

Promoting Prosociality via Micro-acts of Joy: A Large-Scale Well-Being Intervention Study

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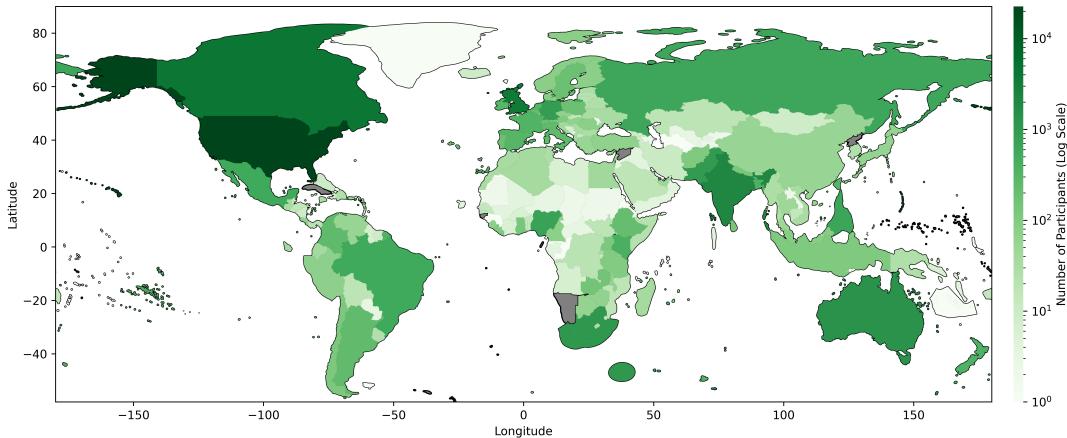


Figure 1: Global Participation of BIG JOY from Jul 1st, 2022 to Feb 1st, 2025, covering over 48,000 participants from over 200 countries or territories. The study spans one week, each day delivering one micro-act of joy as the intervention. Our analysis focuses on 18,248 participants with complete prosociality measurement before and after the BIG JOY.

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Abstract

Prosociality has been well-documented to positively impact mental, social, and physical well-being. However, existing studies of interventions for promoting prosociality have limitations such as

small sample sizes or unclear benchmarks. To address this gap, we conducted a global-scale well-being intervention deployment study, BIG JOY, with more than 18,000 participants from 172 countries and regions. The week-long BIG JOY intervention consists of seven daily micro-acts (*i.e.*, brief actions that require minimal effort), each adapted from validated positive psychology interventions. The analyses of large-scale intervention data reveal unique insights into the impact of well-being micro-acts across diverse populations, patterns of responses, effectiveness of specific micro-acts and their nuanced impacts across different populations, linkages between improvements in prosociality and in well-being, as well as the potential for machine learning to predict changes in prosociality. This study offers valuable insights into a set of design guidelines for future well-being and prosociality interventions. We envision our work as a stepping stone towards future large-scale prosociality interventions that foster a more unified and compassionate world.

CCS Concepts

- Human-centered computing → Empirical studies in HCI; • Applied computing → Psychology.

Keywords

Prosocial behavior, Well-being, Behavior-change intervention, Global intervention, Micro-acts

ACM Reference Format:

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1 Introduction

Prosociality is defined as voluntary actions intended to benefit others [10, 59]. It can manifest in various forms, through acts of kindness and generosity [14, 41], such as care-giving, sharing resources, helping those in need, and offering emotional support. While prosocial actions are typically considered altruistic and beneficial to recipients, research also suggests that prosocial behavior benefits actors from multiple perspectives, positively impacting their mental health (*e.g.*, improving mood and relieving stress) [64, 86], social well-being (*e.g.*, reduced loneliness and enhanced social connections) [20, 70], and even physical health [105]. Prosociality is becoming increasingly recognized as a critical factor for public health [50].

With the promising benefits of prosocial behavior, psychological and human factors research has been conducted on interventions that promote prosociality. Existing psychology-based intervention methods focus on enhancing values that are relevant to prosocial behaviors [21, 39, 46, 87], such as gratitude, generosity, empathy, and social connection [39, 58, 83]. These approaches often utilize exercises like journaling that encourage reflection on positive things [22] and acts of kindness that foster empathy and mutual support [21, 32]. More recently, the development of computation has led to more design and development of technology-based

interventions in the HCI community that leverage advances in computational tools to foster prosociality [19, 56, 89]. For instance, researchers have developed apps that incorporate gamification elements to encourage prosocial attitudes and teach essential social skills like collaboration and empathy [11, 81, 91]. In addition, some work has explored music-based approaches that utilize the emotional resonance and the collaborative nature of music to promote prosocial attitudes and behavior [18, 52].

Although prior work has shown promising outcomes, there are several noticeable gaps in existing intervention methods. One major gap is **the limitation of small sample sizes**, with most studies involving less than a few hundred participants [37]. This restricts the reliability and generalizability of findings, and makes it difficult to draw broad conclusions about the effectiveness of interventions. Limited by sample sizes, no prior work was able to investigate **different populations' reactions to prosociality interventions**. There is also a lack of **the systematic comparison between different intervention techniques**. Rigorous and scientific understanding of people's prosocial behaviors and intervention outcomes necessities a large-scale study that involves a wide range of populations across the world, which is essential to guide effective design of prosociality intervention techniques in the HCI community.

To address these gaps, we designed and conducted *BIG JOY*, a large-scale global intervention study aimed at enhancing well-being and prosociality through daily micro-acts delivered via digital technology. First launched on January 1st, 2022, BIG JOY attracted more than 48,000 participants by February 1st, 2025, and continues to attract more to date. This paper focuses on 18,248 participants from 172 countries and regions who completed the intervention study (completed both the onboarding and closing surveys). This study represents the first comprehensive and rigorous empirical analysis of promoting prosociality on such a large scale, directly addressing the gap of limited sample sizes and population diversity in previous research.

The BIG JOY is a structured, one-week experience that employs a micro-act-based design, where participants engage in one micro-act each day for seven days, delivered through digital devices. We picked and designed seven micro intervention techniques that are well-documented for promoting happiness and prosociality and that can be easily integrated into daily life. In a large-scale global deployment, participants would naturally have various levels of engagement (*i.e.*, each user might do a different subset of seven micro-acts). This provides an opportunity for comparing the seven prosocial interventions in a natural experiment setup. Following a user design process with a pilot study, we built the interventions with a reactive web-based interface that is accessible through mobile devices, laptops, and desktops. Each micro-act requires less than 10 minutes, making them easy to engage. For each participant, prosociality was assessed once prior to the BIG JOY intervention (*i.e.*, onboarding survey) and again after the week of intervention (*i.e.*, closing survey), together with other self-report measures of physical, mental, and social well-being. We also gathered participants' text input as they engaged with digital daily micro-acts, and invited participants to reflect on their experience each evening.

Building upon the rich data from BIG JOY, we aim to answer several research questions (RQ's) that enhance the understanding of people's prosocial behaviors and intervention outcomes. First, with

the vast number of participants from the world, we are interested in understanding prosociality within different socio-demographic groups (**RQ1**: How does prosociality vary amongst people?). More importantly, such rich data enables us to address novel questions that no prior work was able to. For instance, there is a lack of the understanding of diverse population groups' reactions to prosociality interventions (**RQ2**: Does the one week intervention increase prosociality and how does the effect vary across populations?). Meanwhile, we are also interested in understanding differences in impact of specific micro-acts on prosociality, as well as the variance across population (**RQ3**: How does each micro-act influence prosociality?). Prior literature has posited the overall links between prosociality and other well-being aspects, but no prior work has investigated these links in the context of interventions (**RQ4**: How are prosociality changes related to the changes on other aspects of well-being?). Finally, the large-scale data enables the possibility of training machine learning (ML) models to predict intervention outcomes, leading to our final research question (**RQ5**: Can we predict changes in prosociality from other well-being measures?). Our results provide valuable insights into these RQs, yielding new findings about prosociality across diverse populations and offering unprecedented insights into how well-being promoting interventions both hinge upon and influence prosociality. For example, some groups showed differential benefits to prosociality: Those who are male, of certain ethnic groups (black, Latinx), and of lower subjective social status, showed significantly greater improvements in prosociality post intervention. We synthesize our findings into a set of design guidelines for future prosocial interventions.

In summary, by designing and conducting one of the largest-scale digital intervention studies for well-being and prosociality that involves over 18,000 participants from 172 countries and regions in the past two years, we contributed to the HCI community with the following new insights on human prosocial behavior and interventions:

- **Empirical validation and novel insights on prosocial characteristics:** Our study provides large-scale empirical validation of prior findings on prosocial behavior. We not only confirm established findings, but also introduce novel insights that challenge and refine prior understandings of the association between prosociality and demographic factors (RQ1). Our results further reveal novel, unprecedented insights into the diverse intervention impacts across different populations (RQ2), as well as differences in how specific intervention strategies foster prosocial behavior (RQ3).
- **Understanding the interplay between prosociality and physical, mental, and social well-being:** Our findings highlight the interconnected nature of prosocial behavior and well-being metrics (RQ4). We further demonstrate the feasibility of ML models to predict intervention outcomes based on the participants' initial well-being and demographic characteristics, which suggests the potential of personalized interventions for prosociality (RQ5).
- **Design guidelines for future prosocial interventions:** Building on our data-driven insights, we provide a set of actionable design guidelines for future intervention techniques to promote prosociality in diverse populations. We

envision future technology-driven methods that can clarify distinct facets of prosociality, optimize micro-acts for accessibility and engagement, tailor specific interventions to population-specific responses, and integrate holistic well-being perspectives to enhance prosocial gains.

2 Background

We provide a brief background introduction to prosociality (Section 2.1) and existing intervention techniques to promote prosociality (Section 2.2).

2.1 Prosociality

Prosociality entails benevolent attitudes and beliefs, and actions intended to benefit others [10, 59]. Prosocial actions are generally voluntary and can take various forms both materially or spiritually [14, 41]. Examples of material prosocial acts include sharing resources, such as giving food to someone who is hungry, or providing help, like assisting an elderly person in crossing the street [34, 98]. And spiritual prosocial acts involve offering emotional support, such as comforting someone in distress, or providing guidance, like giving advice to a person facing a difficult decision [27, 99].

While there are obvious benefits for recipients of prosocial behaviors, research has also shown that enacting prosocial behaviors can lead to significant gains as well [15]. For instance, prosocial tendencies in children have been shown to have a significant positive impact on their performance in school and later academic achievement, and such children are also less at risk for problem behaviors [5, 14, 85]. Moreover, research has also shown that people who exhibit prosocial behavior tend to experience better moods in general [76]. Prosociality also helps reduce the risk of loneliness and the harmful emotional impact of stress [76]. Besides the mental benefits, prior work also suggests that prosociality is positively related to better physical health [65, 74, 105].

These findings indicate that prosocial behavior is not merely an altruistic act but a mutually beneficial exchange that fosters both the well-being of others and the self [14, 15]. It creates a positive feedback loop where the act of helping others enhances one's own mental and physical health, thereby encouraging further prosocial behavior [26, 105].

2.2 Prosociality Interventions

Given the wide-ranging benefits of prosociality on the quality of life, there has been a range of research about developing interventions to encourage prosocial behavior [5, 17, 42, 54]. Specifically, studies in psychology have designed interventions to improve social well-being and enhance prosocial behavior [39, 44, 46, 58]. These interventions often aim to promote or instill values that contribute to well-being and motivate prosocial behavior. For example, gratitude interventions encourage people to count their blessings in life, including goodness that might be a result of other people's behavior. Many of these methods have been shown to increase positive emotional experience and prosociality [22, 83]. Another example is awe – a complex emotional response to encountering something vast that challenges ordinary expectations and assumptions, often evoked through immersion in nature – has been found to reduce

self-focus, and promote social connection and prosociality [87]. Research also indicates that engaging in acts of kindness is rewarding and enhances prosociality [21]. Additionally, interventions aimed at encouraging active-constructive responding to others, *i.e.*, showing enthusiasm for others' happiness, have demonstrated positive success in promoting prosociality [32, 101].

Closer to the HCI community, with the recent advance in computational technology, researchers have explored various technology-based interventions as a new way to deliver interventions for promoting prosociality [78, 85]. One notable method is game-based interventions, especially for children [24, 38, 91]. While video games have traditionally been studied for their negative impacts on children, recent literature has begun to explore their potential for enhancing prosocial behavior [73, 94]. These games can take various forms. Some promote values closely related to prosociality, such as empathy and humane attitudes [8, 11]. Others are designed for social skills training [19, 81] or specific behaviors like bystander "upstanding" behavior in bullying [25, 93]. Another thread of research involves integrating music-based approaches with technology. Some studies utilized data from music platforms (*e.g.*, Spotify) to explore the relationship between music and prosociality. For instance, some work showed the direct impact of music and musical features on promoting prosocial behaviors [18, 56]. Others investigated how collaborative music creation activities can foster prosociality among users [52, 60], by promoting empathic responses and theory of mind skills like empathy and perspective taking [57, 75, 82].

Although these intervention studies have shown promising outcomes, their findings are limited by small sample sizes (typically no more than a few hundred participants), which limits the generalizability of the results across populations [80]. It is unclear how different population groups may react to prosociality intervention. Meanwhile, while prior work has explored a range of intervention techniques, there is a lack of rigorous comparison across these intervention techniques on their effectiveness, not to mention the further investigation on different population's reactions towards diverse intervention techniques. To address these gaps, we selected to compare seven simple and well-established well-being intervention techniques and conducted BIG JOY, a global field experiment that stands as one of the largest digital intervention studies on well-being and prosociality. To our knowledge, BIG JOY is the first study to offer a comprehensive and rigorous empirical analysis of promoting prosociality on such a large scale.

3 Micro-Act Intervention Design

Building on existing literature on well-being and prosociality, we went through a user design process and finalized seven micro-act interventions for BIG JOY.

3.1 Design Process

For a large-scale global study, ensuring the sustained engagement of participants with the intervention is a critical success factor. Therefore, instead of adopting existing interventions directly, we leverage micro-acts as brief, scalable interventions that integrate seamlessly into users' daily routines, minimizing the effort required and enhancing user engagement.

Our design process was conducted as follows. Two authors, with more than twenty years of research experience in well-being and prosociality intervention, curated a pool of feasible intervention candidates. These candidates were selected based on their strong documentation in the literature [3] and their accessibility to the general population with basic digital devices such as smartphones or laptops (*i.e.*, they do not require specialized devices or additional software installation).

The selected interventions were modified to be micro-acts to ensure conciseness and brevity while preserving their core functions and intended outcomes. To evaluate the feasibility and effectiveness of these interventions, we conducted a pilot study involving 10 end-users and 4 well-being experts over a two-week period. Feedback from this study was collected by the end of the two weeks and guided the refinement process, enabling us to identify the top seven intervention candidates preferred by end-users and experts. We further optimized the brevity of the intervention, which was confirmed by end-users as one of the key factors for maintaining engagement and good usability.

3.2 Micro-Act Intervention Design

The final seven micro-act interventions are listed as follows. These micro-acts are designed to be completed in less than 10 minutes each day and compatible with most common digital devices, making them accessible and sustainable for users.

Do Something Kind. Users are asked to come up with five acts of kindness for others in a single day and then briefly write down what they did. Acts of kindness, such as prosocial spending [6] or volunteer work [69], are well-documented to boost happiness, health, and overall well-being, reinforcing the reciprocal nature of prosociality [21, 46].

Make a Gratitude List. Users reflect and list out eight aspects of their lives for which they feel grateful. This task encourages participants to focus on the positive and grateful aspects of their experiences, a practice known to enhance well-being and improve mood [28, 48, 58, 83]. Expressing gratitude (*e.g.*, "counting your blessings") directly connects to prosociality by fostering a sense of appreciation and contentment that can extend to others [22, 83].

Celebrate Another's Joy. Users are instructed to ask a friend to share something fun, inspiring, or something that recently made them feel proud. They were also encouraged to nod, smile, and offer supportive words in response to their friend's story. This intervention is based on the concept of "capitalization", where individuals share positive events with others [1]. Research has shown that capitalization has positive effects on both the capitalizers (those sharing the good news) and the responders (those listening), including enhanced interpersonal relationship and prosociality [32, 101].

Dwell in Awe. Users watched a short, relaxing video of nature accompanied by calming music, which is designed to evoke the emotion of awe. Awe emotion has been characterized by two central themes: "vastness" and "accommodation" [44]. Vastness refers to experiences significantly larger than the self, whether in terms of physical size, social status, or symbolic magnitude, while accommodation is the process of adjusting mental frameworks to

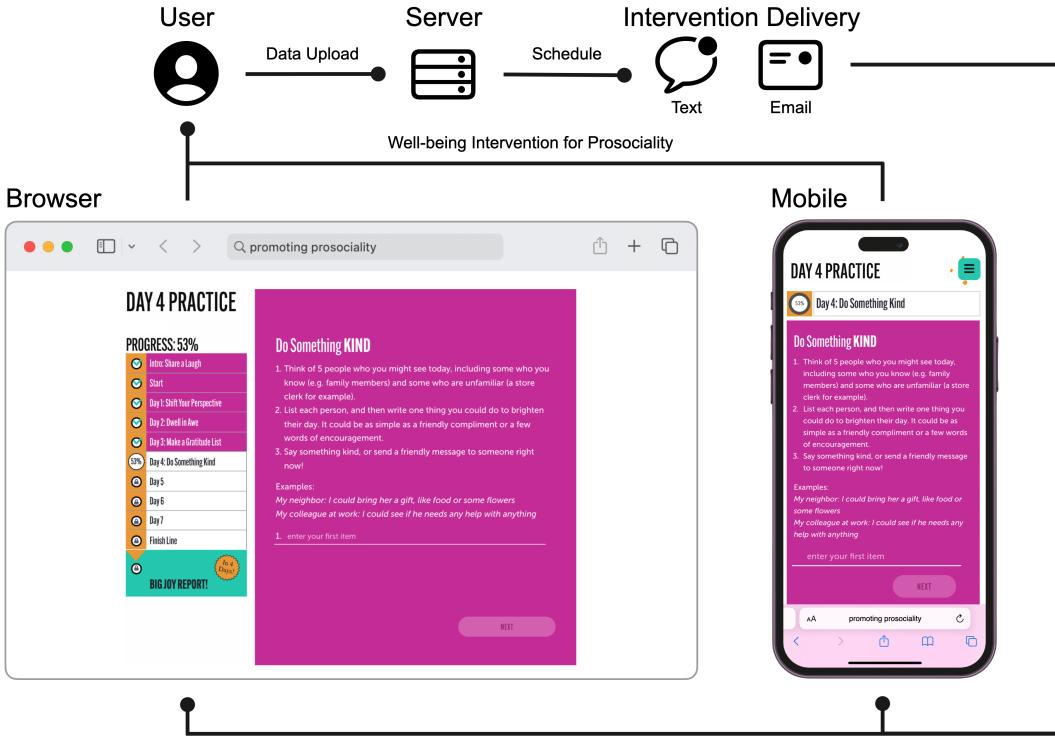


Figure 2: BIG JOY Intervention Pipeline and Reactive Interfaces on Multiple Platforms. The example shows the *Do Something Kind*, and the interfaces of all seven micro-acts are listed in Appendix A.

comprehend such overwhelming experiences. One way to evoke awe is through the beauty of nature via biophilia [100]. Therefore, a video showcasing the wonders of nature is an effective method to evoke awe in users. Experiencing awe can shift users' perspectives away from self-focus and towards a broader, more connected view of the world. It has been shown to increase prosocial behaviors, such as patience and a willingness to help others [79], aligning directly with the goals of this intervention.

You are a Force of Good. Users listen to a brief, guided reflection focused on extending compassion and goodwill to others, such as through loving-kindness practices. This intervention cultivates feelings of social support and positive emotions and physical health [31, 47], all of which are crucial components of prosocial behavior.

Tune in to What Matters. Users rank four prosocial values – virtue, fairness, goodwill, and unity – in order of importance, and then describe how their top-ranked value is reflected in their life. This task draws on “self-affirmation theory”, which involves reinforcing their core values in response to self-threatening events or information [2]. Such exercises have been shown to enhance self-resources and broaden perspectives [84, 104], with the potential to strengthen their prosocial tendencies.

Shift Your Perspective. Users first describe a recent situation when something did not go their way, or when they felt frustrated, irritated, or upset. Following this, they are instructed to list three things that could help them view the situation from a more positive perspective. This cognitive reappraisal technique can help users

regulate their emotions by reinterpreting the situation, which has been associated with fewer depressive symptoms and an increase in positive emotions [23, 90, 95].

Some of the micro-acts (e.g., *Do Something Kind* and *Dwell in Awe*) are designed to directly target prosociality based on the established literature, while others (e.g., *Shift Your Perspective*) aimed to enhance general emotional well-being, thereby indirectly promoting prosociality through improved well-being.

3.3 Implementation

We implemented the seven micro-act intervention as a web-based application that is compatible on mobile phones, tablets, and desktops. Figure 2 shows the overall pipeline with an intervention example. The specific interface and instructions of these micro-acts can be found in Appendix A.

By embedding these brief interventions into daily life, we aim to foster prosocial behavior on a large scale, demonstrating the power of small actions in enhancing people's prosociality.

4 Large-Scale Global Study

Based on our micro-act-based intervention design, we built a web-based interface to implement these micro-acts and conducted a large-scale study across the world.

4.1 Global Participation

After obtaining IRB approval, we promoted our BIG JOY study globally with a web link at the end of film screenings of “Mission: Joy - Finding Happiness in Troubled Times”, email newsletters and

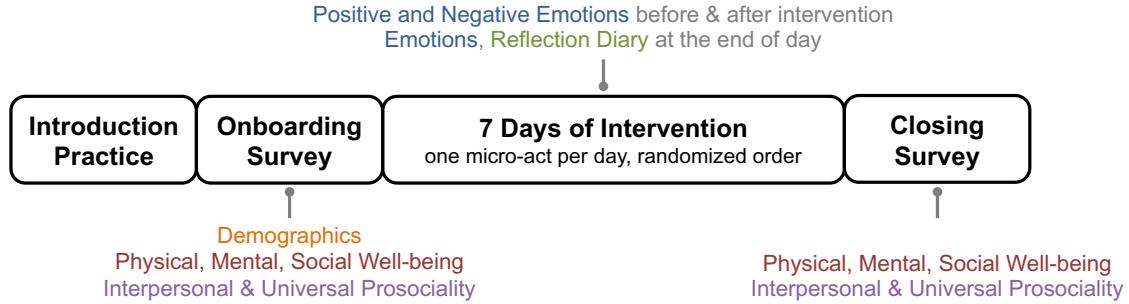


Figure 3: The 1-Week Intervention Procedure of BIG JOY.

media interviews about the film, social media postings, academic conferences, website content, and word of mouth. People volunteered to participate in the study through a link¹. The primary goal of this study was to empirically understand people's reactions to micro-interventions in diverse contexts, rather than to control or predetermine the sample size. Participation was open to all individuals willing to contribute, ensuring an inclusive and diverse dataset. The study was launched on Jan 1st, 2022, and continues to run until now. In this paper, we focused on a snapshot of data from Jul 1st, 2022 to Feb 1st, 2025, covering over 48,000 participants from over 200 countries or territories. Figure 1 visualizes the geographical distribution of participation. Among these participants, 18,248 of them from 172 countries and regions completed both onboarding and closing surveys of the study, and this subset constitutes the primary focus of our analysis. The large-scale participation reflects the global interest in the study topic and ensures sufficient data for robust insights.

4.2 Intervention Procedures

Our intervention lasted for eight days in total, including introduction, onboarding, micro-act-based seven-day interventions, and closing. Figure 3 presents the whole procedure.

4.2.1 Introduction Practice. Upon registration of the study, participants first went through an introduction micro-act practice: they would listen to a short audio clip of various human laugh sounds [51]. Participants were asked to rate their own level of current positive and negative affect, once before the micro-act and

once after the micro-act. Following prior research on emotional granularity, we adopt a slider with a simple visual analogue scale (value range 0 “Not at all” to 100 “A lot”, so that users won’t see the numerical value) [43, 88]. After this practice task, participants could proceed to formally register and join the full STUDY study.

We added this opening micro-act to create a comfortable and engaging atmosphere, and to familiarize participants with the real-time emotional feeling questions. Meanwhile, it also served as a screening stage to ensure that the remaining participants were comfortable with the study procedures, enhancing data quality.

4.2.2 Onboarding. Participants entered the onboarding stage immediately after they chose to join the formal study. After signing a consent form, participants filled out a *baseline* survey, including the following items:

- Demographics: age, gender, country of residence, ethnicity, Subjective Social Economic Status (Subjective SES) [49].
- Mental well-being: positive and negative emotions, life satisfaction, happiness, agency, resilience.
- Physical well-being: physical health and sleep quality.
- Social well-being: social relationships contentment, compassion, and common humanity [12].

In particular, **prosociality** was measured from two aspects [14, 53]: (a) **interpersonal** prosociality, which focuses on behavior in interpersonal contexts; and (b) **universal** prosociality, which focuses on behavior that will benefit the greater humanity and environment. Table 1 lists the specific four questions to assess these two aspects. Split-half reliability analysis indicated high internal consistency of the two measures (Spearman-Brown coefficients

¹BIG JOY Website: <https://ggia.berkeley.edu/BigJOY>

Category	Question Text (rating from 0 – strongly disagree, to 10 – strongly agree)
Interpersonal Prosociality	I have made people feel cared for and supported.
Universal Prosociality	I have helped people who seem to be going through difficult times.
Universal Prosociality	I have felt willing to make sacrifices to my quality of life to improve the standard of living for other people.
Universal Prosociality	I have felt willing to make sacrifices to my standard of living to protect the natural environment.

Table 1: Specific Questions to Measure Two Aspects of Prosocial Behavior: (a) Interpersonal prosociality focuses on helping individuals through caring interpersonal interactions; (b) Universal prosociality focuses on greater humanity and environment.

0.75 and 0.74), and the correlation between these two aspects was moderate (Spearman $\rho = 0.40$).

4.2.3 Seven Days of Micro-Acts. In the next seven days after onboarding, participants received an email or a text message prompt every morning at 8 AM, inviting them to one of the seven micro-acts (as shown in Section 3). The order of the seven micro-acts was randomized across participants.

Before seeing the instructions for each micro-act, participants were first asked to report their current level of positive and negative affect (similar to Section 4.2.1). And right after completing each micro-act, they were asked to report their affect again. Moreover, each evening at 6 PM, participants received another email or text prompt, asking them to report their affect in-the-moment, and post any reflections about their experience of doing the micro-act earlier in the day (with a free-text input box). In total, participants reported their emotions three times a day. Meanwhile, we recorded participants' interaction logs with the web app, including records of audio playing (*You Are A Force of Good*) /video watching (*Dwell in Awe*) and text entries (other 5 micro-acts). These data would indicate the engagement of certain micro-act of each participant.

4.2.4 Closing. By the end of the seven days, participants were prompted to complete a closing survey, with the same items of mental, physical, and social well-being, including the same questions for assessing interpersonal and universal prosociality. Then, a summary report was presented to each participant, illustrating their engagement and a summary of changes in their self-reported emotional feelings and well-being over the past seven days.

5 Results

Among 48,686 users who registered for the BIG JOY study, 18,248 completed the whole procedure and answered both the onboarding and closing surveys. The majority of completed participants are female (Female: 14998, Male: 2718, Non-binary: 175, Other: 41, Undisclosed: 356) and are in middle age (mean=52, std=17). We focus on this set of users to answer our research questions.

To simplify the results, we average the interpersonal and universal prosociality measures into an “overall” prosocial score (0 to 10) when their results are similar. We present the two measures separately and highlight their difference where appropriate.

5.1 RQ1: How Does Prosociality Vary amongst People?

We first investigated baseline prosocial behavior among demographic groups before interventions.

Age. There was a small positive correlation between age and prosocial score (Spearman's $\rho = 0.14, p < 0.001$). In general, older age groups tended to be higher on prosociality (e.g., 6.99 ± 0.02 for ≥ 65 vs. 6.29 ± 0.05 for ≤ 24 , Cohen's $d = 0.46$). A Kruskal-Wallis test indicated statistical significance ($p < 0.001$). A post-hoc Dunn's test with Holm-Bonferroni correction showed pairwise significance², except among the three younger groups ≤ 24 , 25-34, 35-44 (see Figure 5 left). These findings are supported by previous literature on the age-prosociality relationship [30, 55, 61], possibly due to changes in motivation or resources [16, 40, 61, 92].

Gender. In general, males had lower prosocial scores (6.53 ± 0.03) than females (6.81 ± 0.01), non-binary (6.77 ± 0.12), and others (6.82 ± 0.24). A Kruskal-Wallis test indicated statistical significance ($p < 0.001$), and post-hoc tests showed a significant difference between males and females ($p < 0.001, d = 0.15$).

Subjective Social Economic Status (SSES). We observed a small positive correlation between SSES and prosocial score ($\rho = 0.15, p < 0.001$). Participants were split into four SSES groups: 0-3, 4-6, 7-9, and 10. Those with SSES=10 had significantly higher prosociality than others ($ps < 0.01, ds = 0.10 - 0.29$). Prior literature showed conflicting findings on the relationship between SSES and prosocial behavior (e.g., [72] vs. [7]). Our findings support that people with higher subjective SES tend to be more prosocial (see Figure 5 right).

²If not mentioned explicitly, the same non-parametric tests were used in the rest of the paper.

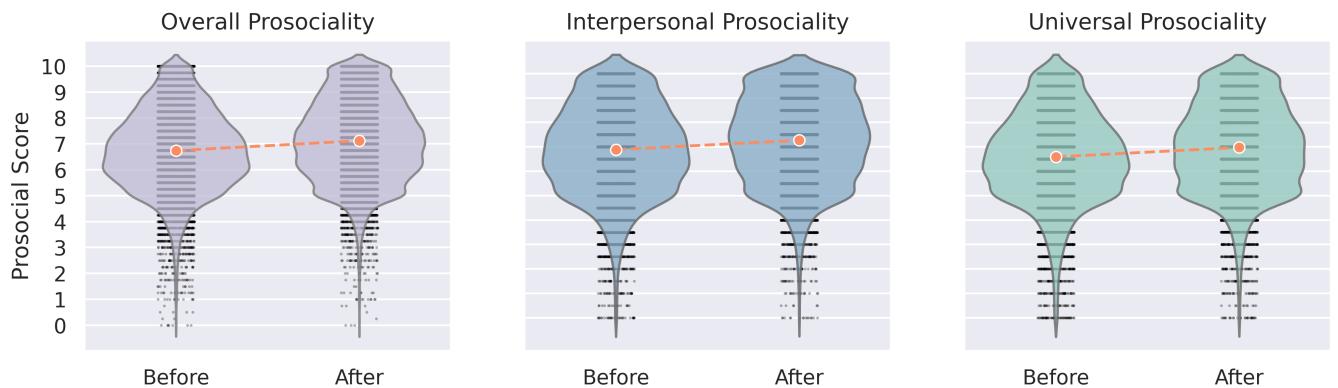


Figure 4: Prosocial Scores before and after Seven-Day Intervention. Orange dots represent the average prosocial scores. All scores show significant increases: $\Delta_{\text{overall}}=0.38 \pm 0.01$, Effect size using Cohen's d were in the small effect range: $d=0.24$; $\Delta_{\text{interpersonal}}=0.38 \pm 0.02, d=0.21$; $\Delta_{\text{universal}}=0.38 \pm 0.02, d=0.20$.

Ethnicity. Most participants were White ($N=13250$, 72.6%). Indigenous people, although with a small number ($N = 58$), had the highest prosociality score (7.09 ± 0.21), with small to medium effect sizes compared to other groups ($ds = 0.21 - 0.36$). The second highest group was those identifying with more than one ethnicity (6.92 ± 0.04).

Country of Residence. In addition to ethnicity, country of residence can provide another cultural perspective. Due to the large number of countries, we focus on the top 10 countries with the most participants. A Kruskal-Wallis test indicated a statistically significant difference in prosocial scores across countries ($p < 0.001$). Among the top 10, participants from the Philippines had the highest prosocial score (6.99 ± 0.14), followed by Mexico (6.97 ± 0.10) and US (6.83 ± 0.015). In contrast, participants from Great Britain (6.43 ± 0.04) reported the lowest prosociality scores. These results support existing research on ethnicity, culture, social connection, and prosocial behavior [9, 35], and offer new insights into populations that are previously unexplored, such as Indigenous participants or people from Philippines and Mexico.

More detailed results of our analysis can be found in Appendix B. Overall, many of our results were supported by or provided new evidence to previous literature. We discuss more in Section 6.1.

5.2 RQ2: Does The Intervention Increase Prosociality?

Most findings of RQ1 validate prior work with a much larger scale of user samples. What's more interesting are the new research questions that can be answered via our study. Starting from RQ2, we present new findings that go beyond existing literature on prosociality intervention.

After seven days of intervention, participants showed a significant increase in prosociality (from 6.73 ± 0.01 to 7.12 ± 0.01 , $\bar{d} = 0.39 \pm 0.01$, $p < 0.001$), with a small to medium effect size ($d = 0.24$, see Figure 4). This was consistent across interpersonal prosociality (from 6.88 ± 0.01 to 7.27 ± 0.01 , $\bar{d} = 0.39 \pm 0.01$, $p < 0.001$, $d = 0.21$) and universal prosociality (from 6.59 ± 0.01 to 6.97 ± 0.01 , $\bar{d} = 0.38 \pm 0.01$, $p < 0.001$, $d = 0.21$). We also conducted the analyses with the same demographic groups as in Section 5.1.

We fitted a generalized linear mixed model (GLMM) with measurement time (before and after the seven-day intervention), the four demographic aspects, and their interactions with the measurement time as the factors. The model details can be found in Appendix B.6. We highlight the main results as follows.

Age. All age groups showed a significant increase in prosociality ($ps < 0.001$). We did not observe significance for the interaction effect between age and intervention ($p = 0.14$). As shown in Figure 5, the prosociality increase was similar across age groups.

Gender. ANOVA of the GLMM indicated the significance of all gender-related factors ($ps < 0.001$). Post-hoc analysis showed that both females and males had significant increases in prosociality scores (female: $\bar{d} = 0.37 \pm 0.014$, $d = 0.24$; male: $\bar{d} = 0.47 \pm 0.042$, $d = 0.27$). Although males initially had the lowest prosociality, they exhibited the largest improvement among all gender groups, particularly with significance over females' improvement (*i.e.*, the delta of the delta, $p < 0.001$, $d = 0.10$).

Subjective SES (SSES). An ANOVA indicated the significance among SSES-related factors ($ps < 0.001$). Post-hoc analysis showed that although all SSES groups had significant increases in prosociality, the improvement greatly varied. People with SSES 0-3 ($\bar{d} = 0.50 \pm 0.071$, $d = 0.28$) and 4-6 ($\bar{d} = 0.47 \pm 0.028$, $d = 0.29$) have significantly more improvement compared to people with SSES 7-9 ($\bar{d} = 0.35 \pm 0.014$, $d = 0.23$) or 10 ($\bar{d} = 0.16 \pm 0.1$, $d = 0.09$, all $ps < 0.01$).

Ethnicity. With an ANOVA indicating the significance among all ethnicity factors ($ps < 0.001$), post-hoc analysis showed that all ethnicity groups had significant increases in prosociality ($ps < 0.001$, $ds = 0.21 - 0.37$), except Indigenous people ($d = 0.08$), likely due to the limited number of participants. It is noteworthy that Black/African/Caribbean ($\bar{d} = 0.66 \pm 0.085$, $d = 0.37$) and Latin American/Hispanic ($\bar{d} = 0.53 \pm 0.078$, $d = 0.34$) had the biggest improvement in prosociality.

Country of Residence. An ANOVA indicated the significance of country-related factors ($ps < 0.001$). Post-hoc analysis revealed significant increases in prosociality scores across all countries after the intervention ($ps < 0.001$, $ds = 0.19 - 0.43$). Notably, countries with high initial prosocial scores continue to have the biggest improvement (Philippines, $\bar{d} = 0.73 \pm 0.2$, $d = 0.41$; Mexico $\bar{d} = 0.47 \pm 0.13$, $d = 0.31$). We further grouped countries and analyzed prosociality based on the development stages of countries. Participants from both developed and developing countries had similar initial prosociality scores (6.75 ± 0.01 vs. 6.66 ± 0.03 , $p < 0.05$). However, people from developing countries ($\bar{d} = 0.54 \pm 0.04$, $p < 0.001$, $d = 0.3$) exhibited a greater improvement than the developed countries ($\bar{d} = 0.35 \pm 0.01$, $p < 0.001$, $d = 0.23$), as indicated by the interaction effect in Figure 5.

Overall, most demographic groups show a significant increase in prosociality after the intervention study. Participants with lower prosociality at the beginning of the study (males, and people with lower SSES) tended to exhibit greater improvement, except for the age group factors (younger people had a similar trend as older people). Meanwhile, participants from developing countries exhibited similar initial prosociality but greater improvement than those from developed countries. Our results serve as the first large-scale field experimental evidence showing relationship between demographic groups and prosocial intervention effects (see more discussion in Section 6).

5.3 RQ3: How Do Micro-acts Influence Prosociality?

In this section, we broke down the intervention week into seven micro-acts and investigated how participation in the different micro-acts would change participants' prosocial behavior. With various demographic information, we further investigate different population groups' reactions across these micro-acts.

5.3.1 Dosage Analysis. Throughout the week of intervention, participants could complete up to seven micro-acts (recall all intervention designs in Section 3). We define "dosage" as the number of micro-acts completed by a participant, with possible values ranging from 0 (only doing the onboarding and closing, but skipping all

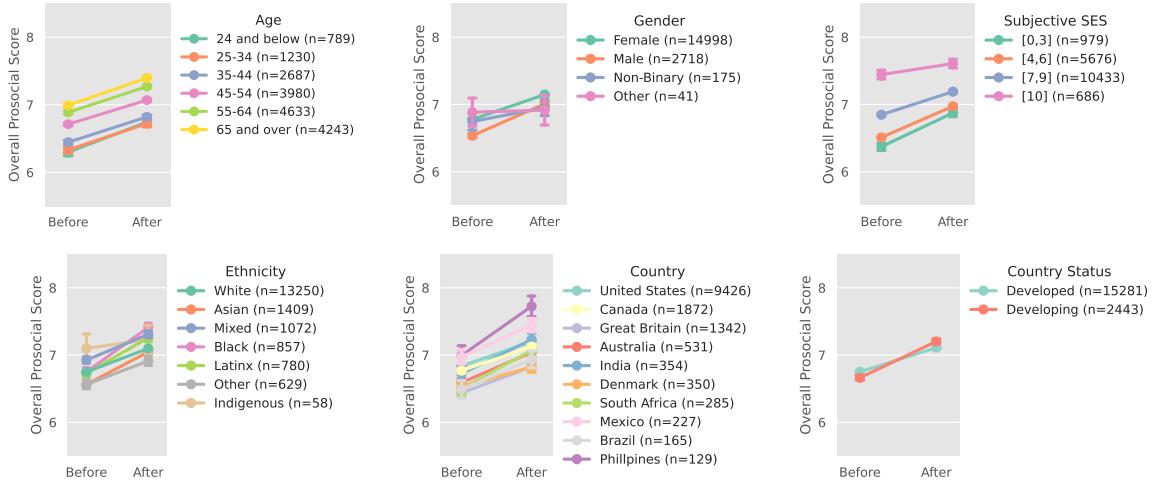


Figure 5: Overall Prosocial Scores before and after Interventions across Demographic Groups.

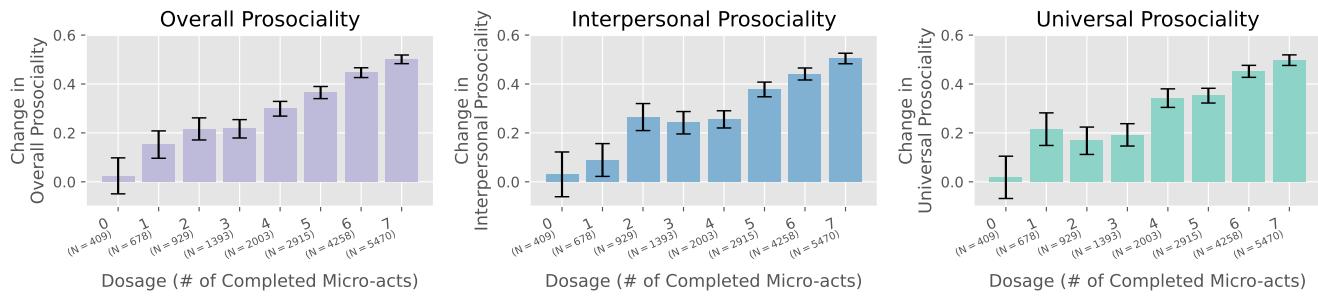


Figure 6: Improvement in Prosociality with The Number of Completed Micro-acts (Dosage). All three measures of prosociality indicate significant positive correlations ($\rho = 0.08, 0.06, 0.07$, respectively, $p < 0.01$).

micro-acts in the week) to 7 (doing the whole set of micro-acts). The large-scale study enables a natural experiment setup. Participants who skipped all micro-acts ($N=409$) served as the baseline control group.³

Our analysis indicated that people who did at least one micro-act (dosage ≥ 1) would have a significant improvement in prosociality after the study ($d = 0.10 - 0.38$, $p < 0.01$). We observed a positive correlation between dosage and prosociality scores ($\rho = 0.08$, $p < 0.001$). A Kruskal-Wallis test indicated the significance of dosage ($p < 0.001$). In particular, compared to people who skipped all micro-acts (dosage=0), people who did seven micro-acts (dosage=7) have an average of 0.48 ± 0.073 more increase in prosociality score ($d = 0.34$). This is consistent for both interpersonal prosociality ($\rho = 0.06$, $p < 0.01$) and universal prosociality ($\rho = 0.07$, $p < 0.001$). Figure 6 depicts the steadily increasing trend of prosociality as the dosage increases.

5.3.2 Comparison among Micro-acts. We further investigated how each micro-act influences prosociality. Since we only have one interpersonal or universal prosociality change score per person, we

³It is noteworthy that in the natural experiment setup, the baseline is not a randomized control group.

fitted GLMM models, with each micro-act as a binary factor (0/1 representing the participant had skipped/completed the micro-act), while controlling the order of the seven micro-acts. We analyzed the effects of the seven micro-acts on interpersonal and universal prosociality separately. Figure 7 illustrates the coefficient results, i.e., the impact of each micro-act on prosociality.

Our results show similarities in the impact of different micro-acts on the two aspects of prosocial behaviors. Specifically, *Shift Your Perspective* and *Tune in to What Matters* did not have a significant impact on interpersonal ($\beta = -0.01, 0.05$, $p = 0.50, 0.07$) or universal prosociality ($\beta = -0.002, 0.03$, $p = 0.92, 0.25$). All the rest of the five micro-acts have significant impacts on both aspects of prosocial behaviors ($\beta = 0.07 - 0.13$, $p < 0.05$), thus portraying their effectiveness at increasing prosocial behaviors among people.

5.3.3 How Do People React Differently across Micro-Acts? Building on the findings presented in Figure 7, we further investigate the results by examining variations across different population groups. For each group, we fitted another set of GLMMs, following the same method in Section 5.3.2. Since this cross-micro-act analysis is rooted in a natural experimental setup, a group needs to be sufficiently large to ensure enough variation across the seven micro-acts for

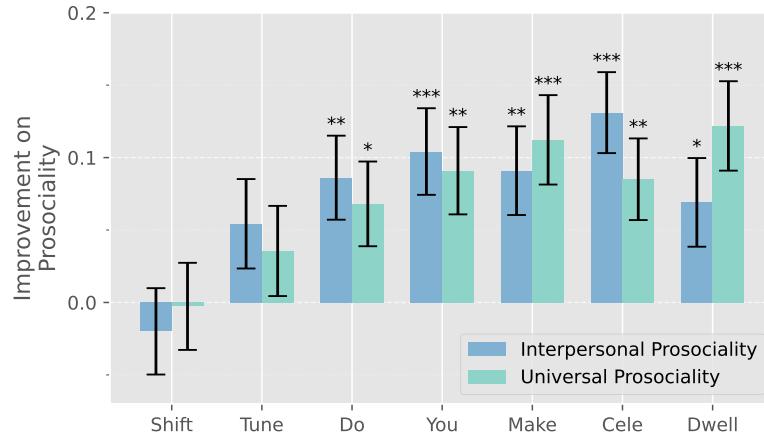


Figure 7: Effect of Each Miro-Act on Interpersonal and Universal Prosociality. Significance symbols indicate the significance level of the improvement (over zero, $p < 0.05^*$, $< 0.01^{}$, $< 0.001^{***}$).**

meaningful analysis. Therefore, we consolidated some population groups and concentrated on those with at least 1000 samples. Our analysis reveals many interesting insights.

Age. We categorized age into three groups: younger (34 years or below), middle-aged (35–55 years), and older (55 years or above). Figure 8a presents notable differences among these groups. For younger individuals, *Do Something Kind* was the only micro-act with a significant improvement in both interpersonal and universal prosociality. Among middle-aged participants, the most impactful micro-acts were *Celebrate Another's Joy* (for interpersonal prosociality) and *Dwell in Awe* (for universal prosociality). Both *Celebrate Another's Joy* and *Dwell in Awe* maintained their positive effect for older individuals, with the former emerging as the most impactful micro-act for this age group.

Gender. Figure 8b compares the results for the two primary gender groups. Notably, the five effective micro-acts identified in Figure 7 significantly influenced females across both prosociality categories, with the exception of *Do Something Kind* for interpersonal prosociality. However, males exhibited responses to only a subset of these micro-acts. For interpersonal prosociality, only *You Are A Force of Good* demonstrated positive impacts, whereas for universal prosociality, only *Make A Gratitude List* and *Dwell in Awe* showed effectiveness. Interestingly, *Shift Your Perspective* shows a significant negative impact on males for interpersonal prosociality.

Subjective SES (SSES). For SSES, we consolidated the four groups into two categories (≤ 6 or > 6 out of 10). As depicted in Figure 8c, the reactions of these two groups diverged significantly. *Dwell in Awe* was the sole micro-act that improved prosociality universally across both groups. Participants with lower SES exhibited responses to *Tune in to What Matters*, *You Are A Force of Good*, and *Do Something Kind*, while those with higher SES showed significant reactions to *Celebrate Another's Joy* and *Make A Gratitude List*.

Ethnicity. Due to limited sample sizes, all non-White participants were grouped together and compared against White participants.

Figure 8d reveals contrasting outcomes. Among the five effective micro-acts identified in Figure 7, White participants responded positively to all, while for Non-White participants, *Celebrate Another's Joy* was no longer effective. Meanwhile, among the other two micro-acts that are less effective in Figure 7, Non-White participants also showed strong responses to *Tune in to What Matters* in both interpersonal and universal prosociality.

Country of Residence. For simplicity, we focus on development status as shown in Figure 8e. Participants from developed countries exhibited results closely aligned with those in Figure 7. However, participants from developing countries show different responses. Among the five effective micro-acts, only *Do Something Kind* remained effective in both aspects of prosociality, whereas *Tune in to What Matters* demonstrated positive effects on interpersonal prosociality.

Overall, our analysis highlights considerable variability in the effectiveness of interventions across population groups. Different populations showed distinct reactions to the seven micro-acts. To provide additional perspective, Table 12 in Appendix C summarizes the significant impacts of each micro-act on specific groups. Overall, *Make A Gratitude List*, *Celebrate Another's Joy*, and *Dwell in Awe* emerged as the most effective interventions, showing generalizability across a wide range of groups. We further discuss how these findings can inform future designs in Section 6.2.

5.3.4 What Do People Write in Different Micro-Acts? Participants had several opportunities to enter texts during the intervention week: in-situ practice text entry during the micro-act (3 of 7 had such intervention design⁴, see in Section 3), quick notes right after completing the micro-act, and reflection notes at the end of each day. We focused on the five micro-acts that showed significant impacts on prosociality in Figure 7 and highlighted some results with word cloud analysis.

⁴These three micro-acts require users' in-situ text entry: *Do Something Kind* (five action items), *Make A Gratitude List* (eight things that they are grateful in life), *Tune in to What Matters* (a description of a negative experience, with the note of reframing).

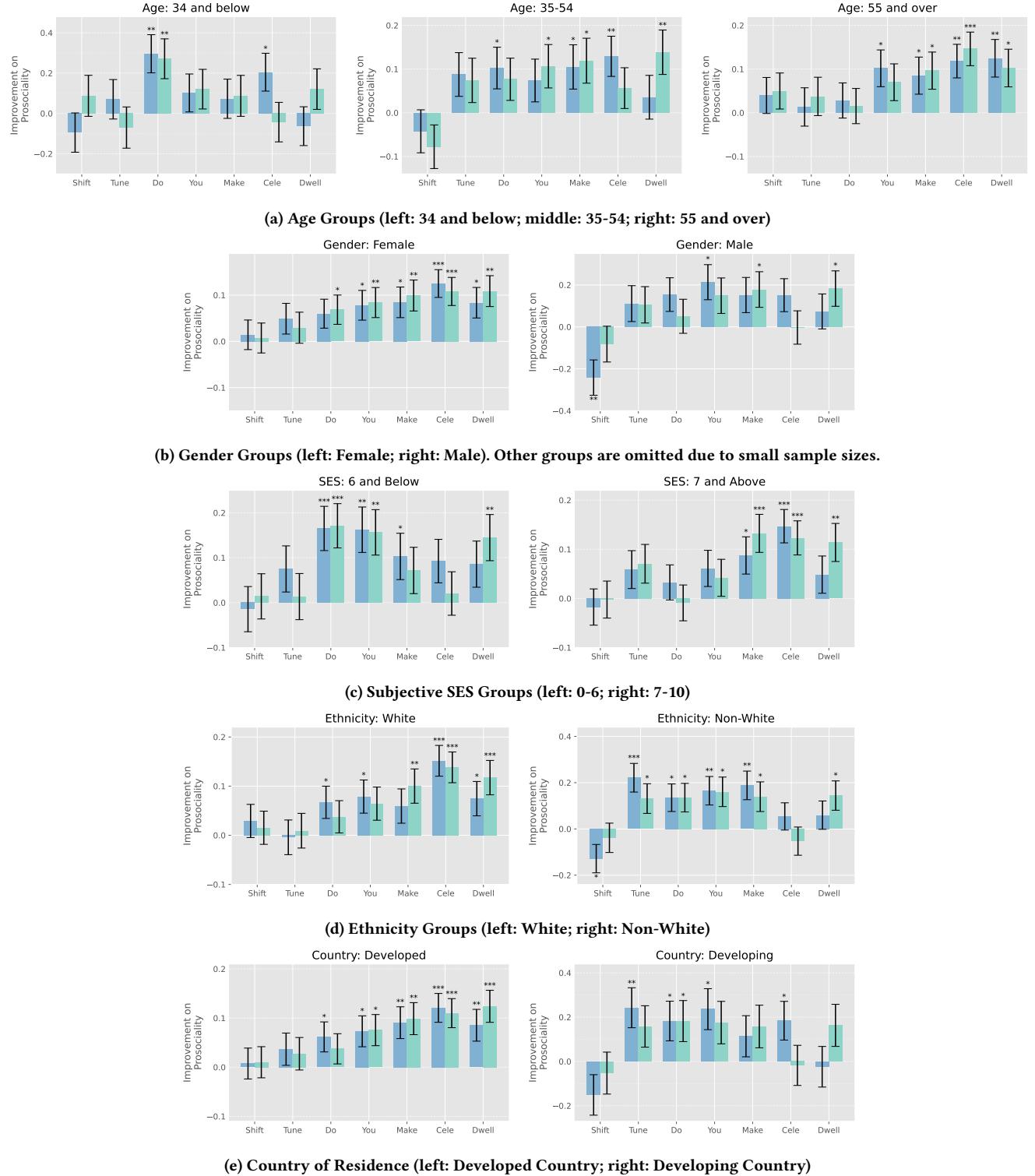


Figure 8: Effect of Each Miro-Act across Different Population Groups: (a) Age, (b) Gender, (c) Subjective SES, (d) Ethnicity, (e) Country of residence. Micro-act names are abbreviated as the first word. Other setup is the same as Figure 7.

Figure 9a and 9b summarize users' in-situ practice entry of two micro-acts. For *Do Something Kind*, participants frequently mentioned verbs like "give", "help", "compliment", "call", "hug", "smile".

These acts covered a number of actions that are kind to others. Nouns like "friend" and "neighbor" indicated who participants did



Figure 9: Word Clouds of Users' Text Entry for Different Micro-Acts. (a-b) Users' in-situ entry during the intervention practice. (c-e) Users' reflection text at the end of the day.

the kindness for. For *Make A Gratitude List*, “friend” and “family” stood out as the most common recipients that participants are grateful toward. And “health”, “love”, “life”, “work” are representative aspects of participants’ gratitude lists.

Figure 9c to 9e highlight participants’ reflection notes at the end of the day. These entries were quite aligned with the intervention design. In particular, after watching an outdoor video in *Dwell in Awe*, participants often mentioned “nature” and “beauty”. It was encouraging to see participants also bring up “calm”, “love”, and “relax”, reflecting the potential benefits of this micro-act, especially for universal prosociality (see Section 5.3.2). Appendix E provides a more quantitative statistical summary of the text data among seven micro-acts.

5.4 RQ4: How Are Prosociality Changes Related to The Changes on Other Aspects of Well-Being?

We further explored the relationship between prosociality improvement and other well-being characteristics. For this purpose, we divided participants into three groups based on their prosociality changes: those who showed increased prosociality ($\text{change} \geq 0.5$, $\bar{\Delta} = 1.43 \pm 0.01$, $N=8751$), remained stable ($-0.5 < \text{change} < 0.5$, $\bar{\Delta} = -0.09 \pm 0.003$, $N=5801$), or showed a decrease in prosociality ($\text{change} \leq -0.5$, $\bar{\Delta} = -1.45 \pm 0.01$, $N=3503$). We highlighted six characteristics that cover three well-being aspects: social (compassion and social relationship contentment, 0 - 10), mental (resilience and happiness, 0 - 10), and physical (physical health and sleep quality, 1 - 5) well-being.

Social Well-being. As one of the social well-being aspects, prosociality had strong positive correlations with other social characteristics [20, 70]. In particular, the changes in participants’ compassion

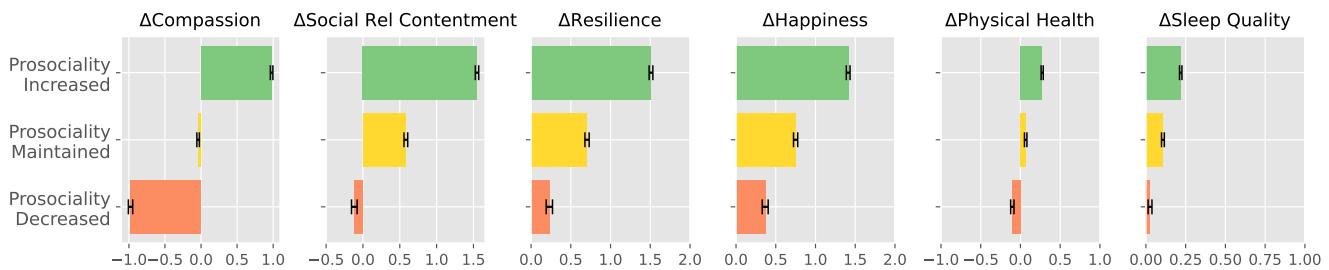


Figure 10: Comparison of Other Six Aspects among Participants with Different Prosociality Changes. The analysis covers three well-being aspects: (1) social well-being (compassion, social relationship contentment); (2) mental well-being (resilience and happiness); and (3) physical well-being (physical health and sleep quality).

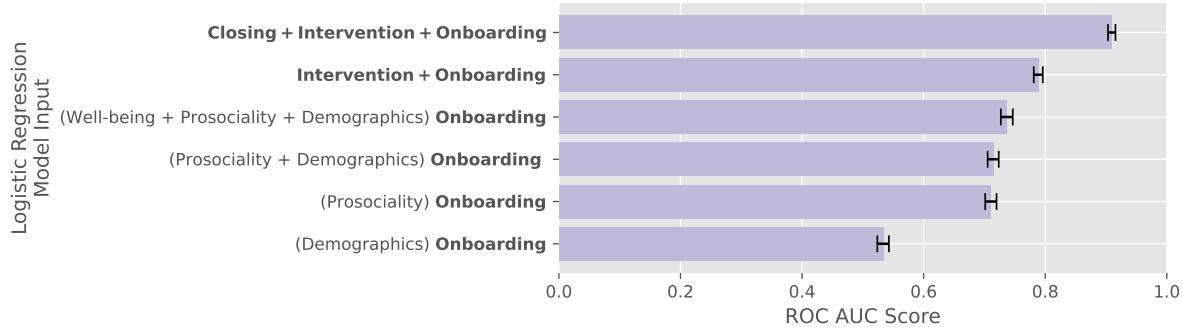


Figure 11: Prosociality Improvement Prediction with Different Set of Features.

and social relationship contentment had the most significant correlation coefficients ($\rho = 0.50$ and 0.35 , respectively, $p < 0.001$). The two left graphs in Figure 10 present the difference across the three groups. Compassion had a very similar numeric pattern as prosociality (average score 0.98 ± 0.02 , -0.04 ± 0.02 , and -0.97 ± 0.03 among the three groups, $p < 0.001$, with a large effect size $\eta^2 = 0.18$ [77]). For social relationship contentment, there was a minimal decrease in the group with decreased prosociality (1.55 ± 0.02 , 0.59 ± 0.02 , and -0.07 ± 0.04 , $p < 0.001$, with a medium to large $\eta^2 = 0.09$).

Mental Well-being. In contrast to social well-being, mental health characteristics show a small increase even in groups with decreased prosociality. However, these characteristics also have medium positive correlations with prosociality, which is supported by literature [64, 86]. Resilience and happiness are two representatives ($\rho = 0.27$ and 0.23 , $p < 0.001$). They also have small to medium effect sizes (for resilience, 1.49 ± 0.02 , 0.68 ± 0.02 , and 0.19 ± 0.04 , $p < 0.001$, $\eta^2 = 0.05$; for happiness, 1.42 ± 0.02 , 0.75 ± 0.03 , and 0.32 ± 0.04 , $p < 0.001$, $\eta^2 = 0.04$).

Physical Well-being. We also observed weak positive correlations between prosociality and physical health/sleep quality ($\rho = 0.14/0.12$, $p < 0.001$). Although the effect sizes are small (η^2 s = 0.01), our results provide encouraging evidence of the positive relationship between prosocial behavior and physical well-being [13, 65, 74]. We will discuss more about these results and social science literature in Section 6.

Similar to RQ3, we also compared the results among different population groups. In general, correlations between prosociality and well-being changes across groups are quite close. We observed slightly stronger correlation on social well-beings for older people (compassion $\rho = 0.52$, social relation contentment $\rho = 0.37$) than younger people ($\rho = 0.46$ and 0.33 , respectively, $\Delta\rho = 0.05$), slightly stronger correlation on mental well-being for non-White people (resilience $\rho = 0.30$, happiness $\rho = 0.27$) than White people ($\rho = 0.26$ and 0.22 , $\Delta\rho = 0.05$), and consistent stronger correlation on people from developing countries than those from developed countries ($\Delta\rho = 0.04$ – 0.05). More detailed results are listed in Table 13 in Appendix D.

5.5 RQ5: Can We Predict Prosociality Changes from Other Well-being Aspects?

As shown in RQ4, participants had different intervention responses due to individual heterogeneity. In the last RQ, we investigated whether we could predict participants' prosociality improvement from their other characteristics. This may suggest future directions for personalized intervention delivery.

We divided features into several categories: (1) *Onboarding*, which included all data collected during the onboarding session. They were further divided into demographics, well-being features (examples in Section 5.4 were a subset). We also added the onboarding prosociality features, as we were interested in how the initial prosocial behavior could predict their improvement. (2) *Intervention*,

Ablation Condition	Acc	Recall	Precision	F1	ROC AUC
Onboarding + Intervention + Closing	0.844 ± 0.005	0.845 ± 0.005	0.842 ± 0.006	0.842 ± 0.006	0.909 ± 0.006
Onboarding + Intervention	0.739 ± 0.008	0.739 ± 0.008	0.731 ± 0.008	0.729 ± 0.009	0.789 ± 0.007
Onboarding (Well-being + Prosociality + Demographics)	0.713 ± 0.001	0.713 ± 0.001	0.701 ± 0.012	0.697 ± 0.012	0.737 ± 0.010
Onboarding (Prosociality + Demographics)	0.694 ± 0.010	0.694 ± 0.010	0.678 ± 0.010	0.674 ± 0.011	0.714 ± 0.009
Onboarding (Prosociality)	0.695 ± 0.009	0.695 ± 0.009	0.679 ± 0.009	0.673 ± 0.010	0.711 ± 0.009
Onboarding (Demographics)	0.652 ± 0.012	0.652 ± 0.012	0.426 ± 0.015	0.515 ± 0.015	0.533 ± 0.010

Table 2: Logistic Regression Performance of Prosociality Improvement Prediction in The Ablation Study.

which included data during the intervention week. This involved whether a person did a micro-act, their change in positive and negative affect after the micro-act, as well as their reflection at the end of the day. (3) *Closing*, which were data collected in the closing survey, excluding prosocial questions. We encoded categorical variables as integers (e.g., age group, gender, ethnicity) instead of dummy variables to control the number of variables. Average value imputation was used to handle missing data.

As a proof of concept, we focused on binary classification (increased prosociality vs. decreased prosociality as defined in Section 5.4). We used an 80/20 random split for the training/testing set and repeated 10 times. We compared multiple off-the-shelf machine learning models, including Logistic Regression (LR), Support Vector Machine (SVM), Random Forest (RF), Naive Bayes (NB), and Multi-Layer Perceptron (MLP). Our results revealed that LR had the best overall performance. Grid search on hyperparameters did not reveal significant differences in the results, so we adopted a basic LR model (l_2 penalty, regulation coefficient $C = 1$).

We conducted an ablation study with different feature set combinations of *Onboarding*, *Intervention*, and *Closing*. Figure 11 visualizes the results. When including all features, an LR model achieved an F1 score of 84.4% and an ROC AUC of 0.909. Removing *Closing* features would lead to a drop of 11.3% and 0.120 for the F1 score and ROC AUC. This was expected given the significant correlation between the change in well-being variables and the change in prosociality (Figure 10). Removing *Closing* features would lose the information of the change of other well-being variables.

When only using the *Onboarding* features, the LR model achieved an F1 score of 69.7% and an ROC AUC of 0.737. Compared to the models mentioned above, this was more realistic as a “future prediction” setup, without data during or after intervention. Among the three subcategories within *Onboarding* features, demographics had relatively the least impact, followed by well-being features and onboarding prosociality. More result details can be found in Table 2.

6 Discussion

We conducted one of the largest happiness and prosocial intervention studies, BIG JOY, involving 15,186 users across 164 countries and regions. By analyzing our large-scale data, our results provided valuable insights for various research questions, from understanding the basic prosocial characteristics, the impact on prosociality across different micro-acts, its relationship with other well-being aspects, and the potential of prosociality improvement prediction. In this section, we discuss deeper insights that can be gained from the results in Section 5.

6.1 New Evidence for Existing Literature and Beyond

Our study contributes significant new evidence to the existing body of research on prosocial behavior (RQ1). From the demographics perspective, prior work has suggested that older people [55, 61], females [29, 62], and those with higher subjective SES [7] tend to have more prosocial behaviors. Our findings are in line with the prior literature, providing new evidence with large-scale data. More importantly, starting from RQ2, our intervention study indicates novel insights into the improvement of prosociality from short

term interventions that prior work did not address. For instance, our results suggest that although males and people with lower subjective SES tend to be relatively lower in prosociality at the beginning, they showed significantly higher increases in prosociality after the intervention. Prior research indicates the relationship among ethnicity, culture, and prosocial behavior [9, 35]. For example, some studies have shown that Black, Latinx, and Indigenous populations often exhibit higher levels of prosocial behaviors compared to White populations [67]. But no prior work has compare the influence on intervention across these groups. Our study adds to this understanding by providing data-driven insights on the high baseline prosociality among Indigenous groups. We further show that Black/African/Caribbean and Latin American/Hispanic groups demonstrated even greater improvements in prosocial behavior following interventions. A similar pattern is also observed for people from developing countries. These findings highlight the value of our study in expanding our understanding of how demographic factors interact with prosocial interventions and suggest that targeted interventions may be particularly beneficial for certain groups.

From the well-being perspective, previous research has suggested the relationship between prosociality and physical [13, 65, 74], mental [64, 86], and social well-being [20, 70], but there has been no large-scale study to verify such associations in a data-driven way. More importantly, no prior work has explored their relationship in the intervention context (i.e., correlation relationship of the pre-post intervention delta). Our study addresses this gap, demonstrating that the improvement of prosociality is positively correlated with various aspects of well-being, such as compassion, social relationship contentment, resilience, and happiness. Moreover, our findings suggest that while prosocial behavior is more positively correlated with mental and social well-being domains, it also has a significant association with physical well-being improvement. These results not only confirm the theoretical relationships proposed in earlier work, but also provide empirical evidence that underscores the potential of prosocial interventions to enhance overall well-being on a global scale. This underscores the importance of integrating prosociality-focused practices into broader well-being initiatives.

Additionally, our findings contribute the first data-driven comparison among the seven well-documented interventions, providing nuanced insights into how different interventions influence prosocial behavior. For example, our data suggests the lack of impact on prosociality in *Shift Your Perspective* and *Tune in to What Matters*. These micro-acts, while beneficial for enhancing general mental well-being and reinforcing core values [23, 84], may not directly cultivate the outward-focused behaviors that define prosociality. On the other hand, the selective impact of *Dwell in Awe* on universal prosociality (but not on interpersonal prosociality), offers an interesting insight. Awe has been shown to expand individuals’ perceptions of their place and foster a sense of connectedness to things that are larger than oneself [44, 87]. In our study, this broader connection may encourage behaviors that benefit society or the environment as a whole (which is aligned with universal prosociality), rather than directly enhancing interpersonal interactions (which is closer to interpersonal prosociality). These results provide evidence from a new perspective on the impact of awe that can potentially extend the existing literature [71]. These findings underscore the importance of aligning intervention design with the

specific dimensions of prosocial behavior that are being targeted, which can guide the development of more tailored interventions.

6.2 Design Guidelines of Well-Being Interventions for Prosociality

Building on our large-scale findings, we propose several design guidelines that can inform the creation of digital interventions aimed at fostering prosociality. By integrating insights from demographic variations and the nuanced effects of different micro-acts, these guidelines help future interventions be more inclusive and impactful.

Guideline 1: Encourage Sustained and Cumulative Engagement. Our analysis in Section 5.3.1 revealed a clear dose-response relationship: the more micro-acts participants completed, the greater their improvements in prosociality. This finding underscores the importance of designing interventions that keep users engaged over time. Other than our current micro-act design to ensure a light time commitment, other strategies might include setting manageable daily goals, providing timely reminders and prompts, and incorporating progress tracking or gamified elements. By making it both feasible and motivating to return each day, interventions can help participants accumulate prosocial gains gradually, ultimately resulting in more substantial prosociality improvement.

Guideline 2: Leverage Contextual Information to Recommend Tailored Micro-Acts. A central lesson from our global sample is that user backgrounds – demographic, socio-economic, cultural – significantly influence the efficacy of prosocial interventions. As discussed above, our results in Section 5.1 and 5.2 showed that certain groups, such as Black/African/Caribbean and Latin American/Hispanic participants, those with lower subjective SES, and males, started with lower prosocial scores on average but experienced relatively larger boosts. Meanwhile, effective interventions are not merely about offering variety, but also about delivering the right content to the right person. We should move beyond a one-size-fits-all approach and consider personalized design that adapt to a user's context [36]. Our subgroup analyses in Sec 5.3.2 and 5.3.3 show that certain populations benefit more from specific micro-acts, reflecting variations in cultural norms, personal histories, or value systems. For instance, *Tune in to What Matters* only showed significant impact on participants who were non-White or from developing countries. *Make A Gratitude List* and *Celebrate Another's Joy* tend to work for a broader range of population groups. Designing systems that leverage demographic, contextual, and engagement data can help ensure users are more receptive to micro-acts particularly conducive to their growth. This can involve simple demographic-based recommendations or more advanced ML models that predict which interventions are most likely to boost prosociality for a given user, ultimately enabling a more personalized well-being experience. Section 6.3 dives deeper in this aspect.

Guideline 3: Diversify Intervention Types to Target Distinct Facets of Prosociality. In addition to diverse impact across population groups, our results in Section 5.3 also show that different micro-acts vary in their influence on interpersonal and universal prosociality. Acts like *Make A Gratitude List* and *Celebrate Another's Joy* enhanced both forms, while others like *Dwell in Awe* mainly

fostered universal prosociality. This suggests another direction to further diversify the intervention in addition to Guideline 2. Other than using algorithms to optimize intervention delivery, another possible design is to provide users with a diverse “menu” of micro-acts that allows for flexibility in addressing the nuanced dimensions of prosocial behavior. A system could integrate multiple types of interventions across interpersonal and universal interventions, so that users can select or be guided toward activities most aligned with their personal values and aspirations.

Guideline 4: Integrate Holistic Well-Being Perspectives to Reinforce Prosocial Gains. Moving the lens beyond prosociality to include broader well-being, we observed that improvements in prosociality positively correlate with other well-being facets—including compassion, social relationship contentment, resilience, and even physical health. These results highlight the interconnectedness of prosociality with broader well-being domains. Future design can foster lasting change by incorporating content that encourages users to reflect not only on acts of kindness or gratitude, but also on how these behaviors fit into their broader mental, social, and physical well-being goals. Drawing connections between daily prosocial acts and long-term personal and community well-being may deepen users' motivation and yield more enduring, holistic benefits.

Future work can explore systematic approaches to evaluate the effectiveness of these guidelines. One potential avenue is conducting controlled studies where different intervention designs are implemented based on our guidelines, followed by empirical assessments of user engagement, retention, and behavioral impact. Additionally, integrating these guidelines into existing well-being applications and measuring long-term behavioral changes could provide valuable validation.

6.3 Future Enhancement Towards Intelligent Interventions

In this work, our BIG JOY did not collect additional contextual information from participants (other than demographics and well-being aspects) and adopted a static intervention delivery time. With our current data serving a foundation for population-level analysis, we envision potential directions for future improvement towards more intelligent, personalized, and adaptive interventions.

6.3.1 Personalized and Just-in-Time Intervention. The predictive ML models developed in Section 5.5 for prosociality improvement highlight the potential of personalized interventions in enhancing prosocial behavior. Our findings suggest that initial prosociality scores and well-being features collected during the onboarding process are promising predictors of how much a participant's prosociality will improve following the intervention. This insight opens the door to using AI methods to tailor interventions to individual characteristics, potentially optimizing the effectiveness of such interventions. In the current study design, the impacts of seven micro-acts are entangled. Although we could break down the analysis across populations groups and use GLMMs to compare the effectiveness of each micro-act (Section 5.3), these are still population-level results. It's challenging to explore individual-level questions such as “which intervention works best for a single participant”. This shed light on a potential future research direction, where each experimental

group adopts one micro-act. By understanding the specific factors that contribute to greater prosociality improvements across different micro-acts, we can design more targeted intervention strategies that cater to the unique needs of different participant groups.

Another aspect that requires further exploration is the timing of intervention. In our current design, the daily intervention is delivered at a fixed time of 8 AM, regardless of individual participants' schedules or readiness. However, participants' availability and receptivity to interventions can vary significantly throughout the day, influenced by factors, such as stress levels, daily routines, or unexpected events. Future work should focus on understanding these temporal dynamics to identify the optimal moments for delivering just-in-time interventions. Methods such as micro-randomized trials [45] can be used to collect diverse data with interventions delivered at randomized times. This would enable the development of Just-in-Time Adaptive Interventions (JITAI) [66], which dynamically adjusts the timing and content of interventions to fit participants' needs, moving closer to the goal of personalized, adaptive, and effective behavioral interventions.

6.3.2 Connection with Other Data Sources. Although our current study mainly relied on self-reported data, we envision a future opportunity to integrate other data sources, such as smartphone sensors or wearable devices, to enhance the robustness of our findings. These additional data sources could provide objective measurements of participants' physical and emotional states, offering a more comprehensive understanding of the impact of prosocial interventions [63, 97, 103]. For instance, integrating data from wearable devices that monitor physiological indicators such as heart rate variability or sleep patterns could help us better understand the relationship between prosocial behavior and physical well-being. Moreover, smartphone sensor data could offer insights into participants' behaviors such as mobility patterns [97, 102], social interactions [33, 96], and screen usage [68, 104], which could further enriching our analysis. By leveraging data from mobile and wearable devices and self-reported data, we can gain a more holistic view of how prosocial interventions affect various aspects of well-being. This would further facilitate the development of JITAIIs that connect different data sources in real-time and ensure that participants receive support precisely when they need it most.

6.4 Limitations

Despite the strengths of our study, there are several limitations in the current work. First, our participant pool was not fully representative of the global population, with a predominance of middle-class, female participants, which may limit the generalizability of our findings. Second, the absence of a randomized control group makes it difficult to isolate the effects of our interventions from other factors that may have influenced participants' prosociality. Additionally, the intervention period was relatively short, raising questions about the long-term sustainability of the observed effects. Finally, our reliance on self-reported data introduces the potential for bias and inaccuracy, as participants' responses may be influenced by social desirability or other factors. As discussed in Section 6.3, future research should address these limitations by incorporating more diverse participant samples, including randomized control groups,

extending the duration of interventions, and integrating objective measures to validate self-reported outcomes.

7 Conclusion

In this study, we conducted BIG JOY, a large-scale global intervention designed to promote emotional well-being and prosocial behavior through daily micro-acts. By engaging over 18,000 participants from 172 countries and regions, our study showed significant improvements in prosocial behavior, with variations based on demographic factors such as age, gender, ethnicity, and socioeconomic status. Our results indicate that different micro-acts had distinct impacts on prosociality, and that their impact varied, sometimes dramatically, across populations, highlighting the need for tailored interventions that align with specific behaviors and target groups. In addition, we explored the relationship between prosociality and other well-being aspects, which confirmed the positive correlations with social, mental, and physical well-being. Our study also revealed the potential of using ML models to predict intervention outcomes. Overall, our research not only extends existing literature with stronger evidence, but more importantly, it illustrates a wide range of novel findings and offers new insights into designing future personalized prosocial interventions. We envision our work as a stepping stone toward large-scale initiatives to create global-scale interventions that can foster a more compassionate and connected world.

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A Appendix: Micro-act Instruction and Interface

A.1 Details about the Micro-Acts

Micro-Act	Instructions	Reflection Questions
Celebrate Another's JOY	<ul style="list-style-type: none"> Choose a buddy. Ask them to share a joyful experience. Listen actively and ask questions. Respond with positive affirmations. 	<ul style="list-style-type: none"> What feelings arose when discussing joy? What supportive things did you say? How do you think sharing joy made them feel?
Shift Your PERSPECTIVE	<ul style="list-style-type: none"> Recall a recent frustrating experience. Identify 3 positive outcomes from that experience. 	<ul style="list-style-type: none"> Was this approach familiar or different? How did you shift from negativity to positivity? How can you remind yourself to find the positive?
Do Something KIND	<ul style="list-style-type: none"> Choose 5 people you might see today. List one kind thing you could do for each. Act on one kind gesture immediately. 	<ul style="list-style-type: none"> Who did you choose and what did you do/say? What feelings or thoughts arose while brainstorming? Which kind acts from your list can you do today?
TUNE IN to WHAT MATTERS!	<ul style="list-style-type: none"> Rank the core values (Virtue, Fairness, Goodwill, Unity) in order of importance to you. 	<ul style="list-style-type: none"> How does your #1 core value manifest in your life? What feelings or thoughts arose while reflecting on your #1 value? What other core values are important to you?
Make a GRATITUDE LIST	<ul style="list-style-type: none"> Reflect on sources of goodness in your life. List 8 things you are grateful for. 	<ul style="list-style-type: none"> What sensations, feelings, or thoughts arose while making your list? How have others contributed to goodness in your life?
Dwell in AWE	<ul style="list-style-type: none"> Watch an awe-inspiring video (not provided). Pay attention to your senses and feelings. 	<ul style="list-style-type: none"> What was your favorite part of the video? Did you experience any physical sensations or shifts in your emotions or thoughts?
YOU are a FORCE OF GOOD	<ul style="list-style-type: none"> Listen to a short audio clip (not provided). 	<ul style="list-style-type: none"> Did you experience any physical sensations? Did you notice any feelings or thoughts? Can reflecting on being a force for good change your experiences?

Table 3: Details of the Micro-Acts

A.2 Interface of the Micro-Acts

(a) Make A Gratitude List

(b) Dwell In Awe

(c) Celebrate Another's Joy

(d) Tune In To What Matters

(e) Do Something Kind

(f) Shift Your Perspective

(g) You Are A Force Of Good

Figure 12: Interface of Seven Micro-Acts in The Study.

B Appendix: Prosociality Breakdown Pre- and Post-Intervention

B.1 Prosocial Scores by Age

Age	Number of Responses	Opening Score	Closing Score	Δ Score
24 and below	789	6.29 ± 0.05	6.74 ± 0.06	0.45 ± 0.078
25-34	1230	6.33 ± 0.04	6.72 ± 0.04	0.39 ± 0.057
35-44	2687	6.44 ± 0.03	6.82 ± 0.03	0.38 ± 0.042
45-54	3980	6.71 ± 0.02	7.07 ± 0.02	0.36 ± 0.028
55-64	4633	6.88 ± 0.02	7.26 ± 0.02	0.38 ± 0.028
65 and above	4243	6.99 ± 0.02	7.39 ± 0.02	0.40 ± 0.028

Table 4: Prosocial Scores by Age.

B.2 Prosocial Scores by Gender

Gender	Number of Responses	Opening Score	Closing Score	Δ Score
Female	14,998	6.77 ± 0.01	7.14 ± 0.01	0.37 ± 0.014
Male	2,718	6.53 ± 0.03	7.00 ± 0.03	0.47 ± 0.042
Non-Binary	175	6.74 ± 0.12	6.95 ± 0.12	0.21 ± 0.170
Other	41	6.88 ± 0.21	6.91 ± 0.22	0.03 ± 0.304

Table 5: Prosocial Scores by Gender.

B.3 Prosocial Scores by Subjective SES

Subjective SES	Number of Responses	Opening Score	Closing Score	Δ Score
0-3	979	6.37 ± 0.05	6.87 ± 0.05	0.50 ± 0.071
4-6	5,676	6.50 ± 0.02	6.97 ± 0.02	0.47 ± 0.028
7-9	10,433	6.84 ± 0.01	7.19 ± 0.01	0.35 ± 0.014
10	686	7.44 ± 0.06	7.60 ± 0.06	0.16 ± 0.085

Table 6: Prosocial Scores by Subjective Socioeconomic Status (SSES).

B.4 Prosocial Scores by Ethnicity

Ethnicity	Number of Responses	Opening Score	Closing Score	Δ Score
White	13,250	6.74 ± 0.01	7.09 ± 0.01	0.35 ± 0.014
Other	629	6.56 ± 0.06	6.91 ± 0.06	0.35 ± 0.085
Asian	1,409	6.56 ± 0.04	7.04 ± 0.04	0.48 ± 0.057
Black	857	6.75 ± 0.06	7.41 ± 0.06	0.66 ± 0.085
Mixed	1,072	6.92 ± 0.04	7.30 ± 0.05	0.38 ± 0.064
Latinx	780	6.72 ± 0.06	7.25 ± 0.05	0.53 ± 0.078
Indigenous	58	7.09 ± 0.21	7.23 ± 0.21	0.14 ± 0.297

Table 7: Prosocial Scores by Ethnicity.

B.5 Prosocial Scores by Country

Country	Number of Responses	Opening Score	Closing Score	Δ Score
USA	9,426	6.83 ± 0.01	7.20 ± 0.01	0.37 ± 0.014
Canada	1,872	6.76 ± 0.03	7.12 ± 0.03	0.36 ± 0.042
Great Britain	1,342	6.43 ± 0.04	6.82 ± 0.04	0.39 ± 0.057
Australia	531	6.59 ± 0.06	7.03 ± 0.06	0.44 ± 0.085
India	354	6.72 ± 0.09	7.23 ± 0.09	0.51 ± 0.113
Denmark	350	6.52 ± 0.08	6.82 ± 0.08	0.30 ± 0.127
South Africa	285	6.50 ± 0.10	7.06 ± 0.09	0.56 ± 0.135
Mexico	227	6.97 ± 0.10	7.44 ± 0.09	0.47 ± 0.135
Brazil	165	6.49 ± 0.13	6.93 ± 0.12	0.44 ± 0.177
Philippines	129	6.99 ± 0.14	7.72 ± 0.15	0.73 ± 0.205

Table 8: Prosocial Scores by Country.

Country Status	Number of Responses	Opening Score	Closing Score	Δ Score
Developed	15,281	6.75 ± 0.01	7.10 ± 0.01	0.35 ± 0.014
Developing	2,443	6.66 ± 0.03	7.20 ± 0.03	0.54 ± 0.042

Table 9: Prosocial Scores by Country Classification.

B.6 GLM Output Details

Table 10: GLM Results for Merged Prosocial Behavior Pre- & Post-Intervention (Main Effects)

Variables	β	σ^2	p-value	95% Conf Int for β	Sig. Level
Intervention (pre)					
Post-Intervention	0.520	0.079	0.000	(0.364, 0.676)	***
Age Group (24 and below)					
25-34	0.111	0.081	0.172	(-0.048, 0.269)	
35-44	0.198	0.074	0.007	(0.054, 0.343)	**
45-54	0.476	0.072	0.000	(0.335, 0.617)	***
55-64	0.649	0.072	0.000	(0.509, 0.790)	***
65 and over	0.749	0.073	0.000	(0.606, 0.891)	***
Gender (Male)					
Female	0.314	0.036	0.000	(0.243, 0.385)	***
Non-Binary	0.576	0.132	0.000	(0.318, 0.834)	***
Other	0.475	0.289	0.100	(-0.091, 1.041)	
Ethnicity (White)					
Asian	-0.122	0.061	0.046	(-0.241, -0.002)	*
Black	0.165	0.079	0.037	(0.010, 0.320)	*
Indigenous	0.591	0.231	0.010	(0.139, 1.043)	*
Latinx	0.071	0.077	0.358	(-0.080, 0.222)	
Mixed	0.258	0.055	0.000	(0.150, 0.365)	***
Other	-0.018	0.075	0.813	(-0.164, 0.129)	
Subjective SES Group ([0-3])					
[4-6]	0.040	0.057	0.489	(-0.073, 0.152)	
[7-9]	0.359	0.056	0.000	(0.249, 0.469)	***
[10]	0.953	0.082	0.000	(0.791, 1.114)	***
Countries (United States)					
Australia (AU)	0.066	0.102	0.519	(-0.135, 0.267)	
Brazil (BR)	0.476	0.072	0.000	(0.335, 0.617)	***
Canada (CA)	-0.122	0.041	0.003	(-0.202, -0.042)	**
Denmark (DE)	-0.101	0.093	0.276	(-0.284, 0.081)	
Great Britain (GB)	-0.236	0.049	0.000	(-0.332, -0.139)	***
India (IN)	0.226	0.099	0.023	(0.031, 0.420)	*
Mexico (MX)	0.143	0.121	0.238	(-0.095, 0.381)	
Philippines (PH)	0.607	0.150	0.000	(0.313, 0.901)	***
South Africa (ZA)	-0.281	0.101	0.005	(-0.478, -0.084)	**

Note: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Table 11: GLM Results for Merged Prosocial Behavior Pre- & Post-Intervention (Interaction Terms)

Variables	β	σ^2	p-value	95% Conf Int for β	Sig. Level
Intervention × Age Group (24 and below)					
25-34	0.005	0.071	0.947	(-0.135, 0.144)	
35-44	-0.054	0.065	0.406	(-0.181, 0.073)	
45-54	-0.053	0.063	0.403	(-0.177, 0.071)	
55-64	-0.002	0.063	0.980	(-0.125, 0.122)	
65 and over	0.022	0.064	0.731	(-0.104, 0.147)	
Intervention × Gender (Male)					
Female	-0.112	0.032	0.001	(-0.174, -0.049)	***
Non-Binary	-0.254	0.116	0.028	(-0.481, -0.027)	*
Other	-0.305	0.254	0.230	(-0.803, 0.193)	
Intervention × Ethnicity (White)					
Asian	0.098	0.054	0.067	(-0.007, 0.203)	
Black	0.191	0.070	0.006	(0.054, 0.327)	**
Indigenous	-0.095	0.203	0.641	(-0.493, 0.303)	
Latinx	0.205	0.068	0.002	(0.072, 0.338)	**
Mixed	-0.005	0.048	0.918	(-0.100, 0.090)	
Other	-0.004	0.066	0.956	(-0.133, 0.125)	
Intervention × SES Group (SES Group 1)					
SES Group 2	0.016	0.051	0.757	(-0.083, 0.115)	
SES Group 3	-0.094	0.049	0.055	(-0.191, 0.002)	*
SES Group 4	-0.338	0.072	0.000	(-0.480, -0.196)	***
Intervention × Country (United States)					
Australia (AU)	-0.067	0.090	0.460	(-0.243, 0.110)	
Brazil (BR)	-0.094	0.049	0.055	(-0.191, 0.002)	*
Canada (CA)	0.014	0.036	0.694	(-0.056, 0.085)	
Denmark (DE)	-0.050	0.082	0.544	(-0.210, 0.111)	
Great Britain (GB)	-0.338	0.072	0.000	(-0.480, -0.196)	***
India (IN)	0.106	0.087	0.226	(-0.065, 0.276)	
Mexico (MX)	0.121	0.107	0.258	(-0.089, 0.330)	
Philippines (PH)	0.218	0.132	0.098	(-0.040, 0.477)	
South Africa (ZA)	0.142	0.089	0.110	(-0.032, 0.315)	

Note: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

E Appendix: Statistical Summary of Users' Text Input

To better understand the text data generated during the Reflection sections of each micro-act, we categorized user inputs into seven representative clusters. The clustering process was conducted using the GPT-4o model by OpenAI [4]. First, we built a dictionary of words input by participants in the free-text Reflection boxes. From this dictionary, we filtered for words with a frequency of 20 or more occurrences, resulting in a list of 918 words. This list was then fed to the GPT-4o model, which generated seven representative clusters. For each cluster, the model also provided a list of representative words. These clusters, along with some of their key representative words, are as follows:

- **Emotions and Feelings:** e.g., “delighted,” “overwhelmed,” “anxious,” “joyful,” “uplifted,” etc.
- **Self and Personal Growth:** e.g., “strength,” “belief,” “heal,” “growth,” “empower,” etc.
- **Nature and Sensory Experiences:** e.g., “forest,” “river,” “earth,” “sun,” “moon,” etc.
- **Social Relationships and Community:** e.g., “family,” “friend,” “neighbor,” “partner,” “child,” etc.
- **Actions and Daily Activities:** e.g., “walk,” “talk,” “climb,” “speak,” “listen,” “interact,” “meditate,” etc.
- **Mind and Mental States:** e.g., “mindfulness,” “reflect,” “understanding,” “perspective,” etc.
- **Communication and Expression:** e.g., “note,” “message,” “word,” “call,” “communicate,” etc.

Next, we analyzed the distribution of text inputs across these categories for each micro-act. This was done by extracting the words from participants' reflections and calculating the distribution of these words across the seven clusters. Figure 13 visualizes these distributions for all micro-acts. The patterns that emerge from these visualizations provide insight into how different interventions function. For instance, in the micro-act “Dwell In Awe,” a significant proportion of text was categorized under “Nature and Sensory Experiences,” whereas in “Celebrate Another’s Joy” and “Do Something Kind,” there was a strong alignment with the “Social Relationships and Community” cluster, reflecting the interpersonal focus of these acts.

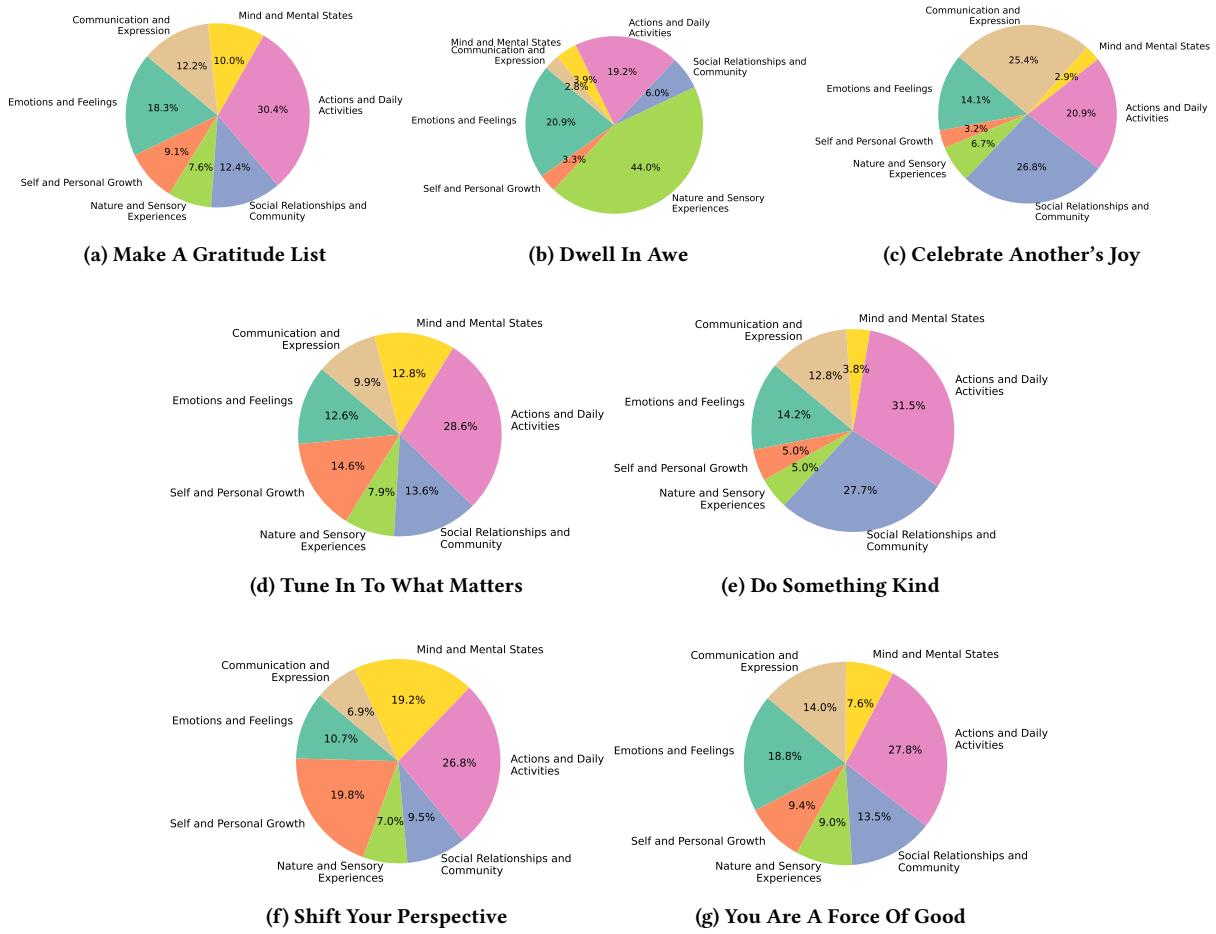


Figure 13: Pie Charts Representing the Distribution of Clusters amongst The Reflection Texts of Micro-Acts.