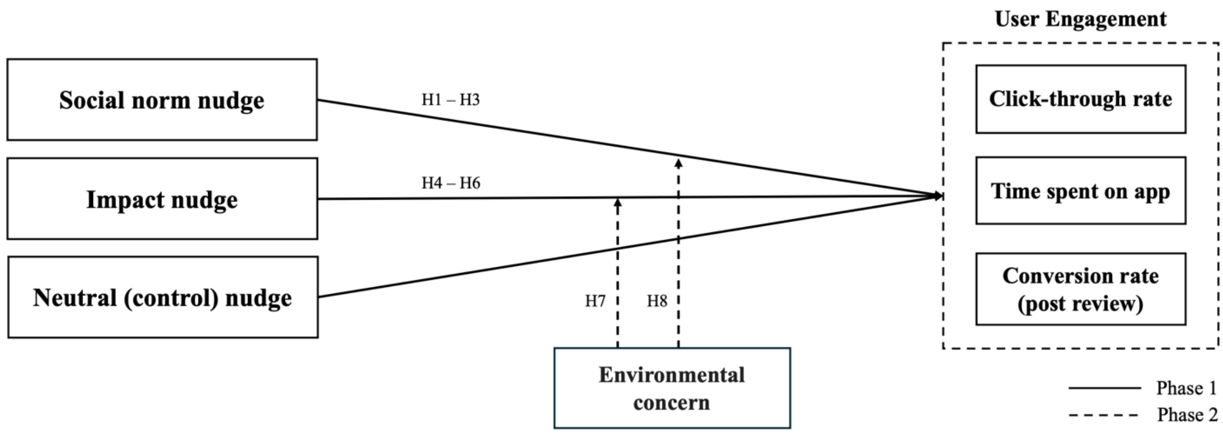


**Table 2**

*Overview of Hypothesis*

| Number | Hypotheses |
|---|---|
| H1 | The social norm nudge will have a significant positive effect on CTR compared to a neutral nudge. |
| H2 | The social norm nudge will have a significant positive effect on time spent on app compared to a neutral nudge. |
| H3 | The social norm nudge will have a significant positive effect on CR compared to a neutral nudge. |
| H4 | The impact nudge will have a significant positive effect on CTR compared to a neutral nudge. |
| H5 | The impact nudge will have a significant positive effect on time spent on app compared to a neutral nudge. |
| H6 | The impact nudge will have a significant positive effect on CR compared to a neutral nudge. |
| H7 | The effect of the impact nudge on user engagement will be positively moderated by EC, meaning that increased EC will enhance engagement with the impact nudge. |
| H8 | The effect of the social norm nudge on user engagement will be positively moderated by EC, meaning that increased EC will enhance engagement with the social norm nudge. |

## 4a. Methodology: Phase 1

Phase 1 of the methodology section describes a large-scale field experiment conducted on the Abillion app. In this phase, the main effects of the digital nudges are tested (H1 to H6).

### 4a.1 Abillion

To address the research objectives of this study, a case study will be conducted together with the company Abillion (Abillion, n.d.). This is a globally operating digital platform that facilitates the sharing of plant-based and ethical consumer experiences. Abillion has an active app and website, but for this study we will only focus on the app. Although Abillion primarily operates as a review-based platform for vegan restaurants and sharing food and products, its significance for this study stems from its explicit commitment to sustainability, community empowerment and generating positive social impact through the user experience. As the company's CEO and founder Vikas Garg stated: *"I hope that this company can create a consumer behaviour change and to make the world better and more conscious"*. Abillion's mission to promote a more sustainable, ethical and compassionate world is put into practice through an system in which reviews not only inform other consumers but also earn credits. These credits can then be donated to nonprofit organizations, allowing users to contribute to positive social impact through a donation system. With this mission at its core, Abillion presents itself as a highly relevant case for exploring how nudges can increase user engagement within sustainability and impact focused digital platform.

From an academic perspective, Abillion offers a very valuable setting for current study as the platform has over 13 million active users and operates across many countries worldwide. This makes it an ideal context to test the impact of green nudges.

### 4a.2 Variables and Measures

#### *4a.2.1 Independent Variables: Nudge Conditions*

The three conditions tested in the experiment correspond to three nudges (social norm, impact and a neutral control), all based on different theories and serving as independent variables. The nudges were delivered in the form of push notifications.

First, the social norms nudge leverages descriptive social proof to stimulate user engagement. Participants in this condition received the following notification; "Over half of Abillion users near you post weekly. Join them and share a review today as well!". This message is based on Social Proof Theory (Cialdini, 2001) and highlights peer behaviour to create normative pressure, encouraging users to align their behaviour with that of the majority. The intent is to leverage peer influence by suggesting that engagement is popular and normative.

Second, the impact nudge is designed to activate users' intrinsic motivations by emphasizing the social and environmental significance of their actions. The push notification reads: "Every post supports charities, people and business. Make a real difference by sharing yours today!". This message appeals to value-congruent motivations and aligns with the principles of Environmental Self-Identity Theory (van der Werff et al., 2013). It aims to reinforce users' self-concept as socially and environmentally responsible individuals, thereby encouraging higher engagement on the platform.

Lastly, to test the effect of the two nudging strategies, a neutral control condition is incorporated. Users in this condition received the following notification: "Found something great? Share your experience on Abillion today!". This notification contains no social proof or value-based framing. It simply functions as a neutral reminder to share a review, thereby providing a baseline for comparison against the impact of the experimental nudges.

To compare and minimize variation between the conditions, all nudges followed the same structural format. Each message consisted of two parts. The first part introduced a motivational framing aligned with the underlying theory. The second part of each message encouraged the user to share their experience on the Abillion platform. This enhances internal validity. In table 3 a summary of the nudges is presented.

**Table 3**

*Summary of the Nudges*

| **Nudge Type** | **Text** |
|---|---|
| Social Norm | "Over half of Abillion users near you post weekly. Join them and share a review today as well!" |
| Impact | "Every post supports charities, people and business. Make a real difference by sharing yours today!" |
| Control | "Found something great? Share your experience on Abillion today!" |

#### *4a.2.2 Dependent Variables: Engagement Metrics*

The dependent variables are three forms of user engagement, recorded by the Abillion data team through their backend analytics system. The three key engagement measures are CTR, time spent on app and CR. These three behavioural engagement types can be linked back to the COBRA model by Muntinga et al. (2011), which distinguishes between passive forms of engagement like consumption and more active forms like contribution and creation. This allows us to later explore whether the nudges primarily influence low-effort behaviours which are scrolling and clicking or also drive higher-effort actions such as posting a review (CR).

First, CTR; In this context, CTR refers to whether the user clicked on the push notification when it appeared. For each condition, the platform calculated the proportion of users who opened the app via the notification out of all users who received that notification. This metric captures immediate engagement prompted by the message, a direct reaction to the nudge in the form of clicking to see more content. A higher CTR suggests that the push notification effectively captured users' interest and prompted them to open the app.

Second, time spent on app; This measures the duration of the user's session after engaging with the notification, recorded in minutes. The app tracked how long the users continued to browse or interact with content on Abillion after receiving the notification on their phone. This metric reflects the sustained engagement on the app. The platform could register zero seconds of additional usage if a user did not go on the app after receiving the notification. By comparing average session lengths across conditions, we assess whether certain nudges lead users to spend more time exploring the app's offerings.

Lastly, CR; A conversion was defined as posting a review on the app. For the experiment, a binary indicator was recorded for whether each user performed a conversion after receiving the notification. This metric represents high level engagement, indicating that the nudge not only got the user's attention but also motivated them to complete a meaningful action on the app.

**4a.3 Sample Selection**

The first phase of the experiment started in the middle of april 2025. All active users of the Abillion app were considered participants in the study, as the nudges were integrated into the app environment itself. Although the entire user base was targeted, not all participants may have received or viewed the nudges. This could be due to several factors, such as users having push notifications disabled, have not used their phone for an extended period of time, or simply overlooking the message. Because no direct recruitment took place in phase 1 and all users were passively exposed within the app ecosystem, the sampling strategy can best be described as naturalistic and platform-based. No information was provided to users about the experiment at the time of exposure, ensuring ecological validity and minimizing demand characteristics. This phase allowed for the most realistic form of testing the effect of the green nudges in a real-world context.

### 4a.4 Research Design and Data Collection Procedure

Adopting a between-subjects design participants were randomly assigned to one of three experimental conditions: (1) a social norms nudge, (2) an impact nudge, or (3) a neutral control nudge. The nudges were delivered through Abillion’s existing push notification system, with each participant receiving the assigned message twice, with a five to seven day interval between notifications.

This decision to send the nudges twice was informed by previous research highlighting the importance of notification frequency in digital engagement. Some studies suggest that moderate exposure, like one or two notifications per day, can be effective for increasing engagement, especially when the content is relevant and not commercial in nature (Morrison et al., 2017). However, other research shows that in commercial contexts, a lower frequency may be more appropriate. Wohllebe et al. (2021), for example, found that sending more than one push notification per week can significantly increase the likelihood of users uninstalling the app in their experiment. Based on these findings, current study chose to send the nudges approximately once per week, which is more suitable in a commercial setting. It is still interesting to examine the effect of notification frequency and whether repeated exposure is truly necessary to achieve a significant impact. Therefore, this study evaluates the effect of both notification rounds separately. This comparison adds nuance to the understanding of how notification timing and frequency influence user response.

Notifications were localized and sent in five languages (English, Spanish and Italian, Portuguese and French), ensuring cultural and linguistic relevance for the diverse user base. The between-subjects design ensures that each participant is exposed to only one experimental condition, thereby avoiding carryover effects and enabling valid cross-group comparisons (Field, 2013).

The randomization process is managed by Abillion's development team. Engagement was monitored using Abillion's backend analytics system, which recorded user interactions throughout the intervention period. All engagement data was logged continuously.

### 4a.5 Data Preparation

The datasets were obtained from the Abillion data team and delivered in separate spreadsheets, each corresponding to the different rounds, so one for round 1, one for round 2. Because these datasets were distributed across multiple sheets, they were manually merged into a single Excel file. During this process, a new categorical variable was created to indicate the if the data is from round 1 or round 2.

It is important to note that the data was aggregated at the group level, not at the level of individual users. Each row therefore represented summary behavioural data for a specific condition rather than individual user responses.

Because the original dataset only included percentage values for CTR and CR, along with the total number of impressions, it was necessary to compute absolute values for the number of clicks and conversions. Two new variables were therefore created by multiplying the percentage values (CTR and CR) by the corresponding number of impressions. This made it possible to collect clear count data needed for the statistical analysis. These computed values were added as additional columns in SPSS.

### 4a.6 Data Analysis Procedure

To assess how the different nudging strategies affected user behaviour in the app, the data was analyzed using IBM SPSS Statistics (version 30.0.0.0) and Microsoft Excel.

The choice of statistical methods was guided by the type of dependent variable being analyzed, proportional (CTR and CR) versus continuous (time spent on app). For the CTR and CR, which are both expressed as proportions, a Z-test for two independent proportions was conducted. This test is appropriate for determining whether the proportion of users who clicked or converted differs significantly between two groups, particularly when working with large sample sizes. A weighted regression was considered but not used, because the analysis focused on comparing group-level proportions rather than individual responses. In this case, the Z-test was a more straightforward and appropriate method for testing differences between groups. Before conducting the Z-tests, the clicks, conversions and impressions for both rounds were extracted into separate SPSS datasets. These were exported to Excel, where a custom spreadsheet was used to calculate Z-scores, pooled proportions, standard errors and p-values. Effects with a p-value below 0.05 were considered statistically significant.

The Z-test was used in two steps. First, to compare each nudge type (social norm and impact) to the neutral nudge within both round 1 and round 2. Second, to test whether the effect of each nudge changed between rounds, allowing for analysis of potential interaction effects. Based on the Excel outputs, interaction plots were then manually created to visualize differences across rounds.

For the time spent on the app, a series of independent samples t-tests were performed using SPSS. The t-test is well-suited for assessing differences in means between two unrelated groups. These tests were used to compare mean session duration between nudge conditions (social norm vs. neutral) and between rounds (Round 1 vs. Round 2). All associated graphs and tables for this analysis were generated directly within SPSS and the results are interpreted.

## 4b. Methodology: Phase 2

Phase 2 of the methodology section focuses on a self-report survey among a subset of Abillion app users. In this phase, the moderating effect of EC is examined and hypotheses 7 and 8 are tested.

### 4b.1 Design

One week after the final notification was sent by Abillion, an online survey was distributed to the users who had been exposed to one of the three experimental conditions in Phase 1 to test the moderating effect of EC. The survey was administered via Qualtrics and distributed through two channels: an in-app post of the Abillion team itself and via targeted email with the question if people want to participate in the survey. Participants were informed that the study was part of a broader academic project, but the exact hypotheses and research intention were not disclosed to reduce bias. Participation was voluntary and anonymous.

The survey began with a question about the baseline platform usage of a user designed to distinguish whether the user was a passive or active user which could possibly be a confounding factor, so this was included as a control variable. This was followed by a question in which they needed to indicate if they did remember seeing a push notification. After that a question was presented which showed the three nudges (social norm, impact-based and neutral) and asked the participants which they saw. Based on their selection, participants were retrospectively categorized into one of the three conditions. Next, participants answered a series of questions regarding their engagement with the Abillion app after seeing the nudge. Following, participants completed the EC-scale. Participants who indicated that they did not recall seeing any notification were not assigned to an experimental condition but were nevertheless retained in the dataset. Since they completed the EC scale, their responses provided a useful baseline control group for assessing general environmental attitudes which can be compared to the experimental group. Including this control group strengthened the analysis by offering a comparison point unaffected by the nudging intervention, thereby enhancing the internal validity of the findings.

Finally, the survey collected demographic information, including age, gender, education level. These variables served to characterize the sample and were included as potential control variables as well in analyses. The survey required approximately 5–7 minutes to complete and all data were automatically anonymized and compiled into a dataset for statistical analysis. The full survey is included in Appendix F.

## 4b.2 Variables and Measures

### *4b.2.1 Independent Variable: Nudge Condition*

The independent variable in Phase 2 remained the type of digital nudge to which participants had been exposed during Phase 1. As no new manipulation was introduced in this phase, participants were retrospectively categorized based on their recall of the notification they received. Therefore, further methodological details regarding the nudges are not repeated here but can be found in the table 3 in part 4a.2.1 of the methodology section.

### *4b.2.2 Dependent Variable: User Engagement*

The dependent variable in Phase 2 is user engagement, measured subjectively through participants' self-assessments in the survey. Unlike Phase 1, which relied on backend behavioural data, this phase captures participants' perceived engagement with the app after seeing the nudge.

To measure user engagement, a custom three-item scale was developed (table 4). Participants were asked to indicate their agreement with the following statements on a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree). These items were designed to reflect both immediate and sustained aspects of user engagement, including behavioural intention (1), sustained engagement (2) and future engagement likelihood (3). A composite engagement variable was computed to facilitate statistical analysis. Since all items were phrased in the same direction, higher scores on the composite variable reflect greater engagement with the Abillion app. The mean score of the three items was computed and used as the dependent variable.

**Table 4**

*User Engagement Scale*

| No. | Statement |
|---|---|
| 1 | "The notification made me more motivated to post or share content on the Abillion app" |
| 2 | "After seeing the notification, I spent more time using the Abillion app than I normally would," |
| 3 | "The notification made me more likely to return to the Abillion app again soon." |

#### *4b.2.3 Moderator: Environmental Concern*

The moderator in this study is EC, included to examine whether individual differences in pro-environmental attitudes influence the effectiveness of the different green nudges on user engagement. EC was based on a three-item scale adapted from environmental attitude research by Vainio and Paloniemi (2014) and shown in table 5. Participants were asked to indicate their level of agreement with the following statements on a 5-point Likert scale (1 = strongly agree, 5 = strongly disagree). These items reflect skepticism toward ECs and were therefore reverse-coded to ensure that higher scores corresponded to higher EC. A composite score was calculated by averaging the three items. The resulting reverse-coded mean score was used as the moderator variable, where higher values represent stronger EC.

**Table 5**

*Environmental Concern Scale*

| No. | Statement |
|---|---|
| 1 | “We worry too much about the future of the environment and not enough about prices and jobs,” |
| 2 | "People worry too much about human progress harming the environment,” |
| 3 | “Many of the claims about environmental threats are exaggerated.” |

#### *4b.2.4 Control Variables*

To account for potential confounding influences on the relationship between the variables, several demographic and contextual characteristics were included as control variables. The inclusion of these variables serves to isolate the unique effects of the experimental manipulation and the moderator, thereby enhancing the internal validity of the findings and ensuring that observed effects are not attributable to underlying user differences (Field, 2013).

Age was included as a control variable as prior research suggests that age can influence responsiveness to digital nudging strategies, as cognitive processing styles and technology adoption vary across age groups (Yang & Shih, 2020).

Gender is a control because it is often associated with differences in digital engagement patterns and responsiveness to persuasive messages (Orji et al., 2014).

In addition, participants were asked to indicate their highest completed level of education as educational background has been linked to differences in digital literacy and environmental awareness, both of which may impact engagement behaviour (Muhdhar et al., 2024).

Finally, baseline platform usage was taken into account to control for differences in how users typically engaged with the Abillion app before the intervention. Making a clear distinction between active and passive users helped reduce the risk of confounding, since both usage frequency and behaviour type could influence how users respond to nudges as active users already are more engaged than passive users.

### 4b.3 Data Preparation

Before conducting the regression and moderation analyses, the dataset was carefully cleaned. Participants who did not complete the full survey were removed from the data and all irrelevant variables were excluded.

To examine the moderating role of EC on the relationship between nudge type and user engagement, a series of variable transformations were carried out. For the regression analysis, two dummy variables were created: one for the social norm nudge and one for the impact nudge, with the neutral nudge as the reference category. Additionally, mean scores were computed for the engagement scale and the EC scale. These scores were calculated by taking the average of the related survey questions and the results were added to the dataset.

### 4b.4 Data Analysis Procedure

To investigate whether the effectiveness of different nudging strategies is moderated by EC, Phase 2 employed a regression-based moderation analysis using IBM SPSS Statistics (version 30.0.0.0) using the PROCESS macro (Model 1), developed by Hayes (2017). A regression analysis is well-suited for phase 2, because this phase uses individual-level data and it allows for testing interaction effects (moderation), which many other statistical methods do not handle as clearly.

The analysis proceeded in two stages. First, linear regression models were run to estimate the main effects of each nudge condition and EC on user engagement. Second, the interaction term (made by the PROCESS model) between the nudge condition and EC was included to test for moderation effects. In each model, control variables were added to reduce potential confounding bias.

Prior to the regression, the data was evaluated for all core assumptions, including linearity, normality of residuals and multicollinearity, prior to interpretation. Also, variance Inflation Factor (VIF) and Tolerance scores were also checked to rule out multicollinearity

## 5a. Results: Phase 1

### 5a.1 Sample

In total, the dataset reflects 492,400 impressions, distributed across two experimental rounds. Impressions refer to the number of users who received the nudge within the app. Round 1 accounted for 269,100 impressions (54.64%), while Round 2 contributed the remaining 223,300 (45.36%). This near-even split supports balanced comparisons across experimental stages. A breakdown by nudge condition reveals that each nudge type (social norm, impact-based and control) was relatively evenly distributed within each round, with proportions ranging from approximately 32% to 35% as is shown in table 6.

Language distribution further shows that the reach of the nudges was skewed toward English-speaking users, who represented more than 63% of all impressions across both rounds. Italian and Spanish-speaking users also formed substantial subgroups, whereas French and Portuguese users remained underrepresented, together making up less than 5% of impressions in each round. These differences are a result of the platform's language preferences and the geographic spread of the users (table 7).

**Table 6**

*Total Impressions of App Users in the Two Rounds for each Nudge Type*

| Language | Impressions (Round 1) | % of Round 1 | Impressions (Round 2) | % of Round 2 |
|---|---|---|---|---|
| Social Norm | 87,700 | 32.59% | 73,600 | 32.96% |
| Impact | 86,400 | 32.11% | 72,800 | 32.60% |
| Control | 95,000 | 35.30% | 76,900 | 34.44% |

*Note.* Percentages represent the proportion of total impressions within each round.

**Table 7**

*Total Impressions of App Users in the Two Rounds for each Language*

| Language | Impressions (Round 1) | % of Round 1 | Impressions (Round 2) | % of Round 2 |
|---|---|---|---|---|
| EN | 170600 | 63.40% | 142100 | 63.64% |
| ES | 32500 | 12.08% | 29200 | 13.08% |
| FR | 7500 | 2.79% | 1600 | 0.72% |
| IT | 53900 | 20.03% | 46600 | 20.87% |
| PT | 4600 | 1.71% | 3800 | 1.70% |

*Note*. Percentages represent the proportion of total impressions within each round.

Although the dataset itself does not include individual-level demographic variables, internal analytics from Abillion report that approximately 64% of users identify as female and 36% as male, with an average user age of around 40 years old. See table 8 for the full age distribution of the users on the Abillion app.

**Table 8**

*Age Distribution of Users on Abillion*

| Age Group | Percentage of Users |
|---|---|
| 18–24 | 13% |
| 25–34 | 23% |
| 35–44 | 18% |
| 45–54 | 20% |
| 55–64 | 15% |
| 65+ | 11% |

### 5a.2 Descriptive Statistics

Descriptive statistics were calculated for each nudge condition, separately for round 1 and round 2. These include impressions and the engagement metrics (CTR, CR and session duration) based on aggregated group-level data. To enable fair comparisons, group means were adjusted for differences in group size. Appendix A (tables 21–26) provides a full overview, including minimum, maximum, mean values and total impressions. CTR reflects the percentage of users who clicked the notification, CR the percentage who posted a review and session duration the total minutes users in each condition spent in the app post-nudge.

### 5a.3 Pretests

Before proceeding with hypothesis testing, a series of robustness checks were conducted to ensure that the aggregated dataset was suitable for the selected statistical analyses. Prior to conducting Z-tests for independent proportions, standard assumptions were evaluated to ensure the validity of the statistical procedure. First, the groups being compared were mutually exclusive and independent, ensuring that each user was exposed to only one experimental condition. The outcome tested with the Z-test (CTR and CR) reflect binary events, satisfying the requirement of having a dependent variable with two possible outcomes. Although raw counts of successes and failures were not directly available, the number of total impressions per group was known and the proportional data allowed for estimation of underlying frequencies. Based on these group sizes and observed proportions, it was assumed that both the expected number of successes (np) and failures (n[1–p]) exceeded the minimum threshold of ten in all comparisons. This justified the application of a normal approximation to the binomial distribution and thus supported the use of Z-tests to assess differences in CTR and CR between condition (Agresti & Franklin, 2005).

For the analysis of time spent on app, independent samples t-tests were used to compare group means. Although typical assumptions such as normal distribution of residuals and homogeneity of variance apply primarily to individual-level data, the use of large sample averages per group supports the application of t-tests under the Central Limit Theorem (Central limit theorem, 2008). Therefore, the t-test was considered appropriate for detecting meaningful differences in user engagement duration between conditions.

Lastly, the dataset was reviewed for completeness and consistency. As the data was sourced directly from backend app logs and aggregated at the platform level, it contained no missing values or outliers. Together, these checks confirm that the data meets the assumptions necessary to proceed with hypothesis testing.

## 5a.4 Hypothesis Testing

### *5a.4.1 Hypotheses 1: Effect Social Norm Nudge on CTR*

In round 1, participants exposed to the social norm nudge exhibited a higher CTR of 1.26%, compared to 0.95% in the neutral control group. A Z-test for proportions confirmed that this difference was statistically significant, with a Z-score of 6.39 and a p-value less than .001. This result supports the hypothesis that the social norm nudge effectively increased CTR upon first exposure. The corresponding effect size, calculated using Cohen's *h*, was 0.03, which is considered small. This indicates that although statistically significant, the practical impact of the nudge on CTR in the first round was modest.

In round 2, the CTR in the social norm condition increased slightly to 1.33%, while the CTR in the neutral group dropped sharply to 0.26%. The Z-test comparing these two proportions yielded a highly significant result, Z = 23.61, $p < .001$. The effect size in round 2, based on Cohen's *h*, was 0.13, which represents a small-to-moderate effect.

To examine whether the effect of the social norm nudge itself changed across rounds, a direct comparison between round 1 and round 2 was conducted. Although the CTR increased from 1.26% to 1.33%, this change was not statistically significant (Z = –1.37, p = .169). This indicates that the impact of the social norm nudge remained stable between the two rounds, with no significant increase due to repeated exposure.

In contrast, the neutral control condition showed a significant decline in effectiveness over time. The CTR fell from 0.95% in round 1 to 0.26% in round 2. This reduction was statistically significant, Z = 17.74, $p < .001$, suggesting that user responsiveness to the neutral nudge diminished substantially across rounds.

Taken together, these findings confirm the hypothesis: the social norm nudge had a significantly positive effect on CTR compared to a neutral nudge. Moreover, while the effect of the social norm nudge remained consistently high across the rounds, the neutral condition significantly decreased as shown in figure 2.

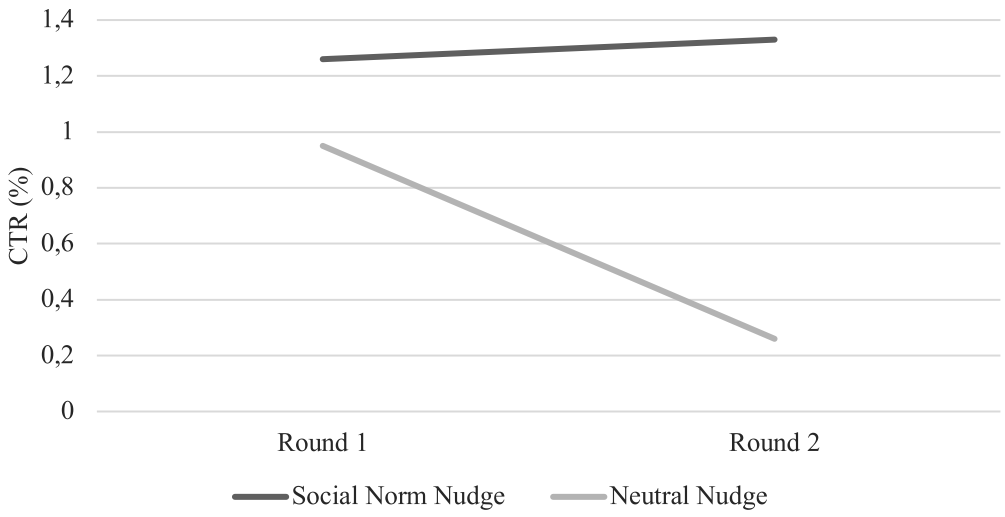
**Table 9**

*Results Z-test, Social Norm Nudge vs Neutral Nudge on CTR*

| **Round** | **Pooled Proportion** | **Standard Error** | **Z-Score** | **P-Value** |
|---|---|---|---|---|
| Round 1 | 0.01095 | 0.00049 | 6.39 | < .001 |
| Round 2 | 0.00786 | 0.00046 | 23.61 | < .001 |
| Round 1 vs 2 (Social) | 0.01293 | 0.00056 | -1.37 | 0.169 |
| Round 1 vs 2 (Control) | 0.00639 | 0.00039 | 17.74 | < .001 |

**Figure 2**

*Change in CTR Across Rounds, Social Norm and Control Nudge*




*Note.* The effect of social norm nudge across round was not significant (p=.169). The effect of neutral nudge (control) was negatively significant (p = <.001).

### *5a.4.2 Hypothesis 2: Effect of Social Norm Nudge on Time Spent on App*

In round 1, participants who received the social norm nudge spent significantly more time on the app on average than those in the neutral nudge condition after seeing the nudge. An independent samples t-test confirmed that this difference in mean session duration was statistically significant, with a t-value of 359.94 and a p-value of < .001. The mean difference between the two groups was 0.047 minutes. The difference is time is very small because the average session time was calculated by dividing the total time of all the users by the number of impressions and as mentioned earlier some users may not have opened the app after receiving the nudge, which is why the mean value is very small. Still, the effect is statistically significant because it's based on very large scale. Although the effect was statistically significant, the practical magnitude of the difference was small, as reflected in a Cohen's d of 0.03. This indicates that while the nudge led to a reliable increase in time spent on the app, the actual difference per user session was modest.

In round 2, participants in the social norm nudge condition again demonstrated a significantly higher average session duration compared to those in the neutral nudge condition. An independent samples t-test revealed a statistically significant difference in mean time spent on the app, with a t-value of 310.11 and a p-value less than .001. The mean difference between groups was 0.105 minutes. The effect size was small (Cohen's d = 0.07).

To assess whether the impact of the social norm nudge on user engagement changed over time, a comparison was made between round 1 and round 2. An independent samples t-test revealed a statistically significant difference between the two rounds, with a t-value of 487.74 and a p-value less than .001 ($p < .001$). This result suggests that the average time users spent on the app under the social norm nudge increased in round 2 compared to round 1.

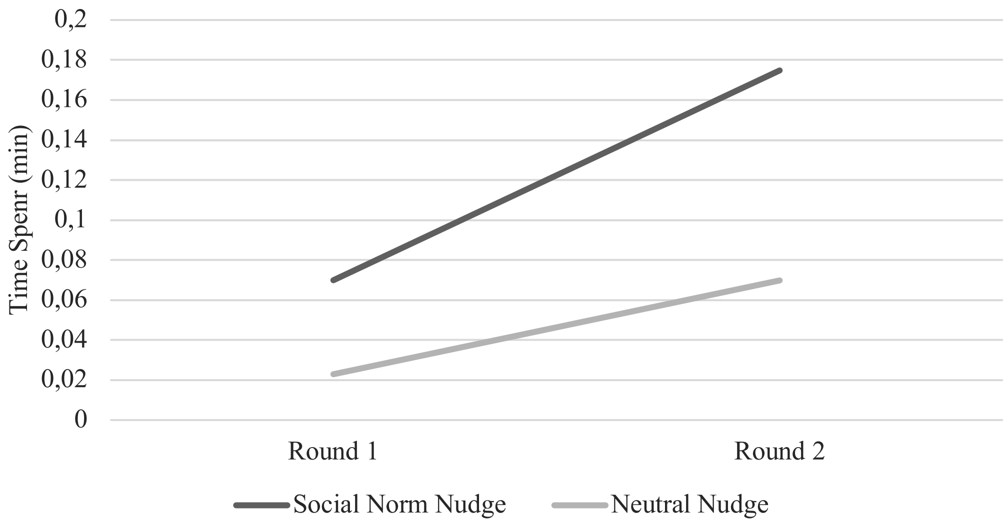
**Table 10**

*Results T-test, Social Norm Nudge vs Neutral Nudge on Time Spent on App*

| **Round** | **Comparison** | **t-value** | **p-value** | **Cohen's d** |
|---|---|---|---|---|
| Round 1 | Social Norm vs. Neutral | 359.94 | < .001 | 0.03 |
| Round 2 | Social Norm vs. Neutral | 310.11 | < .001 | 0.07 |
| Interaction | Round × Nudge (Social Norm) | -344.60 | < .001 | 0.06 |
| Interaction | Round x Nudge (Neutral) | -268.99 | <.001 | 0.04 |

**Figure 3**

*Change in Time Spent on App Across Rounds, Social Norm and Control Nudge*




*Note.* The effect of social norm nudge across round was positive significant (p= <.001). The effect of neutral nudge (control) was positive significant as well (p = <.001).

### *5a.4.3 Hypotheses 3: Effect Social Norm Nudge on CR*

Participants who received the social norm nudge in round 1 demonstrated CR of 1.82%, whereas participants in the neutral control condition showed a much lower CR of 0.53%. A Z-test for the difference in proportions confirmed that this effect was statistically significant, with a Z-score of 25.94 and a p-value of <.001, indicating a reliable positive effect of the social norm message on user conversion behaviour during the first notification round. The corresponding effect size, based on Cohen's h, was 0.13, which represents a small-to-moderate effect. This suggests that although the difference in conversion was statistically strong, the practical impact of the nudge is meaningful but not large.

In round 2, the social norm nudge again outperformed the neutral control. The CR in the social norm group slightly increased to 1.92%, while the CR in the control group dropped to just 0.26%. This difference was again statistically significant, with a Z-score of 31.26 and a p-value of 0. The effect size in this round was 0.18.

To assess whether the effect of the social norm nudge changed over time, a direct comparison was conducted between round 1 and round 2 within the social norm condition. The CR increased slightly from 1.82% to 1.92%, but this change was not statistically significant, $Z = -1.34$, $p = .179$. This suggests that while the conversion rate remained consistently high, there was no evidence of a cumulative effect or increase in persuasive strength across rounds.

By contrast, the neutral condition showed a substantial decline in conversion effectiveness over time. From 0.53% in round 1, the CR dropped to 0.26% in round 2. This decline was statistically significant, $Z = 8.76$, $p < .001$, indicating that participants became less responsive to the neutral nudge over repeated exposures.

Taken together, these findings support Hypothesis 3. The social norm nudge had a significantly higher conversion rate than the neutral nudge in both rounds.

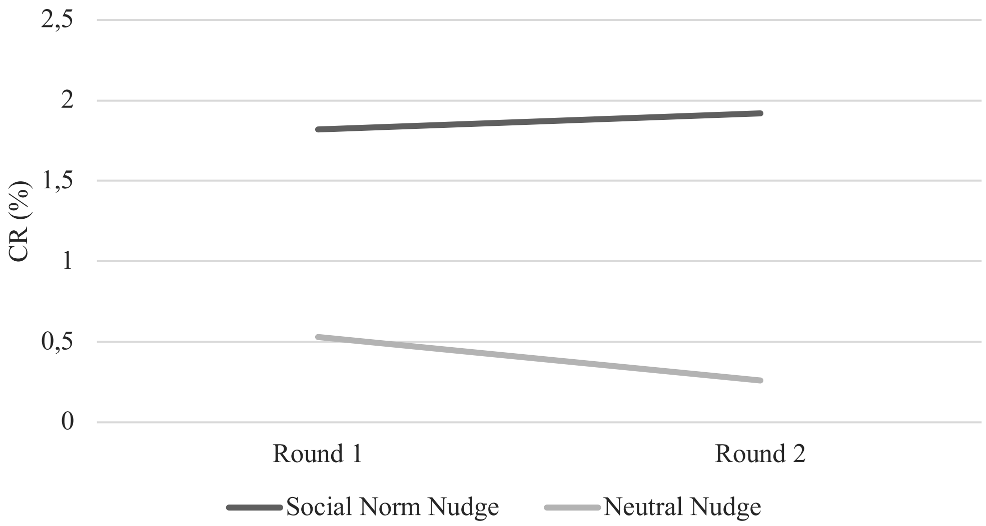
**Table 11**

*Results z-test, Social Norm Nudge vs Neutral Nudge on CR*

| **Round** | **Pooled Proportion** | **Standard Error** | **Z-Score** | **P-Value** |
|---|---|---|---|---|
| Round 1 | 0.01151 | 0.00050 | 25.94 | <.001 |
| Round 2 | 0.01069 | 0.00053 | 31.26 | <.001 |
| Round 1 vs 2 (Social) | 0.01866 | 0.00068 | -1.34 | .179 |
| Round 1 vs 2 (Control) | 0.00408 | 0.00031 | 8.76 | < .001 |

**Figure 4**

*Change in CR on App Across Rounds, Social Norm and Control Nudge*




*Note.* The effect of social norm nudge across round was not significant (p= .179). The effect of neutral nudge (control) was negatively significant (p = <.001).

### *5a.4.4 Hypotheses 4: Effect of Impact Nudge on CTR*

In round 1, participants who received the impact nudge achieved a CTR of 1.04%, while those in the neutral control group exhibited a slightly lower CTR of 0.95%. A Z-test for independent proportions revealed that this difference was statistically significant, with a Z-score of 2.11 and a p-value of .035. The effect size, based on Cohen's h, was 0.01, indicating a very small practical difference between the groups. These results suggest that, upon first exposure, the impact nudge led to a modest but statistically significant increase in CTR compared to the neutral condition.

In round 2, participants who received the impact nudge achieved a CTR of 1.51%, whereas those in the neutral control condition showed a considerably lower CTR of 0.26%. A Z-test for independent proportions confirmed that this difference was highly significant, with a Z-score of 26.08 and a p-value of < .001. The corresponding Cohen's h was 0.14. This result indicates that, in the second round of exposure, the impact nudge was substantially more effective in driving user click behaviour than the neutral nudge.

To assess whether the effectiveness of the impact nudge changed over time, a direct comparison was made between round 1 and round 2 within the impact condition. The CTR increased from 1.04% in round 1 to 1.51% in round 2. This difference was statistically significant, with a Z-score of –8.34 and a p-value of < .001. These findings suggest that the persuasive effect of the impact nudge strengthened over time.

In contrast, the neutral nudge showed a decline in CTR across rounds. From 0.95% in round 1, the CTR fell to 0.26% in round 2. This decline was significant ($Z = 17.74$, $p < .001$), highlighting a clear decrease in effectiveness over time for the neutral message.

Taken together, the results confirm Hypothesis 4. The impact nudge had a statistically significant positive effect on CTR compared to a neutral nudge. Notably, while the effect of the impact nudge significantly increased across rounds, the neutral nudge became less effective over time, showing a clear difference in impact compared to the other nudges (figure 5).

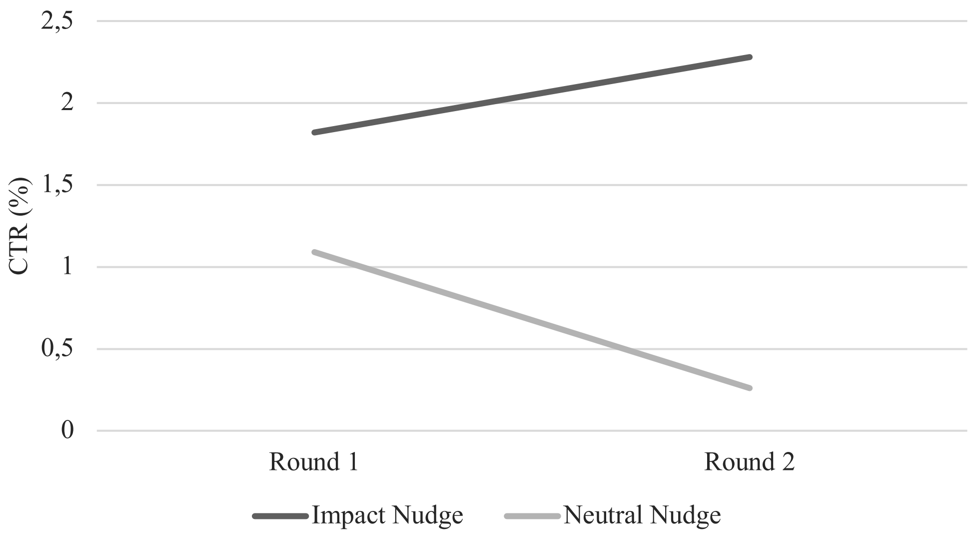
**Table 12**

*Results z-test, Impact Nudge vs Neutral Nudge on CTR*

| **Round** | **Pooled Proportion** | **Standard Error** | **Z-Score** | **P-Value** |
|---|---|---|---|---|
| Round 1 | 0.00992 | 0.00047 | 2.11 | .035 |
| Round 2 | 0.00863 | 0.00048 | 26.08 | < .001 |
| Round 1 vs 2 (Social) | 0.01257 | 0.00056 | -8.34 | < .001 |
| Round 1 vs 2 (Control) | 0.00639 | 0.00039 | 17.74 | < .001 |

**Figure 5**

*Change in CTR on App Across Rounds, Impact and Control Nudge*




*Note.* The effect of impact nudge across round was positively significant (p= < ,001). The effect of neutral nudge (control) was negatively significant (p = <.001).

### *5a.4.5 Hypothesis 5: Effect Impact Nudge on Time Spent on App*

In round 1, participants who received the impact nudge spent significantly more time on the app compared to those who received the neutral nudge because the mean session duration was higher in the impact condition (M = 0.0791, SD = 0.01665) than in the neutral condition (M = 0.0223, SD = 0.01743). An independent samples t-test confirmed that this difference was statistically significant, $t(180{,}956.29) = 709.68$, $p < .001$. The mean difference between the two conditions was 0.05681 minutes. The absolute difference between groups is again very small because the data is aggregated across all users, including those who may have spent zero minutes in the app but were still included in the analysis. These results suggest that even upon first exposure, the impact nudge was more effective in encouraging users to spent more time in the app compared to a neutral nudge.

In round 2, participants who received the impact nudge again spent significantly more time on the app compared to those who received the neutral nudge. The average session duration was substantially higher in the impact condition (M = 0.2148, SD = 0.05550) than in the neutral condition (M = 0.0698, SD = 0.05089). An independent samples t-test confirmed that this difference was statistically significant, $t(146{,}777.66) = 525.96$, $p < .001$. The mean difference in session duration was 0.14498 minutes.

To assess the consistency of the impact nudge over the two rounds, the average time spent on the app was compared between Round 1 and Round 2. An new independent samples t-test confirmed that this increase between rounds was statistically significant for the impact nudge condition, $t(83{,}857.81) = -636.01$, $p < .001$, with a small effect size (Cohen's $d = 0.04$).

Similarly, the neutral nudge also led to a significant increase in average session duration, from round 1 to round 2. This difference was statistically significant, $t(91{,}527.42) = -247.47$, $p < .001$, although the effect size was again small (Cohen's $d = 0.04$).

The interaction pattern is visualized in Figure 6 and demonstrates that while both nudges became more effective over time, the increase in engagement was considerably steeper for the impact nudge. This suggests that repeated exposure to the impact message strengthens its ability to drive user behaviour more effectively than a neutral message.

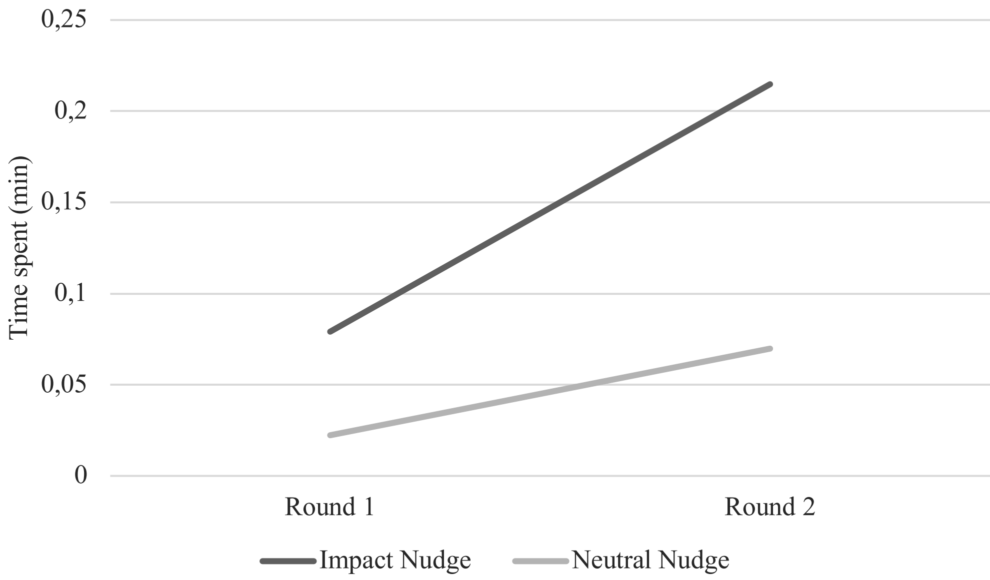
**Table 13**

*Results t-test, Impact Nudge vs Neutral Nudge on Time Spent on App*

| Round | Comparison | t-value | p-value | Cohen's d |
|---|---|---|---|---|
| Round 1 | Impact vs. Neutral | 268.99 | < .001 | 0.03 |
| Round 2 | Impact vs. Neutral | 359.94 | < .001 | 0.07 |
| Interaction | Round × Nudge (Impact) | -683.11 | < .001 | 0.06 |
| Interaction | Round x Nudge (Neutral) | -268.99 | <.001 | 0.04 |

**Figure 6**

*Change in Time Spent on App Across Rounds, Impact and Control Nudge*




*Note: The effect of impact nudge across round was positively significant (p= < ,001). The effect of neutral nudge (control) was positively significant as well (p = <.001).*

### *5a.4.6 Hypotheses 6: Effect Impact Nudge on CR*

In the first round, participants exposed to the impact nudge achieved a CR of 2.08%, while those in the neutral control group had a substantially lower CR of 0.53%. A Z-test for proportions confirmed that this difference was statistically significant, with a Z-score of 29.51 and a p-value of <.001. This result provides strong evidence that the impact message led to a significantly higher CR than the neutral condition during the first round of notifications.

In round 2, the CR in the impact condition was slightly lower, at 1.81%, yet still substantially higher than the 0.26% observed in the neutral group. This comparison also yielded a highly significant result (Z = 29.99, p = < .001), confirming that the impact nudge continued to outperform the neutral nudge in eliciting conversion behaviour during the second round.

To determine whether the effectiveness of the impact nudge changed over time, a direct comparison was conducted between round 1 and round 2 within the impact condition. The CR decreased slightly from 2.08% to 1.81% and this difference was statistically significant, $Z = 3.87$, $p < .001$. This suggests that although the impact nudge remained highly effective, its influence on conversion behaviour may have slightly diminished over repeated exposure.

By contrast, the neutral condition showed a decline as well. The CR dropped from 0.53% in round 1 to 0.26% in round 2. This change was statistically significant ($Z = 8.76$, $p < .001$), indicating a meaningful decrease in responsiveness to the neutral nudge across rounds (figure 7).

Taken together, these results confirm Hypothesis 6. The impact nudge had a statistically significant positive effect on CR compared to the neutral nudge in both notification rounds. Although its effectiveness showed a slight decline over time, it consistently outperformed the neutral control condition.

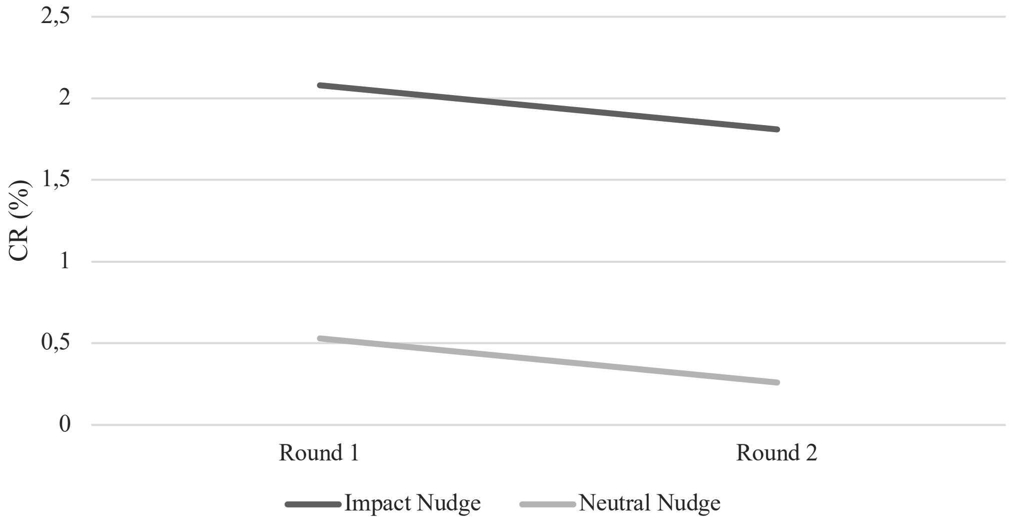
**Table 14**

*Results z-test, Impact Nudge vs Neutral Nudge on CR*

| **Round** | **Pooled Proportion** | **Standard Error** | **Z-Score** | **P-Value** |
|---|---|---|---|---|
| Round 1 | 0.01269 | 0.00053 | 29.51 | 0 |
| Round 2 | 0.01014 | 0.00052 | 29.99 | 0 |
| Round 1 vs 2 (Social) | 0.01959 | 0.00070 | 3.87 | < .001 |
| Round 1 vs 2 (Control) | 0.00408 | 0.00031 | 8.76 | < .001 |

**Figure 7**

*Change in CR on App Across Rounds, Impact and Control Nudge*




*Note.* The effect of impact nudge across round was negatively significant (p= < ,001). The effect of neutral nudge (control) was negatively significant as well for CR (p = <.001).

Table 15 below provides a comprehensive overview of the results for each hypothesis. The full Excel and SPSS outputs can be found in Appendices C and D.

**Table 15**

*Summary of the Hypothesis*

| **H** | **IV** | **Dependent Variable** | **Z value / T value** | **Cohen's D / Cohen's H** | **Significant** | **Effect Direction** | **Conclusion** |
|---|---|---|---|---|---|---|---|
| H1 | SNN | CTR | Z = 6.39 (R1), Z = 23.61 (R2) | 0.03 (R1), 0.13 (R2) | Yes | Positive | Supported |
| H2 | SNN | Time Spend on App | t = 359.94 (R1), t = 310.11 (R2) | 0.03 (R1), 0.07 (R2) | Yes | Positive | Supported |
| H3 | SNN | Conversion | Z = 25.94 (R1), Z = 31.26 (R2) | 0.009 (R1), 0.14 (R2) | Yes | Positive | Supported |
| H4 | IN | CTR | Z = 2.11 (R1), Z = 26.08 (R2) | 0.12 (R1), 0.17 (R2) | Yes | Positive | Supported |

| H | IV | Dependent Variable | Z value / T value | Cohen's D / Cohen's H | Significant | Effect Direction | Conclusion |
|---|---|---|---|---|---|---|---|
| H5 | IN | Time Spend on App | t = 268.99 (R1), t = 359.94 (R2) | 0.03 (R1), 0.07 (R2) | Yes | Positive | Supported |
| H6 | IN | Conversion | Z = 29.51 (R1), Z = 29.99 (R2) | 0.14 (R1), 0.17 (R2) | Yes | Positive | Supported |

*Note*. Social Norm Nudge (SNN), Impact Nudge (IN)

# 5b. Results: Phase 2

## 5b.1 Descriptive Statistics of the Total Sample

A total of 214 individuals began the online survey. After excluding participants who did not complete the relevant sections of the questionnaire, the final sample consisted of 179 participants who provided sufficient data. For the main analyses, only participants who completed the full survey and indicated that they had seen the nudge were retained. This resulted in an experimental group of 118 participants and a control group of 61 participants who did not recall seeing the nudge but filled in the EC-scale.

The sample ranged in age from 18 to 68 years (M = 37.31, SD = 12.37). In terms of gender, 56.7% identified as female (n = 101), 35.4% as male (n = 63), while 7.9% identified as other or preferred not to disclose their gender (n = 14).

Participants' educational backgrounds were diverse. The majority reported having completed primary education (39.9%), followed by bachelor's degrees (23.0%), secondary education (21.3%), master's degrees (10.1%) and doctoral degrees or equivalent (4.5%). The average education level was 3.28 on a 6-point scale. Participants also represented a variety of nationalities and languages, with Spanish and English being the most common.

## 5b.2 Descriptive Statistics per Condition

Participants saw one of the three nudges: social norm nudge (n = 35), impact nudge (n = 50) and neutral control nudge (n = 33). Demographic information on gender, age and education for each condition is provided in Table 16.

**Table 16**

*Demographic Data of the Sample per Nudge Type*

| Demographic Category | Social Norm | Impact | Neutral |
|---|---|---|---|
| N | 35 | 50 | 33 |
| Female | 25.7% | 67.4% | 45.2% |
| Male | 71.4% | 23.9% | 51.6% |
| Other/No answer | 2.9% | 8.7% | 3.2% |
| 18–24 | 11.4% | 14.6% | 16.1% |
| 25–34 | 48.6% | 41.7% | 29.0% |
| 35–44 | 31.4% | 16.7% | 25.8% |
| 45–54 | 0.0% | 16.7% | 22.6% |
| 55–64 | 8.6% | 8.3% | 6.5% |
| 65–74 | 0.0% | 2.1% | 0.0% |
| Bachelor | 14.3% | 20.0% | 36.4% |
| Doctorate | 28.6% | 22.0% | 12.1% |
| Other | 5.7% | 10.0% | 12.1% |
| Primary | 8.6% | 6.0% | 6.1% |
| Secondary | 42.9% | 42.0% | 33.3% |

*Note.* The percentage values indicate how much each category contributes to the total for that variable.

To assess whether participants were equally distributed across the three experimental conditions in terms of demographic characteristics, some statistical tests were conducted to test the difference between groups. First, chi-square tests were conducted for gender and education level. For gender, the results revealed a statistically significant difference between conditions, $\chi^2(6, N = 118) = 21.78$, $p = .001$, indicating that gender was not evenly distributed across the nudge types. This imbalance is also clearly reflected in table 16, which shows that 71.4% of participants in the social norm condition identified as male, compared to only 23.9% in the impact condition and 51.6% in the neutral condition. Conversely, the impact condition had a disproportionately higher percentage of female participants (67.4%) compared to the other conditions which could influence the results. Therefore, gender will be statistically controlled for in the analyses.

In contrast, the chi-square test for education level was not significant, $\chi^2(8, N = 118) = 7.65$, p = .469. This means that participants with different education levels were fairly evenly spread across the three conditions. Lastly, a Kruskal–Wallis test was conducted to examine whether participants' age differed across the three conditions. The result was not significant, H(2) = 0.06, p = .971, indicating that age was also evenly distributed among conditions

**5b.3 Control Group**

To examine whether participants who reported seeing the nudge differed in their level of EC compared to those who did not, an independent samples *t*-test was conducted. Participants who indicated that they had seen the nudge (*n* = 117) reported slightly lower EC scores (M = 3.81, SD = 1.15) than those who did not (*n* = 66, M = 4.12, SD = 1.07) but Levene's test for equality of variances was not significant, $F(1, 177) = 2.62$, $p = .107$, indicating that the assumption of homogeneity of variances was met. Therefore, the t-test assuming equal variances was interpreted. The difference in EC between groups was not statistically significant, $t(177) = –1.74$, $p = .083$ (two-tailed). The observed mean difference was –0.31 (SE = 0.18). Also the confidence interval included zero, suggesting that the observed difference may be attributable to sampling variability and is not reliably different from zero.

These results suggest that the group of participants who reported seeing the nudge did not differ meaningfully in their baseline level of EC compared to those who did not. This supports the assumption that EC is equally distributed across all participants.

### 5b.4 Scale reliability

A reliability analysis was conducted to verify the consistent measurement of constructs, assessed through Cronbach's Alpha values. The reliability scales are found in Table 17 and show that each construct has a Cronbach alpha above 0.7 thus can be used for further analysis.

**Table 17**

*Scale Reliability*

| **Construct** | **Reliability** | **Nr. of items** |
|---|---|---|
| EC | .832 | 3 |
| User Engagement | .890 | 3 |

### 5b.5 Correlations

A correlations matrix was made to look at how the variables correlate with each other and if these correlations are in line with theory or alarming (Table 32 in Appendix E).

As expected, the impact nudge and social norm nudge were negatively correlated ($r = –.001$, $p < .001$), reflecting their mutually exclusive assignment. The neutral condition served as the reference group and was not included in the correlation analysis. Engagement correlated significantly with EC ($r = .452$, $p < .001$), indicating a link between pro-environmental attitudes and platform engagement. Engagement also showed positive correlations with the social norm nudge ($r = .297$, $p < .01$) and the impact nudge ($r = .025$, $p < .05$), suggesting both nudges contributed to increased engagement as expected.

Gender was significantly correlated with both nudges ($p < .001$), indicating potential gender differences which was also visible in the descriptive statistics. Age did not significantly correlate with engagement ($r = .289$, $p > .05$) or EC ($r = .091$, $p > .05$), but did show a strong correlation with gender ($r = .645$, $p < .001$). Education and employment status were not significantly correlated with the main outcome variables. Active and passive user types were strongly correlated ($r = .643$, $p < .001$), indicating that passive users were also more likely to be actively engaged.

Overall, the correlation results support the theoretical expectations and reveal no concerning patterns that would affect the interpretation of the main findings.

**5b.6 Assumption Tests**

To check the assumption of linearity before running the regression, a scatterplot and P–P plot of standardized residuals were inspected. The P–P plot showed the points followed the diagonal line closely, indicating normally distributed residuals and supporting linearity (Appendix B, Figure 9).

In addition, the scatterplot of residuals displayed no visible patterns or curved shapes in the scatterplot, which suggests that the relationship between the independent variables and the outcome was sufficiently linear. This further confirms that the model meets the linearity assumption (Appendix B, Figure 10).

The histogram showed a fairly even, bell-shaped curve that matched the normal line, which suggests that the residuals were close to normally distributed (Appendix, Figure 11).

Multicollinearity was evaluated using both the Variance Inflation Factor (VIF) and Tolerance statistics. The VIF values for both predictors were 1.000 and the corresponding Tolerance values were also 1.000. These values indicate a complete absence of multicollinearity, as they fall well within accepted thresholds (VIF $< 5$; Tolerance $> .10$). Additional support for this conclusion was provided by the collinearity diagnostics, where the highest condition index was 7.52, far below the critical value of 30.

Based on these results, all predictors are suitable for inclusion in the regression and moderation analyses.

## 5b.7 Hypothesis Testing

### *5b.7.1 Hypothesis 7: Moderating effect of EC on Impact Nudge*

**Control variables**. All control variables were included in the model and from the output only gender emerged as a statistically significant predictor ($B = -0.394$, $p = .007$). This means that participants identifying as male showed significantly lower engagement levels compared to females. All other control variables, including passive and active users, education level and age, were not significantly associated with engagement, indicating that these background and behavioural factors did not meaningfully explain variation in engagement within the model. All control variables were entered as covariates in the moderation analysis. This ensured that the reported effects of the nudge condition and EC reflect their contributions to engagement, independent of these background variables.

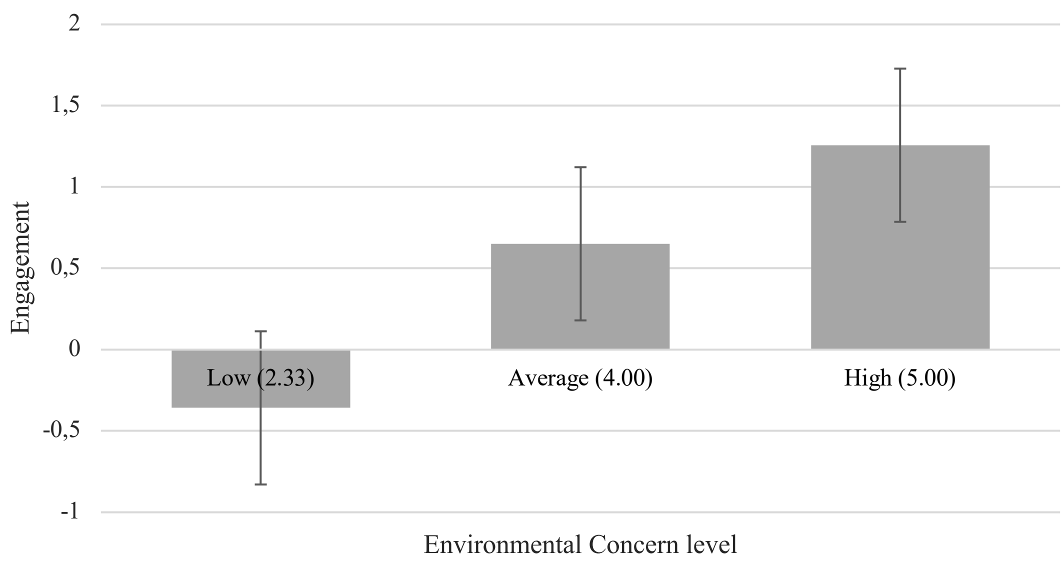
**Main effect**. Regarding the main effects, exposure to the impact nudge significantly predicted lower engagement, $B = -1.770$, $SE = 0.773$, $t = -2.29$, $p = .024$, with a 95% confidence interval ranging from –3.304 to –0.236. This finding was contrary to expectations and suggests that, on average, participants who received the impact nudge reported significantly lower engagement than those in the control condition. In contrast, EC was a significant positive predictor of engagement itself, $B = 0.259$, $SE = 0.117$, $t = 2.22$, $p = .029$, 95% CI [0.027, 0.491], indicating that individuals with higher levels of EC reported greater engagement, regardless of nudge condition.

**Moderation.** The results showed a significant interaction between the impact nudge and EC ($B = 0.585$, $SE = 0.189$, $p = .003$) meaning that the effect of the nudge on engagement depended on how environmentally concerned users are. Adding this interaction to the model also significantly improved its overall explanatory power ($\Delta R^2 = .060$, $F(1, 104) = 9.60$, $p = .003$).

To better understand this effect, the impact of the nudge was tested at different levels of EC. For users with low EC (score = 2.33), the nudge had a negative non-significant effect on engagement ($B = –0.33$, $p = .38$). At average EC (score = 4.00), the nudge had a positive and significant effect ($B = 0.65$, $p = .005$). This effect was even stronger for users with high EC (score = 5.00), where the nudge significantly increased engagement ($B = 1.23$, $p < .001$). These findings are shown in figure 8.

**Figure 8**

*Impact Nudge Effect on Engagement at Varying Levels of EC*




*Note*: The graph shows that the impact nudge becomes more effective in increasing engagement as EC rises.

These findings support hypothesis 7. The proposed moderation effect suggests that the impact nudge becomes more effective as users' EC increases, leading to higher engagement only among those who already care about the environment. Table 18 shows the results of the regression and the interaction on the impact nudge with EC.

**Table 18**

*Moderation of EC on User Engagement by the Impact Norm Nudge*

| Variable | *b* | *SE* | *t* | *p* | *95% CI (LL)* | *95% CI (UL)* |
|---|---|---|---|---|---|---|
| Constant | 3.8412 | 0.7859 | 4.8875 | 0.0000 | 2.2825 | 5.3999 |
| Impact Nudge | -1.7701 | 0.7734 | -2.2887 | 0.0241 | -3.3040 | -0.2363 |
| EC | 0.2590 | 0.1169 | 2.2151 | 0.0290 | 0.0271 | 0.4909 |
| Impact Nudge × EC | 0.5850 | 0.1912 | 3.1658 | 0.0030 | 0.2261 | 0.9845 |
| Age | 0.0031 | 0.0101 | 0.3103 | 0.7570 | -0.0168 | 0.0231 |
| Gender | -0.3859 | 0.1432 | -2.6953 | 0.0082 | -0.6659 | -0.1020 |
| Education Level | -0.0454 | 0.0688 | -0.6598 | 0.5109 | -0.1819 | 0.0911 |
| Active User | -1.4476 | 0.9698 | -1.5240 | 0.1306 | -3.3396 | 0.0445 |
| Passive User | -0.1556 | 0.0926 | -1.6801 | 0.0960 | -0.3392 | 0.0281 |

#### *5b.7.2 Hypothesis 8: Moderating Effect of EC on Social Norm Nudge*

**Control variables**. In the first step, the control variables were included similar as for hypothesis 7. The results indicated that none of the control variables significantly predicted user engagement. Specifically, frequency of passive use ($B = –0.119$, $p = .242$), frequency of active use ($B = –0.100$, $p = .341$), age ($B = 0.003$, $p = .778$), employment status ($B = –0.014$, $p = .832$), education level ($B = 0.026$, $p = .727$) and gender ($B = –0.216$, $p = .177$) all failed to reach statistical significance.

These findings suggest that none of the measured demographic or usage-related variables had a meaningful independent effect on engagement levels in the current model.

Despite their lack of significance, these variables were retained as covariates in all analyses to still control for them.

**Main Effects**. The regression analysis revealed a significant main effect of EC on engagement, but not for the social norm nudge. Specifically, EC significantly predicted higher user engagement, B = 0.475, SE = 0.116, t = 4.088, p = .0001, with a 95% confidence interval ranging from 0.245 to 0.706. This indicates that individuals with higher levels of EC reported significantly greater engagement.

In contrast, the social norm nudge condition did not significantly predict user engagement, B = –0.535, SE = 0.868, t = –0.616, p = .5389, 95% CI [–2.257, 1.187]. This suggests that, on average, participants exposed to the social norm nudge did not report higher engagement levels compared to those in the control group.

**Moderation Effect.** Also, no significant interaction was found between the social norm nudge and EC, B = 0.168, SE = 0.222, t = 0.757, p = .4504, 95% CI [–0.272, 0.607]. This indicates that EC did not significantly moderate the relationship between the social norm nudge and engagement**.** Thus, Hypothesis 7 was not supported; the effectiveness of the social norm is not strengthened by an higher individual level of EC. An overview of all results can be found in table 19.

**Table 19**

*Moderation of EC on User Engagement by the Social Norm Nudge*

| Variable | *b* | *SE* | *t* | *p* | *95% CI (LL)* | *95% CI (UL)* |
|---|---|---|---|---|---|---|
| Constant | 2.4266 | 0.8180 | 2.9664 | 0.0037 | 0.8042 | 4.0489 |
| SocalNudge | -0.5353 | 0.8683 | -0.6166 | 0.5389 | -2.2573 | 1.1867 |
| EC | 0.4754 | 0.1163 | 4.0882 | 0.0001 | 0.2448 | 0.7061 |

| Variable | ***b*** | ***SE*** | ***t*** | ***p*** | ***95% CI (LL)*** | ***95% CI (UL)*** |
|---|---|---|---|---|---|---|
| Social Nudge × EC | 0.1679 | 0.2215 | 0.7577 | 0.4504 | -0.2715 | 0.6072 |
| Age | 0.0031 | 0.0109 | 0.2829 | 0.7778 | -0.0185 | 0.0247 |
| Gender | -0.2155 | 0.1585 | -1.3600 | 0.1768 | -0.5298 | 0.0988 |
| Education Level | 0.0263 | 0.0749 | 0.3506 | 0.7266 | -0.1223 | 0.1748 |
| Active User | -0.1002 | 0.1048 | -0.9564 | 0.3411 | -0.3081 | 0.1076 |
| Passive User | -0.1191 | 0.1011 | -1.1778 | 0.2416 | -0.3196 | 0.0814 |

Table 20 provides a summary of the hypothesis testing results for the two moderation models examined in this study.

**Table 20**

*Summary of the Hypothesis*

| **Hypothesis** | **DV** | **Significant?** | **Effect Direction** | **Conclusion** |
|---|---|---|---|---|
| H7 | Engagement | No | Positive | Supported |
| H8 | Engagement | No | - | Not Supported |

# 6. Discussion

This study aimed to determine how two types of green digital nudges (social norm and impact nudges) affect user engagement on a sustainability-oriented app, compared to a neutral message. The goal was not only to test whether these nudges increase engagement, but also to examine whether their effectiveness depends on users' level of EC. In doing so, the study enriches the literature by confirming how EC influences the effectiveness of impact nudges and fills a gap by revealing the previously unexplored role of EC in shaping responses to social norm nudges. This helps to identify for whom green nudging is most effective within a real-world digital context.

## 6.1 Discussion of Results

First, all hypotheses in phase 1 of the study were supported, indicating that both the social norm nudge and the impact nudge had significant positive effects on user engagement. These findings are in line with previous research showing that nudges can effectively influence user behaviour in digital environments (Weinmann et al., 2016; Hummel & Maedche, 2019; Schneider et al., 2020). Given the extremely large sample size of this study, it was anticipated that many comparisons would yield statistically significant results. As Cohen (1992) points out, large samples increase statistical power, making even relatively small effects more likely to reach significance. Thus, although statistical significance provides valuable insights, it is just as important to evaluate the size of the effects to fully understand their practical relevance which will be discussed in the following sections.

### *6.1.1 Effect of Social Norm Nudge on Engagement (H1, H2, H3)*

The social norm nudge was effective in significantly enhancing all forms of user engagement relative to the neutral nudge, which supports hypothesis 1 to 3. The results indicate that social norm nudges can trigger quick, intuitive responses and increase engagement in an environmentally focused context, confirming the effectiveness as green nudges.

To begin with, the social norm nudge had a significant positive effect on CTR, which confirms that social norm nudges can effect the low level engagement (consuming level of the CORBA model of Muntinga, 2011). While the effect size was small, its significance suggests that a subtle references to what others do can still influence user behaviour. Users may have perceived that if many others were engaging, it was natural or expected to do the same. Similar was found by prior research, for example findings of Bakshy et al. (2012) show that even a minimal social cue, like displaying a single peer's name, can cause significant increases in click-through rates.

Beyond initial engagement, the social norm nudge also resulted in increased time spent on the app. This suggests that social norm nudges may not only facilitate entry but also help maintain user attention, even if their impact wanes over time. However, the effect size was again very small (0.03 and 0.07) which was quite expected as sustained engagement normally comes from intrinsic motivation, while this is not something a social norm nudge provides. Another reason for this could be because time spent on the app is influenced by additional factors such as app design, content relevance and personal interest (Okonkwo, 2024). As a result, the practical effect of a single nudge on this engagement metric is inherently limited.

Finally, the social norm nudge had a positive effect on CR, showing that this nudge can even encourage higher-effort actions as posting a review. While the effect size here again was not very big (0.14). People generally have a strong tendency to align with perceived social norms, often adjusting their behaviour to match what others around them are doing (Asch, 1956). In this case, the social norm nudge explicitly stated that others were posting reviews, which likely reinforced the perceived expectation to do the same. As a result, users exposed to this nudge were significantly more likely to post a review compared to those who saw the neutral nudge. This shows that social validation can encourage both simple and more effortful actions, especially when the behaviour is presented as something others do and it supports environmental goals.

Overall, this is all in line with prior research and shows the social norm nudge can serve as a strong green nudge which impacts low and high effort engagement as is shown from the COBRA model (Muntinga et al., 2011). This makes the social norm nudge a powerful green method that companies can use to change behaviour, especially when it comes to environmental issues.

#### *6.1.2 Effect of the Impact Nudge on Engagement (H4, H5, H6)*

Similar to the social norm nudge, the impact nudge demonstrated a statistically significant effect compared to the neutral nudge on low and high levels of engagement as was expected and is in line with prior literature.

First, regarding the effect on CTR; although the effect size was small, its impact remains meaningful given the large-scale implementation of the nudge. The impact nudge's emphasis on 'supporting charities and making a real difference' may have triggered a sense of purpose in users, which in turn increased their likelihood of clicking. As proposed in the introduction, value-congruent messaging can function as a motivational cue that draws attention and prompts immediate, low-effort engagement (Schubert, 2016).

Moreover, the impact nudge showed comparable effectiveness at the high-effort engagement level, by a significant increase in CR. Conversion (classified under the "creation" level of the COBRA model) require stronger motivational drivers (Muntinga et al., 2011). The impact nudge, which emphasizes the consequences of one's actions, appears to resonate more with users' intrinsic motivations and environmental self-identity (van der Werff et al., 2013). As Taufik et al. (2015) demonstrate, when people feel emotionally connected to environmental causes and believe their actions can make a real difference, they are more inclined to engage in behaviour that affirms this identity. In this context, the impact nudge on CR may has a somewhat bigger effect size (Cohen's $H$ = 0.17), compared to the other engagement levels tested in this study, which is notably given that conversion requires high motivation and effort. This may suggest that the impact nudge effectively activated deeper internal drivers. Research shows that messages highlighting the consequences of one's actions on the environment can increase moral engagement and the feeling of personal impact, which in turn drives pro-environmental behaviour (Bamberg & Möser, 2006). In this case, the impact nudge may have made users feel that their actions (writing a review) contribute to a greater cause, making them more willing to go beyond passive engagement.

Compared to its somewhat stronger effects on CTR and CR, the impact nudge showed a very small effect on time spent on the app, with Cohen's $d$ values of 0.03 and 0.07. Importantly, these effects were still statistically significant. This suggests that the nudge had a meaningful influence on sustained engagement. However, the relatively smaller effect size implies that time spent on app is likely influenced by a broader range of factors beyond just the nudge itself. Unlike CTR or CR, which are possible more directly tied to the content and framing of the message, session duration may depend more on aspects such as content relevance, user goals, app design, interface usability, quality and enjoyment (Okonkwo, 2024; Pinho et al., 2019). As a result, a single nudge may have only limited power to affect how long users remain active within the app. Overall, this shows that the impact nudge can be seen as an effective green nudge in an online environment as well, confirming earlier research that such messages can help promote sustainable behaviour.

### *6.1.3 Effect of EC as Moderator (H7, H8)*

As hypothesized (H7), users' level of EC strongly moderated the effectiveness of the impact nudge. Although the impact nudge initially showed a negative main effect on engagement, further analysis revealed that this effect depends strongly on users' level of EC. This indicates that individuals with low EC showed a negative response to the impact nudge, whereas those with high EC showed a strong increase in engagement in reaction to the same nudge. This finding makes theoretical sense as individuals who are concerned about the environment are especially responsive to nudges that reflect their personal values. This also aligns with previous research that has shown that individuals with high EC are more likely to respond positively to approaches that align with their pro-environmental identity, because such messages affirm their self-concept and reflect their moral values (Bolderdijk et al., 2013; van der Werff et al., 2013). The impact nudge matched the values of users with strong EC and encouraged them to engage. Further, EC also had a positive main effect on engagement, which could be explained by the fact that individuals with higher EC are more active on Abillion because they want to make an impact, regardless of the presence of a nudge itself. Overall, the results of H7 build on current literature by confirming that an impact nudge is most effective among users who are very climate conscious.

Contrary and interestingly, highly environmental concerned users were no more influenced by the social norm nudge than users with lower EC (H8). This is an unexpected finding given our theoretical reasoning that people with strong EC might be extra responsive to others' behaviours, as social norm theory suggests that individuals are more likely to align their actions with perceived group norms, especially when those norms are consistent with their personal values (Cialdini et al., 1990; Schultz et al., 2007). One potential explanation for this finding is that individuals with high EC may already feel internally motivated to act pro-environmentally, making external cues as social norm nudges less salient. This could also explain the significant positive main effect found of EC on engagement regardless of the nudges. For these individuals, behaviour may be guided more by personal standards than by the behaviour of others. As a result, their behaviour may be less influenced by social norm nudges, which tend to leverage situational social cues and cognitive shortcuts rather than appealing to deeply held values.

Another possible explanation lies in the concept of norm saturation. Research suggests that when individuals are already strongly aligned with a given norm, such as pro-environmental behaviour in the case of those with high EC, additional normative messages may yield diminishing marginal returns or even be disregarded (Goldstein et al., 2008; Bicchieri, 2017). In such instances, the social norm nudge may merely reinforce a behaviour that is already internalized, providing little added motivational value. So this ceiling effect could explain why EC did not moderate the effect of the social norm nudge.

This highlights an important consideration for green nudging, while social norm messages can be powerful, their effectiveness may plateau among individuals who already strongly identify with environmental values. This study adds to the literature by clarifying a gap about the effect of EC on social norms. The results show that personal values matter and that a one-size-fits-all approach is ineffective. Therefore, tailoring messages to individual differences is needed.

### *6.1.4 Effect of the Different Rounds*

While not hypothesized, this study also examined how the effectiveness of the push notifications evolved over time. Specifically, whether their impact differed between the first and second notification rounds, which were spaced approximately 5 to 7 days apart. This exploratory component of the research aimed to deepen our understanding of how nudge frequency influences their effectiveness.

The results reveal several noteworthy patterns. Most strikingly, the neutral control condition consistently demonstrated a significant decline in effectiveness across rounds, both in CTR and CR. This finding suggests that repeated exposure to generic or non-compelling push notifications can lead to a form of user disengagement, which highlights an adverse effects over time. A possible explanation for this is, when notifications lack relevance or are poorly timed, users may perceive them as intrusive or as noise which can reduce their engagement. Gavilan and Martínez-Navarro (2022) found that insufficiently tailored, so they don't evoke an emotional reaction in people, or inappropriately timed push notifications were commonly described as annoying or disruptive, undermining their intended effect. These findings highlight that both the content of the message and how often it is delivered are key factors for achieving optimal impact.

Further, the social norm and impact nudges showed mixed patterns across rounds, with some indications of increased effectiveness, while other cases showed no change or even a slight decline. The impact nudge showed a significant improvement in CTR and time spent on the app in round 2, although its effect on conversion rate slightly declined. The social norm nudge remained relatively stable in CTR and CR but significantly increased time spent on the app in the second round. These results indicate that nudges with clear psychological mechanisms are a bit more resilient to repetition and could benefit from a second exposure in a short time. This is supported in the literature by Nowak et al. (2023) who found that norm-nudges that clearly show what others expect are less likely to lose their effect when repeated. However, it is important to note that the strength and direction of these effects varied within the current study. It is therefore important to approach the delivery of push notifications with care. While excessive frequency can reduce their effectiveness, in some cases, slightly increased exposure may actually boost user engagement.

This variation suggests that a more detailed follow-up study focusing specifically on notification frequency under different conditions would be highly valuable in understanding when and how repetition supports or hinders engagement specifically for green nudges.

## 6.2 Limitations and Future Research

One limitation of this study concerns the interpretation of CTR as a measure of user engagement. In practice, a push notification can act simply as a trigger to unlock the phone, without the user paying attention to its actual content. Users may then tap on one of the notifications more or less randomly, sometimes without even reading it, just to open their phone. In some cases, they might open the app briefly and leave again to do something else on their phone. As a result, the recorded click does not always reflect real interest or purposeful engagement with the notification. This can give a somewhat skewed picture of CTR. Therefore, although CTR is a useful metric, it should be interpreted with care. However, given the very large sample size in this study, such random variation is expected to distribute relatively evenly across experimental conditions. As a result, while this limitation introduces a degree of noise in the measurement of CTR, it is unlikely to have systematically biased the comparison between nudging strategies.

Another limitation of the current study is that EC was measured through self-report in the second phase of the study. Although the second phase offers valuable insights into participants' EC as underlying motivation of behaviour, the use of self-report measures is inherently more sensitive to bias and less accurate. Additionally, the relatively small sample size limited the statistical power of this phase. A stronger approach to measure the moderation effect would be to measure the level of EC of an individual and then track their behaviour on the Abillion app accordingly. By linking the EC score of this specific user to their engagement behaviour after receiving the nudges, future studies could measure the moderation effect more accurately and on a much larger scale where the participants are fully unaware of being part of a study. This would also increase the ecological validity of phase 2. In fact, the current study aimed to take this approach, but due to technical limitations it was not possible to match user-level platform data to an internal EC-questionnaire. Therefore, a self-report method in phase 2 was ultimately chosen to assess EC and engagement in a way that was feasible given the limitations. Future research could build on these findings by taking this approach.

Further, although baseline data on user engagement was initially made available by the platform, it turned out to be incomplete. As a result, it could not be reliably used in the analysis to compare pre- and post-intervention behaviour. This limited the ability to assess whether the observed engagement in the experimental conditions truly reflected a behavioural change due to the nudges over time. While comparisons with a control group and with the two rounds still offered valuable insights, the absence of a usable baseline reduced the opportunity to compare the effect before the nudging with the responses after seeing the nudge. Future research would benefit from incorporating a complete baseline measurement to allow for an even more compelling interpretations of nudge effectiveness.

### 6.3 Managerial Implication

This study provides valuable insights for app managers, digital marketers and organizations who use digital platforms as their core business. The results suggest that green digital nudges in the form of push notifications can meaningfully increase user engagement, particularly when the content of these nudges resonates with users' values. Both nudges examined in the study demonstrated notable effectiveness. However, the role of EC in moderating these effects suggests that nudging should not be seen as a one-size-fits-all solution. Instead, it should be viewed as a strategic tool that can be tailored to different user segments. For example, platforms with a strong focus on sustainability may benefit most from impact nudges, as these resonate with users' intrinsic motivations. In contrast, platforms targeting a broader audience may see greater success using social norm nudges. Therefore, it is essential for companies to consider the nature of their platform and audience when designing nudges in order to maximize their effectiveness.

# 7. Conclusion

As the climate crisis intensifies, inspiring sustainable behaviour at scale is no longer a luxury, it's a necessity (IPCC, 2022). In this urgent context, green digital nudges offer a powerful tool for encouraging sustainable behaviour. This large-scale real-world study provides strong evidence that social norm and impact nudges can significantly increase user engagement on a social media app explicitly designed to make impact for a better world. Because the app incentivizes plant-based consumption and donations to environmental causes, increased engagement directly supports societal goals. These findings underline the potential of nudging not just for commercial purposes, but also as a powerful tool to advance environmental sustainability. (Thaler & Sunstein, 2021; Berger et al., 2022).

This study helps fill a gap in the literature by showing that, although EC is known to boost responses to impact nudging, little is known about whether it also affects how people respond to social norm nudges in digital sustainability context. This study adds to the debate by offering insights that EC significantly strengthens engagement with impact nudges, but does not influence the effectiveness of social norm nudges in the same way. These findings have important practical implications. Platforms with highly engaged, sustainability-oriented audiences should prioritize impact nudges, while platforms with a broader or less environmentally concerned user base may benefit more from social norm nudges.

In conclusion, this study shows that when nudging aligns with user values and platform goals, it has the potential to move beyond theory and create real-world impact. In the hands of designers, policymakers and purpose-driven platforms, green nudging provides more than just user engagement. It presents a clear path toward a more sustainable future.

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# Appendices

## Appendix A: Descriptive Statistics Nudges Phase 1

**Table 21**

*Round 1 – Social Norm Nudge*

| | N | Minimum | Maximum | Mean | Std. Deviation |
|---|---|---|---|---|---|
| Impressions | 87700 | 800 | 58000 | 42991.22 | 21151.940 |
| CTR (%) | 87700 | .00 | 2.33 | 1.2572 | .67266 |
| CR (%) | 87700 | .00 | 4.65 | 1.8246 | 1.47339 |
| Session duration | 87700 | .640 | 3731.96 | 2909.80 | 1297.36 |

**Table 22**

*Round 1 – Impact Nudge*

| | N | Minimum | Maximum | Mean | Std. Deviation |
|---|---|---|---|---|---|
| Impressions | 86400 | 700 | 54700 | 40036.11 | 19481.283 |
| CTR (%) | 86400 | .00 | 1.75 | 1.0438 | .38036 |
| CR (%) | 86400 | 1.09 | 14.29 | 2.0819 | 1.38997 |
| Session duration | 86400 | 50.17 | 4971.67 | 3472.72 | 1981.11 |

**Table 23**

*Round 1 – Control Nudge*

| | N | Minimum | Maximum | Mean | Std. Deviation |
|---|---|---|---|---|---|
| Impressions | 95000 | 2000 | 57900 | 40478.53 | 22034.666 |
| CTR (%) | 95000 | .00 | 1.38 | .9457 | .56823 |
| CR (%) | 95000 | .00 | 1.09 | .5292 | .34952 |
| Session duration | 95000 | 9.152 | 742.86 | 659.31 | 198.82 |

**Table 24**

*Round 2 – Social Norm Nudge*

| | N | Minimum | Maximum | Mean | Std. Deviation |
|---|---|---|---|---|---|
| Impressions | 73600 | 500 | 47400 | 34848.10 | 17048.924 |
| CTR (%) | 73600 | .00 | 3.31 | 1.3348 | 1.01628 |
| CR (%) | 73600 | .00 | 4.00 | 1.9155 | 1.21439 |
| Session duration | 73600 | 9.007 | 8361.21 | 6286.49 | 3042.86 |

**Table 25**

*Round 2 – Impact Nudge*

| | N | Minimum | Maximum | Mean | Std. Deviation |
|---|---|---|---|---|---|
| Impressions | 72800 | 500 | 45400 | 33151.65 | 15966.499 |
| CTR (%) | 72800 | .00 | 2.52 | 1.5111 | .64274 |
| CR (%) | 72800 | .00 | 2.02 | 1.8122 | .28254 |
| Session duration | 72800 | 69.418 | 11484.29 | 7937.19 | 4611.22 |

**Table 26**

*Round 2 – Control Nudge*

| | N | Minimum | Maximum | Mean | Std. Deviation |
|---|---|---|---|---|---|
| Impressions | 76900 | 600 | 49300 | 36078.93 | 17847.010 |
| CTR (%) | 76900 | .00 | 1.01 | .2599 | .38327 |
| CR (%) | 76900 | .00 | 1.01 | .2582 | .30047 |
| Session duration | 76900 | 11.334 | 2473.25 | 1783.36 | 496.28 |

**Appendix B: Pre Tests**

**Figure 9**

*Normal P–P plot of Regression Standardized Residual*

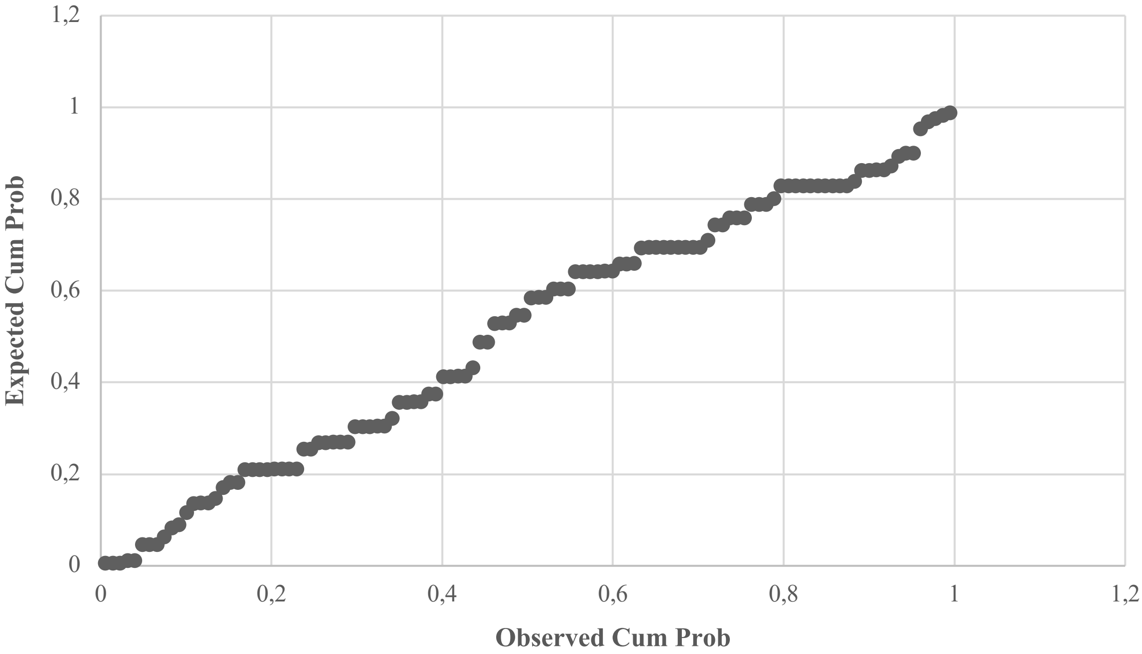



**Figure 10**

*Scatterplot*

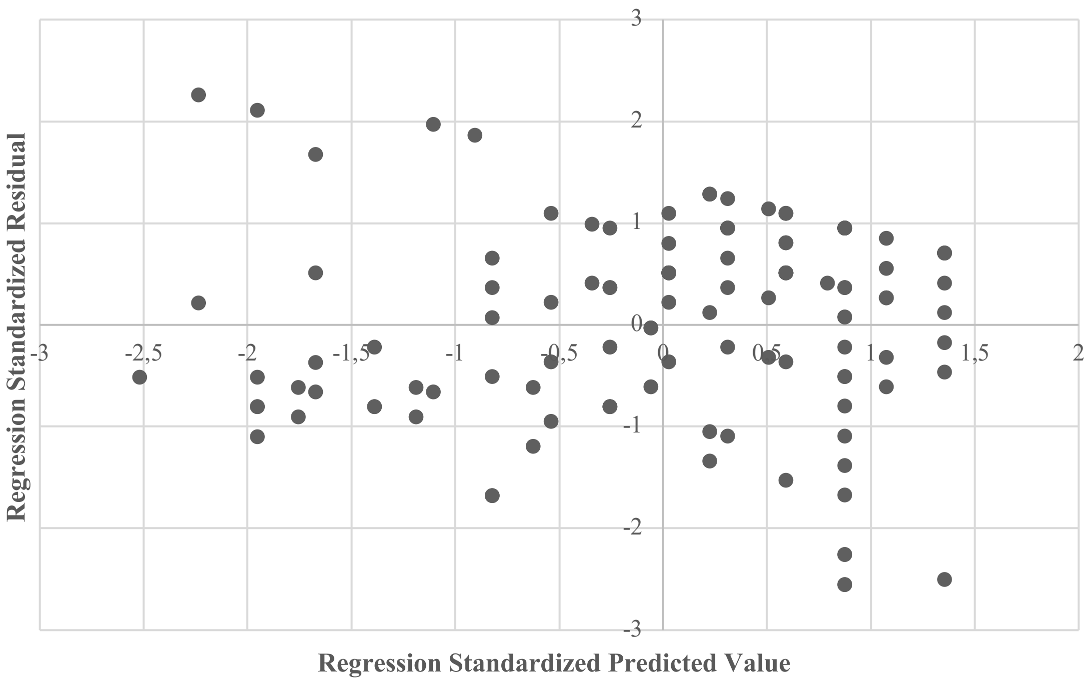
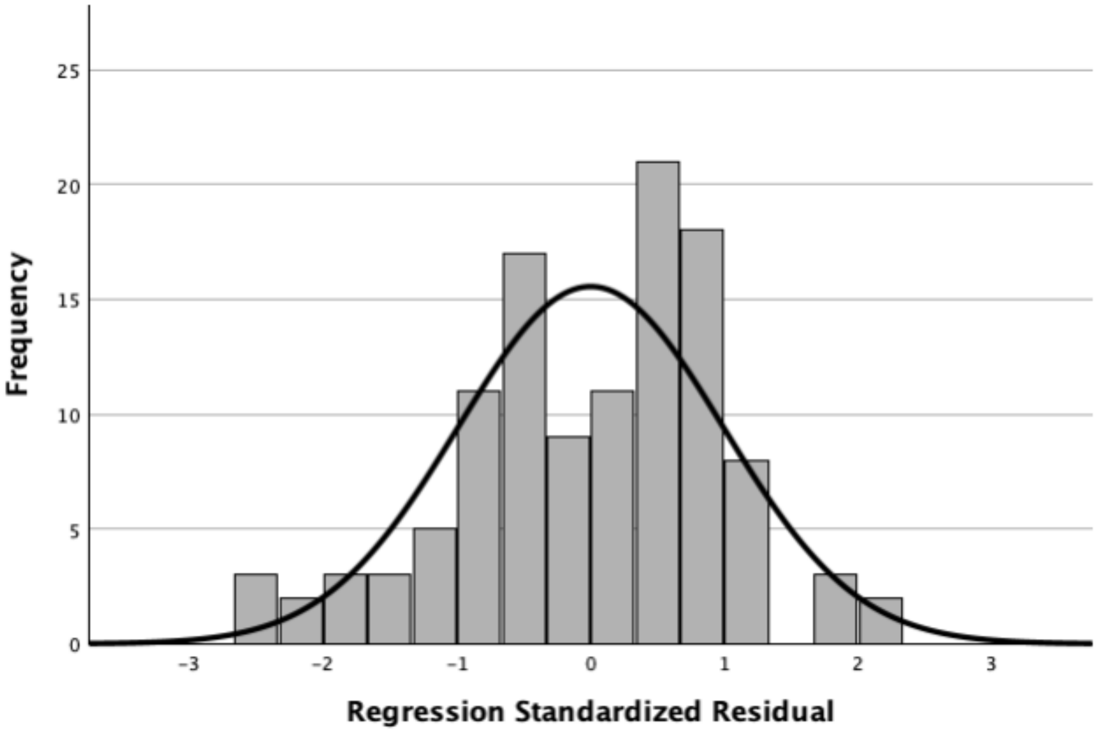


**Figure 11**

*Histogram, DV; User Engagement, Regession Standardized Residual*




*Note.* Mean = 4.05$^{E}$-16, Std. Dev = 0.991, N = 117

## Appendix C: Results t-test Time Spent on App

**Table 27**

*Results T-test of Social norm nudge (type 1) vs neutral nudge (type 3) in Round 1*

| | Type | N | Mean | Std. Deviation | Std. Error Mean |
|---|---|---|---|---|---|
| **Mean session duration** | 1 | 87700 | .0688 | .03445 | .00012 |
| | 3 | 95000 | .0223 | .01743 | .00006 |

| | | Levene's Test for Equality of Variances | | t-test for Equality of Means | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | Significance | | | | 95% Confidence Interval of the Difference | |
| | | F | Sig. | t | df | One-Sided p | Two-Sided p | Mean Difference | Std. Error Difference | Lower | Upper |
| **Mean session duration** | Equal variances assumed | 8604.300 | <.001 | 368.566 | 182698 | <.001 | <.001 | .04655 | .00013 | .04631 | .04680 |
| | Equal variances not assumed | | | 359.944 | 127474.772 | <.001 | <.001 | .04655 | .00013 | .04630 | .04681 |

**Table 28**

*Results T-test of Social norm nudge (type 1) vs neutral nudge (type 3) in Round 2*

| | Type | N | Mean | Std. Deviation | Std. Error Mean |
|---|---|---|---|---|---|
| **Mean session duration** | 1 | 73600 | .1749 | .07736 | .00029 |
| | 3 | 76900 | .0698 | .05089 | .00018 |

| | | Levene's Test for Equality of Variances | | t-test for Equality of Means | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | Significance | | | | 95% Confidence Interval of the Difference | |
| | | F | Sig. | t | df | One-Sided p | Two-Sided p | Mean Difference | Std. Error Difference | Lower | Upper |
| **Mean session duration** | Equal variances assumed | 1.959 | .162 | 312.819 | 150498 | <.001 | <.001 | .10516 | .00034 | .10450 | .10582 |
| | Equal variances not assumed | | | 310.114 | 126426.849 | <.001 | <.001 | .10516 | .00034 | .10450 | .10583 |

**Table 29**

*Results T-test of Impact nudge (type 2) vs neutral nudge (type 3) in Round 1*

| | Type | N | Mean | Std. Deviation | Std. Error Mean |
|---|---|---|---|---|---|
| **Mean session duration** | 2 | 86400 | .0791 | .01665 | .00006 |
| | 3 | 95000 | .0223 | .01743 | .00006 |

| | | Levene's Test for Equality of Variances | | t-test for Equality of Means | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | Significance | | | | 95% Confidence Interval of the Difference | |
| | | F | Sig. | t | df | One-Sided p | Two-Sided p | Mean Difference | Std. Error Difference | Lower | Upper |
| **Mean session duration** | Equal variances assumed | 314.485 | <.001 | 708.149 | 181398 | <.001 | <.001 | .05681 | .00008 | .05665 | .05696 |
| | Equal variances not assumed | | | 709.677 | 180956.293 | <.001 | <.001 | .05681 | .00008 | .05665 | .05696 |

**Table 30**

*Results T-test of Imapct nudge (type 2) vs neutral nudge (type 3) in Round 2*

| | Type | N | Mean | Std. Deviation | Std. Error Mean |
|---|---|---|---|---|---|
| **Mean session duration** | 2 | 72800 | .2148 | .05550 | .00021 |
| | 3 | 76900 | .0698 | .05089 | .00018 |

| | | Levene's Test for Equality of Variances | | t-test for Equality of Means | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | Significance | | | | 95% Confidence Interval of the Difference | |
| | | F | Sig. | t | df | One-Sided p | Two-Sided p | Mean Difference | Std. Error Difference | Lower | Upper |
| **Mean session duration** | Equal variances assumed | 167.950 | <.001 | 527.202 | 149698 | <.001 | <.001 | .14498 | .00027 | .14444 | .14552 |
| | Equal variances not assumed | | | 525.955 | 146777.660 | <.001 | <.001 | .14498 | .00028 | .14444 | .14552 |

## Appendix D: Results Z-test CTR and CR

### Table 31

*Results Z-test from Excel*

**SOCIAL NORM NUDGE ON CTR**

| Condition | Round | Clicks | Impressions | CTR | Other Condition | Other Clicks | Other Impressions | Other CTR | Pooled Proportion | Standard Error | Cohens H | Z-Score | P-Value | Significant? |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Social Norm | Round 1 | 1102,56 | 87700 | 0,01257195 | Neutral | 898,38 | 95000 | 0,009456632 | 0,010952053 | 0,000487376 | 0,02992369 | 6,392022758 | 1,63705E-10 | Yes |
| Social Norm | Round 2 | 982,41 | 73600 | 0,013347962 | Neutral | 199,83 | 76900 | 0,00259857 | 0,007855415 | 0,000455238 | 0,129587378 | 23,61270197 | 0 | Yes |

**COMPARISON**

| Comparison | Total Clicks R1 | Total Impressions R1 | CTR R1 | Total Clicks R2 | Total Impressions R2 | CTR R2 | Pooled Proportion | Standard Error | Z-Score | P-Value | | Significant? |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Round 1 vs 2 (Social) | 1102,56 | 87700 | 0,01257195 | 982,41 | 73600 | 0,013347962 | 0,012926038 | 0,000564659 | -1,374302889 | 0,16934767 | | No |
| Round 1 vs 2 (control) | 898,38 | 95000 | 0,009456632 | 199,83 | 76900 | 0,00259857 | 0,006388656 | 0,000386479 | 17,74497585 | 0 | | Yes |

**IMPACT NUDGE ON CTR**

| Condition | Round | Clicks | Impressions | CTR | Other Condition | Other Clicks | Other Impressions | Other CTR | Pooled Proportion | Standard Error | Cohens H | Z-Score | P-Value | Significant? |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Impact | Round 1 | 901,85 | 86400 | 0,010438079 | Neutral | 898,38 | 95000 | 0,009456632 | 0,00992409 | 0,000465993 | 0,009892711 | 2,106140487 | 0,035192151 | Yes |
| Impact | Round 2 | 1100,06 | 72800 | 0,015110714 | Neutral | 199,83 | 76900 | 0,00259857 | 0,0086833 | 0,000479767 | 0,144478164 | 26,07961079 | 0 | Yes |

**COMPARISON**

| Comparison | Total Clicks R1 | Total Impressions R1 | CTR R1 | Total Clicks R2 | Total Impressions R2 | CTR R2 | Pooled Proportion | Standard Error | Z-Score | P-Value | | Significant? |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Round 1 vs 2 (Impac) | 901,85 | 86400 | 0,010438079 | 1100,06 | 72800 | 0,015110714 | 0,012574812 | 0,000560598 | -8,335086236 | 0 | | Yes |
| Round 1 vs 2 (control) | 898,38 | 95000 | 0,009456632 | 199,83 | 76900 | 0,00259857 | 0,006388656 | 0,000386479 | 17,74497585 | 0 | | Yes |

**SOCIAL NORM NUDGE ON CR**

| Condition | Round | Conversions | Impressions | CR | Other Condition | Other Conversions | Other Impressions | Other CR | Pooled Proportion | Standard Error | Cohens H | Z-Score | P-Value | Significant? |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Social Norm | Round 1 | 1600,2 | 87700 | 0,018246294 | Neutral | 502,71 | 95000 | 0,005291684 | 0,011510181 | 0,000499499 | 0,125369525 | 25,93519382 | 0 | Yes |
| Social Norm | Round 2 | 1409,8 | 73600 | 0,019154891 | Neutral | 198,59 | 76900 | 0,002582445 | 0,010686977 | 0,000530225 | 0,17601447 | 31,25547903 | 0 | Yes |

**COMPARISON**

| Comparison | Total Conversions R1 | Total Impressions R1 | CR R1 | Total Conversions R2 | Total Impressions R2 | CR R2 | Pooled Proportion | Standard Error | Z-Score | P-Value | | Significant? |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Round 1 vs 2 (Social) | 1600,2 | 87700 | 0,018246294 | 1409,8 | 73600 | 0,019154891 | 0,01866088 | 0,000676479 | -1,343127545 | 0,179230678 | | No |
| Round 1 vs 2 (control) | 502,71 | 95000 | 0,005291684 | 198,59 | 76900 | 0,002582445 | 0,004079697 | 0,0003092 | 8,762098991 | 0 | | Yes |

**IMPACT NUDGE ON CR**

| Condition | Round | Conversions | Impressions | CR | Other Condition | Other Conversions | Other Impressions | Other CR | Pooled Proportion | Standard Error | Cohens H | Z-Score | P-Value | Significant? |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Impact | Round 1 | 1798,76 | 86400 | 0,020818981 | Neutral | 502,71 | 95000 | 0,005291684 | 0,012687266 | 0,000526152 | 0,143969946 | 29,51103989 | 0 | Yes |
| Impact | Round 2 | 1319,28 | 72800 | 0,018121978 | Neutral | 198,59 | 76900 | 0,002582445 | 0,010139412 | 0,000518054 | 0,168376362 | 29,99594341 | 0 | Yes |

**COMPARISON**

| Comparison | Total Conversions R1 | Total Impressions R1 | CR R1 | Total Conversions R2 | Total Impressions R2 | CR R2 | Pooled Proportion | Standard Error | Z-Score | P-Value | | Significant? |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Round 1 vs 2 (Impact) | 1798,76 | 86400 | 0,020818981 | 1319,28 | 72800 | 0,018121978 | 0,019585678 | 0,000697145 | 3,868640731 | 0,000109444 | | Yes |
| Round 1 vs 2 (control) | 502,71 | 95000 | 0,005291684 | 198,59 | 76900 | 0,002582445 | 0,004079697 | 0,0003092 | 8,762098991 | 0 | | Yes |

## Appendix E: Correlation Table

**Table 32**

*Pearsons correlation table*

| | Variable | M | SD | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | Impact Nudge | .4194 | .49546 | | | | | | | | | | |
| 2 | Social nudge | .2984 | .45941 | <.001** | | | | | | | | | |
| 3 | Engagement | 3.41 | 1.268 | 0.025* | 0.297 | | | | | | | | |
| 4 | EC | 3.92 | 1.129 | 0.091 | 0.95 | <.001** | | | | | | | |
| 5 | Education | 3.29 | 1.548 | 0.918 | 0.939 | 0.799 | 0.546 | | | | | | |
| 6 | Employment status | 2.49 | 1.768 | 0.952 | 0.102 | 0.911 | 0.865 | 0.898 | | | | | |
| 7 | Gender | 1.77 | .714 | <.001** | <.001** | 0.431 | 0.017* | 0.061 | 0.49 | | | | |
| 8 | Age | 37.38 | 12.381 | 0.946 | 0.568 | 0.971 | 0.913 | 0.645 | <.001** | 0.318 | | | |
| 9 | Active user | 2.57 | 1.182 | 0.352 | 0.395 | 0.289 | 0.48 | 0.578 | 0.05 | 0.233 | 0.15 | | |
| 10 | Passive user | 3.08 | 1.301 | 0.201 | 0.143 | 0.06 | 0.136 | 0.882 | 0.782 | 0.643 | 0.43 | <.001** | |

*Note.* **. Correlation is significant at the 0.01 level (2-tailed). *. Correlation is significant at the 0.05 level (2-tailed

**Appendix F: Survey Abillion**

Welcome!

In collaboration with the University of Amsterdam, we’re conducting a academic study on the effectiveness of different types of push notifications on engagement with the Abillion app. We would really appreciate it if you could take a few minutes to complete the following survey.

Your answers are completely anonymous and will only be used for research purposes. The findings will help researchers and businesses understand how to best use sustainability to engage users in digital environments. The survey takes no more than 5 minutes.

Thank you so much for your time and contribution!

How frequently do you use the Abillion app to view other users' posts or reviews?

- ◯ I rarely use the app (less than once a month)
- ◯ I use the app occasionally (1–2 times a month)
- ◯ I use the app sometimes (1–2 times a week)
- ◯ I use the app regularly (3–5 times a week)
- ◯ I use the app daily or almost daily

How frequently do you share a photo / review on your Abillion profile?

- ◯ I never post on the app
- ◯ I post occasionally (every 2–3 months)
- ◯ I post sometimes (1–2 times a month)
- ◯ I post regularly (1–2 times a week)
- ◯ I post frequently (3 or more times a week)

Do you remember seeing a push-notification in the Abillion app last week that encouraged you to share your experience / post a review?

◯ Yes

◯ No

**The following questions only apply if you answered "yes" to the previous question. If not, please scroll down to the bottom of the page to continue.**

Which push-notification did you see?

◯ "Over half of abillion users near you post weekly. Join them and share a review today as well!"

◯ "Every post supports charities, people and business. Make a real difference by sharing yours today!"

◯ "Found something great? Share your experience on abillion today!"

What did you do after receiving the notification?

◯ I clicked the notification and posted a review

◯ I clicked the notification but did not post a review

◯ I saw the notification but didn't click on it

◯ I don't remember

**This next section contains three questions about your engagement after receiving the push-notification. For each statement, please indicate how much you agree or disagree based on your own experience**

The notification made me more motivated to post or share content on the Abillion app

◯ Strongly disagree

◯ Somewhat disagree

- Neither agree nor disagree
- Somewhat agree
- Strongly agree

After seeing the notification, I spent more time using the Abillion app than I normally would.

- Strongly disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Strongly agree

The notification made me more likely to return to the Abillion app again soon.

- Strongly disagree
- Somewhat disagree
- Neither agree nor disagree
- Somewhat agree
- Strongly agree

**The next section includes three questions about the environment and climate. We're interested in your thoughts on this topic. For each statement, please indicate the extent to which you personally agree or disagree.**

We worry too much about the future of the environment and not enough about prices and jobs.

- Strongly disagree
- Somewhat disagree

◯ Neither agree nor disagree

◯ Somewhat agree

◯ Strongly agree

People worry too much about human progress harming the environment.

◯ Strongly disagree

◯ Somewhat disagree

◯ Neither agree nor disagree

◯ Somewhat agree

◯ Strongly agree

Many of the claims about environmental threats are exaggerated.

◯ Strongly disagree

◯ Somewhat disagree

◯ Neither agree nor disagree

◯ Somewhat agree

◯ Strongly agree

**Finally, we'd like to understand a little about your background**

What is your age?

________________________________________________________________

What is your gender?

◯ Male

○ Female

○ Other

○ Prefer not to say

What is your current employment status?

○ Full-time

○ Part-time

○ Self-employed

○ Unemployed

○ Retired

○ Student

What is the highest level of education you have completed?

○ No formal education

○ Primary education

○ Secondary education

○ Bachelor’s degree

○ Master’s degree

○ Doctorate / PhD or equivant