The Effect of Social Media on Subjective Well-Being and Decision-Making

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Abstract

The number of social media users worldwide is increasing every year, expected to reach 5.85 billion by 2027. With the growing influence of social media, there have also been rising concerns about its potential negative effects on mental health and well-being. This study incorporates evidence from psychological and economic research to investigate the impact of social media on subjective well-being and decision-making in a novel approach. By conducting an online experiment, inconsistencies were compared in responses to economic trade-offs and happiness questions between a treatment group exposed to social media and a control group. This was achieved by creating a binary variable for each trade-off, which was then used as the dependent variable in a general-to-specific modelling approach, resulting in the construction of a total of three logistic regressions. The findings indicate an increased divergence between expressed preferences and hypothetical choices in the presence of social media. Additionally, the study provides evidence of lower stated happiness levels in the treatment group.

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1 Introduction

The number of social media users worldwide is increasing every year. It increased from 3.71 billion in 2020 to 5.05 billion in 2024. By 2027, the number of users is further expected to rise to 5.85 billion (Statista (2024a); Statista (2024b)). The high user numbers are also accompanied by long usage times. The average amount of time spent on social media worldwide was 2 hours and 23 minutes, equating to around 35.8% of the daily online activities and visits on average across 6.7 different social media platforms in 2024 (DataReportal, 2024). An examination of these figures reveals the undeniable prevalence of social media in the daily lives of billions of people around the world. The importance of social media platforms in modern life is largely unquestioned, especially among younger demographics.

As the influence of social media has grown, so have concerns about its potential negative impact on mental health and well-being. In recent years, the field of psychology has devoted significant research to investigating this concern (Karim et al., 2020). While social media offers undeniable benefits, such as facilitating communication and fostering emotional connections (Deters & Mehl, 2013), its impact on mental health requires careful consideration. There are many findings in the research indicating that social media is associated with negative consequences regarding mental health, such as depressive symptoms or anxiety (Keles et al., 2020). However, the relationship between social media and mental health is far more complex than first thought. Research highlights the importance of examining not only the use of social media itself but also the patterns of use, the motivations behind it, and the underlying mental health of the user (e.g. Davila et al. (2012); Hunt et al. (2018)).

Drawing on psychological insights, economists have also recently developed an interest in the topic, conducting their own investigations. Their analyses focus particularly on the welfare implications of social media in the context of subjective well-being, a proxy for utility used to evaluate self-assessed welfare outcomes (Allcott et al., 2020). Additionally, economists consider addiction patterns as a factor influencing behavioural biases in decision-making, particularly when designing incentives to mitigate harmful usage patterns, such as limiting social media use. Finally, they link mental health problems to lower productivity outcomes, a concern at both the microeconomic and macroeconomic levels (Allcott et al. (2022); Braghieri et al. (2022)).

This research contributes to the growing research field on the impact of social media from a behavioural economic point of view, offering an interdisciplinary approach. Specifically, it investigates how exposure to social media platforms influences subjective well-being and decision-making processes. Therefore, the study employs a unique experimental approach based on a survey design developed by Benjamin et al. (2012). Their research examined the outcomes of participants engaging in economic trade-offs, by comparing subjective well-being questions and hypothetical choices. Building on this work, this study introduces a social media priming element within the experimental design. This allows the investigation of the immediate effect of social media on both subjective well-being and decision-making and, in essence, aims to determine whether participants choose options in economic scenarios that align with their stated preferences for happiness in comparison to hypothetical situations. To investigate the influence of social media on subjective well-being and decision-making, this research compares the inconsistencies in responses to economic scenarios when they are framed both as happiness questions and as hypothetical choice questions. The comparison is made between the treatment group, which was exposed to social media, and the control group. This design allows for an empirical assessment of social media's impact using a novel approach.

The rest of this study is structured as follows: After defining social media in Section 2, a literature review in Section 3 covers the current state of research in regard to the psychological implications of social media and its economic effects on welfare outcomes. Section 4 presents the methodology for the conducted experiment, followed by the results of the experiment in Section 5. Section 6 concludes and discusses the findings.

2 Defining social media

As social media platforms have become ubiquitous in most people's daily lives, defining 'social media' may appear straightforward. There tends to be a consensus regarding which platforms are classified as social media without an explicit definition of the term itself. Nevertheless, it is important to define social media to establish clear boundaries for this research, which investigates the impact of social media on subjective well-being and decision-making. The term 'social media' has its origins in the development of an interactive, text-based online service in Tokyo in 1994, a period marked by the emerging commercialisation of the Internet and its growing relevance to the public. Over time, social media platforms and their functionalities have changed as the underlying technologies have changed. User interactions expanded beyond simple text exchanges to include additional features such as the ability to post and edit images, share videos, and engage in customised experiences such as live streaming (Aichner et al., 2021, p. 215). The technological evolution and growing social importance of social media are also evident in attempts to conceptualise it in the academic literature. Prior to 2010, social media was mainly seen as a digital tool for connecting people with similar interests. However, mainly due to the increasing technological possibilities after 2010, there has been a notable shift in conceptualisation, with a greater emphasis on the relevance of user-generated content, which marks a shift from earlier definitions of social media as merely a tool for networking. Today, social media platforms have become and are considered multi-functional hubs where information from individuals and companies is aggregated and made available online for sharing and discussing (Aichner et al., 2021, p. 220). The dynamic nature of social media entails two main challenges for its definition, as stated by Obar & Wildman (2015, p. 746). The first challenge is the rapid development of technology, which complicates the task of accurately defining the boundaries of social media. The second challenge involves the functional overlap between social media services and other forms of communication, such as email or forums. This overlap raises questions about whether these other technologies could also be considered social media due to their comparable functionalities. Being aware of these challenges, Carr & Hayes (2015) proposed a definition that distinguishes social media as a specific subcategory of media tools designed to enable social interactions, emphasising the active contribution of content creation in light of rapidly evolving technological enhancements. They defined social media as follows:

"Internet-based, disentrained, and persistent channels of masspersonal communication facilitating perceptions of interactions among users, deriving value primarily from user-generated content." The key to defining social media is that these platforms are online tools that can be accessed via the Internet but do not have to be exclusively web-based. In fact, many developers are increasingly focusing on standalone applications that do not require web accessibility. Along with the technological capabilities of the Internet, channel disentanglement is another key aspect in defining social media, as it allows for asynchronous communication, enabling users to interact without having to be online at the same time and, therefore, communicate asynchronously. Carr & Hayes (2015) further emphasised the notion of perceived interactivity, where the essence of social media does not necessarily lie in the actual interaction between users but rather in the user's perception of being in an interactive environment. This perspective broadens the definition of social media and includes platforms where interaction may not directly involve other users but is facilitated by algorithms or features that simulate interaction. As perceived interactivity comes along with user-generated content, the value of social media lies in the interactions and connections between users rather than just the content that is generated itself. User-generated content can be understood as a channel through which users engage with each other, such as by commenting and having discussions. Finally, mass personal communication allows users to share messages that can be seen by many but also enables direct, personal replies. This means communication can shift seamlessly between public and private exchanges, breaking down traditional restrictions between mass and interpersonal communication (Carr & Hayes, 2015, p. 50). Establishing this definition provides a clear baseline of what is meant by social media when it is referred to within the scope of the research and ultimately allows one to narrow down what is meant by investigating the effect of social media on subjective well-being and decision-making.

3 Literature review

The high number of users who interact with social media platforms daily has raised the question in the scientific debate as to what effect social media could potentially have. For the most part, scientific studies have focused on psychological outcomes, including whether and to what extent social media has an impact on mental health and overall well-being. Recently, however, the economic literature has also addressed the question and attempted to determine the welfare effect of social media using, for instance, experimental methods, thus building a bridge to the psychological literature. To build on the existing scientific evidence for this study, the psychological findings on mental health and well-being are presented in the following subsections and subsequently connected to the economic research findings.

3.1 Psychological implications of social media

There is a considerable body of literature dedicated to exploring the psychological implications of social media, focusing on two main areas of research – mental health and general well-being – which, despite their overlapping concepts, maintain distinct areas of focus. Wren-Lewis & Alexandrova (2021, p.698) argued that mental health is not simply the absence of mental illness but the capability to cope resiliently with obstacles and challenges in one's life. This perspective suggests that people can be free of mental illness and still not have the positive psychological functioning that is indicative of sound mental health. The concept of mental health is fundamental, but it is not a complete measure of an individual's well-being. Well-being encompasses a broader range of experiences, including emotions like happiness and fulfilment. Keller (2020) distinguished between mental health and well-being, acknowledging their interrelation but emphasising the need to distinguish between the two. This differentiation is essential, especially in cases where pursuing increased well-being may unintentionally result in negative effects on one's mental health. Conversely, a one-dimensional emphasis on mental health may not fully consider the wider aspects of well-being. Considering this, the present review aims to methodically examine the literature on the psychological impact of social media use, distinguishing between its effects on mental health and well-being.

Mental health

In terms of psychological effects on mental health, previous studies have shown mixed results. Regarding the positive effect, it was shown that the possibility of digital networking among young people has led to an improvement in their psychological health. The positive effects were attributed to the fact that social media platforms provide young people with the opportunity to express their thoughts and feelings, as well as receive social support if needed (Deters & Mehl, 2013). On the other hand, there are several negative effects that have been identified in connection with social media use. In a systematic review of the impact of social media on psychological distress, anxiety, and depression in young people aged 13–18, Keles et al. (2020) identified four distinct domains in the literature related to social media exposure. The first domain is attributed to the total amount of time spent on social media platforms. In connection with the time spent on social media, the type of activity is decisive, where, fundamentally, a distinction is made between active and passive social media use. Active social media use refers to direct interaction by deliberately engaging with content on social media platforms by commenting and posting content. Passive social media use relates to, for example, scrolling without engaging in these direct interactions. The third area relates to investment, which equates to the effort users are willing to put in when spending time on social media, which, for instance, can be how much someone posts identity-related posts. However, investment should be distinguished from addictive patterns, which are also the fourth domain related to mental health problems and social media usage, which is related to behavioural and psychological dependency on social media. Interestingly, Keles et al. (2020, p. 88) concluded that the relationship between social media use and mental health problems is also influenced by societal perceptions and constructs. This suggests that the effects of social media on mental health are not merely direct consequences of individual usage. Instead, they are also shaped by the broader social and cultural context in which these platforms are used. Evidence on time spent on social media has shown mixed results. In a longitudinal study over eight years, social media use was examined in relation to anxiety and depression between the ages of 13 and 20. Both a between-subjects design and a within-subjects design were used in this study. The between-subjects analyses indicated a moderate relationship between mental health issues, specifically depression and anxiety. However, for the within-subjects design, no association was found between time spent on social media and mental health over the entire observation period of eight years (Coyne et al., 2020, p. 6). This study provides a crucial contribution to demonstrating how different methodological approaches can lead to different results in answering a research question. Importantly, this would suggest that the between-subjects design would reveal that people in the sample who were more likely to report mental health problems were also those who were more likely to use social media. In a different experimental study, the time spent on social media was investigated by limiting the use of platforms like Facebook, Instagram, and Snapchat with

a focus on the impact on mental health around depression and loneliness. One-hundred and forty-three students aged between 18 and 24 were divided into two groups, with one group limiting their use of social media to 10 minutes per day over three weeks. The second group maintained its normal social media consumption. The limitation of social media usage times showed that the group with restricted social media use experienced notable decreases in loneliness and depression compared to the control group. Notably, reductions in anxiety in the context of the fear of missing out were observed in both groups, suggesting that participating in the study likely made all participants more conscious of their social media habits, leading them to think more critically about how they engaged with social media (Hunt et al., 2018, pp.751, 767). In a two-part study focusing on the relationship between social network use and depressive symptoms in young adults with an average age of 20 years, the role of online interaction quality was examined. These studies concluded that the quality of social networking interactions has a more profound impact on depressive symptoms than merely the amount of time spent on these platforms. They further identified that individual tendencies towards rumination – repetitive overthinking about one's negative emotions – and co-rumination, which involves extensive discussions of negative emotions with others online, can worsen the effects of social media on mental health. The authors noted that these findings align with existing research, which has established a link between negative interactions with social media content and elevated depressive symptoms (Davila et al., 2012, p. 10–11). In the context of how social media is used (i.e. the previously mentioned area of activity), Escobar-Viera et al. (2018) examined the impact of active compared with passive social media engagement on mental health problems in adults aged 18–49. The study highlighted the importance of considering both the quantity and quality of social media use. The results showed that for every one-point increase in passive social media use, there was a corresponding 33% increase in depressive symptoms. Conversely, higher levels of active social media engagement were associated with a 15% reduction in depressive symptoms. In line with (Davila et al., 2012), these findings suggest that psychological distress may have a reinforcing effect on interacting more passively online for symptoms such as anhedonia, the inability to experience pleasure from activities that are usually found enjoyable. The researchers concluded that while it is difficult to quantify the exact impact of social media on depression, including possible bi-directional effects, based on their findings, it may be beneficial to encourage more active engagement with social media in general. In a further study of the relationship between users' engagement with Instagram and depressive symptoms, engagement was defined not only by how long users interacted with the platform but also by the degree of emotional involvement they showed. This emotional investment was associated with depressive symptoms through the mechanisms of negative social comparison and the extent to which individuals engaged with content from strangers. Participants aged 18 to 29 completed online surveys that measured their depressive symptoms using a depression

scale and assessed their social comparison tendencies. The results suggest that depressive symptoms are more likely to occur in individuals who frequently engage in negative comparisons with other users on Instagram. This was particularly evident in users who follow many strangers (Lup et al., 2015, p. 249–251). Finally, the fourth domain of psychological implications of social media is related to possible patterns of addiction. In a recent cumulative study, it has been empirically shown that social media addiction is negatively associated with both mental health and academic performance among college students. Additionally, the role of self-esteem as a mediating factor between a social media addiction and its outcomes was observed. The findings indicated that social media correlates with lower mental health, which was partially mediated by a decrease in the student's self-esteem. Furthermore, when examining the reverse relationship – with mental health as a predictor and social media addiction as an outcome – the mediating role of self-esteem was found to be insignificant. However, this does not rule out the possibility that declining mental health may contribute to increased social media addiction. Specifically, individuals experiencing poor mental health characterised by low self-esteem may turn to social media as a compensatory mechanism for their lack of real-life social interactions, potentially leading to an over-reliance on these digital platforms (Hou et al., 2019, p. 9–10).

Overall well-being

The second research domain explores the impact of social media on overall well-being. This body of literature presents a range of findings on how social media usage correlates with various aspects of well-being, including perceived life satisfaction or emotional states, not directly linked to mental health problems. For example, one study highlights the complexity of this relationship by highlighting that time spent on Facebook has different effects depending on the user's underlying motivations. In particular, people who use Facebook to keep in touch with existing friends generally report higher levels of life satisfaction than those who use the platform in the hope of making new connections (Rae & Lonborg, 2015, p. 7).Other studies have taken a longitudinal approach, asking participants to report their feelings about using Facebook over two weeks. This method allowed emotional states to be tracked over time. The results suggest that increased Facebook use correlates with a decline in affective subjective well-being, which encompasses the spectrum of positive and negative emotional experiences. Specifically, it was observed that participants who used Facebook frequently reported feeling 8% lower in their emotional state ratings between two points in time compared to periods when they refrained from using Facebook completely (Kross et al., 2013, p. 2–3). Sagioglou & Greitemeyer (2014) examined the immediate emotional impact of Facebook use on life satisfaction, aiming to mitigate retrospective bias. Across three different studies, they consistently found that a 20-minute exposure to Facebook led to a decrease in positive emotions or an increase in negative emotions. This resulted in a

detrimental effect on participants' immediate emotional states compared to a control group that had not used social media for the same period of time (Sagioglou & Greitemeyer, 2014, p. 360–362). This is consistent with research by Tromholt (2016), which showed that individuals who took a break from Facebook experienced a significant increase in life satisfaction and emotional well-being, in contrast to the control group which continued to use the social media platforms. This suggested that a short break from Facebook can lead to significant improvements in both the cognitive and affective dimensions of well-being (Tromholt, 2016, p.662–664). Recent studies have focused on the role of mediating factors in the influence of social media platforms on well-being, providing a more in-depth analysis. De Vries et al. (2018) explored the impact of viewing strangers' Instagram posts on emotions, applying social comparison, and emotional contagion theories. They found that individuals' reactions to positive posts depend on their tendency towards social comparison. Those prone to frequent comparisons experienced a decline in positive emotions, whereas individuals less inclined to compare themselves felt an increase in positivity. Contrary to initial expectations, only positive emotions were affected; negative emotions remained unchanged. This supports earlier findings that social comparison on social media can decrease happiness without inducing negative emotions. One of the key aspects of the dynamics of social media is the impact of self-disclosure. Luo & Hancock (2020) explored the implications of self-disclosure within social media dynamics, proposing a two-process framework that highlights the bi-directional relationship between self-disclosure and well-being. This framework posits that self-disclosure on social media can enhance well-being by fostering a sense of connectedness, potentially alleviating feelings of loneliness and thereby improving overall well-being. Conversely, the framework also considers how states of well-being influence disclosure motivations. For instance, individuals experiencing distress may engage in self-disclosure that portrays an inaccurate self-image, adversely affecting their well-being.

3.2 Economic effects of social media

Given the transformative impact of social media on contemporary society and the findings from psychological research discussed in the previous section, the economic implications of social media platforms have received increased interest. This section is dedicated to exploring the various economic impacts of social media as reported in the existing literature. This allows for an understanding of the economic implications and places the current work within the broader context of existing studies in economics.

For a long time, the positive effects of connectivity and the provision of information through platforms on well-being and mental health have been considered. This has often led to the conclusion that social media platforms are welfare-enhancing (Myers, 2000).

However, the potential negative effects of social media have recently come under increased scrutiny. One of the first areas to address the negative consequences of social media was the field of political economy and its impact on both political and economic outcomes. Levy (2021) contributed to the research by investigating the impact of social media on news consumption and its potential behavioural consequences, particularly in terms of political polarisation. By conducting a field experiment, the study examined the effects of exposure to politically consistent news on social media platforms. The research found that exposure to news that aligns with an individual's political beliefs increases affective polarisation, which refers to the emotional divide between different political factions. This evidence highlights the role of social media in amplifying polarisation, raising critical concerns about its impact on trust in government and the accountability of public officials. The experiment also showed that individuals' core political opinions are not easily influenced by the political bias of the news they consume. This finding is consistent with a broader trend of growing affective polarisation in political discourse, suggesting that the segmentation of news sources into ideologically homogeneous groups may contribute to this phenomenon without necessarily altering individuals' political beliefs (Mason, 2015). This finding is particularly interesting from a behavioural economics perspective, as it highlights how algorithms tend to prioritise content based on users' political preferences, leading to a lack of exposure to contrasting viewpoints. Ultimately, from an economic perspective, it was demonstrated that the processes of affective polarisation can lead to economic uncertainty (Baker et al., 2020).

A few prominent studies have also been dedicated to researching the economic welfare impact of social media, as little is known about this aspect. Mosquera et al. (2020) conducted a field experiment with 1,769 participants from a U.S. university. The experiment examined the effects of restricting access to Facebook on people's engagement in daily activities and their exposure to news by randomly assigning an experimental group with a one-week Facebook restriction and a control group with no restrictions. In addition, it was explored how much monetary value users placed on having access to Facebook. Related to the value individuals placed on using Facebook, the study quantified the value of one week of Facebook access at approximately $67 on average, with a median value of $40. The value placed on Facebook usage increased by 19.6% after participants were restricted from using it for one week. This suggests that not having access to Facebook heightened its perceived value among the users. As discussed in the previous section on psychological implications, the increased value attached to Facebook access could signal addictive behaviour, with the absence of the platform increasing the desire or perceived need for it. Alternatively, this restriction could lead to a feeling of loss of access to information or social connectedness that becomes more severe over time (Mosquera et al., 2020, p. 577). The field experiment also assessed the impact of Facebook use on

subjective well-being across a range of domains. Although no statistically significant results were found for life satisfaction and happiness, the experimental group reported a 17% reduction in feelings of depression, which the authors concluded may indicate that Facebook use can induce feelings of depression. Indirect health measures found that the one-week restriction on Facebook use was associated with an increase in healthy daily activities of 0.86 standard deviations from baseline, with a p-value of 0.057, suggesting a trend towards healthier behaviour in the absence of Facebook use (Mosquera et al., 2020, p. 592). Allcott et al. (2020) followed a similar approach by conducting a large-scale randomised experiment to assess the welfare effects of social media, with a particular focus on restricting Facebook use. To analyse the impact on individual utility, the study used survey-based measures of subjective well-being and text messages to assess patterns of addiction and potential projection bias. Projection bias refers to a cognitive distortion that leads people to overestimate the extent to which future behaviour is influenced by current beliefs and values (Loewenstein et al., 2003). The research found modest but statistically significant improvements in the overall well-being of individuals who temporarily left Facebook. These positive changes included increased levels of happiness and life satisfaction, as well as significant reductions in symptoms of depression and anxiety, which aligns with the previous findings. The index for subjective well-being increased by 0.09 standard deviations, which, in comparison, is an equivalent of a 25% to 40% effect of psychological interventions. Interestingly, while 80% of the treatment group stated that the absence of social media use had a positive effect on them, they were against voluntarily quitting Facebook without receiving any money in exchange.

Another randomised trial examined the relationship between social media addiction and behavioural economic outcomes. In addition to conducting a randomised experiment, Allcott et al. (2022) developed an economic model of digital addiction. This model incorporates projection bias, awareness of habit formation, and self-control issues to explain their influence on digital consumption behaviour. Projection bias, as defined by Loewenstein et al. (2003), causes individuals to underestimate the impact of habit formation on their behaviour, potentially influencing their decisions regarding the use of social media. This bias may lead users to overlook how habitual the use of digital platforms can become, especially when considering the 'costs' associated with increased screen time or the potential for addiction. Building on the insights of Becker & Murphy (1988), awareness of habit formation could lead individuals to reduce their digital consumption if they anticipate negative consequences, such as reduced productivity or well-being. However, projection bias could reduce the effectiveness of this self-regulation because it leads individuals to underestimate how their current preferences for social media use will change over time. The experimental results further illustrate these concepts. The introduction of a monetary incentive to reduce social media usage significantly influenced

the behaviour of participants in the treatment group, suggesting habit formation. While the incentive was active, users in the bonus group reduced their app usage by 56 minutes per day – a 39% decrease compared to the control group. Remarkably, this reduced usage persisted even after the removal of the incentive, with a continued decrease of 19 minutes per day in the following three weeks and 12 minutes per day thereafter (Allcott et al., 2022, p. 2427). As mental illness has been linked to adverse effects on economic outcomes, particularly in the labour market and workforce productivity (Biasi et al. (2021); Shapiro (2022)), an important study examined the impact of social media on mental health using a quasi-experimental design. The impact of social media on mental health was observed using data from the introduction of Facebook at a U.S. college in the mid-2000s by linking survey data on students' mental health. The authors showed that the introduction of Facebook at the college had a negative impact on students' mental health and on their academic performance after the introduction of Facebook. This was explained by the fact that Facebook made it easier to engage in unfavourable social comparisons, particularly among students who may already feel excluded or inferior, such as those who live off campus and/or have a lower socioeconomic status Braghieri et al. (2022).

The research presented here, both in terms of psychological implications and economic effects, has shown that there are significant findings indicating that social media has a negative impact on people's well-being and behavioural patterns. However, the impact of social media on individual decision-making in economic contexts has not yet been studied, particularly in terms of what people think, what decisions they think would make them better off (perceived preferences), and what decisions they actually make (actual choice). Based on the literature and with regard to this study, the following hypotheses are proposed:

Hypothesis 1: Social media use creates divergence between expressed preferences and actual choices in economic decision-making.

Hypothesis 2: Social media has a negative impact on subjective well-being

4 Methodology

4.1 Experimental design

To investigate the effect of social media on subjective well-being and decision-making, an online experiment was conducted using a between-subjects design. The corresponding design for each sequential stage is summarised in Figure 4.1. After clicking on an online link to the experiment using an survey platform, participants were randomly assigned to either a treatment group or an experimental group without their knowledge. To minimise selection bias and ensure the validity of the experimental results, participants were not informed of the specific research question. In the first phase of the experiment, the treatment group was asked to identify which of six topics they most frequently encountered on social media platforms: lifestyle, music, family, beauty, fitness and gym, or art. These categories were chosen based on the distribution of influencers by topics worldwide (Statista, 2022) to ensure that the treatment group's exposure closely mirrored real-life social media usage patterns and to simulate the participants' natural interaction with social media as closely as possible. Afterwards, in the second stage, participants in the treatment group were shown a 25-second video specifically created based on their previously selected category. Each video was created by searching for a popular hashtag on Instagram closely related to the participant's selected category, and content was then filtered to showcase the 'top posts' associated with that hashtag. This approach aimed to reinforce a realistic simulation of content engagement on social media and the experience of scrolling through an Instagram feed in real life. On the other hand, the control group was primed with a neutral image retrieved from the Geneva Affective Picutre Database (GAPED) to ensure that the shown image was neutral (Dan-Glauser & Scherer, 2011). The use of a neutral prime is crucial to provide a controlled reference point that allows any observed differences between the treatment and control groups to be attributed to the effects of the treatment. In the third stage of the experiment, participants were then presented with four economic trade-offs, specifically focusing on social comparison, labor-leisure decision, decision under risk, and tax compliance. The aim of this step was to observe the effects of social media priming on decision-making. Each trade-off presented participants with two alternatives, from which they were required to choose one. Following the survey design of (Benjamin et al., 2012), the trade-offs were first framed in the context of a subjective well-being (SWB) question, asking participants which of the two options they believed would contribute

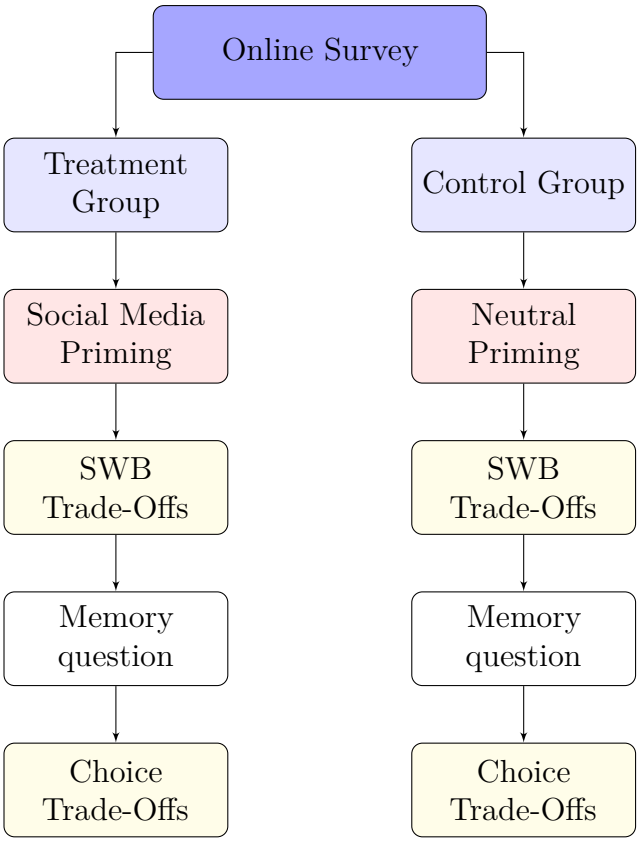


Figure 4.1: Experimental design

more to their overall happiness, which is a proxy for predicting higher well-being or, in economic terms, higher utility. For each SWB-related trade-off, participants rated how they would feel about their chosen option on a five-point Likert scale, ranging from 'rather happy' to 'very happy'. The trade-offs were then presented again as hypothetical choices to elicit what participants would choose in real-life scenarios if they were limited to these options. Each choice-related trade-off was followed by a question about the likelihood of choosing the selected option in reality, rated on a five-point Likert scale from 'rather likely' to 'very likely'. To minimise potential consistency effects, where participants might align their choices more with their previous responses than with their actual preferences between the happiness trade-offs and the choice trade-offs, a memory question regarding the priming from the beginning of the experiment was implemented. Furthermore, for all trade-offs, the presentation of the trade-offs was randomised for each participant to prevent the sequence from influencing subsequent responses and mitigate possible bias due to the shown order. At the end of the online experiment, participants were asked to provide demographic information and their social media usage patterns. To systematically capture the participants' social media usage patterns, a series of questions were formulated based on the Digital Maturity Inventory (DIMI) developed by (Laaber et al., 2023) that also served as control variables. All four economic trade-offs and the types of questions asked are listed in the appendix appendix.

4.2 Data Collection Methods

This study adopts the design of Benjamin et al. (2012) to investigate the effect of social media on subjective well-being and decision-making by adding the social media priming stage as a treatment. This method allows for the assessment of the immediate impact of social media use on individuals' perceptions of their subjective well-being (SWB). In addition, incorporating hypothetical economic choices enables the study of changes in decision-making processes induced by the priming effect. This unique approach makes it possible to determine, by comparing treatment and control groups, whether the influence of social media priming aligns with, or diverges from, the decisions individuals perceive as optimal for enhancing their SWB. Finally, this methodological choice directly addresses the challenge of observing the isolated effects of social media on potential biases in economic decision-making and provides a way to assess its impact in a controlled setting.

Priming as a treatment

Priming is a technique originally used in experimental psychology but which has recently received increasing attention in the economic literature. In psychology, priming is a technique in which exposure to one stimulus influences the response to a subsequent stimulus without conscious guidance or intent. This study employs social media priming that leverages associative priming. In the context of social media, associative priming can refer to how content influences users' thoughts, feelings, and behaviours by creating associations, either consciously or unconsciously (Molden, 2014, p. 4–6). Most economic research often assumes that individuals have stable preferences that do not change over time or across different situations. From this perspective, variations in behaviour are mainly driven by shifts in incentives, expectations, and constraints. The recent body of research on endogenous preferences challenges this idea and suggests that the economic and social context can significantly influence and shape preferences (Cohn & Maréchal, 2016, p. 17). This experiment leverages the concept of priming to explore its effects on economic decision-making and perceptions of happiness. Participants will be exposed to video content created specifically to reflect their most frequently encountered social media categories. By presenting the categories of social media participants most frequently encounter, the aim is to create a personalised priming condition that is mostly related to associative priming. Since social media engagement can go along with emotional involvement (Choudhury et al., 2012), in a broader sense, the use of primes can also be considered the induction of incidental emotions. Incidental emotions are emotions that are not related to actual decision-making processes. For example, Fochmann et al. (2019) showed in an experiment that individuals primed with images that induce positive incidental emotions were less likely to stick to social norms compared to those primed with images that induce negative ones. Although it is ex ante unknown which emotions the videos will induce, participants were asked to rate the Instagram video from 'Negative'

to 'Positive' on a five-point Likert scale at the end of the experiment, which also served as a manipulation check to verify the effectiveness of the priming.

Subjective well-being measure

Presenting participants with economic scenarios and asking them, in the first instance, which option would make them happier is closely related to the study of human happiness in the field of economics. In economic research, survey-based SWB measures are increasingly used as an empirical proxy for utility and enable economists to test and estimate models of preferences and evaluate welfare outcomes, especially when it is difficult to observe actual choices (Chen et al., 2019). In both economics and psychology, SWB measures also serve as a method to capture the individual assessment of one's own state of well-being, which is especially important at the next stage of the data-gathering process to test whether an individual's choices in a hypothetical scenario align with what participants believed would maximise their subjective well-being. In the context of social media use, the use of SWB measures is particularly practical because it has been shown that social media consumption can be associated with lower subjective well-being levels (Wirtz et al., 2021). Interestingly, from a neuroscientific perspective, this could also imply that the potential effects of social media on SWB levels can be correlated with specific brain structures, as shown by Jung et al. (2022). To capture one's own subjective well-being associated with an economic trade-off scenario, the questions were asked: What do you think? Which of the two options would make you happier? Then participants had to choose from one of two options. Furthermore, participants had to answer for each trade-off how happy they would feel with their chosen option on a five-point Likert scale from 'Rather happy' to 'Very happy'. This subsequent question allowed the investigation of the second hypothesis of this study, that social media has a negative impact on subjective well-being, by comparing the stated happiness levels between the treatment and control groups.

Scenarios for economic trade-offs

In everyday life, individuals often must choose between several options and weigh up the trade-offs when making decisions. In economics, trade-offs occur when individuals face scarcity or limited choices that force them to sacrifice one objective to achieve another. This sacrifice is quantified as the opportunity cost, the value of the alternative foregone when choosing between exclusive options (Mankiw, 2018). For this study, presenting trade-off scenarios to participants as a data collection method has several advantages and implications for observing decision-making. The use of trade-offs allows for the simulation of real-life decision-making and the direct observation of the preferences that are chosen when faced with constraints. In terms of opportunity costs, it also provides direct insight into how preferences are expressed when previously exposed to social media content unrelated to the decision itself. The scenarios used in the experiment were designed based on the key elements that are both economically and psychologically relevant in relation to

the use of social media. Eventually, four key areas were identified and chosen as relevant for designing the trade-offs to explore the effect of social media. The limitation to four scenarios in the study was intentionally to reduce the risk of participant dropout and to avoid cognitive fatigue during the experiment. The first economic scenario is related to the aspect of social comparison by presenting a trade-off between relative and absolute income. This is not only relevant for economics; in this relation, life satisfaction was studied, and it was shown that individuals have the tendencies to care more about relative incomes than absolute income (Clark & Oswald, 1996). It is also an important aspect of social media use since individuals are exposed to other people's content on social media, and there is a strong tendency to compare oneself with others (De Vries et al., 2018). The second economic scenario deals with the labor-leisure trade-off, a concept in economics that represents the choices individuals make between spending time on leisure activities and working. Since time is a finite resource, an increase in one activity necessarily comes at the expense of the other (Shimer, 2009). In the context of social media, where lifestyles are often presented in an idealised form and users frequently engage in leisure activities such as travelling, this may highlight economic and social disparities (Vogel et al., 2015). The third economic trade-off, which is relevant for studying the effect of social media on decision-making in the context of well-being, deals with decisions under risk. There is an extensive body of literature in behavioural economics that investigates the relationship between happiness and risk preferences. Although the results are inconclusive in general, there is moderate evidence that higher happiness levels increase patience for waiting for financial rewards (Lane, 2017). Finally, the last scenario incorporates aspects of morality in relation to tax compliance. Social media significantly influences moral behaviour by reducing the costs associated with actions like punishment. This results in an increase in sharing moral content, which can amplify both negative aspects, such as outrage, and positive aspects, such as social support (Van Bavel et al., 2024). Morality, as a central part of tax compliance (Lisi, 2015), was therefore chosen as a suitable trade-off to explore the effect of social media on economic decision-making.

4.3 Empirical Approach

To test the research hypothesis that social media use creates a divergence between expressed preferences and decision-making, the primary focus of the empirical approach lies on the participants' responses to the trade-off questions. The first set of trade-offs elicited which option participants believed would make them happier, followed by questions regarding which option they would actually choose. This approach allows for a comparison of potential divergences in responses between the experimental and control groups. There is an ongoing debate on how to interpret expressed preferences and revealed preferences, namely observed choices. From an economist's perspective, when individuals are faced with

a decision, the prevailing view assumes that preferences are reflected in decisions influenced by incentives, such as the amount of a salary or the price of a good. Furthermore, revealed preferences are considered equivalent to economic welfare, whether at an individual level or aggregated macroeconomically. Kahneman et al. (1997) added a notion to individual decision-making by arguing that the concept of utility has to be extended by experienced utility. Experienced utility is considered a hedonic and affective utility derived from current subjective experience and related to SWB measures, as previously discussed. Based on this dualistic approach to decision-making, it is possible to examine discrepancies between expressed preferences and actual choices, which have already been examined in several studies that have demonstrated the existence of discrepancies between predictions and choices, such as Hsee (1999) & Hsee et al. (2003) which consider such discrepancies as mistakes in human behaviour. To test the second hypothesis that social media has a negative impact on subjective well-being, the stated happiness levels associated with participants' chosen option in each of the trade-offs were analysed by calculating the distribution of stated happiness levels across all four scenarios.

Defining Inconsistencies

Considering this framework, this study investigated inconsistencies that are based on the alignment between responses to happiness and choice trade-offs for each of the four scenarios, with each scenario having two options to choose from. The inconsistency analysis was performed based on the responses to the happiness question and the choices made in the trade-off scenarios for both the experimental group and the control group. To do this for each of the four trade-offs (social comparison, labor-leisure decision, decision under risk, and tax compliance), the responses were compared to the happiness question with the equivalent choice made in the hypothetical choice scenario for both groups. If the responses within the same trade-offs differed, it was defined as an inconsistency. This was done by creating a binary variable for each trade-off, indicating either 1 for inconsistency or 0 for consistency. Furthermore, the binary variables were combined into a single vector for both groups to determine the total number of inconsistencies. To determine the total number of inconsistencies for each participant, the binary variable for inconsistencies was summed up across all four trade-offs. This approach provides a quantifiable and robust empirical method for analysing behavioural deviations between the treatment and control groups and ultimately observing the impact of social media on economic decision-making.

Logistic regression analysis

To extend the analysis with regard to behavioural inconsistencies, a logistic regression was conducted to examine the relationship between total inconsistencies as a binary dependent variable depending on the group assignment and demographic and social media usage patterns (Wooldridge, 2016, p. 225). The logistic regression model is generally specified as

follows:

$$\text{logit}(P(\text{Total_Inconsistencies} = 1)) = \beta_0 + \beta_1 \text{group} + \beta_{demographics} + \beta_{socialmedia_paterns}$$

Where $P(\text{Total_Inconsistencies} = 1)$ represents the probability of observing inconsistencies in a participant's responses. β_0 is the intercept term. β_1 is the coefficient associated with the dummy variable, *group* distinguishing between the treatment group exposed to social media intervention and the control group with no exposure. β_1 in relation to the group assignment represents the log odds of observing inconsistency for the treatment group relative to the control group, which allows to assess whether being in the treatment group is associated with a statistically significant difference. $\beta_{demographics}$ combines the effect of all demographic variables included in the model and therefore represents multiple coefficients. Similarly, $\beta_{socialmedia_patterns}$ aggregates the effects of social media patterns that participants have reported within the experiment.

The empirical approach that was pursued is most closely related to general-to-specific modelling (Campos et al., 2005). For this study, in total, three regressions were performed to analyse the impact on $Total_Inconsistencies$. The first model was constructed as a basic logistic regression model to assess the direct impact of being exposed to social media content exhibiting inconsistencies compared to the control group. As a foundational model, this consequently allows one to analyse whether social media exposure is associated with changes in behaviour. The second model is an expanded model that includes demographic variables such as age, education in years, or income. This inclusion aims to control for individual differences that can potentially confound the relationship with the dependent variable. Finally, in the third model, variables related to specific social media use patterns were included that are methodologically based on the Digital Maturity Inventory (DIMI) (Laaber et al., 2023) to control for theoretically significant aspects of social media engagement on inconsistencies and, therefore, decision-making.

5 Results

Descriptive statistics

Overall, the sample consisted of 76 participants, of whom 44 were randomly assigned to the control group and 32 to the experimental group. The mean age of the participants was 26.73 years, and 50.00% were male, 46.05% female, and 3.95% identified as diverse. The median monthly income in the sample was €1,162.50, with a stated average of 17.23 years of education. Regarding the platforms that were used most frequently, 44 participants said that they use Instagram most often, followed by Twitter, with 12 participants, and YouTube and TikTok, with six participant, respectively. On the other hand, Facebook was not even once checked as one of the options. Concerning social media usage patterns, when asked about how much time participants spend on social media on a normal weekday in their free time, 33 participants answered on a five-point Likert scale, from 1 (never) to 5 (very much), that they spend 'a lot of time' on social media, followed by 28 participants who sometimes spend time on social media. Six individuals stated that they spend 'very much time' on social media, and nine selected never or seldom. Participants were also asked to rate on a scale of 1 (fully agree) to 5 (fully disagree) whether they feel in control of their social media use. Thirty-four individuals stated that they disagreed (4) or fully disagreed (5) with being in control of their social media use, approximately 44.73% of the sample. Twenty-one individuals stated that they have a neutral viewpoint, and another 21 indicated that they agree or fully agree with feeling in control of their social media use (each 27.63% of the sample). When asked about social media use in relation to feeling upset or depressed and whether it takes a long time to feel better again, 25 participants have reported that they either agree or fully agree, which equates to roughly 32.89% of the sample. Meanwhile, 13 individuals positioned themselves as neutral, and 38 individuals either disagreed or fully disagreed (50.00%).

Results for inconsistency

The consistency analysis is based on the previously introduced binary variable, which identifies for each trade-off scenario instances of inconsistencies within both the experimental and control groups. An inconsistency is defined as a discrepancy between the participant's stated trade-off option that would make them happier, which can be interpreted as a choice that maximises their utility, and the eventual chosen option framed as a hypothetical choice scenario, which can be interpreted as expressed preferences or decision utility. Figure 5.1 depicts density histograms of inconsistencies for each group. Density histograms were

selected to compare the distributions of inconsistencies, thereby visualising the relative frequencies due to the differing sample sizes between the experimental and control groups. For the control group, there were 10 inconsistencies, with eight participants exhibiting one inconsistency across four scenarios. Two individuals displayed two inconsistencies over the same number of scenarios. Thirty-four individuals responded consistently, exhibiting no misalignment between the happiness and hypothetical choice questions. In the experimental group, there were 14 inconsistencies. Eight participants exhibited one inconsistency across the scenarios, while four participants exhibited inconsistencies in two scenarios. Unlike the control group, two individuals in the experimental group exhibited three inconsistencies in three out of four scenarios. The remaining 18 respondents answered consistently.

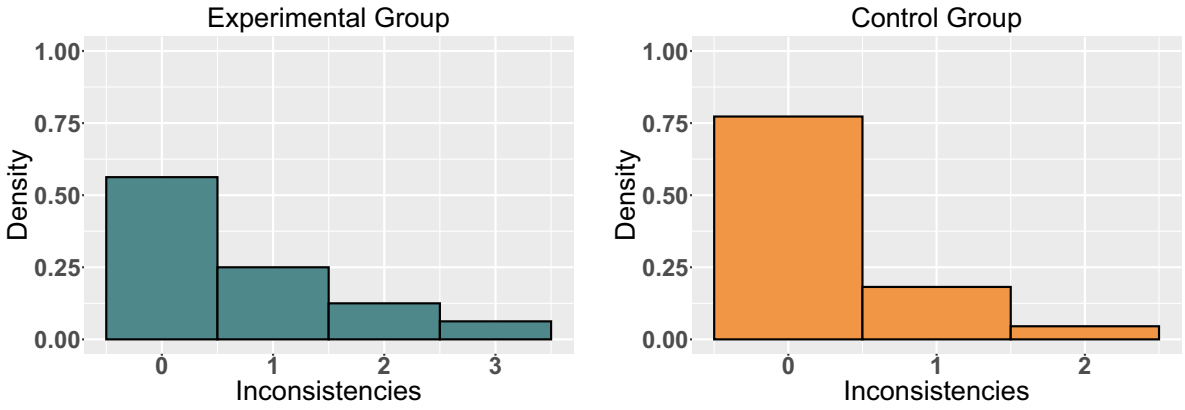


Figure 5.1: Histograms of inconsistencies in experimental and control group

To further assess the overall inconsistency of responses between the experimental and control groups, a 2x2 contingency table was constructed. Table 5.1 shows the frequency of consistent and inconsistent responses within each group. The table reveals that within the

Table 5.1: Distribution of Inconsistencies

	Consistent	Inconsistent	$\sum$
Experimental	106	22	128
Control	164	12	176
$\sum$	270	34	304

experimental group, a higher proportion of consistent responses were observed, with 22 out of 128 participants (17.19%) providing inconsistent responses, as opposed to the control group, which had a lower proportion, with 12 out of 176 participants (6.82%) providing inconsistent responses. Most responses in both groups were categorised as consistent, with 106 out of 128 (82.81%) in the experimental group and 164 out of 176 (93.18%) in the control group. With 76 observations, this resulted in a theoretical maximum of 304 possible instances of consistency or inconsistency. Specifically, there were 270 (88.82%) consistent responses and 34 (11.18%) inconsistent responses in total over both groups. To assess the

significance of differences in inconsistencies between the groups, a Pearson's chi-square test was conducted. Preliminary findings reveal a statistically significant variation in response consistency patterns between the groups, as indicated by a chi-square statistic of $X^2(1) = 7.0115$, $p = 0.008$.

Logistic Regression Results

Table 5.2: Logistic regressions with clustered standard errors

	Model 1	Model 2	Model 3
group	0.058.	0.048*	0.052.
	(0.513)	(0.555)	(0.655)
gender		0.737	0.485
		(0.496)	(0.607)
age		0.064.	0.03*
		(0.067)	(0.08)
educ		0.172	0.149
		(0.116)	(0.186)
income		0.029*	0.01*
		(0.000)	(0.000)
smtime			0.978
			(0.475)
smmood			0.187
			(0.307)
smfomo			0.036*
			(0.371)
smcontrol			0.132
			(0.369)
smpsych			0.425
			0.338)
smemotion			0.076.
			0.472)
smaware			0.724
			0.407)
Constant	0.000	0.47693	0.97419
	(0.364)	2.143)	(3.606)
Observations	76	76	76
Log Likelihood	-45.512	-42.424	-36.667
Akaike Inf. Crit.	95.024	96.848	99.335

Note: ***p<0.001; **p<0.01; *p<0.05; ·p<0.1

The first model examined the direct impact of social media exposure, including only the variable *group* as an explanatory variable. The variable *group* is a dummy variable that indicates the log odds of observing inconsistencies in participant responses relative to the control group. The coefficient of $\beta = 0.972$ indicates that being in the treatment group is associated with higher odds of observing inconsistencies compared to the control group (see Appendix for coefficients). Though, with $p = 0.058$ the group effect is only marginally significant. For the second model, demographic variables were additionally included as explanatory factors for observing inconsistencies. The coefficient for the experimental group (1.094) remains positive and becomes statistically significant at the 0.05 level ($p = 0.048$). This indicates that, even after controlling for demographic variables, being in the experimental group is associated with higher log odds of exhibiting inconsistencies compared to the control group. The age of the participants had a negative coefficient of -0.125, indicating that older participants are less likely to exhibit inconsistencies, although the effect was only marginally significant with $p = 0.0645$. Income shows a small statistically positive effect, observing inconsistencies with an estimated coefficient of 0.0003 with $p = 0.029$. Gender ($p = 0.166$) and the education level in years ($p = 0.172$) did not reach statistical significance. The third model included variables regarding social media usage patterns and self-assessments on emotional and psychological outcomes, along with demographics and group assignment. The effect of the group assignment $p = 0.052$ remains positive and is close to reaching the 5% significance level, further suggesting a difference in inconsistencies based on the priming. The effects of demographics remained the same in their effect, though the effect size changed marginally. However, age became statistically significant ($p = 0.036$), indicating that older participants are less likely to have misalignments in decision-making. For social media usage patterns, $smfomo$ the fear of missing out ($p = 0.03560$) had a significant positive effect on inconsistencies. Finally, emotional involvement in using social media, *smemotion* has a trend towards significance with $p = 0.076$. Regarding the model fit statistics, the log likelihood values indicate the log of the likelihood function, which measures how well the model fits the data. Higher values suggest a better fit. From Model 1 through Model 3, there is a clear improvement in the log likelihood, suggesting that Model 3 fits the data better than the previous two models. AIC is a measure of the relative quality of statistical models for a given set of data. It deals with the trade-off between the goodness of fit of the model and the simplicity of the model. Lower AIC values indicate a model that better explains the variance in the data with fewer parameters. Interestingly, while the log likelihood improves with each model, indicating a better fit, the AIC increases from Model 1 to Model 3. This suggests that although Model 3 fits the data better, it does so at the cost of complexity.

Results for stated happiness levels

After each subjective well-being trade-off, participants were asked to indicate on a Likert scale from 'unhappy' to 'very happy' how happy they would feel with their chosen option. Figure 5.2 shows the average distribution of reported happiness levels for each response option across all four scenarios, expressed in percentages.

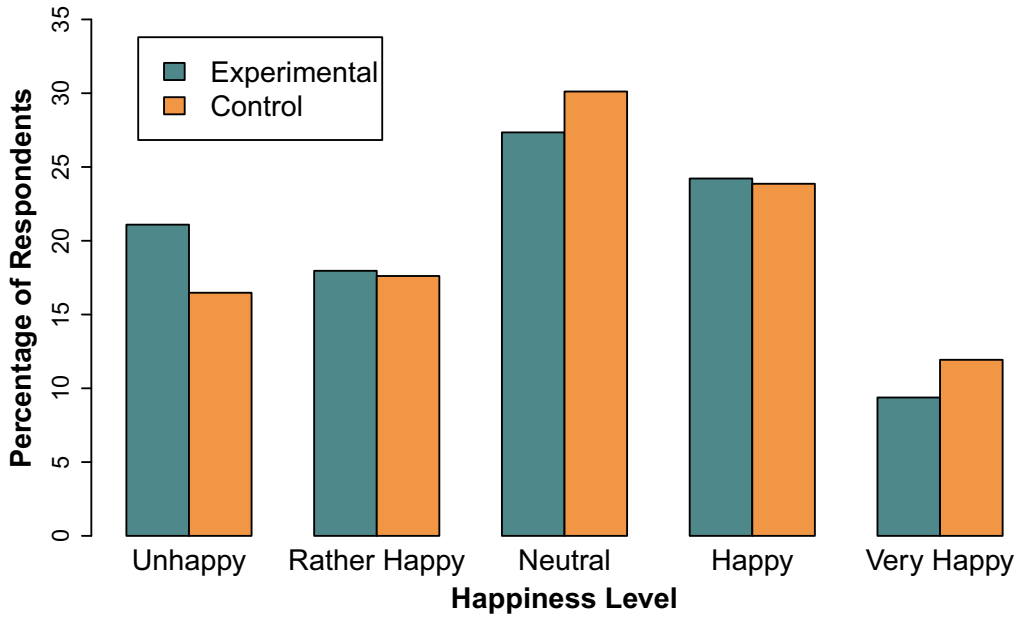


Figure 5.2: Average distribution of stated happiness levels across scenarios in %

In terms of self-reported happiness, the data showed different distributions between the experimental and control groups in all categories. Specifically, for the option 'Unhappy', the experimental group had a slightly higher proportion of respondents (21.09%) than the control group (16.48%). Similarly, the experimental group again had a higher proportion (17.97%) of those who said they were 'rather happy' compared to the control group (17.61%). A notable divergence was observed in the 'Neutral' category, where a significantly higher proportion of control group participants (30.12%) reported this sentiment compared to their experimental counterparts (27.35%). In the 'Happy' category, the experimental group had a slightly higher proportion (24.22%) than the control group (23.86%). In conclusion, the proportion of 'very happy' respondents was higher in the control group (11.93%) than in the experimental group (9.38%).

6 Discussion & Conclusion

Social media has become increasingly important and popular in society in recent years, with 5.05 billion users worldwide in 2024 and a daily usage time of two hours on average. However, as the number of people using social media has grown, so has the question of how it affects people in their everyday lives. One of the first fields of research to address this question was psychology, examining the impact on mental health and well-being.

While it has been found that there can be positive aspects of social media use on mental health due to its easy ways of connecting with other people or being able to express thoughts and feelings, according to Deters & Mehl (2013), psychological studies have also revealed negative effects. There is evidence that spending long periods on social media can be linked to depressive moods and anxiety. Likewise, people who used social media more frequently were also found to be more likely to report mental health problems (Coyne et al., 2020). This is supported by experiments in which social media use was restricted, which showed that limiting social media use can lead to a reduction in levels of depression and loneliness (Hunt et al., 2018). When differentiating the use of social media, further studies have shown that factors such as the repeated reflection of one's own negative thoughts (Davila et al., 2012),or the type of use, especially passive or active use (Escobar-Viera et al., 2018), are parameters that must be considered to understand the effects of social media on mental health. Furthermore, longer periods of use tended to correlate with more negative emotions, which are found to be confounded with one's own self-esteem, the willingness for self-disclosure, and the frequency of comparison with others (De Vries et al. (2018); Luo & Hancock (2020)). As a result of the findings in the field of psychology and social media's impact on everyday life, the economic impact of social media has also been the subject of research in recent years. Although social media platforms drastically reduce the costs of information provision and connectivity between individuals from an economic perspective (Myers, 2000), potential negative effects have been found. In the context of news consumption on social media, exposure to news that aligns with a person's political beliefs has been shown to increase affective polarisation, which refers to the emotional divide between different political factions (Levy, 2021). This behavioural aspect with regard to political outcomes can lead to further economic uncertainty, as highlighted by Baker et al. (2020). In line with the psychological findings, welfare analyses have shown adverse effects on subjective well-being, and on the other hand, restricting social media use was found to be correlated with higher life satisfaction and happiness

levels (Mosquera et al. (2020); Allcott et al. (2020)). In relation to social media addiction, it was found that projection bias and awareness of habit formation can influence digital consumption. Specifically, the underestimation of social media addiction can lead to excessive use despite negative outcomes on productivity and well-being (Allcott et al., 2022). Finally, mental health problems were identified after Facebook was introduced in a U.S. college, particularly affecting students who were more likely to feel excluded or inferior, such as those living off-campus or those of lower socioeconomic status (Braghieri et al., 2022).

Regarding these findings on social media use and its impact on well-being and behaviours, two hypotheses were formulated. First, the use of social media creates a divergence between expressed preferences and actual choices in economic decision-making, suggesting that social media may distort individuals' ability to make decisions in line with what they think would make them happy. Second, social media has a negative impact on perceived happiness. To test the hypotheses, this paper presented an unique approach to investigating the impact of social media on subjective well-being and decision-making. The survey design of Benjamin et al. (2012) was used and adapted to investigate whether an individual's choices in hypothetical scenarios are aligned with what they believe would maximise their subjective well-being. A priming at the beginning of the experiment was introduced to the treatment group to influence participants' responses when making decisions in economic trade-offs, compared to the control group confronted with a neutral priming.

With the help of a created binary variable, the behavioural responses of participants were measured in terms of their consistency in answering happiness and hypothetical choice questions across different scenarios. Based on the experimental design it was expected that there would be a high level of consistency in the responses, so it was particularly interesting to observe the extent to which there would be any deviation when social media priming was introduced prior to the survey. The experimental group displayed a higher rate of inconsistency than the control group. The distribution of these inconsistencies also indicates a broader range of variability in responses. While eight participants also exhibited a single inconsistency, a higher number of participants showed inconsistencies in two scenarios, and notably, two individuals displayed inconsistencies in three out of four scenarios. This increased rate and range of inconsistency suggest that exposure to social media may have influenced participants' alignment between reported happiness and hypothetical choices differently than the control conditions. The level of consistency in responses can be seen as an indicator of the quality or reliability of decision-making processes among participants. Higher consistency suggests that individuals' stated happiness aligns with their hypothetical choices, which is desirable in relation to choice theory (Hsee (1999) Hsee et al. (2003), Kahneman et al. (1997)). Three logistic regression were conducted to further

investigate the relationship between social media exposure and the odds of observing inconsistencies between groups. Participants in the experimental group, representing increased social media exposure, demonstrated a higher likelihood of inconsistencies in their responses compared to the control group. This effect was robust, even after accounting for demographic variables, highlighting the significant influence of social media on cognitive processes. Age and income emerged as significant predictors of response inconsistencies. Older participants showed lower odds of inconsistency, suggesting more stable decision-making processes or different engagement patterns with social media, which was also found in the literature by Deters & Mehl (2013). The fear of missing out (FOMO) and emotional involvement in social media were closely linked to inconsistencies, pointing to the psychological and emotional dimensions of social media use that affect cognitive outcomes, which is aligns with the current state of the literature (e.g. Hunt et al. (2018); Rae & Lonborg (2015)). While the inclusion of additional variables improved the model's explanatory power, it also increased complexity, indicating a balance between capturing the nuances of social media's effects and maintaining model parsimony. Regarding the second hypothesis, the results are mixed. The hypothesis that social media has a negative influence on subjective well-being is particularly true for emotions at the edge (very happy & unhappy) of the Likert scale. In the experimental group, significantly more participants stated that they were unhappy with their chosen option in the scenario. At the same time, more participants in the control group stated that they were very happy with their chosen option, which can be interpreted as diminishing returns on happiness from social media use. The notably higher proportion of 'Neutral' responses in the control group could reflect a lesser engagement with the emotionally polarising content of social media, leading to more moderate emotional states. This might suggest that the absence of social media reduces the intensity of emotional experiences, leading to a more neutral or stable emotional condition.

This study has potential limitations. The relatively small sample size (n = 76) could limit the statistical power of the findings that support the hypothesis, which is why it is important to replicate these findings with a broader sample. Furthermore, the advantages of the self-reported subjective well-being measure can also be its weaknesses in relation to introspective ability, which refers to participants potential inability to accurately assess themselves. Though clustered standard errors were implemented in the logistic regression, possible consistency effects must be taken into account and considered in this study's experimental design. Since this was an online experiment, it would be beneficial to conduct this experiment in a laboratory environment, especially with regards to the presented scenarios, once as a happiness and once as a hypothetical choice, and to emphasise the differences in these types of questions.

As the use of social media increasingly becomes part of daily lives on a worldwide scale, understanding its impact on individuals and society becomes increasingly urgent. The experimental design of the study, particularly the use of social media priming and the assessment of its impact on economic trade-offs, represents a unique methodological contribution and extends how social media can be integrated into experimental research. This study shows that social media content significantly affects how people make economic choices when faced with trade-offs, along with its impact on well-being. Importantly, these findings can inform policymakers about potential strategies to mitigate the negative effects of social media use while enhancing its positive outcomes. Future research should further explore these dynamics, with the aim of refining the understanding of the role of social media in shaping economic decisions and well-being outcomes.

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Appendix

Economic trade-offs

Scenario 1: Decision under risk

Suppose you want to invest half of your savings of €10,000 and have to choose between the following investment opportunities.

Which option do you think would make you happier overall?

Option 1	**Option 2**
You invest half of your savings over a period of 5 years in the start-up of a good friend. With success, you can reach an end capital of €80,000 and enjoy business fame as well as social recognition. However, the risk of failure and the loss of the total investment is 50%.	You invest half of your savings at a fixed interest rate over a period of 5 years without risk and achieve an end capital of €14,000. You gain no fame and no social recognition in society.

Scenario 2: Social comparison

Suppose you want to start a new job and have to choose between two positions. Both positions are identical in every respect and differ only in two aspects.

Which option do you think would make you happier overall?

Option 1	**Option 2**
Your annual income is €105,000, while your colleagues doing the same work earn on average €130,000.	Your annual income is €90,000, while your colleagues doing the same work earn on average €85,000.

Scenario 3: Tax compliance

You have a primary job that covers your basic needs, and you take on a side job to improve your standard of living. However, the additional income increases your tax rate, so that the financial benefit of the side job is almost completely consumed by the higher taxes.

Which option do you think would make you happier overall?

Option 1	**Option 2**
You correctly declare your additional income and slightly improve your standard of living. You fulfil your tax obligations and assume your social responsibility towards society by investing your taxes in education, infrastructure, etc.	You do not declare your additional income in order to increase your standard of living, even though there is a 10% risk of being discovered in a tax audit and facing criminal consequences.

Scenario 4: Labor-leisure decision

Assume you are faced with the choice between two lifestyles that differ in terms of work, income, and leisure time.

Which option do you think would make you happier overall?

Option 1	**Option 2**
With an annual income of €90,000 and a 50-hour week, you earn above-average and enjoy a high standard of living. The longer working hours leave you little time for social activities and personal hobbies.	With an annual income of €20,000 and a 30-hour week, you earn below average and cannot afford a high standard of living. The shorter working hours leave you plenty of time for social activities and personal hobbies.

Social media use patterns: Control variables based on the Digital Maturity Inventory Laaber et al. (2023)

Variable	**Question**
smtime	How much time do you spend on social media on a typical weekday in your free time? Please only think about your free time
smmood	When I haven't used social media for a while, I feel bad.
$smfomo$	When I use social media, I am online because otherwise I feel like I am missing out on something.
smcontrol	When I use social media, I feel like I have control over my usage.
smpsych	When I see something on social media that emotionally stirs me up, I often react too quickly and later regret how I responded online.
smemotion	When I see something on social media that emotionally upsets me, I often react too quickly and later regret how I reacted online.
smaware	When I use social media, I am aware that what I see online does not always correspond to reality.

Logistic regressions

Table A.1: Logistic Regression Model 1

Coefficient	Estimate	Std. Error	z value	Pr(>|z|)
Intercept	-1.223	0.364	-3.356	0.0007***
Group	0.972	0.513	1.895	0.058.

Note: ***p<0.001; **p<0.01; *p<0.05; ·p<0.1

Table A.2: Logistic Regression Model 2

Coefficient	Estimate	Std. Error	z value	Pr(>|z|)
Intercept	-1.524	2.143	-0.711	0.476
Group	1.094	0.555	1.969	0.048*
Gender	0.166	0.496	0.335	0.737
Age	-0.125	0.067	-1.848	0.064.
Education	0.159	0.116	1.363	0.172
Income	0.0003	0.0001	2.183	0.029*

Note: ***p<0.001; **p<0.01; *p<0.05; ·p<0.1

Table A.3: Logistic Regression Model 3

Coefficient	Estimate	Std. Error	z value	Pr(>|z|)
Intercept	-0.116	3.606	-0.032	0.974
Group	1.272	0.655	1.941	0.052.
Gender	-0.423	0.607	-0.696	0.485
Age	-0.184	0.088	-2.090	0.036*
Education	0.269	0.186	1.441	0.149
Income	0.0004	0.0001	2.541	0.011*
smtime	-0.012	0.475	-0.026	0.978
smmood	-0.405	0.307	-1.318	0.187
smfomo	0.777	0.371	2.096	0.036*
smcontrol	0.556	0.369	1.505	0.132
smpsych	-0.270	0.338	-0.797	0.425
smemotion	-0.835	0.472	-1.776	0.076.
smaware	0.143	0.407	0.352	0.724

Note: ***p<0.001; **p<0.01; *p<0.05; ·p<0.1

Happiness levels

Table A.4: Share of happiness levels across all trade-offs between treatment and control group

Experimental / Control	Rather happy				Very happy
Social Comparison	15.62%/15.91%	25.00%/15.91%	28.12%/29.55%	21.88%/15.91%	9.38%/22.73%
Time Preference	15.62%/20.45%	28.12%/27.27%	21.88%/22.73%	28.12%/18.18%	6.25%/11.36%
Decision under risk	18.75%/4.55%	3.12%/9.09%	34.38%/34.09%	34.38%/43.18%	9.38%/9.09%
Tax compliance	34.38%/25.00%	15.62%/8.18%	25.00%/34.09%	12.5%/18.18%	12.5%/4.55%