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Perceptions and Misperceptions of Smartphone Use: Applying the Social Norms Approach

John McAlaney [1,*], Mohamed Basel Almourad [2], Georgina Powell [3] and Raian Ali [4]

1 Faculty of Science and Technology, Bournemouth University, Poole BH12 5BB, UK
2 College of Technological Innovation, Zayed University, Dubai 144534, UAE; basel.almourad@zu.ac.ae
3 Phone Life Balance LTD, Guildford GU2 7SR, UK; georgie@space-app.com
4 College of Science and Engineering, Hamad Bin Khalifa University, Doha 5825, Qatar; raali2@hbku.edu.qa
* Correspondence: jmcalaney@bournemouth.ac.uk

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Abstract: The social norms approach is an established technique to bring about behaviour change through challenging misperceptions of peer behaviour. This approach is limited by a reliance on self-report and a lack of interactivity with the target population. At the same time, excessive use of digital devices, known as digital addiction, has been recognized as an emergent issue. There is potential to apply the social norms approach to digital addiction and, in doing so, address some of the limitations of the social norms field. In this study, we trialled a social norms intervention with a sample of smartphone users (n = 94) recruited from the users of a commercial app designed to empower individuals to reduce their device usage. Our results indicate that most of the sample overestimated peer use of smartphone apps, demonstrating the existence of misperceptions relating to smartphone use. Such misperceptions are the basis for the social norms approach. We also document the discrepancy between self-report and smartphone usage data as recorded through data collected directly from the device. The potential for the application of the social norms approach and directions for future research are discussed.

Keywords: social norms; digital addiction; smartphones; intervention; personality; behaviour change

1. Introduction

As individuals, we are strongly influenced by what we believe to be the norms of our peers [1]. These social norms are often communicated implicitly through social and cultural practices, or explicitly through media communications and other sources [2]. There are different types of social norm, which include perceived norms around behaviour, known as descriptive norms, and perceived norms around attitudes, known as injunctive norms [3]. The concept of perception is important in this area; as has been demonstrated extensively in the literature, individuals are often poor at estimating the behaviour and attitudes of others [3]. In other words, the perceptions we have about others are often misperceptions. The direction of this misperception typically manifests as the individual believing that most others exhibit behaviours or attitudes that are less healthy or socially responsible than is the reality. Examples of this include college students overestimating the frequency and amount of alcohol consumption in their peers [4], individuals underestimating sunscreen use in others [5], and residents overestimating how much electricity their neighbours use [6]. The cause of these misperceptions remains unclear, although suggested mechanisms include psychological factors such as fundamental attribution error, in which we tend to come to simplistic conclusions about the behaviours and attitudes of others [7]. For instance, if an individual regularly observes people smoking cigarettes at a shelter outside of a workplace then they may assume that smoking in that workplace is more widespread than it is. This is because the observer fails to fully consider that the people they see smoking are only a small proportion of the total workforce.

These misperceptions, consistently found across a range of behaviours, have become the basis for the social norms approach. This approach is based on a simple premise, which is that challenging misperceptions can result in a decrease in the target behaviour or attitude [6]. In the early days of the social norms approach, these misperceptions would often be challenged using mass media campaigns disseminated through posters and flyers. Many of these campaigns took place on American college campuses, and often focussed on health behaviours such as alcohol use, drug use and smoking [6]. A typical mass media social norms campaign would include messages such as 'You told us that you think most [college name] students have 6 alcoholic drink when they party—actually most [college name] students have 3 alcoholic drinks or fewer when they party'. With the development of internet technologies, there were several interventions conducted that included presenting individuals with personalised social norms messages, which highlights how the individual's (mis)perceived norm compares to the actual norm. These studies demonstrated that exposure to personalised social norms messages can result in long-term reduction in unhealthy behaviours [6,8]. The social norms approach has been identified by the National Institute on Alcohol Abuse and Alcoholism as one of the most cost-effective strategies for reducing alcohol-related harm in college campus settings [9].

There are limitations to the social norms approach. In the past, it has been heavily reliant on self-report. Whilst there is evidence to support the idea that people are generally reliable sources of information about behaviours such as their own alcohol use [10], it is nevertheless problematic that the 'actual' norm presented in many social norms campaigns is based on a subjective, self-reported figure [11]. In addition, there is a lack of research on how members of the target population interpret and react to being presented with a norm that is likely different from their perceived norm. As observed by one of the founders of the social norms approach [12], no one likes to be told that their view of the world is wrong. There is a risk that an inappropriately delivered social norms intervention will lead to a reactance effect of the type documented in social psychology. This is where an attempt to change a problematic behaviour results in the target population engaging in that behaviour even more strongly [13]. Finally, there is a gap in the social norm literature relating to those who overestimate the behaviour or attitude in question, those who either accurately perceive it, and those who underestimate it. Although it is consistently demonstrated in the literature that most individuals overestimate negative behaviours and attitudes in the their peers, there are also invariably a minority who do not demonstrate these overestimations [3].

There has been some research suggesting that there may be links between personality traits and social norms perceptions [14]. For example, it has been found that the personality trait of openness appears to be associated with an individual's ability to adapt to different social norms when in new social contexts [15]. On the other hand, it has been found that personality traits do not appear to be predictive of whether individuals deviate from established norms [15]. The study reported in this paper provided an opportunity to address this gap in the literature. One other factor which may be important in relation to digital addiction is self-control [16]. Self-control refers to the ability that an individual has to regulate their own behaviour, although, as has been observed, the definition and conceptualisation of the term has become controversial in recent years [17]. It is feasible that self-control is linked to the perceived social norm, given that we use ourselves as a starting point for estimating the behaviour and characteristics of others [18]. However, there is lack of research on the relationship between social norms, self-control, and personality traits.

An area that could both benefit from the social norms approach, and address some of these methodological issues in the field, is digital addiction. This is an emergent area that refers to the problematic use of digital devices. It has been termed internet addiction, amongst other labels, and is a phenomenon that is increasingly being recognised as a behaviour that individuals may want to change [19]. In contrast to offline behaviours, there are additional avenues of prevention and intervention that can be utilised with online behaviours. For example, the exact usage of a device can be objectively tracked and recorded. This removes the need for self-report data. In addition, with devices such as smartphones, it is possible to deliver data-driven, intelligent, automated, and personalised messages directly to individuals. The targeted individual can then provide immediate feedback on the message, allowing for rapid identification of whether the behaviour change campaign being delivered is being received well by the target population. For example, if an individual feels that they are using social media excessively on their smartphone, then the smartphone itself can be used to monitor that behaviour and to deliver appropriate interventions, or alternative forms of support. In our previous research, we have demonstrated that people both desire and accept such systems for digital addiction and related phenomena such as fear of missing out and social media facilitated procrastination [20–23].

In this paper, we trial the application of the social norms approach to combatting digital addiction through smartphone use. By working with the developers of a commercial app, the SPACE app, we aimed to address the following research questions:

R1—Do participants demonstrate similar pattens of misperception with regards to smartphone use as has been found in other behavioural domains?
R2—How accurate are participants self-reported estimations of their smartphone use, as compared to the data recorded directly from their smartphone?
R3—How do age, gender, personality traits and self-control predict self–other discrepancies for smartphone use?
R4—What is the reaction of participants to being presented with the actual norms of smartphone use?

2. Materials and Methods

2.1. Methodology

Participants were recruited with the assistance of the creators of the SPACE app. This is a commercially available app that provides a personalised behaviour change programme designed to enable users to take greater control of their smartphone usage. App users were recruited to act as study participants though an internal advertisement disseminated through the app. Participation in this study was incentivised by the offer of free access to a premium version of the app.

Participants were asked to complete the BFI-10 personality measure [24] and the Brief Self-Control Scale [25]. Demographic data were collected on age, gender, country of residence, employment status and highest level of education. All measures and questions were presented to participants and completed via the SPACE app.

The number of minutes of smartphone use per day and the number of smartphone checks (measured as number of unlocks) were derived from data collected by the SPACE app. Through the survey delivered via the app, participants were also asked to self-report on their minutes of daily smartphone use (phrased to participants as hours/minutes) and number of daily smartphone checks. They were also asked to report their perception of how much time others spend on their smartphone per day, and their perception of how many times others check their smartphones per day. The same question format was then used to collect self-report data and perceived norm data on the specific behaviours of using smartphones for social media, messaging, gaming, and emailing.

The measures were delivered to participants over three consecutive days. This was performed to spread the response burden on them. Questions relating to perceived norms were asked on the first day of participation in this study. On the third day of this study, participants were presented with information about (i) their self-reported behaviour, (ii) their actual behaviour (as recorded by the SPACE app), (iii) their perceived norm of others and (iv) the actual norm of behaviour among other SPACE app users. After each comparison was presented, participants were asked 'How do you feel about this?' with an open box response option provided. An example of this section of this study is as follows:

You thought you checked your smartphones 40 times each day

You actually check your smartphone 83 times each day

How do you feel about this?

[open-text response box]

You thought that other people check their smartphone 90 times a day

Other SPACE users actually check their smartphones 61 times per day in their first day of using the app.

How do you feel about this?

[open-text response box]

Ethical approval for this study was obtained from Zayed University (ethics ID ZU20_003_F). All participants provided informed consent and were made aware that they had the right to withdraw from this study at any time. In addition, all participants in this study were existing users of the SPACE app and had previously agreed to terms and conditions that permitted use of their data for the purposes of research. The identity of participants was not visible to the researchers who conducted the data analysis.

2.2. Data Analysis

Descriptive values were calculated for (i) behaviours recorded directly by the SPACE app, (ii) self-reported behaviours and (iii) perceived behaviours in others.

Self–other discrepancy values were calculated for each behaviour by subtracting the self-reported behaviour from the participant's perception of others on each behaviour. For example, a participant who perceived that others use social media apps for 120 min a day and self-report that they use social media apps 97 min a day would have a self–other discrepancy value of 23. As such, a positive self–other discrepancy value in this scenario would indicate that the participant perceives others to use their smartphone for social media more than they do themselves. Conversely, a negative self–other discrepancy value would indicate that the participant perceives themselves to use their smartphone for social media more than others. As will be discussed in more detail later in the paper, it is important to stress that self–other discrepancy only relates to the perception that the individual has about how they compare to others. This value does not necessarily represent the objective reality of how the individual actually compares to others.

Accuracy of self-report was calculated by subtracting the usage figures recorded by the SPACE app from the self-reported figures from participants. For example, a participant who self-reported that they check their smartphone 50 times a day but who the SPACE app showed checked their phone 80 times a day would have an accuracy score of −30. As such, a negative value indicated that the participant was underestimating their own behaviour, whereas a positive value indicated that the participant was overestimating their own behaviour.

A series of paired sample t-tests were conducted to compare self-reported behaviours to the perceived behaviours of others. This was performed for behaviours of total time per day using smartphones, number of checks (unlocks) on the smartphone, time spent using social media on the smartphone, time spent using messaging apps on the smartphone, and time spent using emailing apps on the smartphone.

Regression analysis was then used to determine what factors predict the (i) the accuracy of self-report of time spent using smartphone and number of checks and (ii) self–other discrepancy values for each of the behaviours (total time per day using smartphones, number of checks (unlocks) on the smartphone, time spent using social media on the smartphone, time spent using messaging apps on the smartphone, time spend using gaming app on the smartphone, and time spent using emailing apps on the smartphone). Within each of these models, the predictors used were gender (male/female); age;

the five personality traits of extraversion, agreeableness, conscientiousness, neuroticism, and openness; and total self-control score.

Content analysis was to categorise the qualitative response to the 'How do you feel about this?' questions that participants were asked on day three and they had been presented with the figures highlighting any discrepancies between (i) their self-reported behaviour and their actual behaviour and (ii) their perception of others and the actual norms of others. Two researchers completed the coding process. Reliability of ratings was determined using the method recommended by Miles and Huberman [26].

3. Results

3.1. Demographics

A total of 94 participants completed this study. Of these, 46 participants (48.9%) identified their gender as male, 45 participants (47.9%) identified their gender as female, and 1 and 2 participants, respectively, either preferred not to answer that question or reported their gender as other. The mean age of the sample was 27.2 years, with a standard deviation of 8.8 years. There was no statistically significant difference between the age of male and female participants, as determined by an independent sample t-test. Most of the participants reported their country as being the USA (31.7%), the UK (13.4%) or Australia (11%). The remaining participants were spread in small numbers across 21 other countries. The most common highest level of education was a university degree (32.3%), followed by postgraduate qualification (19.4%) and compulsory school education (18.3%). The two largest employment status categories were being employed (51.6%) or being a student (40.9%).

3.2. Self–Other Discrepancies

Self–other discrepancy was examined through comparing self-reported behaviour to the perceived behaviour of others (Table 1). Both self-reported and perceived overall time spent using a smartphone per day were higher than the actual norm of 202 min of use per day, as determined from the data recorded by the SPACE app across their users. Similarly, the self-reported and perceived number of smartphone checks per day were higher than the actual norm of 51 checks per day as derived from the data provided from the SPACE app for all users. In terms of specific app-type usage, participants perceived others to spend significantly more time than themselves on social media ($t = -2.88$, df = 90, $p = 0.005$), gaming ($t = -3.47$, df = 90, $p = 0.001$) and email ($t = -2.01$, df = 90, $p = 0.048$). There was no statistically significant difference between self-reported and perceived use of smartphones for messaging purposes. Overall, the expected pattern of participants perceiving others to behave more excessively than they do themselves was not found for time spent using the smartphone or for number of checks. However, the expected pattern was evident in relation to specific use of several app types.

Table 1. Self-reported smartphone behaviours vs. perceived norm for others.

Behaviour	Self-Reported	Perceived
Overall time spent using smartphone per day (minutes)	257.6	250.1
Number of smartphone checks per day	70.2	67.4
Time spent using smartphone per day for social media (minutes)	98.2 *	127.8
Time spent using smartphone per day for gaming (minutes)	31.5 *	60.8
Time spent using smartphone per day for email (minutes)	22.4 *	32.0
Time spent using smartphone per day for messaging (minutes)	66.8	77.5

* Statistically significant difference between self-reported behaviour and perceptions of others.

3.3. Accuracy of Self-Report

There was a statistically significant difference between participant's self-reported overall usage minutes and the actual usage minutes (accuracy of self-report), as determined by the SPACE app data (t = 3.97, df = 90, p < 0.001). A total of 33% of participants self-reported their usage minutes to be equal to or less than their actual usage, indicating an underestimation of personal behaviour. Of the other 67% of participants who overestimated their time spent using smartphones, the mean amount of overestimation was 133.1 min, with a standard deviation of 93.8 min. There was also a statistically significant difference between self-reported number of smartphone checks and the actual number of checks, as determined by the SPACE app data (t = −3.03, df = 90, p = 0.003). A total of 58.2% of participants self-reported their number of checks to be equal to or less than their actual number of checks, as determined through the usage data collected by the SPACE app. This indicated that participants underestimate their own smartphone checking behaviour. The mean amount of underestimation within this group was 77.6 checks, with a standard deviation of 74.3 checks. Taken together, these results indicate that people typically overestimate how much time they spend using their smartphone, but typically underestimate how often they check their smartphone.

3.4. Regression Models

The regression model for accuracy of self-reported time spent using the smartphone was not significant; nor was the regression model for self-reported accuracy of number of checks. This suggests that age, gender, personality, and self-control do not contribute towards how accurate the individual is in judging their own smartphone usage behaviours.

The regression model for self–other discrepancy of time spent using the smartphone was significant (F(8, 71) = 2.22, p = 0.036, R^2 = 0.2, $R^2_{adjusted}$ = 0.11). Within the model, self-control was the only significant predictor (Beta = 0.43, t(79) = 3.12, p = 0.003).

The regression model for self–other discrepancy of number of smartphone checks was significant (F(8, 71) = 2.58, p = 0.016, R^2 = 0.23, $R^2_{adjusted}$ = 0.14). In this model, the two significant predictors were the personality trait of neuroticism (Beta = −0.29, t(79) = −2.32, p = 0.024) and self-control (Beta = 0.28, t(79) = 2.08, p = 0.042).

The regression model for self–other discrepancy of time spent gaming was significant (F(8, 71) = 2.13, p = 0.044, R^2 = 0.19, $R^2_{adjusted}$ = 0.1). In this model, the two significant predictors were the personality trait of openness (Beta = −0.24, t(79) = −2.15, p = 0.035) and gender (Beta = 0.234, t(79) = 2.11, p = 0.038). The latter suggests that female participants were likely to perceive a greater discrepancy.

The regression model for self–other discrepancy of time spent on social media was not significant; nor was the regression model for the self–other discrepancy of time spent on messaging or the model for the self–other discrepancy for time spent on emailing.

3.5. Content Analysis

The qualitative responses for each of the four open-text questions were coded and then grouped into five categories, which were (i) unhappiness/negative, (ii) happiness/acceptance, (iii) surprise, (iv) scepticism and (v) not applicable/other. The happiness/acceptance category included statements where the participant stated that they agreed with the information or expressed some degree of happiness or positivity that the information was correct. The unhappiness/negativity category included statements in which the participant expressed dissatisfaction with the information, whilst not appearing to question the validity of the information. If the participant did expressive disbelief about the information being presented, then this was categorised as scepticism. The surprised category was applied to any participant who provided a comment that suggested the information was not what they were expecting, but who did not suggest that information was inaccurate in some way. Inter-rater reliability, as calculated using the method recommended by Miles and Huberman [26], was found to be 96% agreement on 95% of the codes. It should be noted that most answers provided by participants in response to the open questions were composed of no more than a couple of words, which limited the extent to which qualitative analysis could be applied to this data.

The most common reaction by participants to being presented with information about how much time they spend on their smartphone was happiness/acceptance (55.3%). Approximately one-quarter (26.6%) reacted with unhappiness/negative, with 8.5% expressing surprise and 4.3% expressing scepticism. The most common reaction by participants to being presented with information about how often they check their smartphones was unhappiness/negative (43.6%), with 34% expressing happiness/acceptance of this information. A smaller number expressed surprise (9.6%) or scepticism (8.5%).

The most common reaction to being presented with information about the actual norm of time spent using smartphones was happiness/acceptance (55.3%), with 16% expressing unhappiness/negative, 13.8% expressing surprise and 7.4% expressing scepticism. The most common reaction to being presented with information about the actual norm of number of smartphone checks was also happiness/acceptance (50%), followed by unhappiness/negative (20.2%), surprise (13.8%) and scepticism (5.3%).

4. Discussion

It is interesting that participants did not perceive others to either spend more time using their smartphone, or to check their smartphone more often than the participants themselves. This is in contrast to the social norms literature, where it has been found that individuals typically misperceive the behaviours of their peers, with negative behaviours perceived to be the norm [3]. However, the pattern of results with regards to smartphone use for specific purposes (social media, gaming, emailing) was consistent with the social norms research literature, with participants on average reporting that they spent less time on these activities compared to others. This suggests that any social norms intervention aimed at reducing smartphone use should focus on specific behaviours of app use, rather than just the use of the smartphone as a device.

It is also interesting to note what was not found to be significant. Apart from a single instance in one of the regression models, gender was not found to be a significant predictor of self–other discrepancy. The role of gender in normative misperceptions and the social norms approach has been a matter of debate in the literature. It has been argued that using gender-specific norms in the social norms approach may be appropriate for behaviours such as excessive alcohol use, due to female participants reporting greater self–other discrepancies [27]. In contrast, other studies have found that the inclusion of gender-specific norms appears to have no impact on campaign effectiveness [28]. It has been suggested that whether or not gender is relevant to a perceived social norm is in part determined by how much the behaviour in question is associated with a specific gender [3]. In the case of alcohol consumption, for example, it may that heavy drinking is something that individuals perceive as being primarily a male behaviour, particularly within the context of the American college system, where much of the research literature emerged. In this study, the overall lack of a gender effect on perceived self–other discrepancies may suggest that smartphone and app use are not seen by participants as behaviours that one gender is more likely to engage in than another. The one regression model where gender was significant was using the smartphone for gaming, with female participants demonstrating a greater self–other discrepancy. This would appear to be consistent with the stereotype of gaming being a predominately male activity. If these findings are supported, then they have important implications for the use of the social norms approach in combatting excessive smartphone use. As noted, the use of technology in the social norms approach does make it substantially easier to tailor interventions to specific groups. However, this should only be the case when there is a genuine need for those groups to be targeted.

The five personality traits included in each of the regression models were, overall, not found to be consistent statistically significant predictors of self–other discrepancies. There were some exceptions to this, with for instance an increase in the personality trait of neuroticism being predictive of perceiving others to check their smartphones less often than themselves. This could be explained by individuals who are high in neuroticism being aware of this aspect of their personality and inferring that their neurosis leads them to check their smartphone more often than is normal. Self-control was also a significant predictor in several regression models, albeit not all of them. In each case, an increase in self-control predicted a larger self–other discrepancy value, with most participants perceiving others to have greater smartphone usage than themselves. This was an unanticipated result. As with personality traits, it is possible that individuals are aware of their own self-control tendencies, and those high in self-control assume that others are more likely than themselves to use their smartphone excessively. These findings highlight the need for further understanding as to what determines self–other discrepancies. Doing so will allow for more nuanced and informed social norms intervention strategies. As commented previously, behaviours relating to digital devices are ideally placed for such applications, given the abilities of personalisation, and tailoring that the technology can provide.

Most participants were found to overestimate how much time they spend on their smartphone per day, by an average of over 2 h, but to underestimate how many times they check their smartphone per day, by an average of 77.6 checks. For both time spent and number of checks, the standard deviation was high relative to the mean, suggesting that this gap between self-reported and actual varied substantially across participants. This demonstrates the value of using objective measures of behaviour such as the device usage records that were used in this study. It is of note that participants overestimated time spent but underestimated number of checks. This may relate to the nature of each behaviour. Time spent using a smartphone involves deliberate actions, such engaging with apps. Such activities are easily visualised. As predicted by the availability heuristic, the more easily an individual can imagine something, the more frequent and likely they perceive it to be [29]. Checking your smartphone could in contrast be considered a habitual behaviour, which refers to automatic behaviours that can occur with minimal conscious monitoring [30]. This contrasts with other behaviours that have been studied using the social norms approach, which typically involve conscious and more purposeful decision-making processes such as deciding to drink alcohol. This suggests that interventions that aim to reduce how often individuals check their smartphones may need to first raise awareness of this behaviour to a more conscious level in the individual. This is something that it achievable using technology, such as a notification that prompts the smartphone user that they have already checked their smartphone within recent minutes.

It is acknowledged that there are some limitations to this study. The mean age of the participants (27.2 years) is relatively low. It could be argued that younger adults are the age group most associated with smartphone use. However, as demonstrated within this paper, perceived norms are not always accurate. It would be interesting to explore behaviours and perceived norms of smartphone use in older adults. Studies in other behavioural domains suggest that misperceptions of peer behaviours and attitudes tend to reduce as individuals become older [6]. There is a lack of longitudinal research on this topic. It is also noted that the sample used in this study covered a wide geographical region, consisting primarily of participants from the USA, the UK, and Australia, including participants from 21 other countries. It has been observed that perceived social norms and self–other discrepancies vary by country [4], but there is a lack of research on the relationship between culture and perceived social norms. Given the ability of digital platforms to simultaneously record and collect data across multiple countries at once, at relatively low cost, it is possible that this gap can be more fully addressed in subsequent research.

Only a small number of participants expressed scepticism at the information they were presented with about norms of smartphone usage, but those who did made comments about how, for example, they use their smartphone for purposes such as GPS. This reflects a wider issue in the definition of digital addiction as a problematic behaviour, which is that it can be difficult to separate functional behaviours from excessive ones [19]. If an individual is sent a social norms message that they feel does not demonstrate an understanding of their personal context, then there is a risk that they will have a negative reaction. Nevertheless, most participants in this study did indicate an acceptance of the information that was presented to them, even if, as noted in some instances, they found this information surprising. In addition, in this feasibility study, we only presented the social norms to participants once, and then queried their reaction to this information. To fully test the possibilities in applying the social norms approach to digital addiction, the results of this study must be built upon through conducting randomised control trials with follow-up data collection. This paper takes the first step in this process by providing evidence that normative misperceptions of smartphone use exist. These misperceptions are the basis of the social norms approach, and a pre-requisite for the successful implementation of a social norms campaign.

In this study, we have demonstrated the potential for applying the social norms approach to empower individuals to take greater control of their smartphone use, which in doing so will also help address some of the methodological limitations that are present in the social norms literature. As digital addiction becomes an increasingly prominent societal issue, there is a need for evidence-based strategies to address this new phenomenon.

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References

1. Cialdini, R.B.; Trost, M.R. Social influence: Social norms, conformity and compliance. In *The Handbook of Social Psychology*, 4th ed.; Gilbert, D.T., Fiske, S.T., Lindzey, G., Eds.; McGraw-Hill: New York, NY, USA, 1998; Volume 1–2, pp. 151–192. ISBN 139780470137475.
2. Hogg, M.A.; Reid, S.A. Social identity, self-categorization, and the communication of group norms. *Commun. Theory* **2006**, *16*, 7–30. [CrossRef]
3. Dempsey, R.C.; McAlaney, J.; Bewick, B.M. A critical appraisal of the social norms approach as an interventional strategy for health-related behavior and attitude change. *Front. Psychol.* **2018**, *9*. [CrossRef] [PubMed]
4. McAlaney, J.; Helmer, S.M.; Stock, C.; Vriesacker, B.; Van Hal, G.; Dempsey, R.C.; Akvardar, Y.; Salonna, F.; Kalina, O.; Guillen-Grima, F.; et al. Personal and perceived peer use of and attitudes toward alcohol among university and college students in seven EU countries: Project SNIPE. *J. Stud. Alcohol Drugs* **2015**, *76*, 430–438. [CrossRef] [PubMed]
5. Mahler, H.I.M.; Kulik, J.A.; Butler, H.A.; Gerrard, M.; Gibbons, F.X. Social norms information enhances the efficacy of an appearance-based sun protection intervention. *Soc. Sci. Med.* **2008**, *67*, 321–329. [CrossRef]
6. McAlaney, J.; Bewick, B.; Hughes, C. The international development of the 'Social Norms' approach to drug education and prevention. *Drugs Educ. Prev. Policy* **2011**, *18*, 81–89. [CrossRef]
7. Jones, E.E.; Davis, K.E. From acts to dispositions—The attribution process in person perception. *Adv. Exp. Soc. Psychol.* **1965**, *2*, 219–266.
8. Neighbors, C.; Lewis, M.A.; Atkins, D.C.; Jensen, M.M.; Walter, T.; Fossos, N.; Lee, C.M.; Larimer, M.E. Efficacy of Web-Based Personalized Normative Feedback: A Two-Year Randomized Controlled Trial. *J. Consult. Clin. Psychol.* **2010**, *78*, 898–911. [CrossRef]
9. National Institute on Alcohol Abuse and Alcoholism. *Planning Alcohol InterventionsUsing NIAAA's CollegeAIM Alcohol Intervention Matrix*; National Institute on Alcohol Abuse and Alcoholism: Bethesda, MD, USA, 2015.
10. Midanik, L.T. Validity of self-reported alcohol use: A literature review and assessment. *Br. J. Addict.* **1988**, *83*, 1019–1029. [CrossRef] [PubMed]
11. Pape, H. Young people's overestimation of peer substance use: An exaggerated phenomenon? *Addiction* **2012**, *107*, 878–884. [CrossRef]
12. Perkins, H.W. *The Social Norms Approach to Preventing School and College Age Substance Abuse: A Handbook for Educators, Counselors, and Clinicians*; Jossey-Bass/Wiley: Hoboken, NJ, USA, 2003; p. xvi, 320.

13. Brehm, S.; Brehm, J. *Psychological Reactance: A Theory of Freedom and Control*; Academic Press: New York, NY, USA, 1981.
14. Krick, A.; Felfe, J. Who benefits from mindfulness? The moderating role of personality and social norms for the effectiveness on psychological and physiological outcomes among police officers. *J. Occup. Health Psychol.* **2020**, *25*, 99–112. [CrossRef]
15. Geeraert, N.; Li, R.; Ward, C.; Gelfand, M.; Demes, K.A. A tight spot: How personality moderates the impact of social norms on sojourner adaptation. *Psychol. Sci.* **2019**, *30*, 333–342. [CrossRef] [PubMed]
16. Cudo, A.; Wojtasinski, M.; Tuznik, P.; Griffiths, M.D.; Zabielska-Mendyk, E. Problematic Facebook use and problematic video gaming as mediators of relationship between impulsivity and life satisfaction among female and male gamers. *PLoS ONE* **2020**, *15*, 29. [CrossRef]
17. Gillebaart, M. The 'operational' definition of self-control. *Front. Psychol.* **2018**, *9*. [CrossRef] [PubMed]
18. Kahneman, D.; Slovic, P.; Tversky, A. *Judgment under Uncertainty: Heuristics and Biases*; Cambridge University Press: Cambridge, UK; New York, NY, USA, 1982; 555p.
19. Almourad, M.B.; McAlaney, J.; Skinner, T.; Pleva, M.; Ali, R. Defining digital addiction: Key features from the literature. *Psihologija* **2020**, *53*, 237–253.
20. Alutaybi, A.; Al-Thani, D.; McAlaney, J.; Ali, R. Combating Fear of Missing Out (FoMO) on Social Media: The FoMO-R Method. *Int. J. Environ. Res. Public Health* **2020**, *17*, 6128. [CrossRef]
21. Alrobai, A.; Algashami, A.; Dogan, H.; Corner, T.; Phalp, K.; Ali, R. COPE.er Method: Combating digital addiction via online peer support groups. *Int. J. Environ. Res. Public Health* **2019**, *16*, 1162. [CrossRef]
22. Ali, R.; Jiang, N.; Phalp, K.; Muir, S.; McAlaney, J. The emerging requirement for digital addiction labels. In *Proceedings of the Requirements Engineering: Foundation for Software Quality*; Springer: Cham, Switzerland, 2015; pp. 198–213.
23. Alblwi, A.; Stefanidis, A.; Phalp, K.; Ali, R. Procrastination on social networks: Types and triggers. In Proceedings of the 2019 6th International Conference on Behavioral, Economic and Socio-Cultural Computing (BESC), Beijing, China, 28–30 October 2019.
24. Rammstedt, B.; John, O.P. Measuring personality in one minute or less: A 10-item short version of the Big Five Inventory in English and German. *J. Res. Pers.* **2007**, *41*, 203–212. [CrossRef]
25. Tangney, J.P.; Baumeister, R.F.; Boone, A.L. High self-control predicts good adjustment, less pathology, better grades, and interpersonal success. *J. Pers.* **2004**, *72*, 271–324. [CrossRef]
26. Miles, M.B.; Huberman, A.M. *Qualitative Data Analysis: An Expanded Sourcebook*, 2nd ed.; Sage Publication: Thousand Oaks, CA, USA, 1994.
27. Lewis, M.A.; Neighbors, C. Optimizing personalized normative feedback: The use of gender-specific referents. *J. Stud. Alcohol Drugs* **2007**, *68*, 228–237. [CrossRef]
28. Lojewski, R.; Rotunda, R.J.; Arruda, J.E. Personalized normative feedback to reduce drinking among college students: A social norms intervention examining gender-based versus standard feedback. *J. Alcohol Drug Educ.* **2010**, *54*, 19–40.
29. Tversky, A.; Kahneman, D. Availability: A heuristic for judging frequency and probability. *Cognit. Psychol.* **1973**, *5*, 207–232. [CrossRef]
30. Bargh, J. The four horsemen of automaticity: Awareness, efficiency, intentions and control. In *Handbook of Social Cognition*; Wyer, R., Srull, T., Eds.; Lawrence Erlbaum: Mahwah, NJ, USA, 1994; p. 1040.

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