Mental Health Literacy, Beliefs and Demand for Mental Health Support among University Students*

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Abstract

This paper assesses the impact of a mental health literacy intervention on the demand for mental health support among university students. We run an incentivized survey experiment with 2,978 university students from one of the largest Dutch universities. The literacy intervention provides information on the benefits of care-seeking and its potential returns in terms of academic performance. The intervention increases the willingness-to-pay for a mental health app among male respondents. Moreover, the information increases (decreases) the demand for information about coaching (psychological) services. We document that this substitution is concentrated among students with low to moderate anxiety/depressive symptoms, while the students with severe symptoms increase their demand for coaching without reducing their demand for psychological services. An increased perceived effectiveness of low-intensity therapy is likely to be the mechanism. In a follow-up survey three weeks later, we find that the treated female respondents have improved their mental health. Finally, a model of mental health investment decisions in the presence of (self-)image concerns rationalizes the results.

JEL-classification: C93, D83, D91, I12, I31

Keywords: Mental Health Literacy, Demand for Mental Health Support, Beliefs, Stigma, Survey Experiment

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1 Introduction

Mental health is a global public good (Patel, 2018), as poor mental health can lead to a welfare loss of up to 1% of global GDP (OECD, 2020). Anxiety and depression account for 8% of years lived with disability (Vos et al., 2012). The welfare consequences of mental health issues are multi-fold. Firstly, poor mental health might lead people to biased beliefs about their own abilities, and to misallocate their talent (de Quidt and Haushofer, 2016). Moreover, mental health issues generate large earning penalties in the labor market (Biasi et al., 2021), as well as an increase in the likelihood of unemployment and penalties on the marriage market (Bos and Hertzberg, 2021). Furthermore, mental health issues hinder human capital accumulation for kids and young people (Currie, 2009; Currie and Stabile, 2006; Eisenberg et al., 2009; Heckman et al., 2006; Krishnan and Krutikova, 2013). Finally, the COVID-19 pandemic has exacerbated these difficulties and widened the gender gap in mental health (Adams-Prassl et al., 2021; Giuntella et al., 2021). Therefore, there is a growing need for policies to treat and prevent severe mental illness (Layard, 2013).

In this paper, we study the demand for mental health support among university students and its drivers. We choose to focus on university students because the literature has highlighted the existence of a "gap in the demand for mental health support" among them (Eisenberg et al., 2007; Hill et al., 2020; Sæther et al., 2021; Watkins et al., 2012). The "gap in demand for mental health support" refers to the fact that people who would benefit from mental health support are often not seeking it.[1] We shed light on the effects of mental health literacy intervention on the demand for mental health support in an online survey shared with a representative sample of around 3,000 students from a large Dutch university between October 2021 and November 2021.[2] The literacy intervention is an information treatment that aims at increasing care-seeking behaviour of the students by increasing the perceived benefits of low-intensity therapies (ie. coaching services, online therapies, meditation apps). The low-intensity therapies have two important features: they are effective in a general

[1] In our sample we find that 28.8% of the respondents show symptoms of low mental health. Only 36% of them are receiving support either via professional or via apps.

[2] Authorities reports a worrisome increase in mental health problems among university students in the Netherlands during the pandemic, which makes the understanding of the demand for mental health support even more timely.

population in the US (Shreekumar and Vautrey, 2021), and they make users open to switch to medical treatments (Clay, 2021). [3]

Crucially, we expose only half of the respondents to the information, while the remaining half does not receive any information. We choose to use a literacy intervention for several reasons. Firstly, it is a soft intervention that resembles what students are used to (eg., workshops, focus groups, awareness sessions). This feature of the treatment allows us to study how students change their demand for support in a setting which is fairly realistic for them. Secondly, by highlighting the potential returns from investment in mental health regardless of mental health status, the intervention can promote help-seeking among the general population of students. Finally, recent literature has pointed out the societal benefits of implementing mental health literacy interventions in different contexts (Ridley et al., 2020).

We document five sets of results. First, the average treatment effect of the mental health literacy intervention has a null effect on the willingness to pay (WTP) for a monthly subscription to a mental health app. Ex-post power calculation shows that the effect has modest economic significance. The respondents in the Control group are willing to pay 3.79€ for the app. The intervention increases the WTP by 5.1% SD compared to the WTP in the Control group, which is equal to 3.79€. The effect of the intervention is not significantly different from 0. However, the respondents exposed to the treatment are more likely to demand information about coaching services (8.5% SD) and they are less likely to demand information about psychologist services at the university (4.4% SD). We are the first to document a potential substitution effect of a mental health literacy intervention on the demand for information about mental health support. The students with moderate symptoms of anxiety and depression substitute the information about psychologist services with the information on low-intensity therapies, which could lead them to invest in therapies that are potentially not adequate for their mental health status. On the other hand, the students with low mental health status are acquiring information about high-intensity therapies that could be more appropriate for their mental health status.

Second, there is substantial heterogeneity in the demand for mental health support in

[3]Overall the mental health apps market is growing in such a way that at least 10,000 apps are available on the market (Economist, 2021). There is a dramatic increase in the cases of universities that provide mental health apps to the students, as well as employees for top companies like Nike or McKinsey.

response to higher mental health literacy. Most notably, the gender of the respondents is an important dimension of heterogeneity. We find that male respondents in the Treatment group increase their willingness to pay for the app by 14.6% SD. The high level of Stigma (both Self and Social) among the male respondents might explain why they increase the WTP for a completely anonymous mental health app. On the other hand, the adverse effect of the intervention which leads to the substitution in the information demand is entirely driven by the female respondents.

Third, the intervention increases the perceived effectiveness of mental health apps. This is the main driver affecting the increase for WTP among the male respondents. Moreover, we find suggestive evidence that the intervention increases self-stigma and perceived social stigma related to high-intensity care seeking behavior. We rationalize this effect by saying that an increase in the salience of mental health investment and highlighting the value of low-intensity intervention, the information treatment may make stigma attached to high-intensity treatment more salient.

Fourth, we document the determinants of the demand for mental health support in our sample. In the Control group, the male respondents and the respondents with high mental health status are less willing to pay for the subscription to the mental health app. Moreover, Dutch respondents compared to the International students are less willing to pay for the app. Similarly, male respondents and Dutch respondents are less likely to acquire information about psychological services offered at the university level. Being male and Dutch are also the two main categories that strongly predict high scores for both Self and Social Stigma. This correlational evidence shows the importance of self and social image concerns in shaping the investments in mental health. On the contrary, the respondents who experience more Self Stigma towards mental health care seeking are those who prefer to acquire information for the coaching services at the university, which is a less ego-threatening option.

Fifth, we assess the persistence of the effect of the intervention by running a follow-up survey three weeks later. We find evidence that part of the respondents who were seeking psychological support reduced their participation in psychological therapy. This result speaks to the worry of the medical professionals that low-intensity therapy could completely crowd

out more standard therapies.[4] Moreover, we validate the use of the demand for information for mental health care options as a proxy for the demand for mental health support. We find that acquiring information about the coaching services (psychologist services) is strongly positively correlated with both self-reporting to have sought care from a coach (psychologist) and to planning to seek care from a coach (psychologist). Finally, our results suggest that, on average, the mental health literacy intervention improves the mental health status of specific sub-groups. We find that the female respondents report a significantly improved mental health status a few weeks after the mental health intervention.

We rationalize our experimental results using a theoretical framework. Given the relevance of the students' beliefs in this context, we model how perceived benefits of mental health care, self- (and social) image concerns affect the investments in mental health in a multi-period model. Our results show that: i) if the perceived benefits of any type of care-seeking increase, then more people seek care; ii) if the perceived benefits of low-intensity therapies relative to the high-intensity therapies increase, then more (less) individuals seek care from the low-intensity (high-intensity) therapies and the stigma towards high-intensity therapies increases.

Our results have important implications for the literature studying the causes and the economic consequences of poor mental health (Ridley et al., 2020). To the best of our knowledge, our paper is the first one to assess how a mental health literacy intervention affects the demand for mental health support among university students with incentivized behavioral measures. We also provide evidence that mental health intervention has a potential "adverse" effect because people tend to substitute information about professional support with information about low-intensity therapies rather than complement them.

Our results speak to the stream of literature studying the mental health of students and the role of their peers and teachers in shaping students' mental health (Braghieri et al., 2021; Bütikofer et al., 2021; Kiessling and Norris, 2022). These concerns have become recently relevant in the context of graduate students in Economics (Bolotnyy et al., 2021) and Political Science (Almasri et al., 2021), and medical schools (Anderson et al., 2021). We contribute

[4]https://www.nytimes.com/roomfordebate/2015/09/22/is-depression-treatable-with-a-mobile-phone-app/mental-health-apps-are-not-an-adequate-substitute-for-human-interaction

to this stream of literature by study the drivers of university students' demand for mental health support.

Our paper also speaks to the stream of literature that focuses on the policy evaluation of therapy interventions. Barker et al. (2021) show that Cognitive Behavioral Therapy (CBT) improves people's mental health in the context of Ghana, and it has a persistent effect over time among depressed mothers in Bangladesh (Baranov et al., 2020). On the other hand, Haushofer et al. (2021) find that the effect of cash transfers on both economic and well-being outcomes is considerably larger than the effect of psychotherapy. Furthermore, Romero et al. (2021) finds that cash transfers have a consistently positive impact on people's well-being in the context of developing countries. Finally, Shreekumar and Vautrey (2021) show that 4 weeks of self-therapy with a popular meditation app increases Americans' mental health and improves their economic behavior. We contribute to this stream of literature by studying how people select themselves into therapy and why.

We shed light on how the beliefs and attitudes towards low-intensity therapies and self-stigma shape the demand for mental health support. Our results relate to the stream of literature that study self- and social image concerns, both theoretically (Bénabou and Tirole, 2011) and empirically (Bursztyn et al., 2017, 2020). Our study speaks to a small but growing literature that studies stigma and anticipated discrimination in the context of mental health illness affects people's economic decisions (Eisenberg et al., 2009; Ridley, 2021).

We contribute to the literature that uses information treatments to study people in the context of health economics (see Haaland et al. (2021) for a comprehensive overview of the state of the art of information provision experiments, including in the domain of health economics). Alsan and Eichmayer (2021) study persuasion regarding the medical benefits of influenza vaccination with a particular focus on racial identity. Barari et al. (2020) study public health messaging and social distancing in the context of the coronavirus pandemic. We contribute by analyzing the effects of a mental health literacy intervention on university students' care seeking behavior and beliefs.

We also contribute to the growing field that studies information acquisition in applied settings, specifically in the context of health economics (see Capozza et al. (2021) provide a methodological review in information acquisition in applied settings). Most of the literature

in this sub-field focuses on the testing decisions for fatal diseases (Ganguly and Tasoff, 2016; Oster et al., 2013; Thornton, 2008), while we focus on the demand for information about the support services offered at university (psychologist and coaching). The closest paper to ours is Khan et al. (2021), which studies information demand for coronavirus prevention methods.

Our paper proceeds as follows: In Section 2, we describe the data and the experimental design. In Section 3, we present the results of the intervention and the follow up. In Section 4, we present a theoretical framework to rationalize the results of the intervention. Finally, Section 5 concludes.

2 Sample and Experimental Design

2.1 Sample

We conducted an incentivized survey experiment with a sample of university students from one of the largest Dutch universities. Table B1 in Appendix B shows that the sample is broadly representative of the student population at the university level.

We ran the main study in the last week of October 2021, from October 26th to October 28th . We leveraged a collaboration with the Education & Student Affairs Office, which has shared the survey link with over 30,000 university students via e-mail (see Lergetporer et al. (2018) for a similar approach).

Using the same recruitment procedure, we have conducted a follow up study roughly three weeks after the first study. The follow-up data collection started on November 17th 2021 and it lasted for approximately one week[5].

The choice to focus on University students is worth noting for three significant reasons. Firstly, the literature suggests that the sharp transition at age 18 between child mental health care to adulthood mental health care can have negative consequences on care seeking behavior of individuals. This transition from child and adolescence to adult mental health care creates a gap in demand for mental health support (Eisenberg et al., 2007; Hendrickx et al., 2020).

[5]In the period between the main study and the follow-up, the Dutch government imposed some restrictions on social life and outdoor activities. However, given that these restrictions affect everybody in our sample, the limitations do not have consequences for the internal validity of our study.

The main reason for this challenge is that out-of-pocket payments increase once individuals are above 18 years old (Lopes et al., 2022). We focus on this gap by studying individuals close to this transition period. Secondly, the years spent at university represent a decisive phase for the process of human capital accumulation, and the literature suggests that poor mental health status undermines this process (Eisenberg et al., 2009). Third, university students are one of the groups that shows the highest prevalence of mental health problems (Eisenberg et al., 2009).

It is also noteworthy that in the past decade, many institutions, including universities, started adopting and promoting innovative and lower-intensity wellbeing services. Examples of such services are coaching services, meditation sessions, workshops, and wellbeing and self-care apps. Our intervention mimics promoting low-intensity interventions and studies the consequent (short-term) mental health care demand and wellbeing effects.

2.2 Experimental Design

Part 1: Recruitment and Demographic characteristics We invite the participants to join the study via an invitation email. The message in the email asks for their participation in a survey about habits and wellbeing topics. In the framing of the invitation email (Appendix J) we emphasize the monetary incentives for the participation, the anonymity of the responses, and we provide information about the content of the survey without deceiving the participants. We have shared the survey link with roughly 30,000 students from all the schools of Erasmus University Rotterdam.

Once the participants join the survey, we ask them to create a unique anonymous ID code that allows us to match participants with their follow-up responses and that ensures complete anonymity of the responses. Crucially, the process of generating a unique ID code also serves as an attention check, since it requires participants to read carefully and follow all the instructions, thus having to pay close attention to the text. Finally, we collect self-reported information from the participants on: age, gender, school, level of education, whether they are Dutch, and if so whether they have an immigration background, if not, which geographical region they come from, their GPA, their parents' education, their perceived level of financial

stress, and their self-reported mental health status.

Part 2: Randomization We randomize the participants in one of two experimental conditions. Half of the participants are randomly assigned to receive an information treatment aimed at increasing mental health literacy. The mental health literacy intervention states the following:

> *Mental wellbeing is not binary but is a spectrum. Therefore, the staging approach is a new way to think about someone's mental wellbeing.*
> *This approach implies that taking care of mental health is a continuous process with positive outcomes: regardless of how someone feels right now, taking care of their mental health could always lead to higher wellbeing and fulfillment. The staging approach suggests some simple steps towards higher wellness, such as promoting self-care and increasing monitoring.*
> *These general tips apply to anyone, including university students. For example, research evidence suggests that university students who were investing in their mental health were also showing a better academic performance.*

The information treatment presents the reader with a combination of insights from peer-reviewed publications from the psychological literature (Eisenberg et al., 2009; Patel, 2018). The remaining half of the participants is allocated to the Control group and does not receive any information [6]

The information treatment aims to convey two main insights which are expected to increase the perceived benefits of mental health interventions, as people show to lack the understanding about mental health conditions and their risk factors, symptoms, and potential treatment options (Jorm, 2000). The first part suggests that mental health should not be understood as a binary state (healthy vs ill), but rather as a spectrum, and relatedly, that low-intensity interventions can be beneficial along the whole spectrum. The second part relates more specifically to the educational context and suggests that there can be returns in terms of academic performance to investments in mental health. At the same time, the information aims to resonate with real-life messages and examples of mental health literacy

[6]The control group in this experiment is a passive control group.

campaigns which encourage interventions such as the practice of mindfulness or meditation, the use of mental well-being apps, attendance of mental health workshops, or reliance on coaching.

Part 3: Demand for Mental Health Support app After the exposure to the treatment, we elicit the participants' "willingness-to-pay" for a self-care mental health online app. The app provides health and mood tracking, tools to familiarize with the practice of mindfulness meditation, as well as exercises based on Cognitive Behavioral Therapy, and it has been shown effective in reducing symptoms of depression and anxiety in clinical trials. [7]. To have an incentive-compatible WTP elicitation, we use the Becker-DeGroot-Marschak (BDM) mechanism (following Cullen and Perez-Truglia (2018b)). In the BDM, the respondent's bid is compared to a price that is determined by a random number generator. If the respondent's bid is lower than the price, the respondent gets a dollar amount equal to the price. If the bid is higher than the price, the subject receives the access to a one-month subscription for the mental health app and no dollar amount. The rules of this mechanism make it a dominant strategy for respondents to bid exactly their true valuation for the app. [8]

One important detail of the BDM mechanism is that all subjects must provide a bid for the item at hand, but this bid is not always "executed." We tell subjects that bids from "a few participants" will be chosen at random to be executed (Cullen and Perez-Truglia, 2018a). Subjects find out if their bids are selected only after submitting their survey response to prevent any emotional reaction during the last part of the experiment.

A BDM requires that the participants understand the instruction and fully trust the experimenter's instruction. If at least one of the two conditions does not hold, BDM does not ensure an incentive-compatible WTP elicitation. Results from a recent field experiment document the robustness of WTP elicitation techniques Burchardi et al. (2021). [9]

[7] provides the research evidence on the efficacy of the app. Prior to their bid, we also provide the description of the app to the participants

[8] We follow the same incentive scheme as Allcott et al. (2020).

[9] Burchardi et al. (2021) show that participants' optimal bidding and understanding of the mechanism is not affected by the type of elicitation techniques used, by the moment when the random number is drawn, and by stating that participants cannot influence the random number drawn.

Part 4: Demand for Information about support services Next, we elicit the participants' demand for information about the mental health support services offered at the university (psychological counseling and coaching). Following the approach discussed in Capozza et al. (2021), we ask the respondents to rank the options provided to receive (or not) information. We ask the participants to rank the alternatives from the most preferred one to the least preferred one.[10] After ranking the pieces of information, the participants receive the link to reach the website page about the highest ranked information. The options provided are: psychological service provided by the university, the coaching service provided by the university, and the option to not acquire any information. Crucially, all the services are provided by the university to avoid that the preference for a service provided outside the university over one provided at the university is explained by social image concerns and the desire to avoid social comparisons at university. The default option is receiving no information, so that the decision to acquire information requires participants to actively change the ranking. At the same time, the ranking decision allows us to study whether the information treatment affects the relative demand of information about the university psychologist (more specialized on mental health but more ego-threatening) and about the coaching service (less specialized, but less ego-threatening). This feature of the design allows us to understand to what extent self-image concerns play a role in the information selection of the mental health service to choose.[11]

Part 5: Post Treatment questions We elicit the participants' risk and time preferences using the questions from Falk et al. (2018), as stress seems to influence them (Haushofer and Fehr, 2014). We also ask whether the participants are already receiving support and from which source. We explore these dimensions for potential heterogeneity in the effects of the mental health literacy intervention. Next, we also explore the potential mechanisms behind the help-seeking and information acquisition decisions of the participants. To do so, we ask a battery of post-treatment questions, which are shown to the participants in a random order:

[10] We follow a procedure similar to the one used in Fuster et al. (2021).

[11] In Figures A.25 and A.26 we find that the respondents in the Control group with higher self-stigma are less likely to acquire information about Psychological services and more likely to acquire information Coaching services.

- We elicit the participants' beliefs about the importance of good mental health for educational and labour market outcomes, as these beliefs capture the perceived benefits of good mental health.
- We elicit the participants' beliefs on the effectiveness of the mental health app.
- We use questions from validated scales from psychology to measure the self and social stigma of seeking mental health support.

Part 6: Mental Health Status We assess the participants' mental health status by using the diagnostic tool PHQ-4. PHQ-4 is a reliable and brief screening tool for depression and anxiety (Kroenke et al., 2009; Shreekumar and Vautrey, 2021). We use this tool at the end of the experiment to minimize any priming effect at earlier stages of the experiment. If there is a low correlation between the self-reported mental health status (which we elicit at the beginning of the study) and the diagnosed mental health status might indicate that the students lack in the awareness of their mental health status (Falk et al., 2021).

Experimenter Demand Effect and Follow up Survey Although the experimenter demand effect is usually moderate (de Quidt et al., 2018), we take several measures to make sure to minimize it as much as possible. First of all, our first outcome variable, WTP for the mental health app, is an incentivized behavioral measure that should reduce the concerns for the experimenter demand effect. Moreover, we preserve the anonymity of the participants during the experiment, which should also minimize the experimenter demand effect.

Finally, we recontact the participants to the experiment a few weeks later and we match them to their previous answers by means of their unique ID code and their demographic variables. In this follow up, we assess whether participants have sought help in the two weeks before the follow up and whether they are planning to seek help in the two weeks after the follow up, to understand if the mental health literacy information treatment affected help-seeking behavior in the weeks following the experiment. Moreover, we re-assess the participants' mental health status by means of the PHQ-4 questions. Finally, we also re-elicit the participants' self and social stigma concerns about mental health care-seeking to assess whether treatment effects on these concerns are short-lived.

3 Analysis

In the main survey, we recorded the responses of 3,864 participants. Of the 3,864 participants who started the survey, 572 decided to leave the survey in the first page where they were asked to generate a unique ID code and validate it. 3,292 respondents reached the randomization phase and 2,978 respondents completed the main survey. For the main analysis we focus on the 2,978 respondents who completed the survey in its entirety. The analysis that follows was pre-registered before running the experiment on the AEA RCT Registry. [12]

3.1 Balancing Tests and Attrition

We test whether the participants in the Control and Treatment group are balanced across several observable characteristics. We run two-sided t-tests to assess whether this is the case. Table 1 shows that overall the randomization has successfully worked. We observe small imbalances along three dimensions: Age, being of Dutch nationality, and gender. The participants in the Treatment group are slightly older than the participants in the Control group. Moreover, there are less Dutch students and more female students in the Treatment group than in the Control group. The result from the F-test does not reject the null hypothesis of the two treatment groups being different across all characteristics at standard significance levels.[13]

We also assess whether randomization has fully worked on the full sample. We include all the 3,292 respondents who have reached the randomization phase, and we repeat the same procedure as 1. Table C1 in Appendix C shows that the differences in age, being Dutch, and gender existed at the time of initial randomization and is not a result of differential attrition. Therefore, we conclude that there is no differential attrition of the respondents.

Finally, we check whether the participants in the Treatment group are more or less likely to finish the survey compared to the participants in the Control group. Table C2 in Appendix C shows that this is not the case.

[12] The pre-registration of this trial can be found under the number 0008406.

[13] F-statistics = 1.378, p-value $= 0.19$.

Table 1: Randomization check

Variables	Control	Treatment	p-value
Age	21.49	21.72	0.08*
Dutch	0.62	0.59	0.05*
Female	0.61	0.65	0.03**
Bachelor	0.59	0.58	0.60
Low GPA	0.49	0.49	0.82
Financial Stress	0.20	0.22	0.13
Father's Education	0.37	0.37	0.86
Mother's Education	0.32	0.33	0.56
Low Mental Health	0.14	0.12	0.21
PHQ4	4.29	4.33	0.72
Support			
Psychologist	0.126	0.142	0.18
Coaching	0.026	0.035	0.15
App	0.10	0.12	0.09*
Peers	0.17	0.17	0.91
Family	0.70	0.72	0.16
Observations	1495	1483	

Note: The table shows the demographic characteristics for our sample broken down into Treatment and Control group. t-tests were used to assess whether demographic variables followed the same distribution between Treatment and Control. The third column reports p-values. Age is a continuous variable of the age of the participant. Dutch gets value 1 if the participant has Dutch nationality. Female gets value 1 if the participant reports to identify with female gender. Bachelor is a dummy that gets value 1 if the participant is a bachelor student. Low GPA gets value 1 if the participant reports to have a GPA lower than 7.5. Financial Stress gets value 1 if the participants reports that the current financial situation is "Very Bad" or "Bad". Father's Education and Mother's Education get value 1 if the participant's father and mother, respectively, have an education level below the bachelor. Low Mental Health gets value 1 if the self-reported mental health of the participant is "Very Bad" or "Bad". PHQ4 is a continuous variable for a diagnostic measure of the participant's mental health. This variable is measured after the allocation of the respondents to the Treatment, that is not affecting PHQ4 score. We have also reported the differences of the mental health status across 4 different intervals of PHQ4 score: 0 - 3 (no symptoms); 4 - 6 (mild symptoms); 7 - 9 (moderate symptoms); 10 - 12 (severe symptoms). Support is a dummy variable that gets value 1 if the respondent is receiving from one of the following support sources: Psychologist, Coaching, App, Peers and Family. Significance code: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

3.2 Main Results

Descriptives On a scale ranging from 0 to 10€, the participants in the Control group are willing to pay on average 3.79€ for the mental health app. In terms of preferences for information acquisition, 43.3% of respondents in the Control group are interested in receiving information about the psychological support available at the University; [14] 25.4% is would prefer to receive information about the coaching service available at the university, and the remaining31% is not interested in receiving any information about the two listed options to get mental health support at the university. Finally, in the Control group, 12.6% of the respondents are already receiving support from a psychologist, 10% are using a mental wellbeing app, and roughly 3% are getting support from a coach.

The psychological literature has identified several barriers and facilitators to help-seeking

[14]This is measured as the share of respondents in the control group who ranked receiving information about the psychological service as their preferred option.

among young people. Efficacy beliefs contribute to increase help-seeking intentions, while stigma represents a main barrier to help-seeking. In line with these findings, we find that the beliefs about the effectiveness of the mental health apps strongly predicts the participants' care seeking behaviour. Figure A.17 shows that the students who believe in the high effectiveness of the mental health apps are willing to pay more for them. Figure A.18 documents that the students who believe that better mental health is not beneficial for academic performance tend to reject receiving any information about support services. Figure A.17 shows that the students who believe in a high effectiveness of mental health apps are willing to pay more for them. We also focus on expected returns from investing in mental health. Moreover, Figure A.19 shows that high self-stigma (social stigma) about mental health correlates negatively (positively) with the demand for information about psychological support. On the contrary, Figure A.20 documents the opposite pattern. The students who display higher social stigma, but lower self-stigma are more interested in coaching services.

We also document that Dutch students in the Control group are significantly less willing to pay for the mental health app. They are less likely to demand information about the university's psychologists service, but more likely to demand information about the coaching service, as documented in Figure A.25 and Figure A.26. On the other hand, female participants and participants who display a lower mental health score are willing to pay more for the mental health app (see Figure A.23). Both students who display lower mental health scores and female students are also more willing to acquire information (Figure A.24). More specifically, lower mental health students are more likely to demand information about psychological services, as displayed in Figure A.25.

Finally, 28.8% of the respondents report a value of the PHQ4 higher or equal to 6 [15], which we label as "low mental health status". Among the respondents with low mental health status, we find evidence for a gap in demand for support. Only 36% of them are seeking support (25.5% of them are receiving professional support, and 16.3% of them are using a mental health app). Figure A.29 presents the correlation between the control variables and the reported PHQ4 score of the respondents. Among the characteristics that negatively correlate

[15]The psychological literature identifies 6 as the threshold value for moderate psychological distress, with values 9-12 corresponding to severe psychological distress

with a high PHQ4 score, we find: financial stress; being Dutch, with international students appearing to be struggling more with their mental health than their Dutch peers; being older; and reporting a higher GPA. Among the positive correlates, gender appears to be the most relevant, with female students displaying a PHQ4 score which is 28% higher than the score for the male respondents. We thus find evidence of a gender gap for mental health, which is consistent with findings from the literature (Adams-Prassl et al., 2021; Golin, 2021).

Empirical specification We assess how the mental health literacy intervention changes respondents' demand for mental health support. For that purpose, we estimate the following regression specification with an OLS model:

$$y_i = \alpha + \beta t_i + \Gamma^T X_i + \epsilon_i \tag{1}$$

where y_i is either the willingness to pay (WTP) for the app, or a binary indicator taking value one if the respondent demands information about the psychological service/information about coaching service/no information; t_i is an indicator for whether the respondent i is in the treatment group; X_i is a vector of control variables including: Age, Dutch, Female, Bachelor, GPA, Financial Stress, Father's Education, Mother's Education, PHQ4; and ϵ_i is an individual-specific error term.

Main effect Table 2 presents results of the mental health literacy intervention on the demand for mental health support among participants. Column 1 suggests that, on average, the mental health intervention had a negligible effect on willingness-to-pay for the mental health app. WTP increased by 5.1% SD, but the effect is not significant (p-value = 0.33) [16]. Although not significant, the intervention reduced the probability that the students chose "No information" as their preferred option by 3% SD. We also document an adverse effect of the information treatment, which leads respondents to reduce their likelihood of demanding information about the psychologist service. This corresponded to an increase in the demand of information for the coaching service, suggesting that the intervention induced a substitution in demand for information from high intensity psychological services toward low intensity psychological

[16] An ex-post power calculation shows that the minimum detectable effect in our sample is 7.1% SD.

services. The likelihood of demanding information about psychologist service decreased by 4.4% SD, while demand for information about the coaching service increased by 8.5% SD.

Table 2: Main Results: Demand for Mental Health Support

	Dependent variable:			
	WTP	No Information	University Psychologist	Coaching Service
	(1)	(2)	(3)	(4)
Treatment	0.082	-0.003	-0.033^{*}	0.036^{**}
	(0.085)	(0.017)	(0.018)	(0.016)
Observations	2,978	2,978	2,978	2,978
Controls	YES	YES	YES	YES
Control group mean	3.789	0.310	0.434	0.254
Adjusted R^2	0.043	0.042	0.058	0.020

Note: All specifications are OLS models. Column (1) looks at the willingness to pay for one month of access to the app. Column (2)-(4) look at dummies of putting psychological services, coaching services, and no information as the preferred option respectively. Robust standard errors are reported in parentheses.*Control* variables include: Age, Dutch, Female, Bachelor, GPA, Financial Stress, Father's Education, Mother's Education, PHQ4. Age is a continuous variable of the age of the participant. Dutch is a dummy taking value 1 if the participant has Dutch nationality. Female gets value 1 if the participant reports to identify with female gender. GPA is a categorical variable that spans from "Below 5.5", "5.5-6.5", "6.5-7.5", "7.5-8.5" and "Above 8.5". Financial Stress is self-reported categorical variable for the current financial situation from: "Very Bad", "Bad", "Fair", "Good", "Very Good". Father's Education and Mother's Education level is a categorical variable for the participant's father and mother education level. PHQ4 is a continuous variable for a diagnostic measure of the participant's mental health. Significance code: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Result 1. *On average, the mental health literacy intervention did not significantly increase the students' WTP for the mental health app. Moreover, the intervention reduced the students' demand for information about the psychologist service, but it increased the demand for information about the coaching service correspondingly.*

3.3 Heterogeneity Analysis

To study the heterogeneity of our baseline results, we use Random Forests (CRF; Wager and Athey (2018)). This method is a non-parametric method that allows to relax the assumptions on the unobserved errors and exploit accurately the heterogeneity in our sample[17]. We follow Wager and Athey (2019) to estimate Conditional Average Treatment Effect (CATE) for each of

[17]Appendix F describes in detail the CRF method and how we have implemented it in our analysis.

the observations in our sample, given their characteristics. We use the control variables used in Equation 1 to estimate the CATE's. We look at the distribution of CATE's separately by the dimensions of interests to shed light on heterogeneity of the effects[18].

Heterogeneity by baseline Mental Health (PHQ4)

One of the findings of Result 1 shows that the mental health literacy intervention causes an increase in the demand for information about the coaching services and a reduction in the demand for information about psychological services among university students. Thus, we explore whether the mental health literacy intervention is actually causing an "adverse" effect in the demand for information among the respondents. For example, it could be that the respondents with a lower mental health status, who are more in need of higher-intensity interventions like psychological services, are actually more prone to acquire information about coaching services.

Following Wager and Athey (2019), we estimate CATE's for the effect of the mental health literacy intervention on the main outcomes. Figure 1 shows the distribution of these Conditional Average Treatment Effects by the baseline mental health level (PHQ4). Figure 1a shows that the respondents with better mental health status are those who show a higher ATE for the mental health app. Moreover, Figure 1b shows that the respondents with worse mental health status are less likely to choose not to receive any information about care options. Furthermore, Figure 1c displays that the respondents with low mental health status are more likely to acquire information about psychological services compared to those showing moderate mental health disorders. Finally, Figure 1d suggests that there is limited/no

[18]One can look at the following equation to estimate the heterogeneity:

$$y_i = \alpha + \beta_1 t_i + \beta_2 x_i + \beta_3 t_i \times x_i + \Gamma^T X_i + \epsilon_i$$

where where y_i is either the willingness to pay (WTP) for the app, or an indicator showing if the respondent demands information about psychological service/information about coaching service/no information; t_i is an indicator for whether the respondent i is in the mental health literacy treatment; x_i is a specific dummy for the dimension of heterogeneity that we consider; X_i is a vector of control variables as in the main specification Equation 1 minus the heterogeneity dimension under scrutiny; and ϵ_i is an individual specific error term. The results of such an approach are given in Appendix E. Using the Generalized Random Forest method provides us with more flexibility in model specifications in showing non-linearity. However, the results shown in Appendix E are similar to the findings in this section.

heterogeneity, by baseline mental health level, in the treatment effect on information seeking for coaching services.

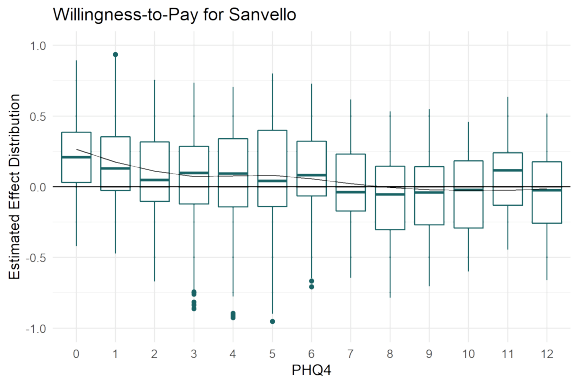
We can conclude that the respondents with better mental health status are more likely to select themselves into low-intensity interventions such as mental health app or coaching services as the result of the literacy intervention. This is appropriate given their mental health status, especially given that there is no change in the information acquisition behaviour on other dimensions (Figure 1b and Figure 1b).

On the other hand, the individuals with poorer mental health status are more likely to demand for information. We observe that these individuals demand more information for coaching services, while there is no evidence that this increase comes at the expense of reduced demand for psychological services. Finally, the respondents with moderate mental health disorders seem to be substituting the access to information about high-intensity care services with information about low-intensity care services. The net wellbeing effect of this substitution is not clear. Commenting on the consequences of such substitution is out of the scope of the paper, however, this finding suggests that literacy interventions promoting low-intensity care have spillovers on demand for high-intensity care.

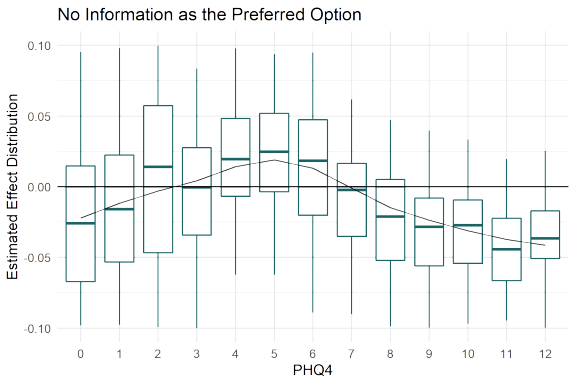
Heterogeneity by Gender

The gender differences in mental health risks, specifically anxiety and depression, are among the most robustly documented phenomena in the literature, with females being more at risk than males (e.g., see McLean et al. (2011); Parker and Brotchie (2010); Piccinelli and Wilkinson (2000); Riecher-Rössler (2017); Salk et al. (2017); Van de Velde et al. (2010)). These gender disparities in depression, for example, are pronounced to an extent that Hyde and Mezulis (2020) suggests that single-gender research designs should be questioned. The gender differences in mental health are also present in the domain of care-seeking behavior. Lopes et al. (2022) report that females decrease their demand for mental health care when monetary costs of care increase. Additionally, there is evidence that different genders benefit differently from psychiatric interventions (Bhalotra et al., 2022).

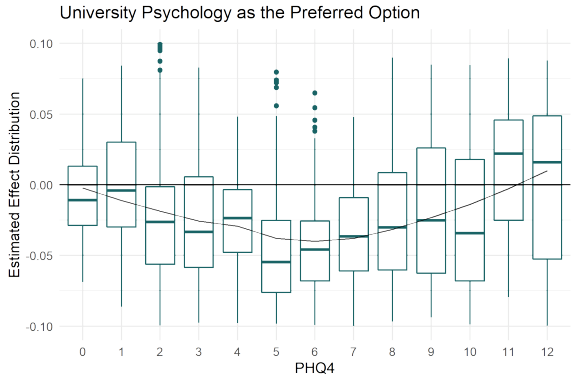
In-line with the existing evidence, we document a strong heterogeneous treatment effect



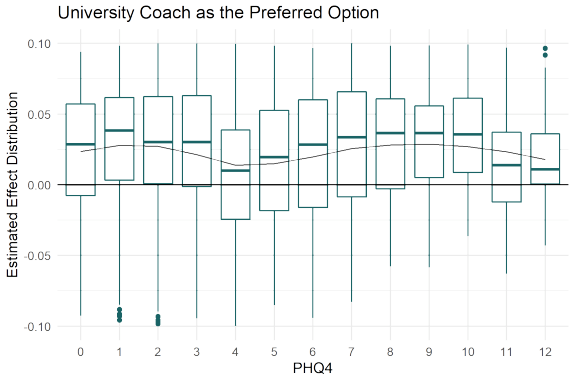
(a) Willingness-to-Pay



(b) No Information



(c) Information on Psychology Services



(d) Information on Coaching Services

*Note: We follow Wager and Athey (2019) to estimate conditional average treatment effects (CATE's) for each of observations in our sample. In the random forest methods, we include Age, Dutch, Female, Bachelor, GPA, Financial Stress, Father's Education, Mother's Education, and PHQ4 as the covariates. Each figure shows the distribution of CATE's by the mental health level (PHQ4 score). The solid line shows the mean of CATE's for each level of PHQ4. In (a), we have the willingness-to-pay for one month of access to Sanvello as the outcome. In (b), the outcome is if the individuals put no-information as their preferred option for information acquisition. In (c), the outcome is if the individuals put information on psychological services as their preferred option for information acquisition. In (d), the outcome is if the individuals put information on coaching services as their preferred option for information acquisition.

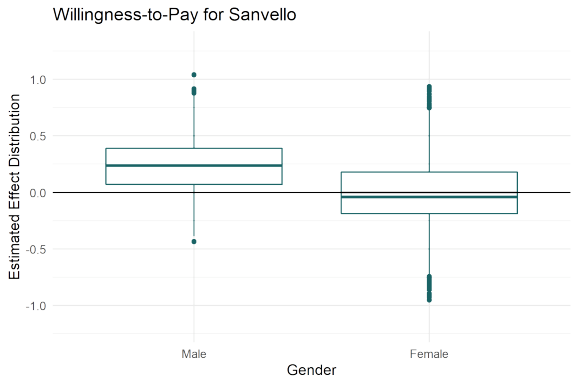
Figure 1: Heterogeneity of the Effects by Baseline Mental Health (PHQ4)

by gender. More specifically, the male respondents increase their willingness-to-pay for the mental health app after being exposed to the intervention, while we do not find any effect for the female respondants (see Figure 2a). A reason behind this effect can be that the female respondents in the control group has a higher WTP compared to the male participants. However, this is unlikely to be driven by a "ceiling-effect", because the female participants show a €4 average WTP which is far from the maximum possible bid (€10). A likely explanation for this gender difference is that the female participants have higher effectiveness beliefs in the baseline. The intervention only changes the aff-effectiveness beliefs for male respondents (Table G1a and Table G1b) Moreover, the male participants report higher self-stigma and social-stigma related to mental health care seeking behavior. This result might imply that the male respondents perceive an anonymous mental health app as a softer and less stigmatized support tool, which increases their average WTP.

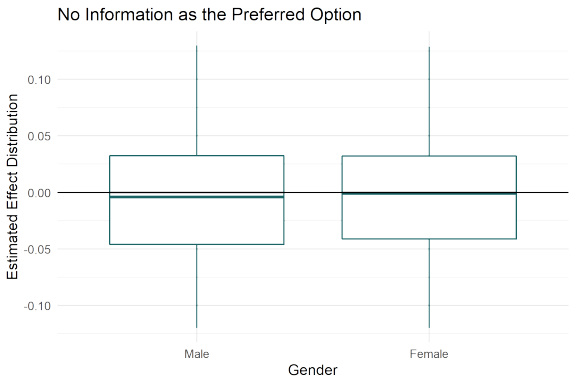
We also split the sample by gender and we run the specification as in Equation 1. In Table E2a, Column 1 shows that the male respondents were driving a significant increase in the WTP for the mental health app by 14.6% SD. In Table E2b, we find that the female respondents are entirely driving the adverse effect in the demand for information about mental health support services. Column 3 and Column 4 in In Table E2b shows that female respondents reduce the information demand for psychologist services and increase the information demand for coaching services.

The CRF confirms that there is a strong heterogeneity in the treatment effects by gender. In Figure 2, sub-figures 2a, 2b, 2c and 2d show a pattern of results that is analogous to what we find in Table E2. On the one hand, male respondents show a larger Average Treatment Effect (ATE) of the mental health intervention on the WTP for the mental health app. On the other hand, female respondents have lower ATE of the mental health intervention on the demand for information about psychological services and a higher ATE on the demand for information about coaching services, in line with the substitution effect in care seeking.

Result 2. *The mental health literacy intervention leads to highly heterogeneous by baseline mental health (PHQ4) and gender. The respondents with moderate mental health disorders are substituting the demand for psychologist service with the demand for coaching service, while the respondents with both high and low mental health status increase their demand for low-intensity care without reducing*

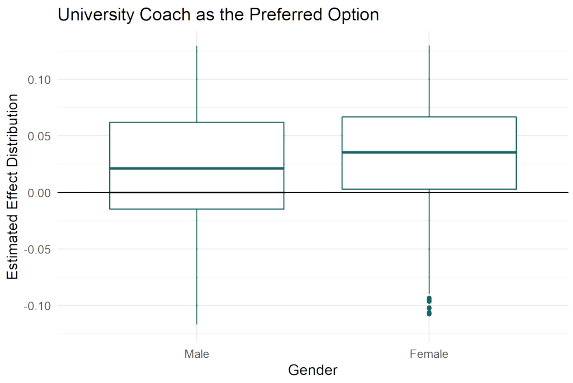


(a) Willingness-to-Pay



(b) No Information

(c) Information on Psychology Services



(d) Information on Coaching Services

*Note: We follow Wager and Athey (2019) to estimate conditional average treatment effects (CATE's) for each of observations in our sample. In the random forest methods, we include Age, Dutch, Female, Bachelor, GPA, Financial Stress, Father's Education, Mother's Education, and PHQ4 as the covariates. Each figure shows the distribution of CATE's for Males and Females separately. In (a), we have the willingness-to-pay for one month of access to Sanvello as the outcome. In (b), the outcome is if the individuals put no-information as their preferred option for information acquisition. In (c), the outcome is if the individuals put information on psychological services as their preferred option for information acquisition. In (d), the outcome is if the individuals put information on coaching services as their preferred option for information acquisition.

Figure 2: Heterogeneity of the Effects by Gender

their demand for high-intensity care. Male respondents react to the treatment by increasing their WTP for the mental health app. Whereas, the treatment causes the female respondents to demand more information for the coaching service and to reduce the demand for psychologist services.

3.4 Mechanisms

Empirical specification We use the following specification to explore which mechanisms play a role in shaping the respondents' reaction to the mental health literacy intervention:

$$m_i = \alpha + \beta t_i + \Gamma^T X_i + \epsilon_i$$

where m_i is a Z-score value obtained from the answers to the underlying mechanism questions.[19]

Understanding the mechanisms Table 3 sheds light on which mechanisms are driving the observed treatment effects. The coefficient in Column 3 shows that the mental health literacy intervention increases the perceived effectiveness of the mental health app. Table G1a from Appendix G shows that most of the effect is driven by the male respondents.[20] This result is coherent with the Result 2, which documents an increase in the WTP for mental health apps among the male respondents.

Table 3 Column 5, and Table G2 Column (2) show some evidence of an increase in stigma following the treatment. The effect could be explained by an increase in the salience of mental health problems, which are mentioned in the information treatment (Bordalo et al., 2016, 2010). The increased perceived benefits of low intensity mental health treatments may result in a stronger association of high intensity treatment with severe mental health problems, which may increase the perception of stigma associated with such treatments. So, care-seeking through the psychologist service could be a signal of worse mental health in a setting where

[19]These questions capture beliefs about the academic and labor market returns of good mental health, beliefs about the effectiveness of the mental health apps, self-stigma and social stigma about mental health care seeking. We have used questions with Likert-scale answers. To construct the Z-scores, we de-mean each answer by the mean answer of respondents in the Control group, and then divide the resulting difference by the standard deviation in the Control group.

[20]Table G1b reports the mechanisms' analysis for the female students. The treatment does not have a significant impact on these factors.

other effective and cheap options are available for mild problems. We discuss the latter mechanism in Section 4. However, when we adjust the p-values for the Self-Stigma and Social Stigma indexes using the "false discovery rate" procedure (Benjamini, 2010), the mental health literacy does not increase Social and Self Stigma at conventional significance levels.

Result 3. *The mental health literacy intervention increases the perceived effectiveness of the mental health app. The effect is mostly driven by the male respondents.*

Table 3: Mechanisms

	Dependent variable:				
	Academic returns	Labor returns	App effectiveness	Self-Stigma	Social Stigma
	(1)	(2)	(3)	(4)	(5)
Treatment	-0.003	0.003	0.103^{***}	0.038	0.058^{**}
	(0.006)	(0.035)	(0.036)	(0.026)	(0.028)
Observations	2,978	2,978	2,978	2,978	2,978
Z-score	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES
Control group mean	0	0	0	0	0
Adjusted R^2	0.039	0.048	0.016	0.063	0.087
Adjusted p-value	NO	NO	NO	0.32	0.13

Note: All specifications are OLS models. Robust standard errors are reported in parentheses. We z-score all the mechanism questions. For each question, we subtract the mean of the control group and divide by the standard deviation of the control group. We adjust the p-value of Self Stigma and Social Stigma with "false discovery rate" procedure. *Control* variables are: Age, Dutch, Female, GPA, Financial Stress, Father's Education, Mother's Education, PHQ4. Significance code: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Self-stigma and Social stigma We investigate what are the factors that influence the stigma that is attached to mental health care seeking. To this purpose, we have created an index of both Self-Stigma and Social Stigma separately.[21] The creation of indexes helps to address the concerns of Multiple Hypothesis Testing.

Figure A.30 shows that Female respondents in the Control group tend to report less self-stigma concerning mental health care seeking behavior, and a similar pattern applies for younger students. On the other hand, respondents with a higher GPA and Dutch students in the Control group report higher perceived stigma attached to mental health seeking behavior.

[21]The Self-Stigma questions measure the attitudes towards mental illness and towards care-seeking.

Figure A.31 depicts a similar picture for Social Stigma. Female respondents report to be less scared to tell their parents about mental health issues and they are less scared of potential discrimination at the university because of their mental health. The opposite pattern emerges for students with high GPA and for Dutch students.

Overall, the strong and positive correlations between Self-stigma and Social stigma and being Dutch can be interpreted as suggestive evidence of the reasons why Dutch students display a lower willingness to pay for the mental health app and why they are less interested in receiving free information about mental health support options available at the university.

3.5 Persistence of the effect

We study the persistence of the effects of the treatment on respondents' self-reported care seeking behavior, beliefs and mental health status. We have recontacted 1121 respondents, which accounts for 37.6% of the total sample.[22] Table H1 in Appendix H shows that the treatment is not leading to differential attrition of the participants into the follow up. Table H2 in Appendix H shows that the sample of the first experiment does not differ from the sample in the follow-up survey.

Figure 3 plots how the mental health of the participants of the main study and follow up evolves over time. The figure shows the respondents from both Treatment and Control group are improving their mental health. However, the average mental health improvement in the Treatment group is larger than the average improvement in the Control group.

[22]Students with a GPA above 6.5 were more likely to join the follow-up than those with a lower GPA.

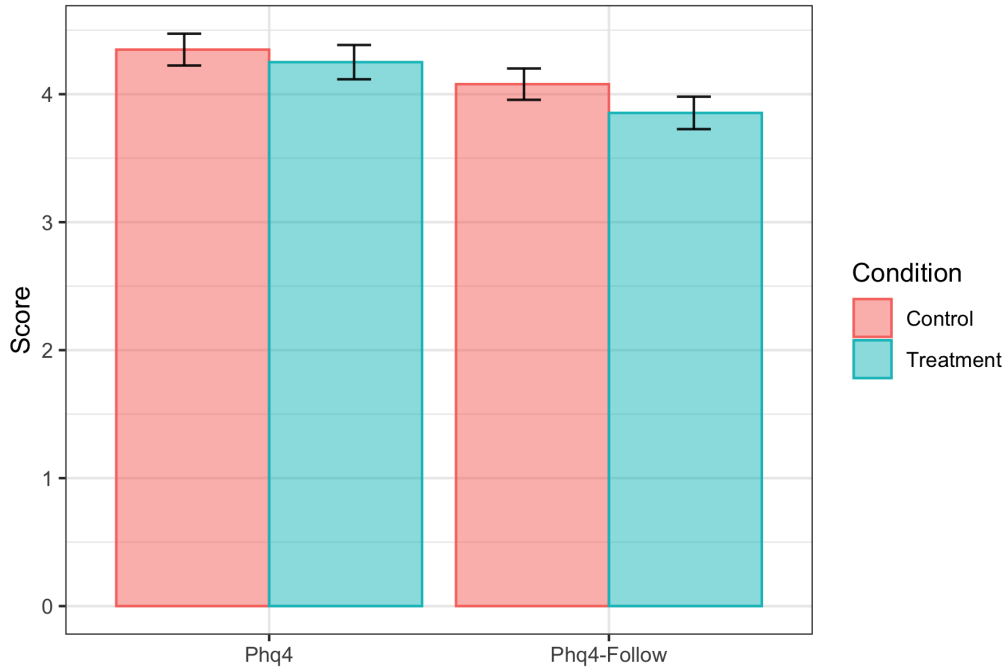


Figure 3: Differences in PHQ4 by Treatment

Table H3 shows that the treatment is improving mental health of the respondents and it is leading more respondents to plan to seek care, although these estimates are not significant at the conventional level. As the heterogeneity analysis of the main result suggests, there is a considerable heterogeneity in the treatment effects between male and female participants. Hence, we split the sample by gender and we study the mental health and the care-seeking behaviour for each sample separately. Table H4b documents that the mental health literacy intervention was leading more female respondents to seek care and plan to do it in the next few weeks. Moreover, we find that the treatment significantly improves the mental health of the female respondents by 0.10 SD. The asymmetric effect of the mental health intervention on the female respondents compared to the male respondents is in line with the results in the literature on the effect of mental health care on students' mental health (Bhalotra et al., 2022).

These effects are striking because the Dutch government announced on November 12th that further measures were going to limit people's freedom to counteract COVID-19 diffusion. These results show that the treatment was somehow making the female respondents more resilient to negative events.

The persistent effects of the mental health literacy intervention on the female respon-

dents' mental health could potentially be driven by female respondents willing to provide a desirable answer. If this was the case, we would find that the treatment improves female respondents' mental health status even more in the first study. To test this conjecture, we regress the respondents' mental health status from the first study on a treatment dummy, a gender dummy, an interaction term between the two dummies, and all the remaining control variables. We find that the interaction term is not statistically different from zero ($\beta = 0.11$ and $p - value = 0.58$), which suggests that it is unlikely that the differences by gender in the PHQ4 score are due to experimenter demand effect.

We validate the use of information demand of mental health care services as a proxy for demand for mental health support. We regress whether the respondents were asking for information about either the psychological services or the coaching services with their past behavior and their planned behavior. Table H5 in Appendix H shows that demand for information predicts well the respondents' self-reported behavior both in two weeks before the follow-up and two weeks after the follow up. Furthermore, we validate the use of the WTP for the mental health app as the main tool to capture demand for mental health support. To this end, we regress whether the participants have been receiving or are planning to receive support (via psychologist, coaching or apps) on the WTP and the demographic controls. We find that WTP is a strong predictor of the respondents' demand for mental health support.

Table H7 shows that, on average, the treatment did not persistently affect the respondents' beliefs about app effectiveness over time. However, the respondents in the Treatment group report to believe more in the effectiveness of coaching services compared to what the respondents in the Control group report (p-value < 0.1).

Moreover, Table H8 shows the persistence of the self-stigma for the respondents in the Treatment group. This result should raise the concern of the long-lasting impact of the self-stigma associated with the discussion around mental illness and mental health care seeking. It is also consistent with the findings of the model in 4 that promoting lower-intensity care can lead to more stigma towards higher-intensity care types such as psychology services. However, the effect is not significant once we adjust the p-value with the "false rate discovery" procedure.

Finally, the respondents in the Control group find the psychological services to be more

effective than both mental health apps and coaching services.[23] Among the respondents from the Control group mental health apps are less stigmatized compared to psychological services (one-sided t-test with p-value < 0.01). The respondents in the Control group who use coaching services report to believe that coaching service is less self-stigmatizing than psychological services (one-sided t-test with p-value < 0.1).

Result 4. *On average, the mental health literacy intervention does not significantly affect the students' intention to seek care (although the estimates are positive). Moreover, the intervention improves the female students' mental health status. There is suggestive evidence that this is due to an increased care seeking behavior, both past and future, of the female students. Furthermore, the demand for information strongly predicts respondents' self-reported care seeking behavior. Finally, there is suggestive evidence that the treatment increases self-stigma towards care-seeking behavior.*

3.6 Robustness checks

Awareness Falk et al. (2021) model the role of limited self-knowledge and how it introduces biases in the survey responses. To account for this concern, we define our respondents as "aware" if their self-reported mental health coincides with the level of mental health captured by the PHQ4 scale. Otherwise, they are labelled as "unaware". 80% of our respondents are aware of their mental health status (either high or low level). Moreover, the correlation between the self-reported mental health level and the PHQ4 score is 67%, which means that the two measures are highly correlated.

We estimate an OLS model similar to the Equation 1 with the inclusion of an indicator which gets the value 1 if the respondents are aware. Table I1 in Appendix I presents the results of this model. The estimates are unchanged compared to the main results from Table 2, which means that the awareness is not playing a substantial role in shaping respondents' behavior.

Demand for Information - Logit models We assess to what extent how our results are robust to the estimation method. We model the respondents' demand for information by

[23] In both cases, we use a one-sided t-test and both p-values < 0.001.

using a random utility model and we estimate it with a Logit model. Table I2 in Appendix I confirms that the mental health intervention causes a shift in the demand for information from the psychological service to the coaching service.

Fast and slow respondents One concern of conducting online survey experiments is that the respondents might not spend enough time or too much time to complete the survey. To account for this concern, we drop the respondents who lie in the 1st and 99th percentile of the completion time for the survey. Then, we re-estimate the OLS model from Equation 1 with the restricted sample.

Table I4 in Appendix I shows the set of estimates virtually unchanged compared to those in Table 2. Therefore, we conclude that our estimates are robust to the potential inattentive respondents.

Experimenter Demand Effect A further concern for our study is that the experimenter demand effect is driving our results. Although de Quidt et al. (2019) shows that experimenter demand effect is usually moderate in the experiment, we provide some arguments to claim why we think it is very unlikely that it might be driving our results.

To make experimenter demand effect the main driver of our results, we would need that at least one of the following conditions is satisfied: (i) the respondents know that they are part of an RCT, (ii) the respondents want to help us and (iii) the respondents know which answers would be helpful.

In our context, the participants do not know that there is another experimental group that might or might not receive information. This implies that the first point might not be a serious concern. Moreover, we do not see a particular reason why the respondents might want to help. If anything, they have incentives to provide their WTP for the mental health app and to acquire information they are interested in. Furthermore, even if they wanted to help us in our research, they would not know which answer would be helpful for us (if any). In addition, our treatment does not make any specific mention of apps or psychologist/coaching services. Therefore, the Result 1 we find it is highly unlikely to be driven by experimenter demand effect. Finally, we have made extra effort to ensure anonymity of the respondents of the

experiment to minimize experimenter demand effect.

4 A Model

In this section, we develop that explains the findings of the experiment. The model builds on the factors that influence care-seeking behavior of individuals including costs, benefits, and self- and social-image concerns.

4.1 Primitives of the Model

The model builds on the primitives of Bénabou and Tirole (2011) and Grossman (2015). Individual A lives for four periods: $t = 0, 1, 2, 3$. In period 0, the Nature draws both the individual's initial mental health, $m \in [0, 1]$ and also the individual's type $s \in \{low, high\}$. The continuous mental health level m captures the continues nature of mental health as discussed in Patel (2018). The type refers to the individuals' characteristics. By introducing the individuals' type alongside with their mental health level, we can formalize the concepts of stigma. Self stigma towards mental-health and health seeking behavior are rooted in negative misperceptions (Link, 1987; Link and Phelan, 2001). These misperceptions are formed in childhood by lay theories that link mental-illness with negative characteristics. The misperceptions and lay theories can be considered to be equivalent to social stigma[24]. Corrigan et al. (2006) argue that self-stigma can be defined as the agreement between one's beliefs and these lay theories. The social stigma is the agreement of the society around the individual with these lay theories and misperceptions. By introducing the type of the individual s, we later allow for a (perceived) correlation between mental health levels of the individual and their characteristics which creates stigma towards mental health problems and possibly care-seeking.

Individual A can decide if and how to invest into her mental-health given her mental health level m, in period $t = 1$, and pay the costs. In period $t = 2$, an observer, O, observes

[24]It is noteworthy that in the context of mental health, the misperceptions are mainly rooted in the historical negative view against mental health problems. However, it can also be the case that the misperceptions contain a kernel of truth as Bordalo et al. (2016) discuss.

A's investment decision. Individual A, gains utility from the beliefs of the observer on her type. Everything equal, she prefers that O believes that she is high type. The observer beliefs on the individual being the high type is the source of stigma. One can think of the observer being a self-observer which does not recall her type but observes her investment decision. The observer can also be viewed as a social observer who only observes the mental health investment decisions and does not know the mental health level, m, of the individual.

In period 3, individual A might receive an output with 1 unit of utility or nothing. This output can represent both higher wellbeing or better labor market/educational outcome of the individual in the medium and long-term. The probability of receiving the unit utility depends positively on individual A's initial mental health endowment and the mental health investment decision.

Period 0 The nature draws the mental health level of the individual A. The initial mental health $m \in [0,1]$ with continuous and strictly positive probability distribution function $f(m)$ (on $[0,1]$), with mean μ_m. The nature also draws the type of the individual $s \in \{low, high\}$. We assume that s is an abstract concept which has no real influence on the final outcome (no kernel of truth). However, individuals prefer to be associated with the high type. We assume that there is a positive association between m and s. This association represents the negative misperceptions and lay theories against lower mental health levels.

Period 1 Observing her mental health level, individual A decides the type of investment (care-seeking) in her mental health $i \in \{0,1,2\}$[25]. The three types of care can represent (1) no care-seeking ($i = 0$), (2) low-intensity interventions to improve coping strategies, awareness, monitoring and and self-care, and etc. ($i = 1$), (3) and more progressive/professional

[25]For simplicity, we assume the individual has full knowledge on her mental health level as well as the investment returns at the time of the investment decision.

treatments ($i = 2$). The cost of care is $c(i)$:

$$c(i) = \begin{cases} 0 & i = 0 \\ c_1 & i = 1 \\ c_2 & i = 2 \end{cases}$$

with $c_2 > c_1 > 0$. The high-intensity intervention is more costly than the low-intensity intervention. The cost can be thought of as the monetary costs as well as emotional opening-up cost, foregone time, or (fixed) social image costs.

Depending on the investment decision, the probability of receiving the unit utility in period 3 can increase by $b(m, i)$, where:

$$b(m,i) \begin{cases} 0 & i = 0 \\ b_1(m) & i = 1 \\ b_2(m) & i = 2 \end{cases}$$

with $b_1(m)$ and $b_2(m)$ being continuous, differentiable, and decreasing functions ($b_i'(m) < 0$, $i \in \{1, 2\}$). The latter assumption intuitively means that the lower mental health of the individual, the more effective the interventions are. We also assume investment type 2 is more effective for poorer mental health (see Patel (2018)); $b_2(0) > b_1(0)$ and $b_2'(m) - b_1'(m) < 0$. This means that the more mentally unhealthy individuals are, the more effective the professional treatment ($i = 2$) becomes. We assume $b_1(1) = b_2(1) = 0$, meaning that the mentally healthy individual would not benefit from any of the investment options. A sketch of the benefits can be seen in Figure 4.

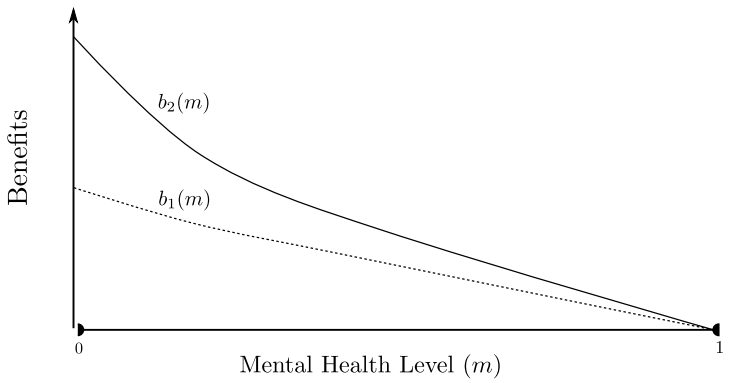


Figure 4: Sketch of Functional Form of the Benefits of Investments

Period 2 There is an observer in period 2: O. Individual A, receives utility from the beliefs that this observer forms about A being high type ($s = high$). O assigns a probability $\hat{p}_O(m)$ for each individual with mental health level m to be the high type. The higher mental health status, the higher probability assigned to the individual being the high type ($\hat{p}'_O(m) > 0$) is. We also assume $\hat{p}_O(m)$ is convex ($\hat{p}''_O(m) \geq 0$). This assumption intuitively means that the beliefs of the observer are more sensitive to reduction in mental health status when individuals are healthy compared to when individuals are unhealthy.

Following Bénabou and Tirole (2011), the observer does not observe any of the type or mental health level of individual A. The only information available to the observer is the investment decision i. Therefore, $P(i) \equiv \int_0^1 \hat{p}_O(m) f(m|i) d(m)$, where $P(i)$ gives the probability of A being the high type and $f(m|i)$ the pdf of the mental health level to be m given the investment decision i. Individual A receives $\lambda_O P(i)$ in terms of utility. λ_O can be thought of as how much the individual cares about her image to the observer. The observer can be thought of as a self-observer who is not able to recall the type and mental health of herself, or can be thought of as a social observer who forms beliefs on the type of individual A, given the investment (care-seeking) decisions. The probability is the association between the care-seeking and the individual being the high type. This roots into the associations between mental health level and being the high type.

Period 3 A receives a unit of utility with probability $u(m) + b(m, i)$. $b(m, i)$ can be thought of as the utility in period 3 of investment/care-seeking decision i in period 1 for an individual

with initial mental health level m.

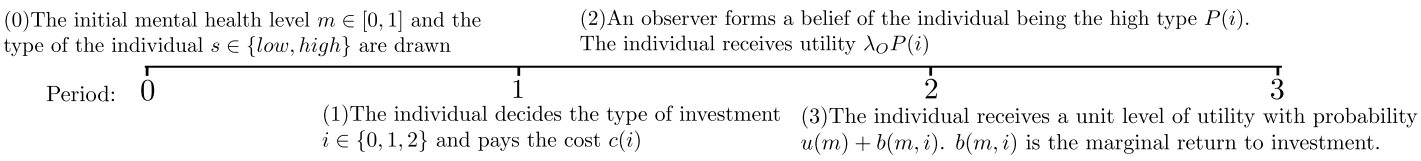


Figure 5: Timing of the Model

Assumptions Here we assume that individuals are uniformly distributed on the unit interval of mental health status, $f(m) = 1$[26].

4.2 Solution

For any individual with initial mental health level m, the expected utility (under Von Neumann--Morgenstern utility function) at the time of investment decision is:

$$\mathbb{E}\left(U(i,m)\right) = u(m) + b(m,i) + \lambda_O P(i) - c(i)$$

so for any m:

$$\mathbb{E}\left(U(i,m)\right) = \begin{cases} u(m) + \lambda_O P(0) & i = 0 \\ u(m) + b_1(m) + \lambda_O P(1) - c_1 & i = 1 \\ u(m) + b_2(m) + \lambda_O P(2) - c_2 & i = 2 \end{cases}$$

so, the solution to this problem can be identified by $i^*(m)$. In other words, knowing the investment decisions for all the initial mental health levels characterizes the equilibrium.

Pooling Equilibria

The pooling equilibria occurs when the individual always decides to seek a certain type of investment independent of the initial mental health endowment; $i^*(m) = i^*$. So, for all

[26]The results hold under milder (sufficient) conditions, namely, if the distribution of initial mental health satisfies the following:

$$\forall m^* \in [0,1] : \left(1 - F\left(m^*\right)\right) \mathbb{E}\left(m | m \leq m^*\right) + F\left(m^*\right) \mathbb{E}\left(m | m \geq m^*\right) \geq m^*$$

initial mental health level, the investment decision is similar. For each pooling equilibrium, it is required that the expected utility of the investment decision is higher than the other investment options. The only possible pooling equilibrium is the pooling equilibrium where nobody seeks care:

$$b_i(m) \leq c_i \; \forall m \in [0,1], i \in \{1,2\}$$

In a context with low benefits of seeking care (especially for those in worse mental health conditions $m = 0$) and high costs of seeking care, nobody is going to seek care[27]. Here we assume that the investment decisions are uninformative about the type of individuals (because everybody has the same strategy independent of her type). In other words, the individuals would not benefit in terms of observer beliefs, if they change their investment decisions. So, we assume the off-equilibrium belief of the observer is similar to the equilibrium belief; $f(m|i) = f(m)$.

With uninformative investment decisions, there is no pooling (or separating) equilibrium that everybody invests/seeks care. The reason is that, for the healthy individuals, it is always strictly beneficial to not invest given no benefit of investment, and nonzero costs[28] ($b_1(1) = b_2(1) = 0,\ c_2 > c_1 > 0$).

Separating Equilibria

It is straightforward to show, given $P(i)$, if there is a mental health level that prefers the lower-intensity intervention over the higher-intensity intervention, then for all the mental health levels above that, the lower-intensity intervention is preferred. The opposite holds for the high-intensity intervention. If there is a mental health level that higher-intensity intervention is preferred to a lower-intensity intervention, for all the mental health levels below, the high-intensity investment is preferred.

Given these patterns, one can show that in all the separating equilibria, there are some individuals who do not seek care. This is due to the fact that for $m = 1$, the benefits of

[27]This condition is sufficient for having a pooling equilibrium where nobody seeks care under reasonable assumption of no (off-equilibrium) association of care-seeking and having better than the average mental health status.

[28]The pooling equilibria that everybody invests $i = 1, 2$ is only possible under the unrealistic off-equilibrium beliefs that not care-seeking is a signal for worse mental health levels.

seeking care is zero while the costs are nonzero[29]. Consequently, we consider two partially separating equilibria where the healthier individuals do not seek care, $i = 0$, and unhealthier individuals only seek one type of care $i = 1$ or $i = 2$. We assume that off-equilibrium beliefs about the other type of investment is similar to the beliefs about the care that is being used in the population; so $P(1) = P(2)$. So, in case of a partially separating equilibrium, there exists a threshold m^* that individuals with $m < m^*$, they all seek the same type of care, and the ones above do not seek care (there is no mixed equilibrium). Note that for this partially equilibrium to hold, we also need that:

$$\begin{cases} b_1(0) - c_1 > b_2(0) - c_2 & if\ i = 1 \\ b_1(m^*) - c_1 < b_2(m^*) - c_2 & if\ i = 2 \end{cases}$$

In this equilibrium characterized by m^*, investment ($i \in \{1, 2\}$) in mental health signals that $m < m^*$:

$$P(i) = \frac{1}{m^*} \int_0^{m^*} \hat{p}_O(m) dm = \mu_s(m < m^*)$$

and in case of no investment:

$$P(0) = \frac{1}{1 - m^*} \int_{m^*}^1 \hat{p}_O(m) dm = \mu_s(m > m^*)$$

Note that $P(0) > P(i)$. Given that the individual with initial mental health level m^* is indifferent between seeking and not seeking care:

$$\frac{b_i(m^*) - c_i}{\lambda_O} = P(0) - P(i) = \mu_s(m > m^*) - \mu_s(m < m^*) \tag{2}$$

So, the net benefit of investment at the threshold ($b_i(m^*) - c_i$) relative to the image importance

[29]Given the patterns explained, it is safe to assume that not care-seeking cannot be associated with worse mental health levels.

(λ_O) is equal to the image costs of the investment. One can show:

$$\frac{\partial m^*}{\partial \lambda_O} < 0$$
$$\frac{\partial m^*}{\partial c_i} < 0$$
$$\frac{\partial m^*}{\partial b_i(m)} \geq 0 \, \forall m \in [0,1]$$

The results indicate that if the importance of image increases or the (monetary or social-image) costs of care-seeking increases, a smaller fraction of individuals (m^*) seek mental-health care. In presence of image concerns, the care-seeking behavior is always suboptimal in the sense that some individuals who would benefit from care seeking ($b_i(m) > c_i$) do not seek care because of the image concerns. Another observation is that if the benefits of care-seeking increases more people seek mental-health care.

Now, we consider fully separating equilibrium. In this equilibrium, there are two thresholds m_1^* and m_2^* such that if $m \in [0, m_1^*)$ then $i^*(m) = 2$, if $m \in (m_1^*, m_2^*)$ then $i^*(m) = 1$ and if $m \in (m_2^*, 1]$ then $i^*(m) = 0$ (See Figure 6). In other words, the individuals with the lowest mental health endowment seek the highest threshold intervention ($i = 2$), the individuals with middle mental health levels seek low-intensity investments ($i = 1$) and individuals who are relatively healthy do not seek any care ($i = 0$).

In this situation, the individuals with mental health level m_1^* and m_2^* are indifferent:

$$\frac{\left(b_2\left(m_1^*\right) - b_1\left(m_1^*\right)\right) - \left(c_2 - c_1\right)}{\lambda_O} = \mu_s(m_1^* < m < m_2^*) - \mu_s(m < m_1^*)$$

and

$$\frac{b_1\left(m_2^*\right) - c_1}{\lambda_O} = P(0) - P(1) = \mu_s(m > m_2^*) - \mu_s(m_1^* < m < m_2^*)$$

one can show:

$$\frac{\partial m_2^*}{\partial \lambda_O} \leq 0, \frac{\partial m_1^*}{\partial \lambda_O} \leq 0$$

$$\frac{\partial m_1^*}{\partial c_1} \geq 0, \frac{\partial m_2^*}{\partial c_1} \leq 0, \frac{\partial m_1^*}{\partial c_2} \leq 0, \frac{\partial m_2^*}{\partial c_2} \leq 0$$

$$\frac{\partial m_1^*}{\partial b_1(m)} \leq 0, \frac{\partial m_2^*}{\partial b_1(m)} \geq 0, \frac{\partial m_1^*}{\partial b_2(m)} \geq 0, \frac{\partial m_1^*}{\partial b_2(m)} \geq 0 \, \forall m \in [0,1]$$

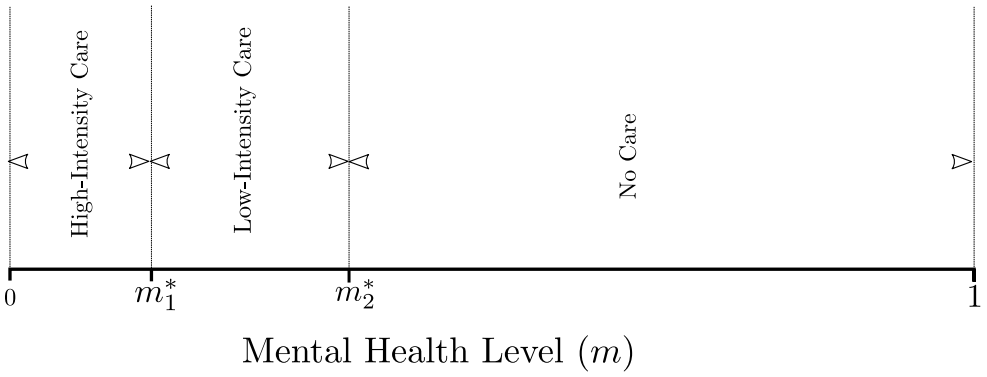


Figure 6: Investment Decisions in Fully Separating Equilibrium

Model Predictions *In a completely separating equilibrium:*

1 *If the perceived benefits of any types of care-seeking increases, more individuals (m_2^*) seek care. The results are in line with the findings in the experiment. We find that for the male students, the information has increased the perceived benefits of the app and also these students are willing to pay more for the app (Table G1 and Table E1).*

2 *If the perceived benefits of low-intensity therapies relative to the high-intensity therapies increase, the number of individuals using low-intensity therapies, ($m_2^* - m_1^*$), increases. This is partly due to the substitution of the high-intensity care with low-intensity care, and partly because of new individuals seeking care.*

In the experiment, we find that as a consequence of the information, the students demand more information on coaching services in the university, and less information on the psychology services. This finding, in Table 2, is in line with the model predictions. As the model suggests, this finding can be explained by the increased perceived benefits of the low-intensity services.

3 *If the perceived benefits of low-intensity therapies relative to the high-intensity therapies increase, less individuals use high-intensity therapies, and this leads to higher stigma against high-intensity therapies. This is because using high-intensity therapies when low-intensity therapies are cheap and effective is a signal of low mental health status which require progressive treatments.*

Looking at Table G2 and Table G3, we find suggestive evidence of increased stigma towards higher-intensity services in the experiment. However, this finding does not survive Bonferroni

correction, and we lack statistical power to have a concluding image here.

4 *If the benefits of low-intensity therapies relative to the high-intensity therapies increases, the effect on stigma against low-intensity therapies is ambiguous. This is because some individuals with low health who would have sought high-intensity care now seek low-intensity care, and some mentally healthy individuals who wouldn't have sought care now use low-intensity care.*

5 Conclusions

We provide evidence of the effect of a mental health literacy intervention on the demand for mental health support among university students. Drawing on a representative sample of the students from a top Dutch university, we document substantial heterogeneity in the demand for mental health support. Male respondents are respond positively to the treatment by increasing their WTP for a monthly subscription to a mental health app. The most likely mechanism behind the effect is an increased perception of efficacy of low-intensity interventions, like online apps. We also show evidence that interest in high-intensity interventions (e.g., seeing a psychologist) can be replaced by interest in low-intensity interventions (e.g., relying on mental health apps and coaching). This result is entirely driven by female respondents. Additionally, the self- and perceived social stigma against high-intensity interventions might increase. In a three weeks later follow up, we document that the female respondents who were treated report a better mental health compared to the ones in the Control group.

Overall, our results suggest that increasing the perceived benefits and efficacy of mental health support services can be a key driver towards increasing take-up rates. Mental health care providers should also account for the heterogeneous effects of mental health literacy and prevention campaigns, since different sub-groups may be more susceptible to reacting to the information provided. Further evidence is needed to understand how different types of information can affect different sub-groups of the population and interact with their prior beliefs. Finally, information encouraging self-care and lower-intensity interventions may induce a shift in demand away from other services which are perceived as substitutes. Similarly, if the reception of mental health literacy information is associated with more stronger perceptions of self- and social stigma, recipients may shift away from traditional

sources of help (e.g. psychotherapy) and towards options around which there is less stigma (e.g. self-help tools or coaching services).

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Appendix

A Figures

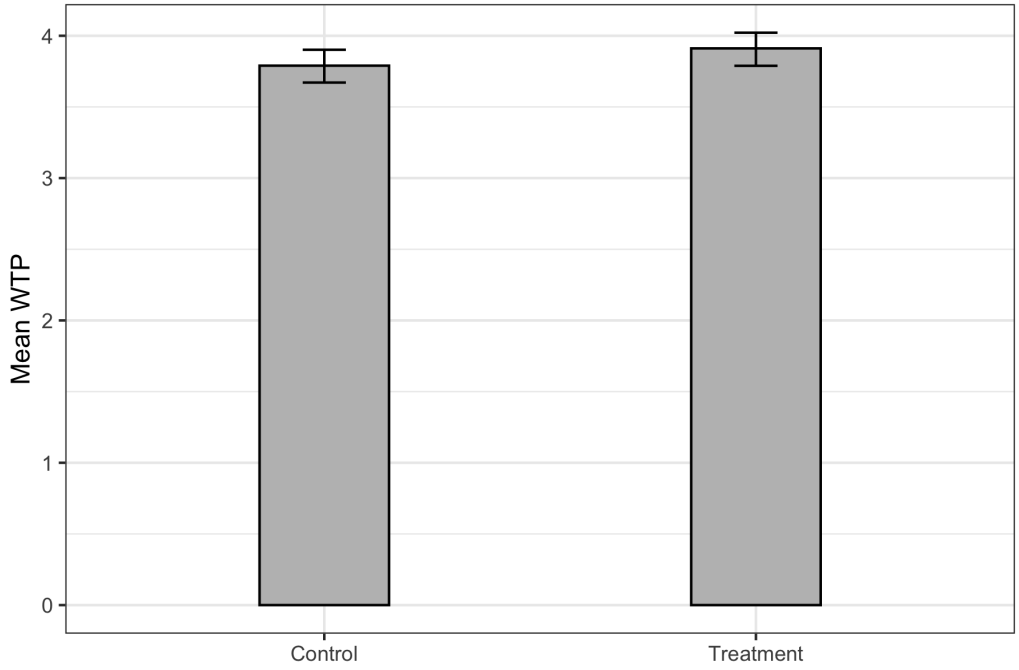


Figure A.1: Demand for Mental Health Support - WTP

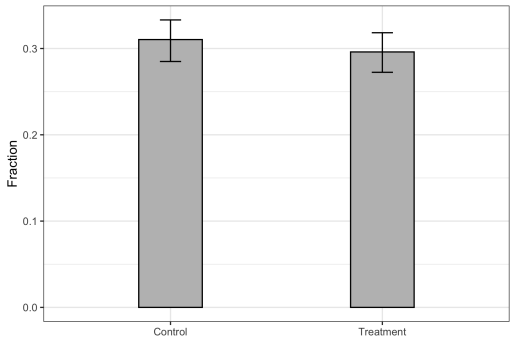


Figure A.2: No Information

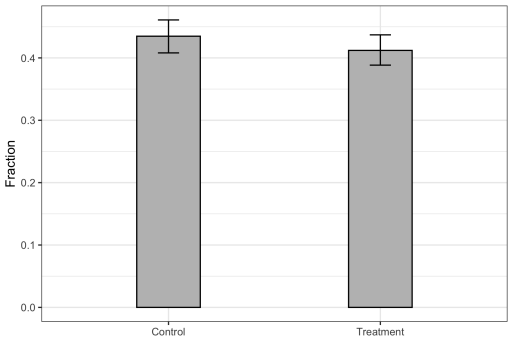


Figure A.3: University Psychologist

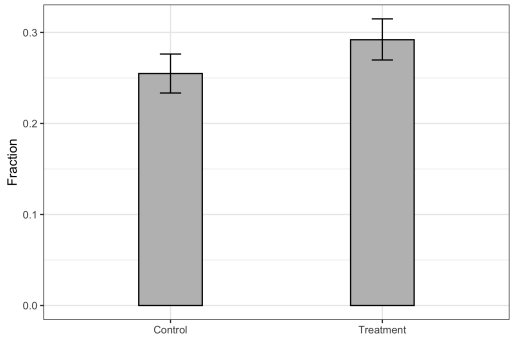


Figure A.4: Coaching Service

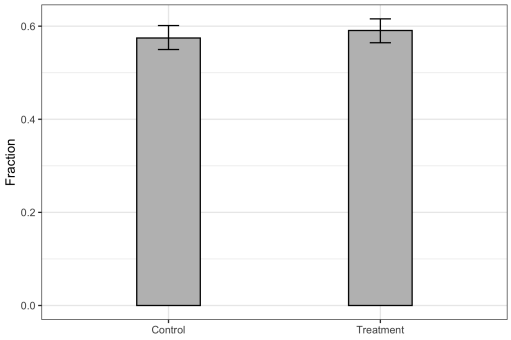


Figure A.5: Any Information

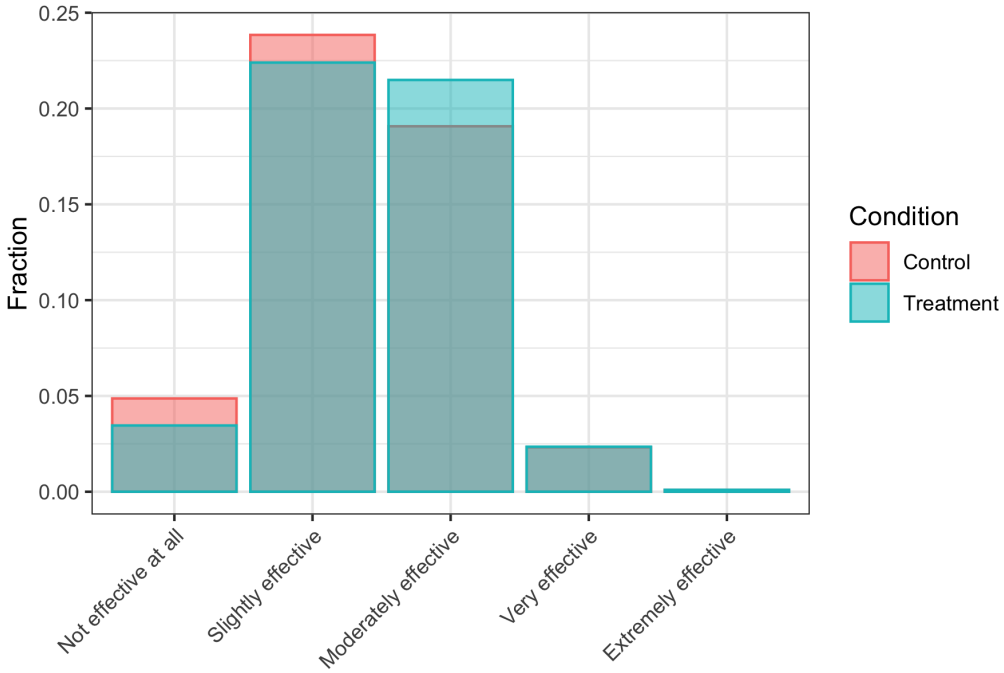


Figure A.6: Beliefs about the effectiveness of the mental health app

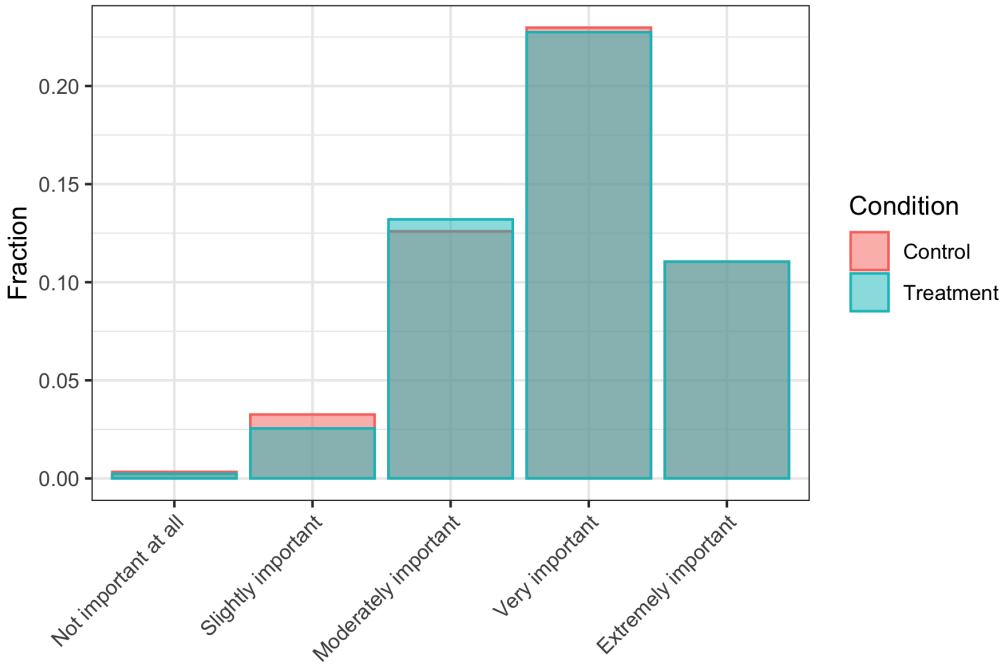


Figure A.7: Beliefs about the labor market returns of mental health

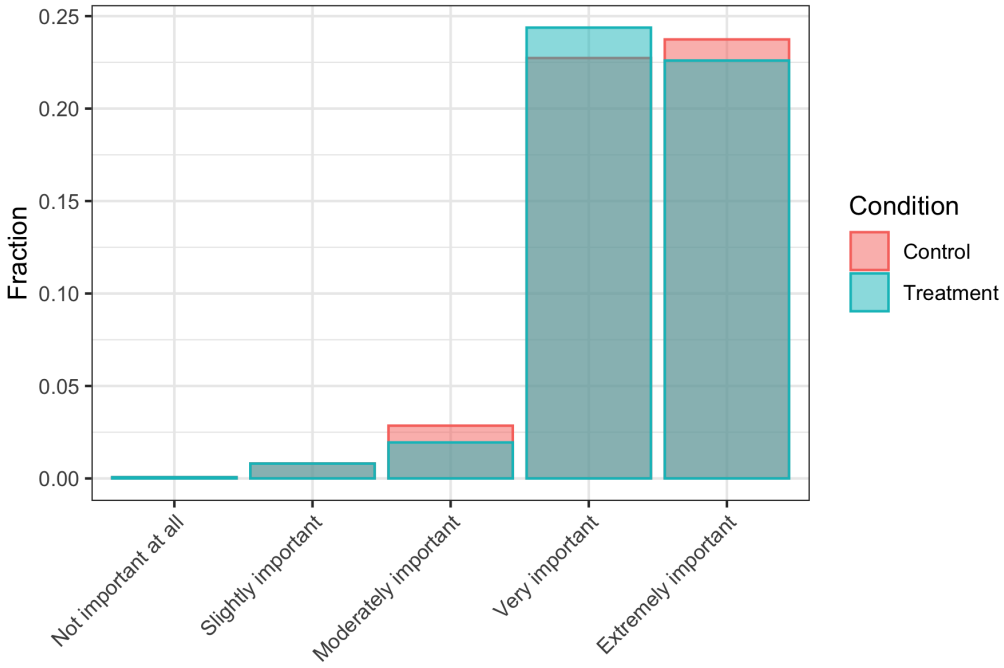


Figure A.8: Beliefs about the academic returns of mental health

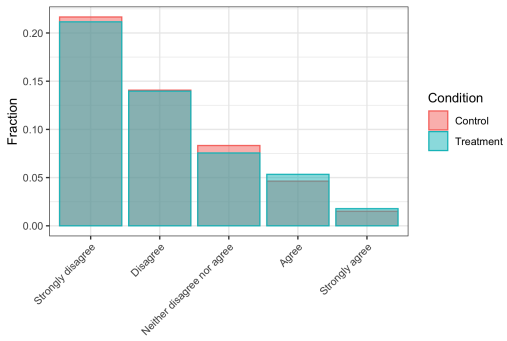


Figure A.9: Feeling inadequate

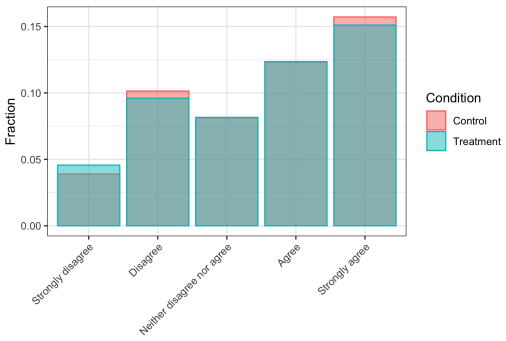


Figure A.10: Self-Confidence

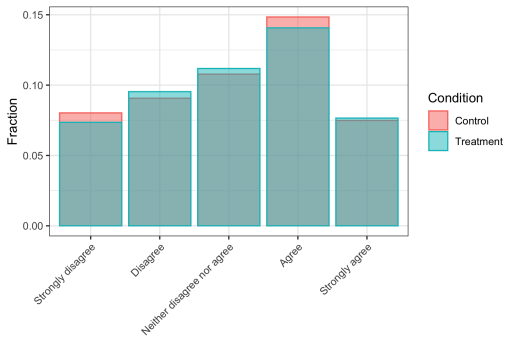


Figure A.11: Feeling worse

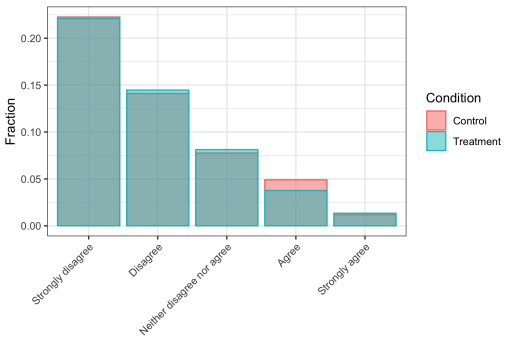


Figure A.12: Feeling less

Figure A.13: Self-Stigma components

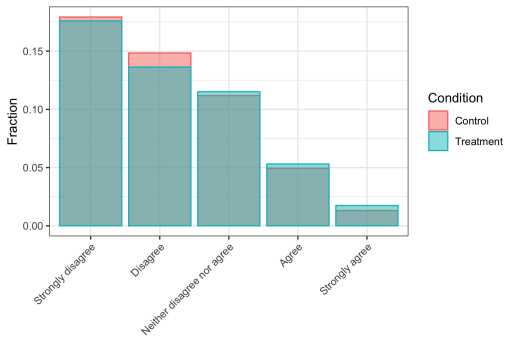


Figure A.14: Perceived discrimination

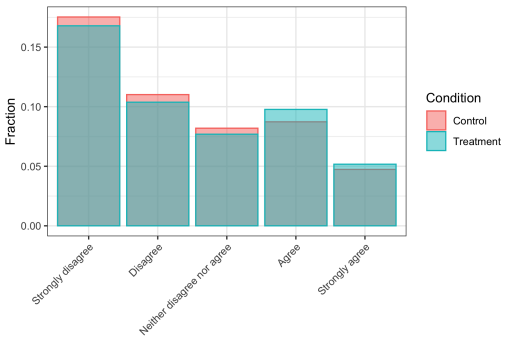


Figure A.15: Worried about Family

Figure A.16: Social Stigma components

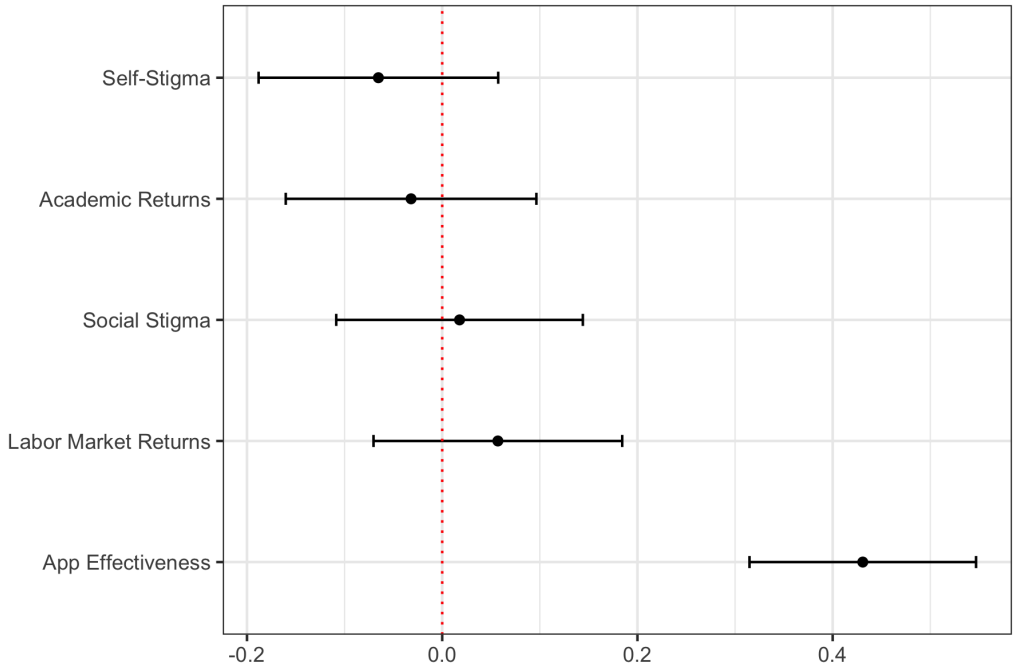


Figure A.17: Drivers of the WTP for mental health app

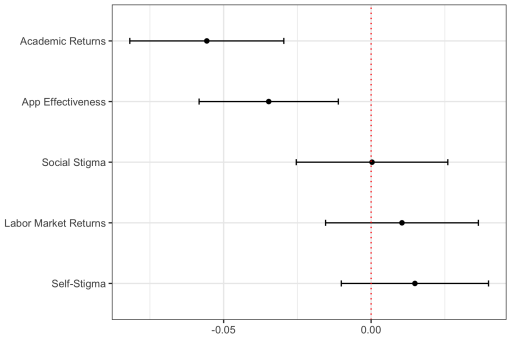


Figure A.18: No Information

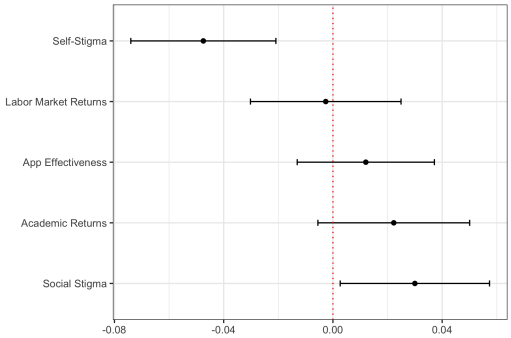


Figure A.19: University Psychologist

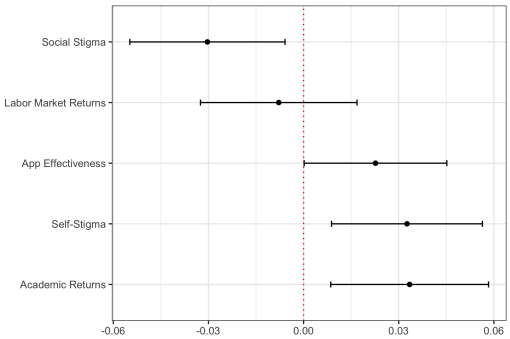


Figure A.20: Coaching Service

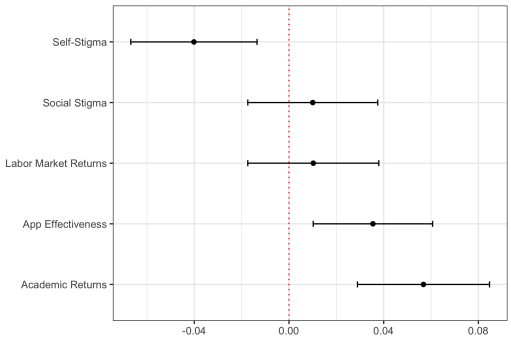


Figure A.21: Any Information

Figure A.22: Drivers of the demand for Information

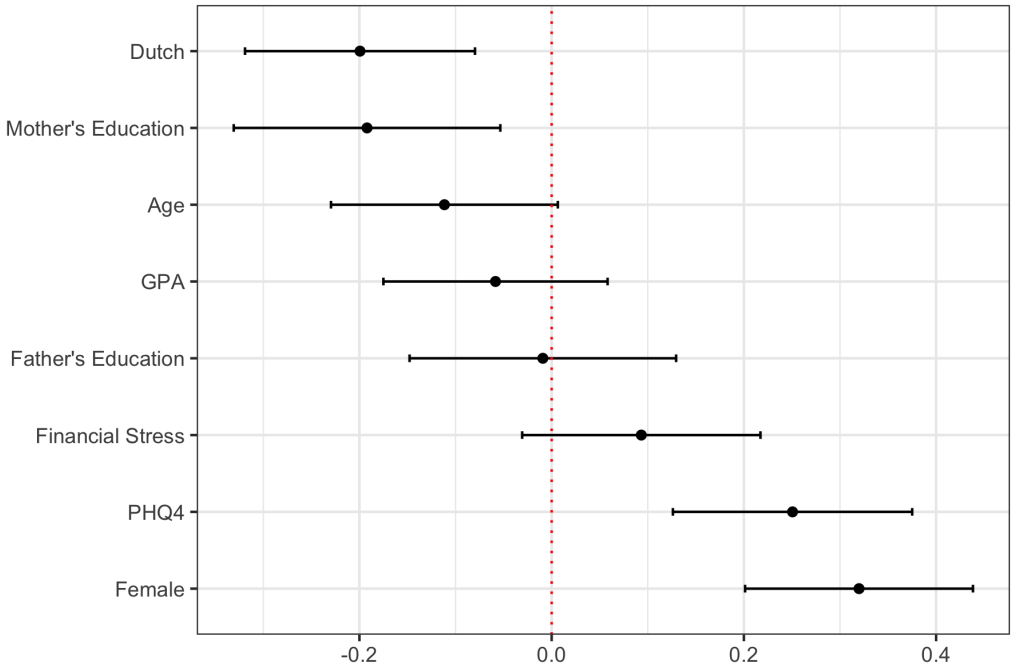


Figure A.23: Correlations between WTP for mental health app and control variables

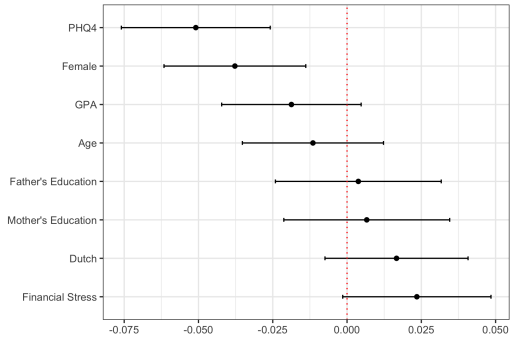


Figure A.24: No Information

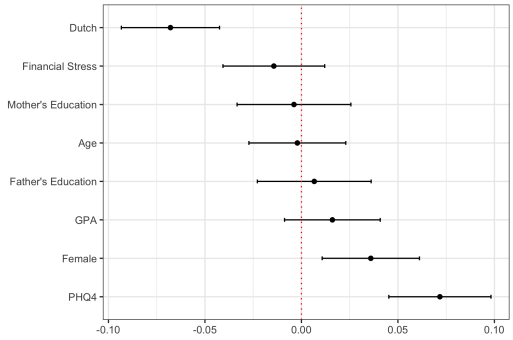


Figure A.25: University Psychologist

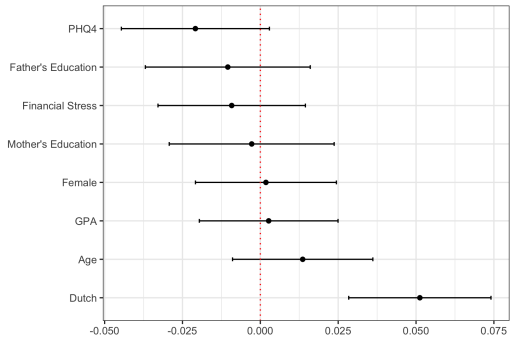


Figure A.26: Coaching Service

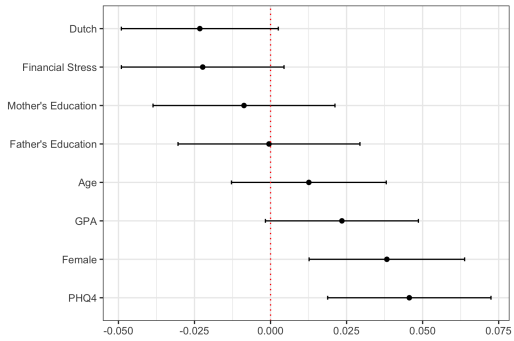


Figure A.27: Any Information

Figure A.28: Correlations between Demand for information and control variables

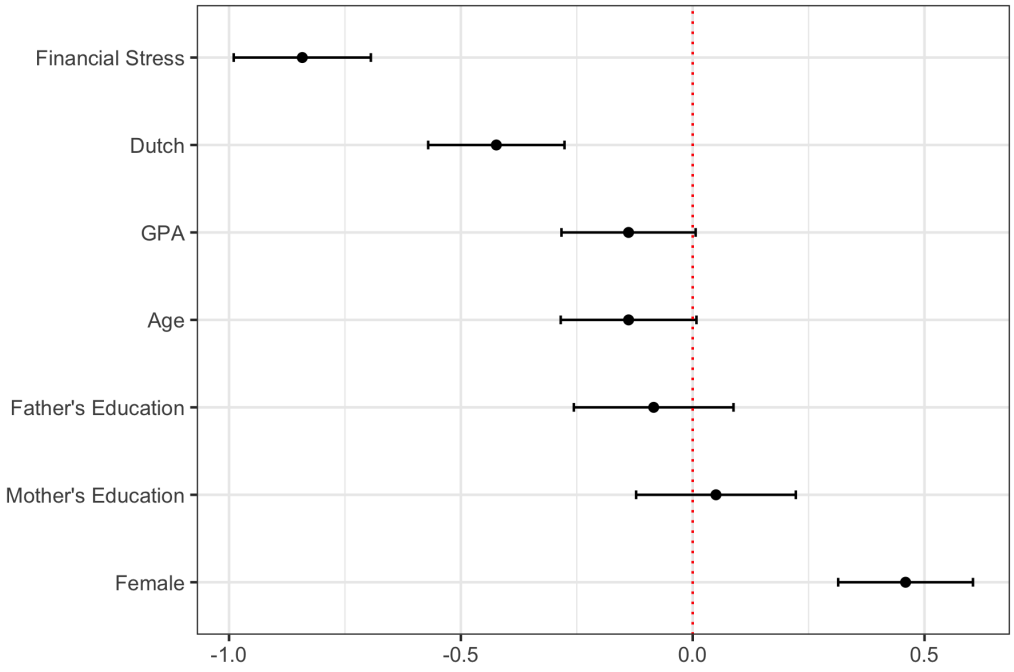


Figure A.29: Correlations between PHQ4 and control variables

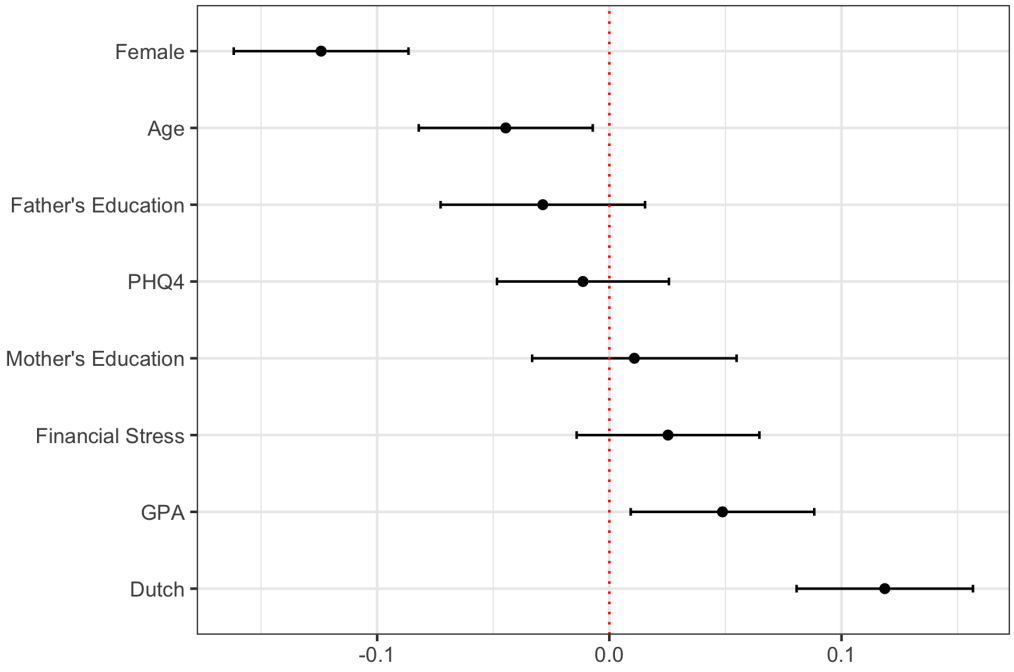


Figure A.30: Correlations between Self-Stigma index and control variables

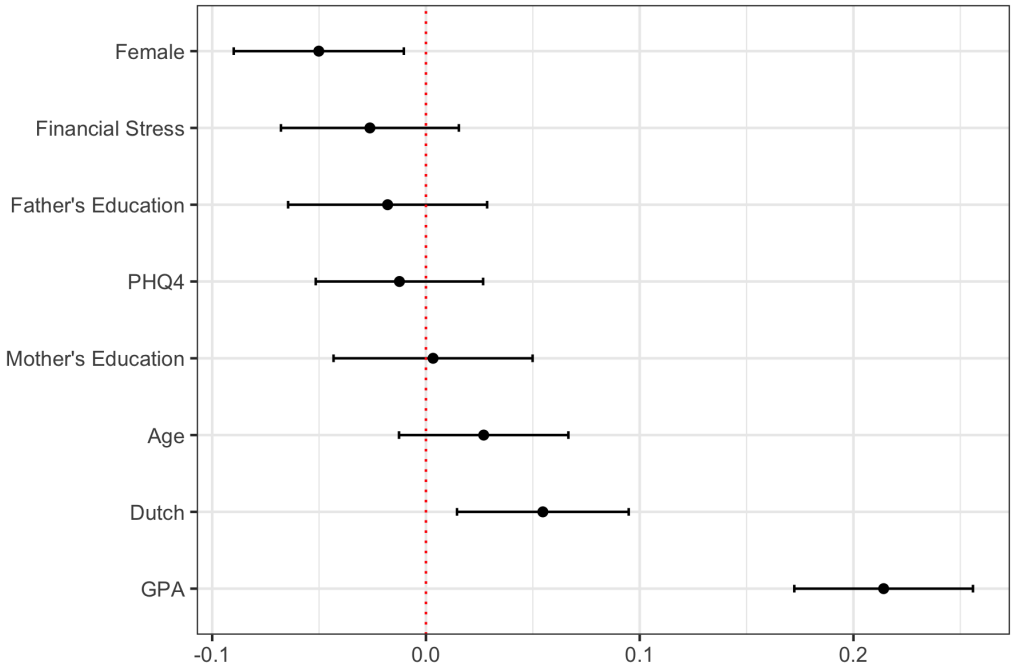


Figure A.31: Correlations between Social stigma and control variables

B Representativeness of the sample

Table B1: Representativeness of the sample

Variables	Population	Sample
Dutch	0.75	0.61
Female	0.53	0.64
Bachelor	0.63	0.59
Faculty		
Economics and Business	0.212	0.183
Health Policy	0.041	0.050
History and Communication	0.063	0.079
Law	0.163	0.076
Philosophy	0.026	0.010
Psychology	0.142	0.21
Liberal Arts	0.018	0.034
Medical School	0.113	0.117
Business School	0.221	0.24
Observations	34122	2978

Note: The table shows the demographic characteristics for our sample compared to the university population. Dutch gets value 1 if the participant has Dutch nationality. Female gets value 1 if the participant reports to identify with female gender. Bachelor is a dummy that gets value 1 if the participant is a bachelor student. Faculty is broken down into the 9 faculties that constitute the university.

C Randomization Check and Differential Attrition

Table C1: Randomization check - Full sample

Variables	Control	Treatment	p-value
Age	21.46	21.67	0.1
Dutch	0.63	0.60	0.08*
Female	0.62	0.66	0.02**
Bachelor	0.59	0.59	0.70
Low GPA	0.50	0.50	0.89
Financial Stress	0.20	0.22	0.08
Father's Education	0.37	0.37	0.89
Mother's Education	0.32	0.33	0.55
Mental Health	0.14	0.12	0.30
PHQ4	4.29	4.33	0.72
Observations	1495	1483	

Note: The table shows the demographic characteristics for our sample broken down into Treatment and Control group. t-tests were used to assess whether demographic variables followed the same distribution between Treatment and Control. The third column reports p-values. Age is a continuous variable of the age of the participant. Dutch gets value 1 if the participant has Dutch nationality. Female gets value 1 if the participant reports to identify with female gender. Bachelor is a dummy that gets value 1 if the participant is a bachelor student. Low GPA gets value 1 if the participant reports to have a GPA lower than 7.5. Financial Stress gets value 1 if the participants reports that the current financial situation is "Very Bad" or "Bad". Father's Education and Mother's Education get value 1 if the participant's father and mother, respectively, do not have a bachelor degree. Low Mental Health gets value 1 if the self-reported mental health of the participant is "Very Bad" or "Bad". PHQ4 is a continuous variable for a diagnostic measure of the participant's mental health. This is measured after the treatment, which is not affecting it. Significance code: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table C2: Differential Attrition

	Dependent variable:	
	Finished	Finished
	(1)	(2)
Treatment	−0.0072	−0.0099
	(0.010)	(0.010))
Observations	3,292	3,292
Controls	NO	YES
Adjusted R^2	−0.0001	−0.0001

Note: The specification is an OLS model. Robust standard errors are reported in parentheses. Outcome variable is Finished, which gets value 1 if the participant has been allocated to the Treatment or Control group and has completed the survey. *Control* variables are: Age, Dutch, Female, GPA, Financial Stress, Father's Education, Mother's Education, Self-reported Mental health. We include the Self-reported Mental Health variable instead of the PHQ4, because most of the respondents who have dropped out did not reach the PHQ4 questions. Significance code: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

D Main results without controls

Table D1: Main Results without Controls

	Dependent variable:				
	WTP	No Information	University Psychologist	Coaching Service	Any Information
	(1)	(2)	(3)	(4)	(5)
Treatment	0.121	−0.014	−0.023	0.037**	0.016
	(0.086)	(0.017)	(0.018)	(0.016)	(0.018)
Observations	2,978	2,978	2,978	2,978	2,978
Control group mean	3.789	0.31	0.434	0.254	0.574
Controls	NO	NO	NO	NO	NO
Adjusted R^2	0.0003	−0.0001	0.0002	0.001	−0.0001

Note: All specifications are OLS models. Robust standard errors are reported in parentheses. Significance code: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

E Heterogeneous Treatment Effects

We present the results of the heterogeneity on all the relevant dimensions besides baseline mental health and gender. We find that the students whose father has a lower educational level are more prone to choose No Information as their favorite option (p-value < 0.1). Similarly, the students whose mother has a lower education level report a lower WTP for the mental health app (p-value < 0.05). These results suggest that the gaps in the demand for mental health support could worsen the life condition of the students potentially with a lower SES. On the other hand, the students with a GPA 7.5 are more prone to demand for information of any type (p-value < 0.1). Finally, the students who report a score for patience above the median are less prone to demand information about coaching (p-value < 0.05), while those who are already receiving some professional support are more likely to demand

information about coaching (p-value < 0.05).

Table E1: Heterogeneous Treatment Effects - Gender

	Dependent variable:				
	WTP	No Information	University Psychologist	Coaching Service	Any Information
	(1)	(2)	(3)	(4)	(5)
Treatment	0.344^{**}	0.010	-0.020	0.010	-0.008
	(0.139)	(0.027)	(0.029)	(0.027)	(0.029)
Female	0.738^{***}	-0.074^{***}	0.063^{**}	0.011	0.081^{***}
	(0.124)	(0.024)	(0.026)	(0.024)	(0.026)
Treatment x Female	-0.429^{**}	-0.023	-0.021	0.043	0.019
	(0.175)	(0.034)	(0.037)	(0.034)	(0.037)
Observations	2,941	2,941	2,941	2,941	2,941
Controls	YES	YES	YES	YES	YES
Control group mean	3.789	0.310	0.434	0.254	0.574
Adjusted R^2	0.046	0.044	0.057	0.018	0.031

Note: All specifications are OLS models. Robust standard errors are reported in parentheses. We restrict the analysis for the heterogeneous treatment effects for the participants who identify themselves as Male or Female. *Control* variables are: Age, Dutch, Female, GPA, Financial Stress, Father's Education, Mother's Education, PHQ4. Significance code: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table E2: Heterogeneous Treatment Effects - Gender

(a) Male

	Dependent variable:				
	WTP	No Information	University Psychologist	Coaching Service	Any Information
	(1)	(2)	(3)	(4)	(5)
Treatment	0.335**	0.012	−0.023	0.011	−0.009
	(0.143)	(0.029)	(0.029)	(0.027)	(0.030)
Observations	1,107	1,107	1,107	1,107	1,107
Controls	YES	YES	YES	YES	YES
Control group mean	3.789	0.310	0.434	0.254	0.574
Adjusted R^2	0.036	0.037	0.031	−0.002	0.039

Note: All specifications are OLS models. Robust standard errors are reported in parentheses. We restrict the analysis for the heterogeneous treatment effects for the participants who identify themselves as Male.*Control* variables are: Age, Dutch, Female, GPA, Financial Stress, Father's Education, Mother's Education, PHQ4. Significance code: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

(b) Female

	Dependent variable:				
	WTP	No Information	University Psychologist	Coaching Service	Any Information
	(1)	(2)	(3)	(4)	(5)
Treatment	−0.093	−0.015	−0.042*	0.057***	0.012
	(0.106)	(0.020)	(0.023)	(0.021)	(0.023)
Observations	1,834	1,834	1,834	1,834	1,834
Controls	YES	YES	YES	YES	YES
Control group mean	3.789	0.310	0.434	0.254	0.574
Adjusted R^2	0.024	0.024	0.059	0.039	0.010

Note: All specifications are OLS models. Robust standard errors are reported in parentheses. We restrict the analysis for the heterogeneous treatment effects for the participants who identify themselves as Female. *Control* variables are: Age, Dutch, Female, GPA, Financial Stress, Father's Education, Mother's Education, PHQ4. Significance code: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table E3: Heterogeneous Treatment Effect - Dutch

	Dependent variable:				
	WTP	No Information	University Psychologist	Coaching Service	Any Information
	(1)	(2)	(3)	(4)	(5)
Treatment	0.228*	0.007	−0.057**	0.050*	−0.005
	(0.135)	(0.026)	(0.028)	(0.026)	(0.029)
Dutch	−0.448***	0.035	−0.137***	0.102***	−0.046*
	(0.131)	(0.026)	(0.027)	(0.025)	(0.028)
Treatment x Dutch	−0.240	−0.016	0.040	−0.023	0.014
	(0.173)	(0.034)	(0.036)	(0.033)	(0.037)
Observations	2,978	2,978	2,978	2,978	2,978
Control group mean	3.789	0.310	0.434	0.254	0.574
Controls	YES	YES	YES	YES	YES
Adjusted R^2	0.043	0.042	0.058	0.020	0.030

Note: All specifications are OLS models. Robust standard errors are reported in parentheses.*Control* variables are: Age, Dutch, Female, GPA, Financial Stress, Father's Education, Mother's Education, PHQ4. Significance code: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table E4: Heterogeneous Treatment Effect - SES

	Dependent variable:				
	WTP	No Information	University Psychologist	Coaching Service	Any Information
	(1)	(2)	(3)	(4)	(5)
Treatment	0.065	0.002	-0.037^{*}	0.034^{*}	0.009
	(0.096)	(0.019)	(0.020)	(0.018)	(0.020)
Low SES	-0.459^{*}	-0.011	0.002	0.008	0.082
	(0.261)	(0.051)	(0.054)	(0.050)	(0.055)
Treatment x Low SES	0.079	-0.026	0.017	0.009	-0.026
	(0.207)	(0.040)	(0.043)	(0.040)	(0.044)
Observations	2,978	2,978	2,978	2,978	2,978
Control group mean	3.789	0.310	0.434	0.254	0.574
Controls	YES	YES	YES	YES	YES
Adjusted R^2	0.043	0.042	0.058	0.020	0.030

Note: All specifications are OLS models. Robust standard errors are reported in parentheses.*Control* variables are: Age, Dutch, Female, GPA, Financial Stress, Father's Education, Mother's Education, PHQ4. Significance code: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table E5: Heterogeneous Treatment Effect - Father's education

	Dependent variable:				
	WTP	No Information	University Psychologist	Coaching Service	Any Information
	(1)	(2)	(3)	(4)	(5)
Treatment	0.137	−0.028	−0.023	0.051**	0.024
	(0.108)	(0.021)	(0.023)	(0.021)	(0.023)
Father's Education	0.293	−0.079	−0.012	0.091	0.089
	(0.367)	(0.072)	(0.077)	(0.071)	(0.078)
Treatment x Father's Education	−0.167	0.063*	−0.024	−0.039	−0.050
	(0.176)	(0.035)	(0.037)	(0.034)	(0.037)
Observations	2,918	2,918	2,918	2,918	2,918
Control group mean	3.789	0.310	0.434	0.254	0.574
Controls	YES	YES	YES	YES	YES
Adjusted R^2	0.046	0.043	0.057	0.020	0.031

Note: All specifications are OLS models. Robust standard errors are reported in parentheses. We run this regression focusing on the participants who have reported their parents' education level. *Control* variables are: Age, Dutch, Female, GPA, Financial Stress, Father's Education, Mother's Education, PHQ4. Significance code: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table E6: Heterogeneous Treatment Effect - Mother's education

	Dependent variable:				
	WTP	No Information	University Psychologist	Coaching Service	Any Information
	(1)	(2)	(3)	(4)	(5)
Treatment	0.205*	−0.011	−0.028	0.039*	0.025
	(0.105)	(0.021)	(0.022)	(0.020)	(0.022)
Mother's Education	0.326	0.039	0.037	−0.076	−0.002
	(0.364)	(0.071)	(0.076)	(0.070)	(0.077)
Treatment x Mother's Education	−0.391**	0.020	−0.011	−0.009	−0.058
	(0.181)	(0.035)	(0.038)	(0.035)	(0.038)
Observations	2,918	2,918	2,918	2,918	2,918
Control group mean	3.789	0.310	0.434	0.254	0.574
Controls	YES	YES	YES	YES	YES
Adjusted R^2	0.047	0.042	0.057	0.020	0.031

Note: All specifications are OLS models. Robust standard errors are reported in parentheses. We run this regression focusing on the participants who have reported their parents' education level. *Control* variables are: Age, Dutch, Female, GPA, Financial Stress, Father's Education, Mother's Education, PHQ4. Significance code: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table E7: Heterogeneous Treatment Effect - Depression

	Dependent variable:				
	WTP	No Information	University Psychologist	Coaching Service	Any Information
	(1)	(2)	(3)	(4)	(5)
Treatment	0.120	0.006	-0.035^{*}	0.029	0.004
	(0.101)	(0.020)	(0.021)	(0.019)	(0.021)
Depression	-0.106	0.068^{*}	-0.002	-0.066^{*}	-0.096^{**}
	(0.199)	(0.039)	(0.041)	(0.038)	(0.042)
Treatment x Depression	-0.118	-0.035	0.006	0.029	0.007
	(0.187)	(0.037)	(0.039)	(0.036)	(0.039)
Observations	2,978	2,978	2,978	2,978	2,978
Control group mean	3.789	0.310	0.434	0.254	0.574
Controls	YES	YES	YES	YES	YES
Adjusted R^2	0.043	0.043	0.058	0.020	0.032

Note: All specifications are OLS models. Robust standard errors are reported in parentheses. The variable Depression gets value 1 if the participant's PHQ4 score is higher or equal than 6. *Control* variables are: Age, Dutch, Female, GPA, Financial Stress, Father's Education, Mother's Education, PHQ4. Significance code: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table E8: Heterogeneous Treatment Effect - Self-Reported Depression

	Dependent variable:				
	WTP	No Information	University Psychologist	Coaching Service	Any Information
	(1)	(2)	(3)	(4)	(5)
Treatment	0.120	0.001	−0.028	0.027	0.002
	(0.091)	(0.018)	(0.019)	(0.018)	(0.019)
Self-Depression	−0.125	0.030	0.020	−0.050	−0.061
	(0.188)	(0.037)	(0.039)	(0.036)	(0.040)
Treatment x Self-Depression	−0.321	−0.032	−0.033	0.065	−0.0002
	(0.247)	(0.048)	(0.052)	(0.048)	(0.052)
Observations	2,978	2,978	2,978	2,978	2,978
Control group mean	3.789	0.310	0.434	0.254	0.574
Controls	YES	YES	YES	YES	YES
Adjusted R^2	0.044	0.042	0.058	0.020	0.031

Note: All specifications are OLS models. Robust standard errors are reported in parentheses. "Self-Depression" gets value 1 if the self-reported mental health is "Very Bad" or "Bad". *Control* variables are: Age, Dutch, Female, GPA, Financial Stress, Father's Education, Mother's Education, PHQ4. Significance code: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table E9: Heterogeneous Treatment Effect - Low GPA

	Dependent variable:				
	WTP	No Information	University Psychologist	Coaching Service	Any Information
	(1)	(2)	(3)	(4)	(5)
Treatment	0.083	0.032	−0.036	0.004	−0.022
	(0.137)	(0.027)	(0.029)	(0.027)	(0.029)
Low GPA	0.248	−0.001	−0.017	0.018	−0.023
	(0.386)	(0.076)	(0.081)	(0.075)	(0.082)
Treatment x Low GPA	−0.045	−0.061*	0.004	0.056	0.034
	(0.181)	(0.036)	(0.038)	(0.035)	(0.039)
Observations	2,593	2,593	2,593	2,593	2,593
Control group mean	3.789	0.310	0.434	0.254	0.574
Controls	YES	YES	YES	YES	YES
Adjusted R^2	0.044	0.047	0.060	0.021	0.030

Note: All specifications are OLS models. Robust standard errors are reported in parentheses. "Low GPA" gets value 1 if the self-reported GPA is below 7.5. We focus on the students who have reported their GPA. *Control* variables are: Age, Dutch, Female, GPA, Financial Stress, Father's Education, Mother's Education, PHQ4. Significance code: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table E10: Heterogeneous Treatment Effect - Risk Preferences

	Dependent variable:				
	WTP	No Information	University Psychologist	Coaching Service	Any Information
	(1)	(2)	(3)	(4)	(5)
Treatment	0.062	-0.012	-0.048^{**}	0.059^{***}	0.018
	(0.116)	(0.023)	(0.024)	(0.022)	(0.025)
Risk Preferences	0.038	0.003	-0.031	0.028	0.011
	(0.121)	(0.024)	(0.025)	(0.023)	(0.025)
Treatment x Risk Preferences	0.044	0.019	0.030	-0.049	-0.030
	(0.170)	(0.033)	(0.035)	(0.033)	(0.036)
Observations	2,978	2,978	2,978	2,978	2,978
Control group mean	3.789	0.310	0.434	0.254	0.574
Controls	YES	YES	YES	YES	YES
Adjusted R^2	0.043	0.042	0.058	0.020	0.030

Note: All specifications are OLS models. Robust standard errors are reported in parentheses. "Risk Preferences" gets value 1 if the Risk Preferences variable is above the median. We use the question from Falk et al. (2018). *Control* variables are: Age, Dutch, Female, GPA, Financial Stress, Father's Education, Mother's Education, PHQ4. Significance code: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table E11: Heterogeneous Treatment Effect - Time Preferences

	Dependent variable:				
	WTP	No Information	University Psychologist	Coaching Service	Any Information
	(1)	(2)	(3)	(4)	(5)
Treatment	0.079	-0.016	-0.047^{**}	0.064^{***}	0.018
	(0.107)	(0.021)	(0.022)	(0.021)	(0.023)
Time Preferences	-0.056	-0.010	-0.050^{*}	0.059^{**}	0.013
	(0.125)	(0.024)	(0.026)	(0.024)	(0.026)
Treatment x Time Preferences	0.009	0.035	0.038	-0.074^{**}	-0.039
	(0.175)	(0.034)	(0.036)	(0.034)	(0.037)
Observations	2,978	2,978	2,978	2,978	2,978
Control group mean	3.789	0.310	0.434	0.254	0.574
Controls	YES	YES	YES	YES	YES
Adjusted R^2	0.043	0.042	0.059	0.022	0.030

Note: All specifications are OLS models. Robust standard errors are reported in parentheses. "Time Preferences" gets value 1 if the Time Preferences variable is above the median. We use the question from Falk et al. (2018). *Control* variables are: Age, Dutch, Female, GPA, Financial Stress, Father's Education, Mother's Education, PHQ4. Significance code: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table E12: Heterogeneous Treatment Effect - Already receiving Support

	Dependent variable:				
	WTP	No Information	University Psychologist	Coaching Service	Any Information
	(1)	(2)	(3)	(4)	(5)
Treatment	0.060	0.010	−0.026	0.016	−0.010
	(0.096)	(0.019)	(0.020)	(0.019)	(0.020)
Already	0.455***	−0.077***	0.073**	0.004	0.102***
	(0.147)	(0.029)	(0.031)	(0.028)	(0.031)
Treatment x Already	0.060	−0.048	−0.036	0.084**	0.048
	(0.199)	(0.039)	(0.042)	(0.038)	(0.042)
Observations	2,978	2,978	2,978	2,978	2,978
Control group mean	3.789	0.310	0.434	0.254	0.574
Controls	YES	YES	YES	YES	YES
Adjusted R^2	0.050	0.050	0.060	0.023	0.041

Note: All specifications are OLS models. Robust standard errors are reported in parentheses. "Already" gets value 1 if the participant is already receiving professional support.*Control* variables are: Age, Dutch, Female, GPA, Financial Stress, Father's Education, Mother's Education, PHQ4. Significance code: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

F Causal Forest

Causal Forest - Methods We complement the Heterogeneity analysis from the Section 3 with non-parametric Causal Random Forests (CRF; Wager and Athey (2018)). There are several advantages of using CRF to complement our parametric analysis. First, CRF allows us to relax functional form assumptions on the structure of the unobserved errors. Secondly, the CRF algorithm allows us to exploit and accurately reflect the heterogeneity in our available sample. Finally, the CRF method allows us to achieve all the desirable statistical properties of regression-based methods – such as asymptotic consistency – without committing to a parametric specification.

The CRF is based on the same set of causal relationships described in Section 3.

We estimate a partial average treatment effect of the mental health literacy intervention on the demand for mental health support, with the following estimator:

$$\hat{\tau} = E[Y(1) - Y(0)]$$

We estimate $\hat{\tau}$ using the *grf* package in R, following Tibshirani et al. (2021).

Following Wager and Athey (2019), we train two separate causal random forests for improved precision. First, we train a pilot random forest on all the covariates in X_i. Then, we train a second forest on only those covariates that saw a number of splits in the first step higher than the mean. This enables the forest to make more splits on the most important features in low-signal situations.

Causal Forest - Results To evaluate the impact of the mental health literacy intervention, we estimate the conditional average treatment effect for the training data using out-of-bag prediction (CATE, corresponding to the $\hat{\tau}$ in Equation F). Table F13 Column 1 shows the values of the Conditional Average Treatment Effect for the different outcome variables we consider in the study. The estimated CATE are very close to the average treatment effect we have obtained with the OLS model in 1 and summarized in Table 2. Therefore, we conclude that our estimates are robust to the heterogeneity in the sample.

Table F13: CATE for the main outcome variables

Variables	ATE	CI 95%	Differences in ATE	CI 95% Differences in ATE
WTP	0.077	$\pm$ 0.166	0.194	$\pm$ 0.331
NoInfo	-0.008	$\pm$ 0.032	0.027	$\pm$ 0.065
Psychologist	-0.034	$\pm$ 0.035	-0.117	$\pm$ 0.069
Coaching Service	0.041	$\pm$ 0.032	0.006	$\pm$ 0.063
AnyInfo	0.011	$\pm$ 0.035	0.072	$\pm$ 0.07

Note: The table shows in Column 2 ATE for the main outcome variables estimated following the procedure from Wager and Athey (2018). Column 3 shows the CI 95% of the ATE. Column 4 shows the differences in ATE between regions of high ATE and low ATE. Column 5 shows the CI 95% of the differences in ATE.

Figure F.1 shows the distribution of the conditional average treatment effects on the main outcome variables. The distributions of the CATE indicates the presence of substantial heterogeneity in the sample, as most of the distributions follow a distribution that resembles a normal distribution. It is worth noting that the CATE distribution for the variable Strong Information shows a bi-modal shape. The reason behind the bi-modality is that mostly bachelor students have a strong preference to acquire information about the support services (positive CATE) compared to the master students (negative CATE).

Causal Forest - Robustness Checks Following Wager and Athey (2018) and Wager and Athey (2019), one heuristic for testing for heterogeneity in CRFs consists in grouping observations in two groups. The groups are formed according to whether the out-of-bag CATE estimates for the observations are above or below the median CATE estimate. Once these two groups are formed, the test for heterogeneity involves estimating average treatment effects in these two subgroups, separately, using a doubly robust approach. Table F13 Column 3 and Column 4 show that the 95% confidence interval for difference in the CATE between the high- and low-CATE does not include 0 for the variables "Information Psychologist" and "Strong Information", which suggest high heterogeneity in the CATE. The test is inconclusive for the variables "WTP", "No Information" and "Info Coaching".

Another test for heterogeneity is the best-linear-predictor (BLP) method (Chernozhukov et al., 2018). As a rule of thumb, a coefficient for the differential forest prediction different from 0 suggests that the forest has captured heterogeneity in the underlying signal (Wager

and Athey, 2019). We find evidence for significant heterogeneity in case of the variables "No Information" (p-value = 0.05), "Information Coaching" (p-value = 0.05) and "Strong Information" (p-value < 0.01).

Both the difference between high and low CATE, and the differential forest prediction suggest that any treatment heterogeneity that may be present appears to be relatively strong for all the variables of interest but "WTP".

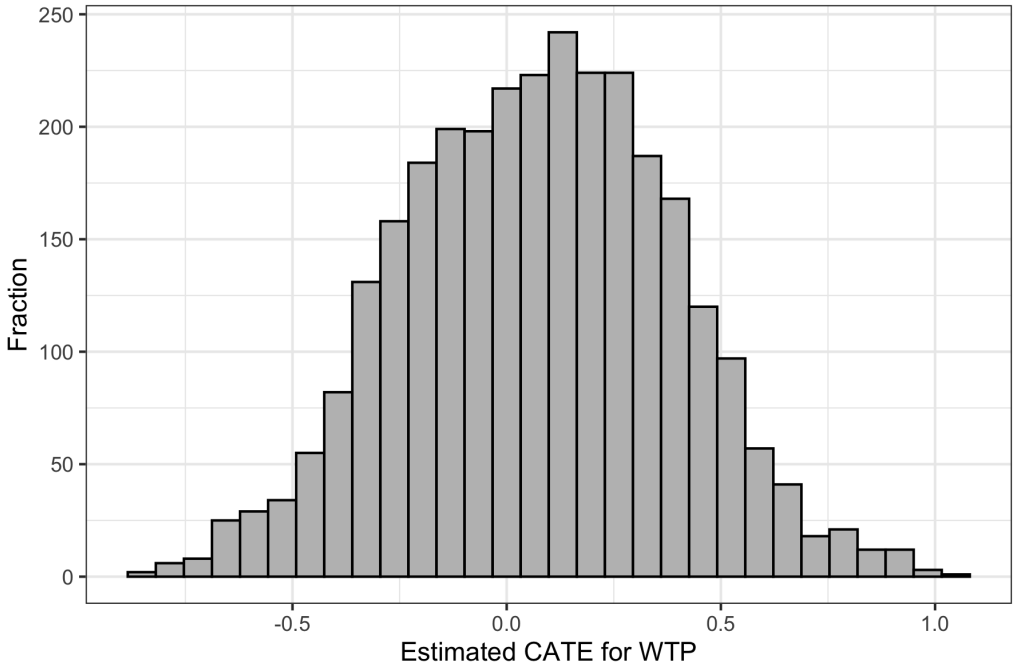


Figure F.1: Estimated CATE for WTP

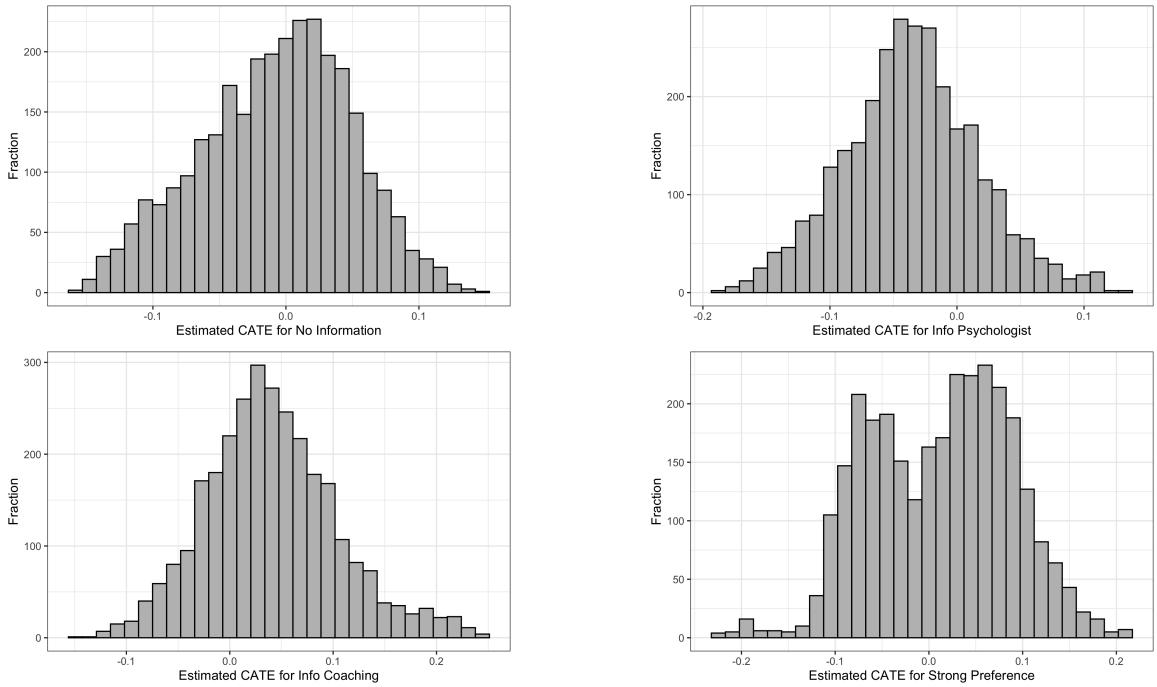


Figure F.2: Estimated CATE for Information Demand

G Mechanisms

Table G1: Mechanisms by Gender

(a) Mechanisms - Male

	Dependent variable:				
	Academic returns	Labor returns	App effectiveness	Self-Stigma	Social Stigma
	(1)	(2)	(3)	(4)	(5)
Treatment	0.008	0.040	0.198***	0.037	0.077
	(0.010)	(0.060)	(0.062)	(0.044)	(0.047)
Observations	1,107	1,106	1,107	1,107	1,107
Z-score	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES
Control group mean	0	0	0	0	0
Adjusted R^2	0.015	0.023	0.007	0.031	0.062
Adjusted p-value	NO	NO	NO	0.82	0.34

Note: All specifications are OLS models. Robust standard errors are reported in parentheses. We z-score all the mechanism questions. For each question, we subtract the mean of the control group and divide by the standard deviation of the control group. We focus on Male participants. We adjust the p-value of Self Stigma and Social Stigma with "false discovery rate" procedure. *Control* variables are: Age, Dutch, Female, GPA, Financial Stress, Father's Education, Mother's Education, PHQ4. Significance code: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

(b) Mechanisms - Female

	Dependent variable:				
	Academic returns	Labor returns	App effectiveness	Self-Stigma	Social Stigma
	(1)	(2)	(3)	(4)	(5)
Treatment	−0.010	−0.024	0.055	0.043	0.043
	(0.007)	(0.044)	(0.045)	(0.033)	(0.035)
Observations	1,834	1,834	1,834	1,834	1,834
Z-score	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES
Control group mean	0	0	0	0	0
Adjusted R^2	0.028	0.067	0.008	0.031	0.096
Adjusted p-value	NO	NO	NO	0.67	0.44

Note: All specifications are OLS models. Robust standard errors are reported in parentheses. We z-score all the mechanism questions. For each question, we subtract the mean of the control group and divide by the standard deviation of the control group. We focus on Female respondents. We adjust the p-value of Self Stigma and Social Stigma with "false discovery rate" procedure. *Control* variables are: Age, Dutch, Female, GPA, Financial Stress, Father's Education, Mother's Education, PHQ4. Significance code: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table G2: Components of Self Stigma

	Dependent variable:				
	Self-Stigma Index	Feeling inadequate	Self-Confidence	Feeling worse	Feeling less
	(1)	(2)	(3)	(4)	(5)
Treatment	0.154	0.071*	0.053	0.028	0.003
	(0.105)	(0.037)	(0.037)	(0.036)	(0.036)
Observations	2,978	2,978	2,978	2,978	2,978
Z-score	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES
Control group mean	0	0	0	0	0
Adjusted R^2	0.063	0.059	0.028	0.017	0.041

Note: All specifications are OLS models. Robust standard errors are reported in parentheses. We z-score all the mechanism questions. For each question, we subtract the mean of the control group and divide by the standard deviation of the control group. *Control* variables are: Age, Dutch, Female, GPA, Financial Stress, Father's Education, Mother's Education, PHQ4. Significance code: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table G3: Components of Social Stigma

	Dependent variable:		
	Social Stigma Index	Perceived discrimination University	Telling Family Psychologist
	(1)	(2)	(3)
Treatment	0.117**	0.049	0.067*
	(0.057)	(0.037)	(0.036)
Observations	2,978	2,978	2,978
Z-score	YES	YES	YES
Controls	YES	YES	YES
Control group mean	0	0	0
Adjusted R^2	0.087	0.060	0.070

Note: All specifications are OLS models. Robust standard errors are reported in parentheses. We z-score all the mechanism questions. For each question, we subtract the mean of the control group and divide by the standard deviation of the control group. *Control* variables are: Age, Dutch, Female, GPA, Financial Stress, Father's Education, Mother's Education, PHQ4. Significance code: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

H Persistence

Table H1: Differential Attrition - Follow up

	Dependent variable:
	Follow-up
Treatment	-0.014
	(0.017)
Observations	2,976
Controls	YES
Adjusted R^2	0.009

Note: The specification is an OLS model. Robust standard errors are reported in parentheses. Outcome variable is Follow-up, which gets value 1 if the participant has joined the Follow-up survey. *Control* variables are: Age, Dutch, Female, GPA, Financial Stress, Father's Education, Mother's Education, PHQ4. Significance code: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table H2: Attrition check

Variables	Total Sample	Follow-up sample	p-value
Age	21.62	21.56	0.64
Dutch	0.59	0.64	0.001***
Female	0.61	0.64	0.13
Bachelor	0.59	0.58	0.39
Low GPA	0.50	0.49	0.55
Financial Stress	0.21	0.20	0.52
Father's Education	0.37	0.37	0.76
Mother's Education	0.33	0.33	0.98
Low Mental Health	0.13	0.13	0.86
PHQ4	4.31	4.30	0.88
Observations	2978	1483	

Note: The table shows the demographic characteristics for our sample broken down into Total sample and Follow-up sample. t-tests were used to assess whether demographic variables followed the same distribution between Total sample and Follow-up sample. The third column reports p-values. Age is a continuous variable of the age of the participant. Dutch gets value 1 if the participant has Dutch nationality. Female gets value 1 if the participant reports to identify with female gender. Bachelor is a dummy that gets value 1 if the participant is a bachelor student. Low GPA gets value 1 if the participant reports to have a GPA lower than 7.5. Financial Stress gets value 1 if the participants reports that the current financial situation is "Very Bad" or "Bad". Father's Education and Mother's Education get value 1 if the participant's father and mother, respectively, have an education level below the bachelor. Low Mental Health gets value 1 if the self-reported mental health of the participant is "Very Bad" or "Bad". PHQ4 is a continuous variable for a diagnostic measure of the participant's mental health. This variable is measured after the allocation of the respondents to the Treatment, that is not affecting PHQ4 score. Significance code: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table H3: Care Seeking and Mental Health - Follow up

	Dependent variable:		
	Did seek care	Plan seek care	PHQ4
	(1)	(2)	(3)
Treatment	0.003	0.022	−0.160
	(0.019)	(0.020)	(0.116)
Observations	1,121	1,121	1,121
Controls	YES	YES	YES
Control group means	0.132	0.151	4.078
Adjusted R^2	0.132	0.171	0.579

Note: The specification is an OLS model. Robust standard errors are reported in parentheses. Outcome variable are: Did seek care, which gets value 1 if the participant was seeking care; Plan seek care, which gets value 1 if the participant is planning to seek care; PHQ4 from the follow up. *Control* variables are: Age, Dutch, Female, GPA, Financial Stress, Father's Education, Mother's Education, PHQ4 from the main study. Significance code: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table H4: Care Seeking and Mental Health by Gender - Follow up

(a) Care Seeking and Mental Health Male - Follow up

	Dependent variable:		
	Did seek care	Plan seek care	PHQ4
	(1)	(2)	(3)
Treatment	−0.033	−0.006	0.116
	(0.021)	(0.025)	(0.189)
Observations	399	399	399
Controls	YES	YES	YES
Control group means	0.132	0.151	4.078
Adjusted R^2	0.072	0.104	0.558

Note: The specification is an OLS model. Robust standard errors are reported in parentheses. We restrict the analysis to the male respondents. Outcome variable are: Did seek care, which gets value 1 if the participant was seeking care; Plan seek care, which gets value 1 if the participant is planning to seek care; PHQ4 from the follow up. *Control* variables are: Age, Dutch, Female, GPA, Financial Stress, Father's Education, Mother's Education, PHQ4 from the main study. Significance code: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

(b) Care Seeking and Mental Health Female - Follow up

	Dependent variable:		
	Did seek care	Plan seek care	PHQ4
	(1)	(2)	(3)
Treatment	0.033	0.039	-0.316^{**}
	(0.028)	(0.029)	(0.148)
Observations	710	710	710
Controls	YES	YES	YES
Control group means	0.132	0.151	4.078
Adjusted R^2	0.127	0.166	0.571

Note: The specification is an OLS model. Robust standard errors are reported in parentheses. We restrict the analysis to the female respondents. Outcome variable are: Did seek care, which gets value 1 if the participant was seeking care; Plan seek care, which gets value 1 if the participant is planning to seek care; PHQ4 from the follow up. *Control* variables are: Age, Dutch, Female, GPA, Financial Stress, Father's Education, Mother's Education, PHQ4 from the main study. Significance code: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table H5: Correlation between information demand for mental health care and self-reported behavior

	Dependent variable:			
	Psychologist past 2 weeks	Coaching past 2 weeks	Psychologist next 2 weeks	Coaching next 2 weeks
	(1)	(2)	(3)	(4)
Info Psychologist	0.024		0.065***	
	(0.018)		(0.020)	
Info Coach		0.030***		0.030**
		(0.011)		(0.012)
Observations	1,121	1,121	1,121	1,121
Controls	YES	YES	YES	YES
Adjusted R^2	0.119	0.033	0.149	0.027

Note: The specification is an OLS model. Robust standard errors are reported in parentheses. We correlate participants' self-reported behavior to seek care in the weeks before the follow-up with their demand for information about mental health support. We repeat the procedure with the self-reported behavior to seek care in the weeks after the follow-up. *Control* variables are: Age, Dutch, Female, GPA, Financial Stress, Father's Education, Mother's Education, PHQ4 from the follow up. Significance code: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table H6: Correlate between Self-reported care seeking behavior and WTP for the app

	Dependent variable:
	Support
WTP	0.012**
	(0.005)
Observations	1,121
Controls	YES
Adjusted R^2	0.188

Note: The specification is an OLS model. We correlate the respondent WTP for the app with their self-reported past care behavior or their intention to seek support in the weeks after the follow-up. Support gets value 1 if the respondent reports to either have sought care via psychologist/coach/apps or to plan to seek care in the weeks after the follow-up. *Control* variables are: Age, Dutch, Female, GPA, Financial Stress, Father's Education, Mother's Education, PHQ4 from the follow up. Significance code: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table H7: Beliefs about effectiveness of mental health support tools - Follow up

	Dependent variable:		
	App effectiveness	Psychologist effectiveness	Coaching effectiveness
	(1)	(2)	(3)
Treatment	−0.057	0.002	0.061
	(0.053)	(0.058)	(0.057)
Observations	1,121	1,121	1,121
Controls	YES	YES	YES
Control group mean	0	0	0
Adjusted R^2	0.190	0.027	0.041

Note: The specification is an OLS model. Robust standard errors are reported in parentheses. We Z-score the beliefs about the effectiveness of App, Psychologist, and Coaching Services using the mean and the standard deviation of the control group. For Column 1, we include the beliefs about effectiveness of app from the main study as control variable. *Control* variables are: Age, Dutch, Female, GPA, Financial Stress, Father's Education, Mother's Education, PHQ4 from the follow up. Significance code: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table H8: Self-Stigma - Follow up

	Dependent variable:
	Self-Stigma
	(1)
Treatment	0.055*
	(0.031)
Observations	1,121
Controls	YES
Control group mean	0
Adjusted R^2	0.270

Note: The specification is an OLS model. Robust standard errors are reported in parentheses. We Z-score the Self Stigma index. We include the Self-Stigma values from the main study as control variable. When we apply the "false discovery rate" procedure to correct for multiple hypothesis testing, we find that the treatment does not have a persistent effect on Self-Stigma. *Control* variables are: Age, Dutch, Female, GPA, Financial Stress, Father's Education, Mother's Education, PHQ4 from the follow up. Significance code: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

I Robustness Checks

Table I1: Robustness Checks - Awareness

	Dependent variable:				
	WTP	No Information	University Psychologist	Coaching Service	Any Information
	(1)	(2)	(3)	(4)	(5)
Treatment	0.083	−0.002	−0.034*	0.036**	0.003
	(0.085)	(0.017)	(0.018)	(0.016)	(0.018)
Observations	2,978	2,978	2,978	2,978	2,978
Controls	YES	YES	YES	YES	YES
Control group mean	3.789	0.310	0.434	0.254	0.574
Adjusted R^2	0.043	0.042	0.058	0.020	0.030

Note: All specifications are OLS models. Robust standard errors are reported in parentheses. We control for "Awareness" of the respondents about their mental health. "Awareness" gets value 1 if the participant's variables "Depression" and "Self-Depression" have the same value.*Control* variables are: Age, Dutch, Female, GPA, Financial Stress, Father's Education, Mother's Education, PHQ4. Significance code: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table I2: Logit Estimates for Demand for Information

	Dependent variable:			
	No Information	University Psychologist	Coaching Service	Any Information
	(1)	(2)	(3)	(4)
Treatment	-0.016	-0.147^{*}	0.191^{**}	0.014
	(0.082)	(0.077)	(0.084)	(0.076)
Observations	2,978	2,978	2,978	2,978
Controls	YES	YES	YES	YES
Log Likelihood	$-1{,}748.095$	$-1{,}926.414$	$-1{,}698.776$	$-1{,}963.781$
Akaike Inf. Crit.	3,554.190	3,910.829	3,455.552	3,985.563

Note: All specifications are Logit models. Robust standard errors to heteroskedasticity are reported in parentheses.*Control* variables are: Age, Dutch, Female, GPA, Financial Stress, Father's Education, Mother's Education, PHQ4. Significance code: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table I3: Logit Estimates for Demand for Information - Odds Ratio

	Dependent variable:			
	No Information	University Psychologist	Coaching Service	Any Information
	(1)	(2)	(3)	(4)
Treatment	0.984	0.863*	1.209**	1.014
	(0.082)	(0.066)	(0.101)	(0.077)
Observations	2,978	2,978	2,978	2,978
Controls	YES	YES	YES	YES
Log Likelihood	−1,748.095	−1,926.414	−1,698.776	−1,963.781
Akaike Inf. Crit.	3,554.190	3,910.829	3,455.552	3,985.563

Note: All specifications are Logit models. Robust standard errors to heteroskedasticity are reported in parentheses.*Control* variables are: Age, Dutch, Female, GPA, Financial Stress, Father's Education, Mother's Education, PHQ4. Significance code: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table I4: Dropping 1st and 99th percentile

	Dependent variable:				
	WTP	No Information	University Psychologist	Coaching Service	Any Information
	(1)	(2)	(3)	(4)	(5)
Treatment	0.089	-0.002	-0.036^{**}	0.038^{**}	0.004
	(0.086)	(0.017)	(0.018)	(0.016)	(0.018)
Observations	2,917	2,917	2,917	2,917	2,917
Controls	YES	YES	YES	YES	YES
Control group mean	3.789	0.310	0.434	0.254	0.574
Adjusted R^2	0.044	0.045	0.061	0.021	0.032

Note: All specifications are OLS models. Robust standard errors are reported in parentheses. We drop the respondents who are at 1st and at the 99th percentile of completion time.*Control* variables are: Age, Dutch, Female, GPA, Financial Stress, Father's Education, Mother's Education, PHQ4. Significance code: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

J Invitation E-mail

The message in the e-mail was written both in English and Dutch, and the English version is reported below:

> Hi,
>
> I am Vahid, part of a research team working on habits and wellbeing topics. Our team invites you to join a survey on this topic that will take less than 10 minutes. There are multiple prizes distributed among those who finish the survey. You can win 100 Euros for participation in the survey (paid in Bol.com or Amazon.nl vouchers by your choice). You can also receive additional rewards depending on your answers in parts of the survey. I want you to know that the survey is completely anonymous!
>
> Click Here to Start the Survey
>
> Thanks a lot for your time and your collaboration!
>
> Warm regards,
>
> Vahid Moghani

K Instructions

This study is part of a scientific research project that aims to promote wellbeing and equality at EUR. You can fill in the survey in Dutch by changing the language using the tool at the top of the page.

This online survey, which takes **around 10 minutes**, is **completely anonymous**, and you are **free to leave the survey at any time**. There is **no deception or false information** involved in any stage of this survey.

By completing the survey, you are eligible to enter a **lottery to win a voucher worth €100.** The voucher can be spent on an online shopping platform of your choice.

By clicking NEXT you explicitly give your consent and agree that:

- We can collect your **anonymous** personal data, and we only use this data for **scientific purposes**. We promise to protect your data according to the new General Data Protection Regulation (GDPR) laws (Read More).
- You confirm that **you are a student at Erasmus University Rotterdam**.
- We reserve the right to exclude respondents from the lottery in case of multiple submitted responses or low-quality/inattentive responses.

If you have any question concerning this experiment, do not hesitate to send an e-mail to **capozza@ese.eur.nl** or **moghani@ese.eur.nl**

1 in every 75 respondents who complete the survey will receive a **€100 voucher**. In addition to this lottery, you have the chance of winning **additional prizes** within the experiment.

Please note that all the prizes in the experiment will be given in the form of vouchers. Participation in the lottery is entirely voluntary.

In case I win the lottery, I want my vouchers (the €100 of participation and other prizes) to be from:

- Amazon.nl ○
- Bol.com ○
- I do not wish to participate in the lottery ○

To start the survey, you need to create a unique code for yourself. This way, your answers will remain anonymous, and you will be able to check later if you win the lottery using your unique code.

To generate your unique code, please type the following from left to right without any space, in lower case letters, in the text box below.

- The first two letters of your father's name (for example, ab)
- Your day of birth (from 1 to 31)
- The first two letters of the name of your elementary school (for example, ab)
- The number of your siblings (0 to 99)
- The last two letters of your mother's name (for example, ab)
- The last two digits of your phone number (00 to 99)

What is your age?

What is your gender?

- Female
- Male
- Other
- Prefer not to say

Were you born in the Netherlands?

- Yes
- No

Were both of your parents born in the Netherlands?

- Yes
- No

In which region were you born?

- Asia Pacific (Central & South Asia, Northeastern Asia, Southeastern Asia)
- Australia and Oceania
- Europe (Northern Europe, Southern Europe, Eastern Europe, Western Europe)
- Middle East/Africa (Middle East, Northern Africa, Southern Africa)
- North America
- South America, Central America, Caribbean

In what degree program are you currently enrolled?

- Bachelor's
- Pre-Master's
- Master's (including MSc., MPhil., LLM., Medical Training)

What is your overall GPA?

- Below 5.5
- 5.5-6.5
- 6.5-7.5
- 7.5-8.5
- Above 8.5
- Prefer not to say

What is the education level of your Mother/Parent A?

- Elementary education or lower
- Secondary education
- Vocational education/MBO
- Higher education (below Master's level)
- Master's
- PhD
- Not applicable

What is the education level of your Father/Parent B?

- Elementary education or lower
- Secondary education
- Vocational education/MBO
- Higher education (below Master's level)
- Master's
- PhD
- Not applicable

How would you describe your mental health currently?

- Very Good
- Good
- Fair
- Bad
- Very Bad

How would you describe your current financial situation?

- Always stressful ◯
- Somewhat stressful ◯
- Sometimes stressful ◯
- Rarely stressful ◯
- Never stressful ◯

Mental wellbeing is not binary but is a spectrum. Therefore, a **staging approach** is a new way to think about someone's mental wellbeing.

This approach implies that taking care of mental health is a **continuous process with positive outcomes:** regardless of how someone feels right now, taking care of their mental health could always lead to higher wellness and fulfillment. The staging approach suggests some **simple steps** towards higher wellness, such as promoting self-care and increasing monitoring.

These general tips apply to anyone, including university students. For example, research evidence suggests that university students who were investing in their mental health were also showing a better academic performance.

Next, you will play against a computer.

We will pick a few participants to implement their choices in this part. You can earn money or receive a service, but **you will never lose money**.

You can receive one month of access to **an app** for **mental health support** (read more about the app here)**.** This self-care app helps individuals to monitor their moods**.** Additionally, the app provides best existing practices to manage stress-, anxiety-, and depression-like symptoms. This app has been evaluated to be effective in medical trials (e.g., see this study).

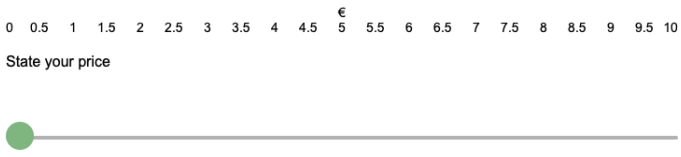
Here, you state a price for one month of access to the app. A computer will bid against you. The computer's bid will be between 0 and 10 independent of your price.

- If your price is higher than the computer's bid, you will receive a one-month subscription to the app for free. In this case, you won't receive any money.
- If your stated price is below or equal to the computer's bid, you receive a payment equal to the computer's bid. In this case, you won't receive the app subscription.

Regardless of the computer's bid, it is always in your best interest to report your true personal valuation for the app as the price.

Regardless of the computer's bid, it is always in your best interest to report your true personal valuation for the app as the price.

What is your stated price to get a **one-month subscription** to this app? Move the slider to insert your answer.



We are going to provide information about the services currently available at EUR to seek mental health care/support. On campus, it is possible to receive support from: University Psychologist and Coaching service.

Please, rank the following options from the most preferred one (1) to the least preferred one (3). You are going to receive information about your most preferred option (or no information if that is your most preferred choice).

University Psychologists service

Coaching service

No information

Below is a link to get more information about coaching services at EUR:

Click here to learn more about coaching services at EUR!

Click NEXT to continue

Below is a link to get more information about psychological counseling opportunities at EUR:

Click here to learn more about psychological counseling at EUR!

Click NEXT to continue

Think about the relationship between mental health and educational performance of the university students and complete the following sentence:

Good mental health is ..... for the students' educational performance in the university.

- Not at all important ○
- Slightly important ○
- Moderately important ○
- Very important ○
- Extremely important ○

Think about the relationship between mental health and future job of the university students and complete the following sentence:

Good mental health during studies is ..... for the students' future job characteristics (e.g. the salary and the type of job).

- ○ Not at all important
- ○ Slightly important
- ○ Moderately important
- ○ Very important
- ○ Extremely important

Which type of mental health care/support are you receiving now:

- ☐ Professional support (i.e. visiting a general practitioner, praktijkondersteuner, psychologist, psychotherapist, or counselor)
- ☐ Coaching services
- ☐ Digital apps (e.g., meditation or self-care apps)
- ☐ Peer-to-peer support
- ☐ Support from family or friends
- ☐ None

How effective do you think digital apps are for mental health?

- Very effective
- Somewhat effective
- Sometimes effective
- Rarely effective
- Never effective

My self-confidence would **NOT** be threatened if I sought psychological help.

(Please use a scale from 0 to 4, where 0 means “Strongly disagree” and 4 means “Strongly agree”.)

0 1 2 3 4

Your Opinion

I would feel worse about myself if I had a mental health disorder (for example anxiety/mood/psychosis syndrome).

(Please use a scale from 0 to 4, where 0 means “Strongly disagree” and 4 means “Strongly agree”.)

0 1 2 3 4

Your Opinion

I would feel less of myself if I received mental health support.

(Please use a scale from 0 to 4, where 0 means “Strongly disagree” and 4 means “Strongly agree”.)

0 1 2 3 4

Your Opinion

Please indicate to what extent **you agree or disagree** with the following statements.

I would feel inadequate if I went to a therapist for psychological help.

(Please use a scale from 0 to 4, where 0 means “Strongly disagree” and a 4 means “Strongly agree”.)

0 1 2 3 4

Your opinion

I would worry about telling my family if I sought professional psychological help (now and in the past).

(Please use a scale from 0 to 4, where 0 means “Strongly disagree” and 4 means “Strongly agree”.)

0 1 2 3 4

Your Opinion

Please indicate to what extent **you agree or disagree** with the following statements.

At university, the teaching staff and the peers think less of students if they find out about their mental health problems.

(Please use a scale from 0 to 4, where 0 means “Strongly disagree” and 4 means “Strongly agree”.)

0 1 2 3 4

Your Opinion

Please tell, in general, how willing or unwilling you are to **take risks**.

Please use a scale from 0 to 10, where 0 means "completely unwilling to take risks" and 10 means you are "very willing to take risks".

0 1 2 3 4 5 6 7 8 9 10

Move the slider

How willing are you to give up something that is beneficial for you today in order to benefit more from that in the future?

Please use a scale from 0 to 10, where 0 means "completely unwilling to give up" and 10 means you are "very willing to give up".

0 1 2 3 4 5 6 7 8 9 10

Move the slider

Over the last 2 weeks, how often have you been bothered by feeling nervous, anxious or on edge?

- Not at all ○
- Several days ○
- More than half days ○
- Nearly every day ○

Over the last 2 weeks, how often have you been bothered by not being able to stop or control worrying?

- Not at all ○
- Several days ○
- More than half days ○
- Nearly every day ○

Over the last 2 weeks, how often have you been bothered by little interest or pleasure in doing things?

- Not at all ○
- Several days ○
- More than half days ○
- Nearly every day ○

Over the last 2 weeks, how often have you been bothered by feeling down, depressed, or hopeless?

- Not at all ◉
- Several days ○
- More than half days ○
- Nearly every day ○

If you are experiencing mental health issues or psychological distress, remember that **you don't have to deal with this alone!**

You can contact your general practitioner or use the university psychologist service if you wish to receive professional advice. **If you urgently need help, don't hesitate to call Stichting by dialing 113.**

Please tick the box to verify that you have read the information. Click Next when you are done!

I have read the information above. ☐

L Instructions Follow Up

This study is part of a scientific research project that aims to promote wellbeing, equality and inclusivity at EUR. Two weeks ago we have asked students to join the first part of the survey. This is a follow up survey.

You can fill in the survey in Dutch as well by choosing Dutch in the tool at the beginning of the page.

This online survey, which takes **around 5 minutes**, is **completely anonymous**, and you are **free to leave the study at any time**.

By completing the experiment, you are eligible to enter a **lottery vouchers worth €200** to spend on an online shopping website of your choice. This is an additional prize to what you could get by joining the first survey.

Please note that all the prizes in the survey will be given in forms of vouchers. Participation in the lottery is entirely voluntary.

By completing the survey, you are eligible to enter a **lottery to win a voucher worth €200.** The voucher can be spent on an online shopping platform of your choice.

By clicking NEXT you explicitly give your consent and agree that:

- We can collect your **anonymous** personal data, and we will only use this data for **scientific purposes**. We promise to protect your data according to the new General Data Protection Regulation (GDPR) laws (Read More).
- You confirm that **you are a student at Erasmus University Rotterdam**.
- We reserve the right to exclude respondents from the lottery in case of multiple submitted responses or low-quality/inattentive responses.

If you have any question concerning this experiment, do not hesitate to send an e-mail to **capozza@ese.eur.nl** or **moghani@ese.eur.nl**

In case, I win the lottery, I want my vouchers (the €200 of participation) to be from:

- Amazon.nl ○
- Bol.com ○
- I do not want to participate in the lottery ○

To start the survey, you need to create a unique code for yourself. This way, your answers will remain anonymous, and you will be able to check later if you win the lottery using your unique code.

To generate your unique code, please type the following from left to right without any space, in lower case letters, in the text box below.

- The first two letters of your father's name (for example, ab)
- Your day of birth (from 1 to 31)
- The first two letters of the name of your elementary school (for example, ab)
- The number of your siblings (0 to 99)
- The last two letters of your mother's name (for example, ab)
- The last two digits of your phone number (00 to 99)

What is your age?

What is your gender?

- Female
- Male
- Other
- Prefer not to say

Were you born in the Netherlands?

- Yes
- No

Were both of your parents born in the Netherlands?

- Yes
- No

In which region were you born?

- Asia Pacific (Central & South Asia, Northeastern Asia, Southeastern Asia) ○
- Australia and Oceania ○
- Europe (Northern Europe, Southern Europe, Eastern Europe, Western Europe) ○
- Middle East/Africa (Middle East, Northern Africa, Southern Africa) ○
- North America ○
- South America, Central America, Caribbean ○

In what degree program are you currently enrolled?

- Bachelor's ○
- Pre-Master's ○
- Master's (including MSc., MPhil., LLM., Medical Training) ○

How would you describe your current financial situation?

- Always stressful ○
- Somewhat stressful ○
- Sometimes stressful ○
- Rarely stressful ○
- Never stressful ○

Please indicate to what extent **you agree or disagree** with the following statements.

I would feel inadequate if I went to a therapist for psychological help.

(Please use a scale from 0 to 4, where 0 means "Strongly disagree" and a 4 means "Strongly agree".)

0 1 2 3 4

Your Opinion

My self-confidence would **NOT** be threatened if I sought psychological help.

(Please use a scale from 0 to 4, where 0 means "Strongly disagree" and 4 means "Strongly agree".)

0 1 2 3 4

Your Opinion

I would feel worse about myself if I had a mental health disorder (for example anxiety/mood/psychosis syndrome).

(Please use a scale from 0 to 4, where 0 means "Strongly disagree" and 4 means "Strongly agree".)

0 1 2 3 4

Your Opinion

I would feel inadequate if I used a mental health app.

(Please use a scale from 0 to 4, where 0 means "Strongly disagree" and a 4 means "Strongly agree".)

0 1 2 3 4

Your Opinion

I would feel inadequate if I used the coaching service of the university.

(Please use a scale from 0 to 4, where 0 means "Strongly disagree" and a 4 means "Strongly agree".)

0 1 2 3 4

Your Opinion

How effective do you think psychological therapy is for mental health?

- Not effective at all ○
- Slightly effective ○
- Moderately effective ○
- Very effective ○
- Extremely effective ○

How effective do you think coaching services are for mental health?

- Not effective at all ○
- Slightly effective ○
- Moderately effective ○
- Very effective ○
- Extremely effective ○

How effective do you think digital apps are for mental health?

- Not effective at all ○
- Slightly effective ○
- Moderately effective ○
- Very effective ○
- Extremely effective ○

In the past two weeks, have you been seeking professional care to improve your mental health?

- Yes ○
- No ○

From which source are you receiving mental health support? You can choose as many options as you want.

- General Practitioner ☐
- Praktijkondersteuner ☐
- Psychologist ☐
- Psychotherapist ☐
- Coach ☐
- Counselor ☐
- Mental health app/online platform ☐
- Other ☐

In the next two weeks, are you planning to seek professional care to improve your mental health?

- Yes ○
- No ○

From which source are you planning to receive mental health support? You can choose as many options as you want.

- General Practitioner ☐
- Praktijkondersteuner ☐
- Psychologist ☐
- Psychotherapist ☐
- Coach ☐
- Counselor ☐
- Mental health app/online platform ☐
- Other ☐

You stated that you are currently **not (or do not plan to)** receiving professional mental health support. The **main reasons** for that are...

You can select up to 3 options.

- [ ] I am not experiencing any distress
- [ ] The distress that I am experiencing is temporary/not serious
- [ ] I use app/online platform to receive support
- [ ] The waiting time to access support is too long
- [ ] I do not know how or where to seek support
- [ ] Support is too expensive
- [ ] I do not have time to seek support
- [ ] Other

Over the last 2 weeks, how often have you been bothered by feeling nervous, anxious or on edge?

- ○ Not at all
- ○ Several days
- ○ More than half days
- ○ Nearly every day

Over the last 2 weeks, how often have you been bothered by not being able to stop or control worrying?

- Not at all ○
- Several days ○
- More than half days ○
- Nearly every day ○

Over the last 2 weeks, how often have you been bothered by little interest or pleasure in doing things?

- Not at all ○
- Several days ○
- More than half days ○
- Nearly every day ○

Over the last 2 weeks, how often have you been bothered by feeling down, depressed, or hopeless?

- Not at all ◉
- Several days ○
- More than half days ○
- Nearly every day ○

If you are experiencing mental health issues or psychological distress, remember that **you don't have to deal with this alone!**

You can contact your general practitioner or use the university psychologist service if you wish to receive professional advice. **If you urgently need help, don't hesitate to call Stichting by dialing 113.**

Please tick the box to verify that you have read the information. Click Next when you are done!

I have read the information above.	☐