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

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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 a field 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 mechanisms. 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

According to the OECD, one in every two people in the world will be affected by mental or neurological disorders at some point in their lives (OECD 2018). Three quarters of mental health disorders emerge by the age of 24, but most cases go undetected and untreated (Kessler et al., 2005). University students have shown a vulnerability for mental health disorders, with survey evidence suggesting a prevalence of depression and anxiety higher than in the general population. The Covid-19 pandemic has exacerbated these issues (Adams-Prassl et al., 2021; Giuntella et al., 2021), increasing the urgency of the problem.

Mental health is a global public good (Patel, 2018) and there are large costs associated with poor mental health, both at individual and societal level. OECD estimates suggest that poor mental health can lead to a welfare loss of up to 4% of global GDP (OECD, 2020). Anxiety and depression account for 8% of years lived with disability (Vos et al., 2012). In the educational context, mental health issues hinder human capital accumulation (Currie, 2009; Currie and Stabile, 2006; Eisenberg et al., 2009; Heckman et al., 2006; Krishnan and Krutikova, 2013). By leading to biased beliefs about one's ability, mental health issues can also lead to the misallocation of talents (de Quidt and Haushofer, 2016). Later in life, mental health issues are associated with large earning penalties in the labor market (Biasi et al., 2021), a higher likelihood of unemployment, and penalties on the marriage market (Bos and Hertzberg, 2021).

Despite the extensive consequences of poor mental health, there is a large gap in demand for mental health support among university students: the majority of students in need is not seeking professional mental health support (Eisenberg et al., 2007; Hill et al., 2020; Sæther et al., 2021; Watkins et al., 2012)¹. The gap persists despite efforts from universities to increase the supply both of psychological counseling and low-intensity psychological interventions²,

¹We use the clinically validated brief screening tool PHQ-4 to assess the mental health of respondents in our study. Scores equal or higher than 6 correspond to moderate to severe depression and anxiety. In our sample, 28.8% of the respondents show symptoms of poor mental health. Only 36% of them are receiving support either from health professionals or by relying on apps.

²With the expression "high/intensity" psychological interventions, we refer to services and treatment options provided by trained medical professionals, while "low-intensity" interventions include both self-help tools and services targeting mental health, but not provided by mental health professionals.

such as coaching and mental health apps³. There is growing evidence that low-intensity interventions, such as well-being apps, are effective in improving mental health (Shreekumar and Vautrey, 2021) and can make users open to switching to services provided by mental health professionals (Clay, 2021).

In this paper, we study the demand for mental health support among university students and its determinants. We ran an online experiment with a broadly representative sample of 2,978 students recruited from a large Dutch university between October and November 2021⁴, and we measured the effects of a mental health literacy intervention. The intervention consisted of an information treatment based on results from two peer-reviewed articles (Eisenberg et al., 2009; Patel, 2018), which conveys two main messages. First, it introduces the staging approach, which highlights that mental health is not a binary status (ill or healthy), but a spectrum. Second, it aims to increase the perceived benefits of improved mental health. The information points out that investing in better mental health, through small steps such as self-care and monitoring, can be beneficial along the entire spectrum and that improved mental health can benefit academic performance.

We randomized half of the respondents to receive the mental health literacy intervention, while the other half did not receive any information. We designed the intervention with a two-fold goal. The first was to have an intervention which would resemble mental health initiatives that students could be exposed to outside of the experimental setting, such as in social media campaigns, workshops, university campaigns, or mental health awareness weeks. This feature of the treatment allows us to study how students change their demand for mental health support in a setting which is fairly realistic for them. The second goal was to target the general student population regardless of their mental health status. This goal was pursued by highlighting the potential benefits of investing in better mental health along the entire spectrum, so that the information treatment could promote help-seeking among all students. The choice to focus on mental health literacy in the information treatment is

³The market of mental health apps has been growing steadily. There are at least 10,000 apps available (Economist, 2021). In parallel, there has been a sharp increase in the number of universities that provide mental health apps to their students (see UCLA Grand Depression Challenge as an example), as well as firms, such as Nike or McKinsey, providing them to their employees.

⁴Dutch authorities reported a worrisome increase in mental health problems among university students in the Netherlands during the pandemic, which made the understanding of the demand for mental health support in this context even more timely.

also consistent with a recent literature suggesting mental health literacy interventions as a tool to increase mental health care demand (Ridley et al., 2020). We relied on two main outcomes to capture demand for mental health support: the first is an incentivized measure of willingness to pay (WTP) for a one-month subscription to a mental health app targeting depression, anxiety, and stress.⁵ The second outcome captured demand for information, by asking students to rank three options: (i) whether they would prefer to receive no information or information about one of two services offered on campus, namely, (ii) psychological counseling and (iii) coaching.

We document four sets of results. First, on average, the mental health literacy intervention has a null effect on the willingness to pay for the app subscription. WTP is measured on an interval between 0€ and 10€. The average WTP in the control group is 3.79€. The treatment estimate suggests an increase by 5.1% of a standard deviation in WTP but is not statistically significant at conventional levels. Ex-post power calculations rule out an average treatment effect of sizeable economic significance on WTP.⁶ Instead, respondents exposed to the information treatment are more likely to demand information about the coaching service – a significant increase by 8.5% of a standard deviation – and less likely to demand information about the psychological counseling service – a significant decrease by 4.4% of a standard deviation.

Distinguishing between psychological counseling and coaching allows us to shed light on the sorting of students into high- versus low-intensity services. This is a crucial aspect of demand for mental health support both because different levels of symptoms severity call for different psychological services and because there are constraints to the supply of high-intensity services such as counseling. In addition, it's important to understand if promoting low-intensity psychological intervention may lead to a substitution away from high-intensity services, with adverse effects for individuals with severe issues. In our setting, students with mental health scores consistent with moderate depression and anxiety substitute information

⁵The app is Sanvello, which allows you to track your moods, meditate, and also practice cognitive behavioral therapy (CBT) by using psychologist-designed tools to help manage stress, anxiety, and depression. There is evidence from clinical trials of its effectiveness in reducing symptoms in a population with a positive screening for psychological distress (Moberg et al., 2019; Ventura and Chung, 2019).

⁶We can rule out an effect larger than 7% of a standard deviation, which is substantially lower than/about half of the average magnitude of treatment estimates in information provision experiment (Haaland et al. (2021)).

about psychological counseling with information about coaching. Instead, for students at the two ends of the spectrum – with scores rated as "no signs of depression" or "severe" –, the evidence suggests that the increase in demand about coaching does not arise from a substitution effect, but corresponds to an increase in overall demand for information.

Second, in line with the psychological literature that documents heterogeneity in mental health risk and help-seeking behavior by gender, we find substantial heterogeneity in the effects of our intervention on demand for mental health support. The self-identified gender of respondents is a central dimension of heterogeneity. Male respondents in the treatment group increase their willingness to pay for the app by 14.6% of a standard deviation (significant at the 5% level). Higher level of stigma (both social and self-) and lower level of care-seeking behavior among male respondents in the control group compared to female respondents can help understand/explain why male students respond to the treatment by increasing their WTP for a private and completely anonymous option for mental health support. On the other hand, the substitution in demand for information is driven by female respondents, who display a higher average demand for information in the control group.

Third, we shed light on the potential mechanisms behind the observed effects. The intervention increases the perceived effectiveness of mental health apps. The effect is driven by male respondents, which is suggestive of beliefs about the app effectiveness being the main driver behind the observed increase in WTP. We also find suggestive evidence that the intervention increases self-stigma and perceived social stigma attached to high-intensity psychological services. By stressing the value of investing in better mental health and highlighting the benefits of small steps, which may be conducive to the use of low-intensity interventions, the information treatment could have the adverse effect of increasing stigma associated to professional mental health support by increasing its salience.

Finally, we assess the persistence of the effect of the intervention by running a follow-up survey three weeks later. We validate the use of our measure of information demand for mental health support options as a proxy for actual demand for mental health support. We find that acquiring information about the coaching services (psychologist services) has a strong and positive correlation with self-reported care-seeking behavior from a coach (psychologist). We also find that, on average, PHQ-4 scores of female respondents who were

exposed to the information treatment are lower than in the control group, consistent with an improved mental health status a few weeks after the mental health intervention.

We rationalize our experimental results using a theoretical framework. Focusing on the role played by students' beliefs, we model how perceived benefits of mental health care and self-image concerns affect investments in mental health in a multi-period model. The model draws insights from the literature studying self- and social image concerns, both theoretically (Bénabou and Tirole, 2011; Grossman, 2015) and empirically (Bursztyn et al., 2017, 2020). The model takes stigma towards poor mental health as given and endogenizes the signal that care-seeking behavior sends about one's mental health and eventually stigma and self-image concerns against care-seeking. To the best of our knowledge, the model is the first formalizing care-seeking behavior in the context of mental health with multiple care options. Our results show that: i) if the perceived benefits of any type of mental health support options increase, then more people seek care; ii) if the perceived benefits of low-intensity relative to high-intensity options increase, then more individuals seek support from low-intensity options, at the expense of high-intensity ones, and the stigma towards the latter increases. By shedding light on how beliefs towards low-intensity therapies and self-stigma shape the demand for mental health support, our results also speak to a small but growing literature that studies how stigma and anticipated discrimination in the context of mental health illness affects people's economic decisions (Eisenberg et al., 2009; Ridley, 2021).

Our results have important implications for the literature studying the causes and the economic consequences of poor mental health (Ridley et al., 2020) and the strand of this literature focusing on the evaluation of mental-health service provision interventions. In the context of Ghana, Barker et al. (2021) show that Cognitive Behavioral Therapy (CBT) improves people's mental and physical health, cognitive and socioemotional skills, and downstream economic outcomes two to three months after delivery. Baranov et al. (2020) show persistent effects on mental health over time among depressed mothers in Bangladesh. On the other hand, in rural Kenya, Haushofer et al. (2021) find the effects of an unconditional cash transfer on both economic outcomes and psychological well-being to be considerably larger than the effects of a five-week psychotherapy program. Romero et al. (2021) shows that cash transfers have a consistently positive impact on people's well-being in developing

countries. In the context of the US, Shreekumar and Vautrey (2021) shows that four weeks of self-therapy with a popular meditation app increases users' mental health and improves their economic behavior. We contribute to this stream of literature by focusing on *demand* for treatment options. The understanding of the drivers of demand is essential for any policy aimed at rolling out or scaling-up a mental-health service provision program that people would have to voluntarily take up. Stigma, low mental health literacy, scheduling concerns, lack of knowledge about the care options, and negative attitudes towards mental health services and professionals are among the most commonly cited barriers to care-seeking, while previous positive experiences with health services and higher mental health literacy facilitate help-seeking behavior⁷. The interventions targeting barriers to care-seeking mostly revolves around reducing stigma and discrimination⁸. However, those interventions mostly rely on small samples and focus on stigma measures as the main outcome, without studying the effects on care-seeking behavior. To the best of our knowledge, this paper is the first one to experimentally assess how a mental health literacy intervention affects the demand for mental health support relying on incentivized behavioral measures. We focus on the population of university students in a developed-country context. Further work is needed to validate our results in other contexts and understanding the drivers of demand for mental health services for other populations.

By focusing on the population of university students, our paper also speaks to the stream of literature studying the determinants of students' mental health and exploring the role played of factors such as peers, teachers and social media (Braghieri et al., 2021; Bütikofer et al., 2021; Kiessling and Norris, 2022). These concerns have also recently gained attention in the context of graduate students in Economics (Bolotnyy et al., 2021), Political Science (Almasri et al., 2021), and medical schools (Anderson et al., 2021). We contribute to this stream of literature by designing a novel mental health literacy intervention and studying its effects on the beliefs and care-seeking behavior of a large population of university students.

Finally, our study speaks to two strands of the literature in health economics. First, the experimental literature studying the effects of information provision interventions on health

⁷See for example Golberstein et al. (2008), Andrade et al. (2014), Clement et al. (2015), Haugen et al. (2017), Aguirre Velasco et al. (2020).

⁸See Thornicroft et al. (2016) for an overview of such interventions

behaviors (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. Second, the literature studying information acquisition (see Capozza et al. (2021) for a methodological review of studies on information acquisition in applied settings). In health economics, most of these studies focused on the decision to get tested for fatal diseases (Ganguly and Tasoff, 2016; Oster et al., 2013; Thornton, 2008). The closest paper to ours is Khan et al. (2021), which studies information demand for coronavirus prevention methods. We contribute to these two strands by providing causal evidence of the effects of a light-touch mental health literacy information treatment on students' beliefs, information acquisition about mental health support services, and incentivized measures of care-seeking.

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 a field 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 week⁹.

The choice to focus on University students is worth noting for three significant reasons. First, in the Netherlands out-of-pocket payments for mental health care increase once individuals are above 18 years old (Lopes et al., 2022). 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). We focus on this gap by studying individuals slightly older than 18 years. Second, 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).

2.2 Experimental Design

Part 1: Recruitment and Demographic Characteristics We invited the participants to join the study via an invitation email.¹⁰ The message in the email asked for their participation in a survey about habits and wellbeing topics. In the framing of the invitation email (Appendix J) we emphasized the monetary incentives for the participation, the anonymity of the responses, and we provided information about the content of the survey without deceiving the participants. We shared the survey link with roughly 30,000 students from all the schools of Erasmus University Rotterdam.

Once the participants joined the survey, we asked them to create a unique anonymous ID code that allowed us to match participants with their follow-up responses and ensured complete anonymity of the responses. Crucially, the process of generating a unique ID code also served as an attention check, since it required participants to read carefully and follow all the instructions. Finally, we collected self-reported information from the participants on: age, gender, school, level of education, whether they were Dutch (if so, whether they had an immigration background; if not, which geographical region they came from), their GPA, their

⁹In 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 restrictions do not have consequences for the internal validity of our study.

¹⁰(White, 2018) show that the identity of the investigator does not affect the participation of the respondents.

parents' education, their perceived level of financial stress, and their self-reported mental health status.

Part 2: Randomization We randomized the participants in one of two experimental conditions. Half of the participants were randomly assigned to receive an information treatment aimed at increasing mental health literacy. The mental health literacy intervention stated 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 presented 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 was allocated to the Control group and does not receive any information ¹¹

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.

¹¹The control group in this experiment is a passive control group.

Part 3: Demand for Mental Health Support App After the exposure to the treatment, we elicited the participants' "willingness-to-pay" (WTP) 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.¹² To have an incentive-compatible WTP elicitation, we used the Becker-DeGroot-Marschak (BDM) mechanism (following Cullen and Perez-Truglia (2018b)). In the BDM, the respondent's bid was compared to a price that was determined by a random number generator. If the respondent's bid was lower than the price, the respondent got a dollar amount equal to the price. If the bid was higher than the price, the subject received 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.¹³

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 at the end of the experiment.¹⁴

Part 4: Demand for Information about Support Services We elicited 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 asked the participants to rank the alternatives from the most preferred to the least preferred one.¹⁵ After ranking the options, the participants received the link to reach the website page about the highest ranked information. The options provided were: psychological service provided by the university, the coaching service provided by the university, and the option to

¹²provides the research evidence on the efficacy of the app. Prior to their bid, we also provide the description of the app to the participants.

¹³We follow the same incentive scheme as Allcott et al. (2020).

¹⁴Burchardi et al. (2021) show that respondents' optimal bidding and understanding of the mechanism is not affected by the type of elicitation techniques used.

¹⁵We follow a procedure similar to the one used in Fuster et al. (2021).

not acquire any information. Crucially, all the services were 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 by the desire to avoid social comparisons at university. The default option was receiving no information, so that the decision to acquire information required participants to actively change the ranking. At the same time, the ranking decision allowed 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).

Part 5: Post Treatment Questions We elicited 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 asked whether the participants were already receiving support and from which source. Moreover, we asked a battery of post-treatment questions, which are shown to the participants in a random order:

- We elicited 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 elicited the participants' beliefs on the effectiveness of the mental health app.
- We used questions from validated scales from psychology to measure the self and social stigma of seeking mental health support.

Part 6: Mental Health Status We assessed 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 used this tool at the end of the experiment to minimize any priming effect at earlier stages of the experiment.

Experimenter Demand Effect and Follow-Up Survey Although the experimenter demand effect is usually moderate (de Quidt et al., 2018), we took several measures to minimize it.

First of all, our first outcome variable, WTP for the mental health app, was an incentivized behavioral measure that should reduce the concerns for the experimenter demand effect. Moreover, we preserved the anonymity of the participants during the experiment, which should also minimize the experimenter demand effect. Furthermore, we recontacted the participants to the experiment a few weeks later and we matched them to their previous answers by means of their unique ID code and their demographic variables. In this follow up, we assessed whether participants had sought help in the two weeks before the follow up and whether they were 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. Finally, we re-assessed the participants' mental health status with the PHQ-4 questionnaire.

3 Analysis

In the main survey, we recorded the responses of 3,864 participants. Of these, 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.¹⁶

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 fewer Dutch students and more female students in the Treatment

¹⁶The pre-registration of this trial can be found under the number 0008406.

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.¹⁷

We also assess whether randomization has 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, nationality, 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 among 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.

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: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

¹⁷F-statistics = 1.378, p-value = 0.19.

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. 43.3% of respondents in the Control group are interested in receiving information about the psychological support available at the University; ¹⁸ 25.4% is would prefer to receive information about the coaching service available at the university, and the remaining 31% 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 psychology literature has identified several barriers and facilitators to help-seeking 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.18 shows that the students who believe in the high effectiveness of the mental health apps are willing to pay more for them. Figure A.19 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.18 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.20 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.21 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.26 and Figure A.27. On the other hand, female participants

¹⁸This is measured as the share of respondents in the control group who ranked receiving information about the psychological service as their preferred option.

and participants who display a lower mental health score are willing to pay more for the mental health app (see Figure A.24). Both students who display lower mental health scores and female students are also more willing to acquire information (Figure A.25). More specifically, lower mental health students are more likely to demand information about psychological services, as shown in Figure A.26.

Finally, Figure 1 shows the distribution of the PHQ4 score of the respondents. 28.8% of the respondents report a value of the PHQ4 higher or equal to 6¹⁹, which we label as "low mental health status".

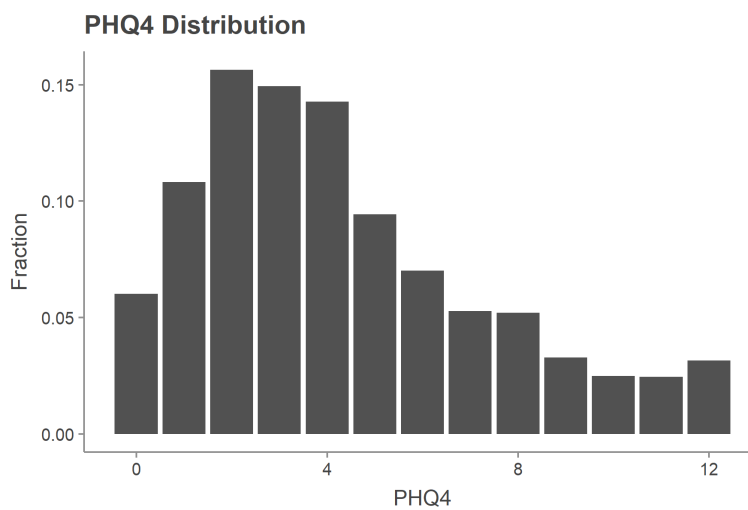


Figure 1: Distribution of PHQ4 score

Figure A.30 presents the correlation between the control variables and the reported PHQ4 score of the respondents. Financial stress, being Dutch, being older, and reporting a higher GPA negatively correlate with the students' mental health status. Most notably, 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).

Figure 2 displays the fraction of the respondents who are seeking professional care by their level of mental health. Among the respondents with low mental health status, we find

¹⁹The psychological literature identifies 6 as the threshold value for moderate psychological distress, with values 9-12 corresponding to severe psychological distress

evidence for a gap in demand for support, which is in line with the literature. 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). Notably, female respondents report to use more professional support than male respondents ($t = -6.1304$, $p\text{-value} < 0.001$), as well as to use more mental health apps ($t = -4.1499$, $p\text{-value} < 0.001$).

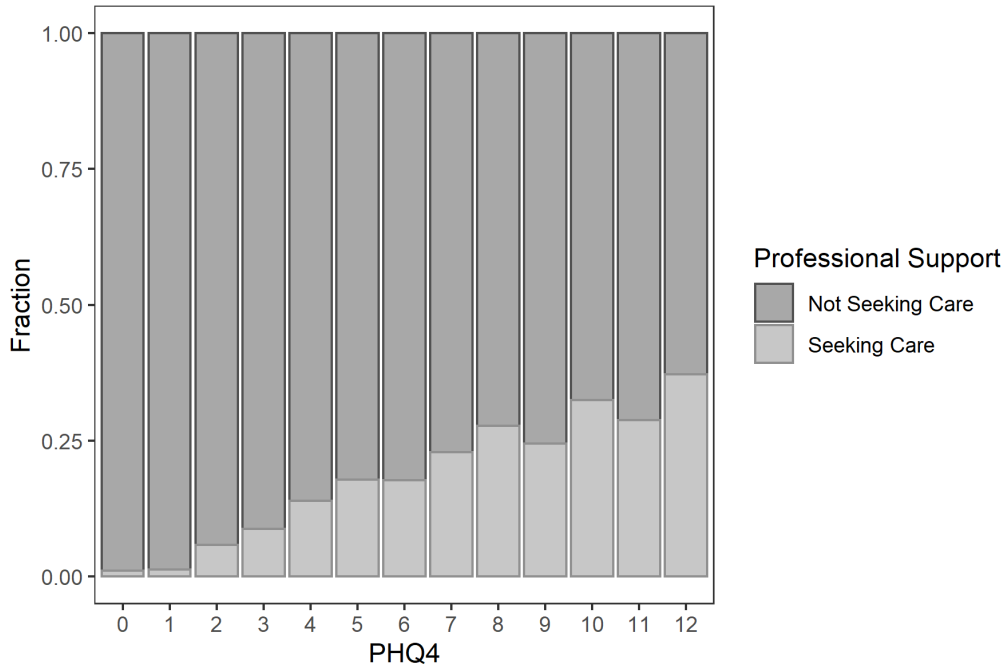


Figure 2: Care Seeking by PHQ4 score

Empirical Specification We assess whether 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:

$$y_i = \alpha + \beta t_i + \Gamma^T X_i + \epsilon_i \quad (1)$$

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 literacy intervention had a negligible effect on willingness-to-pay for the mental health app. WTP increases by 5.1% SD, but the effect is not significant (p -value = 0.33)²⁰. Although not significant, the intervention reduced the probability that the students chose "No information" as their preferred option by 3% SD. We also document a substitution effect of the literacy intervention, that led 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 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.

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 estimate Causal Random Forests models (CRF; Wager and Athey (2018)). This non-parametric method allows to relax the assumptions on the unobserved errors, and exploit accurately the heterogeneity in our sample.²¹ We follow Wager and Athey (2019) to estimate Conditional Average Treatment Effect (CATE) for each of 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

²⁰An ex-post power calculation shows that the minimum detectable effect in our sample is 7.1% SD.

²¹Appendix F describes in detail the CRF method and how we have implemented it in our analysis.

Table 2: Main Results: Demand for Mental Health Support

	<i>Dependent variable:</i>			
	WTP	No Information	University Psychologist	Coaching Service
	(1)	(2)	(3)	(4)
Treatment	0.082 (0.085)	-0.003 (0.017)	-0.033* (0.018)	0.036** (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: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

dimensions of interests to shed light on heterogeneity of the effects²².

3.3.1 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,

²²One can look at the following equation to estimate the heterogeneity:

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

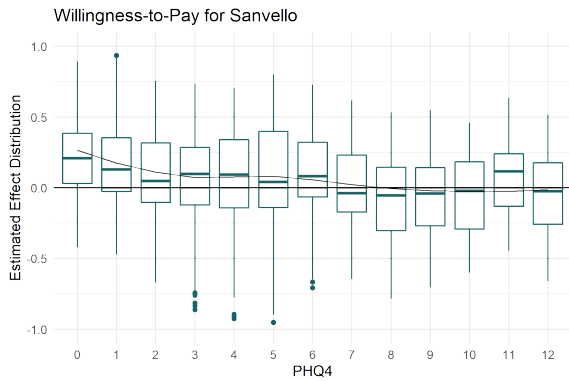
where where y_i is either the willingness to pay (WTP) for the app, or an indicator showing if the respondent demands information about psychological service/information about coaching service/no information; t_i is an indicator for whether the respondent i is in the mental health literacy treatment; 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.

we explore whether the mental health literacy intervention is actually causing an "adverse" substitution 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.

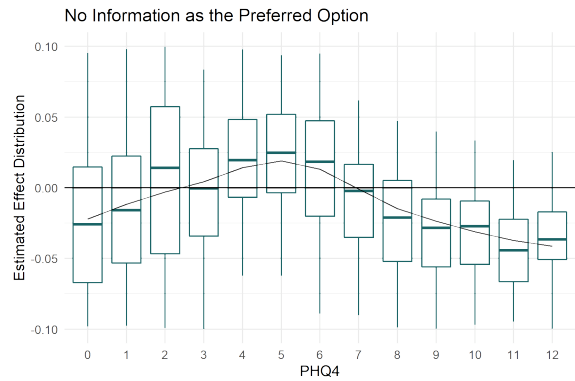
Following Wager and Athey (2019), we estimate CATE's for the effect of the mental health literacy intervention on the main outcomes. Figure 3 shows the distribution of these Conditional Average Treatment Effects by the baseline mental health level (PHQ4). Figure 3a shows that the respondents with better mental health status are those who show a higher ATE for the mental health app. Moreover, Figure 3b shows that the respondents with worse mental health status are less likely to choose not to receive any information about care options. Furthermore, Figure 3c 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 3d suggests that there is limited/no 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 3b and Figure 3b).

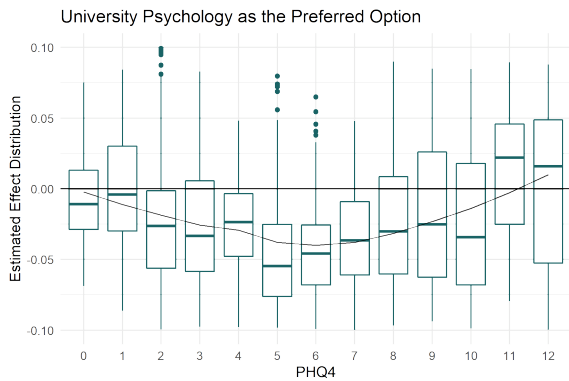
On the other hand, the individuals with poorer mental health status are more likely to demand for information. We observe that these individuals demand more information for coaching services, while there is no evidence that this increase comes at the expense of reduced demand for psychological services. 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.



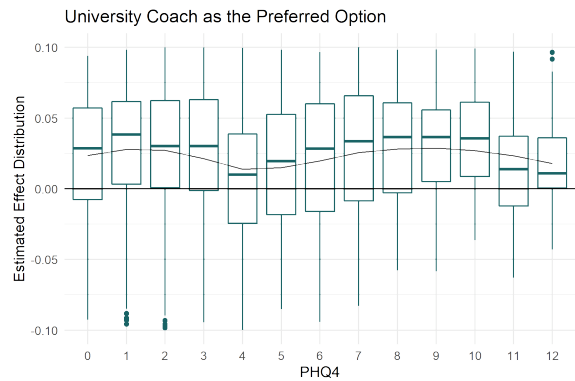
(a) Willingness-to-Pay



(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.

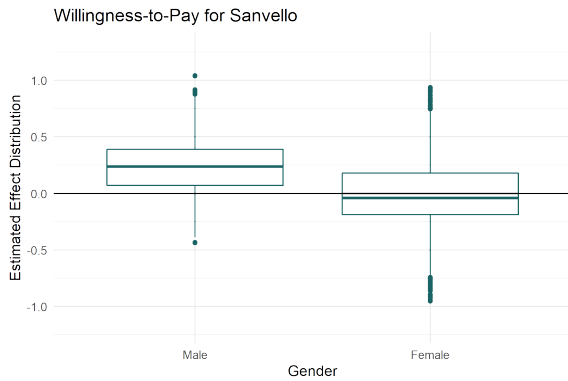
Figure 3: Heterogeneity of the Effects by Baseline Mental Health (PHQ4)

3.3.2 Heterogeneity by Gender

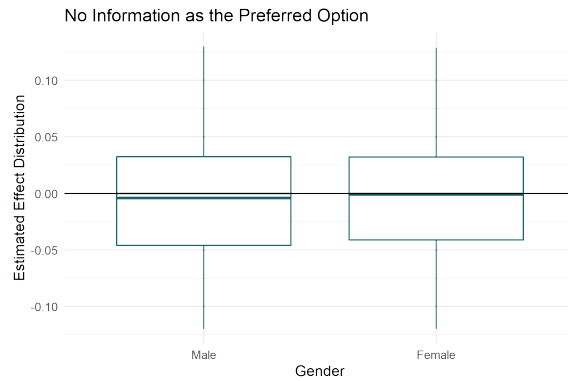
The gender differences in mental health risks, specifically anxiety and depression, are among the most robustly documented phenomena in the literature, with females being more at risk than males (e.g., see McLean et al. (2011); Parker and Brotchie (2010); Piccinelli and Wilkinson (2000); Riecher-Rössler (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 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 respondents (see Figure 4a). 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 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.

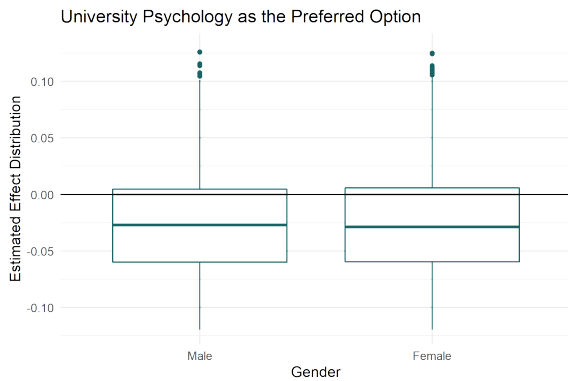
We also split the sample by gender and we run the specification as in Equation 1. In Table E2a, Column 1 shows that the male respondents were driving a significant increase in the WTP for the mental health app by 14.6% SD. In Table E2b, we find that the female respondents are entirely driving the adverse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



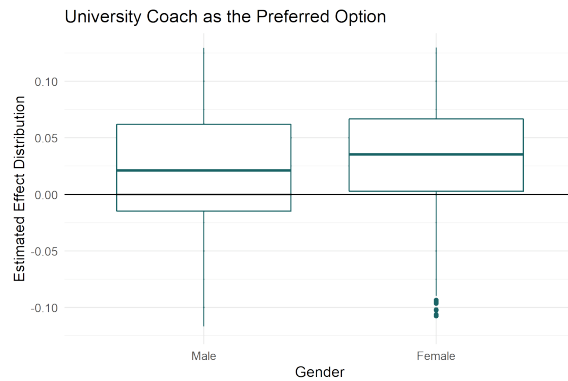
(a) Willingness-to-Pay



(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 4: Heterogeneity of the Effects by Gender

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 4, sub-figures 4a, 4b, 4c and 4d 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 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-scored value obtained from the answers to the underlying mechanism questions.²³

²³These 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.

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.²⁴ 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 mental health literacy intervention (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 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.*

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.²⁵ The creation of indexes helps to address the concerns of Multiple Hypothesis Testing.

Figure A.31 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

²⁴Table G1b reports the mechanisms' analysis for the female students. The treatment does not have a significant impact on these factors.

²⁵The Self-Stigma questions measure the attitudes towards mental illness and towards care-seeking.

Table 3: Mechanisms

	<i>Dependent variable:</i>				
	Academic returns (1)	Labor returns (2)	App effectiveness (3)	Self- Stigma (4)	Social Stigma (5)
Treatment	-0.003 (0.006)	0.003 (0.035)	0.103*** (0.036)	0.038 (0.026)	0.058** (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: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

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. Figure A.32 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 Follow-Up

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.²⁶ Table H1 in Appendix H shows that the

²⁶Students with a GPA above 6.5 were more likely to join the follow-up than those with a lower GPA.

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 5 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.

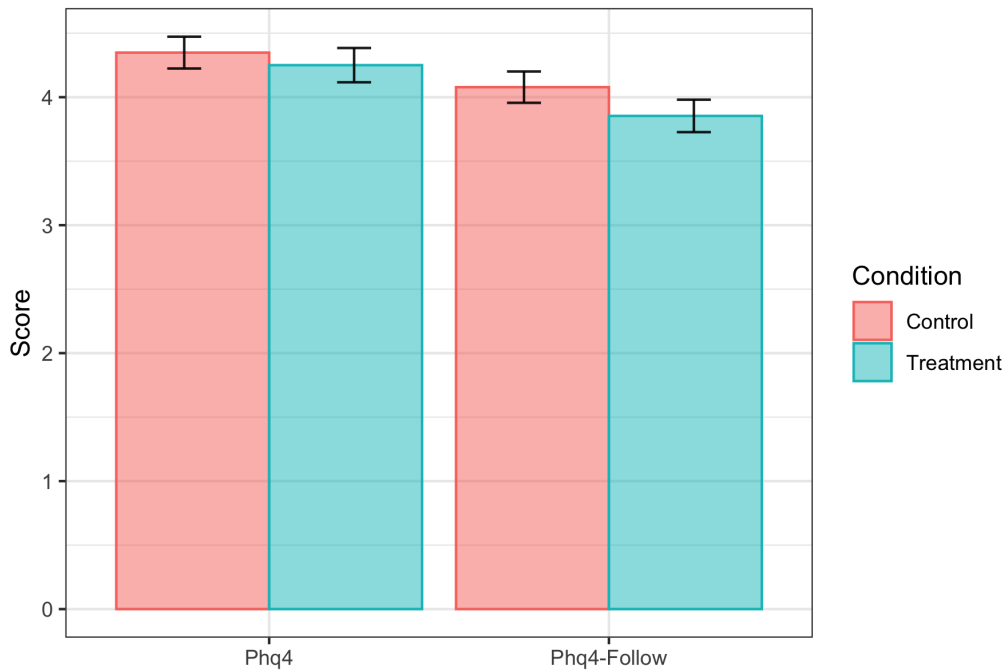


Figure 5: Differences in PHQ4 by Treatment

Table H3 shows that the treatment is significantly increasing the share of students mental health with an improved mental health. The mental health literacy intervention is also leading more respondents to plan to seek care, although these estimates are not significant at the conventional level. Table H4b documents that these effects are driven by female respondents. We we find that the treatment significantly improves the mental health of the female respondents by 0.22 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).

The persistent effects of the mental health literacy intervention on the female respondents' 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.²⁸ 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 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.

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 increases the share of students who report better mental health. This effect is mostly driven by female students. Finally, the demand for information strongly predicts respondents' self-reported 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

²⁷These 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.

²⁸We also validate whether the respondents in the Control group think that 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).

"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 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.

Effects on the "Readers" One concern of providing a literacy intervention is that the respondents might not actually pay attention to the content of the literacy intervention. We assess whether our results are actually driven by "fast reader" respondents. To test this, we actually focus on the respondents from the follow-up who were assigned to the Control group and

those in the Treatment group who are in the 10th percentile for the time spent reading the literacy intervention.

In Appendix I, Table I5 I6 confirm that the substitution effect in demand for information, as well as any improvement in mental health captured in the follow-up are driven by the respondents who actually took enough time to read the literacy intervention.

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 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 continuous 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 stigma²⁹. 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 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

²⁹It 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.

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 $i \in \{0, 1, 2\}$ ³⁰. 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 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

³⁰For 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.

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 6.

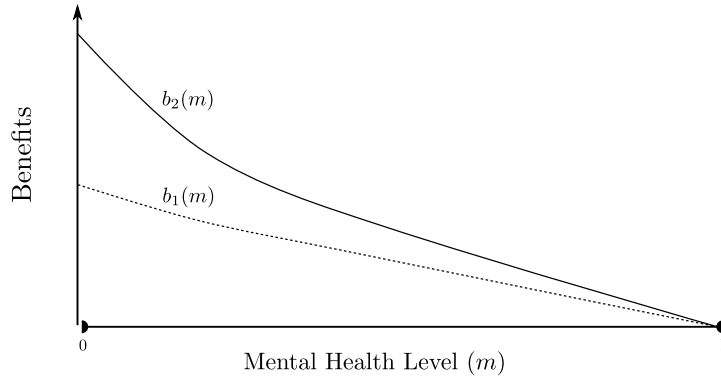


Figure 6: Sketch of Functional Form of the Benefits of Investments

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 .

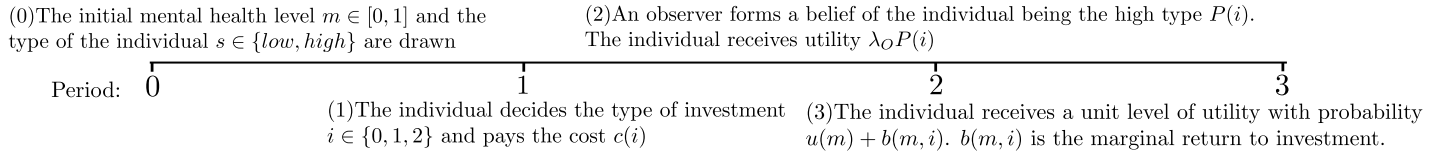


Figure 7: Timing of the Model

Assumptions Here we assume that individuals are uniformly distributed on the unit interval of mental health status, $f(m) = 1$ ³¹.

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:

³¹The results hold under milder (sufficient) conditions, namely, if the distribution of initial mental health satisfies the following:

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

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

so for any m :

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

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 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:

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

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 care³². 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

³²This 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.

always strictly beneficial to not invest given no benefit of investment, and nonzero costs³³ ($b_1(1) = b_2(1) = 0, c_2 > c_1 > 0$).

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 seeking care is zero while the costs are nonzero³⁴. 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:

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

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

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

³³The 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.

³⁴Given the patterns explained, it is safe to assume that not care-seeking cannot be associated with worse mental health levels.

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:

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

So, the net benefit of investment at the threshold ($b_i(m^*) - c_i$) relative to the image importance (λ_O) is equal to the image costs of the investment. One can show:

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

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 8). 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:

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

and

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

one can show:

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

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

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

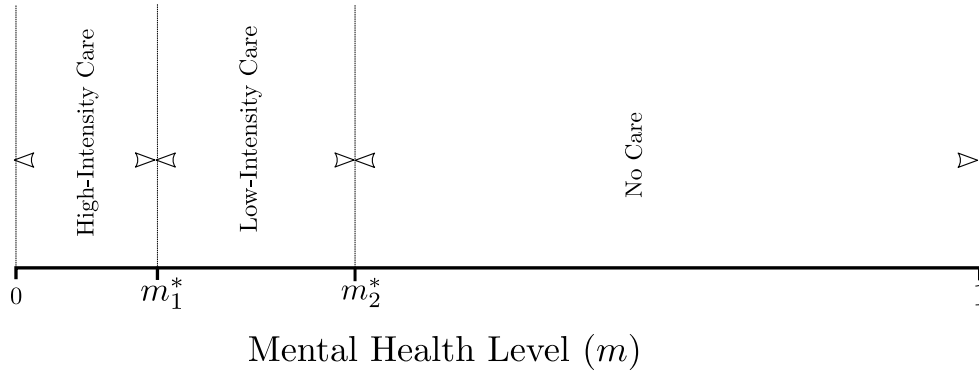


Figure 8: Investment Decisions in Fully Separating Equilibrium

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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For online publication only:

Mental Health Literacy, Beliefs and Demand for Mental Health Support Among University Students

Michelle Acampora, Francesco Capozza, and Vahid Moghani

A Figures

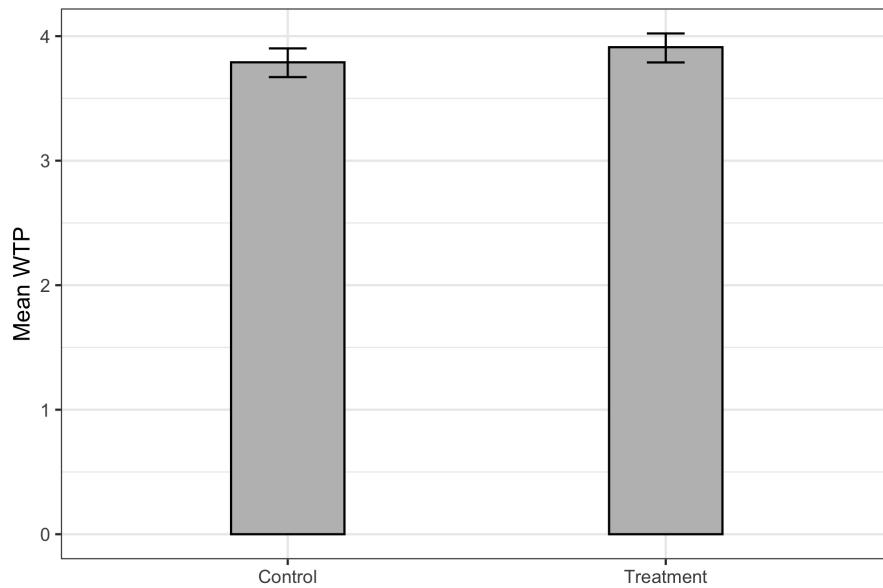


Figure A.1: Demand for Mental Health Support - WTP

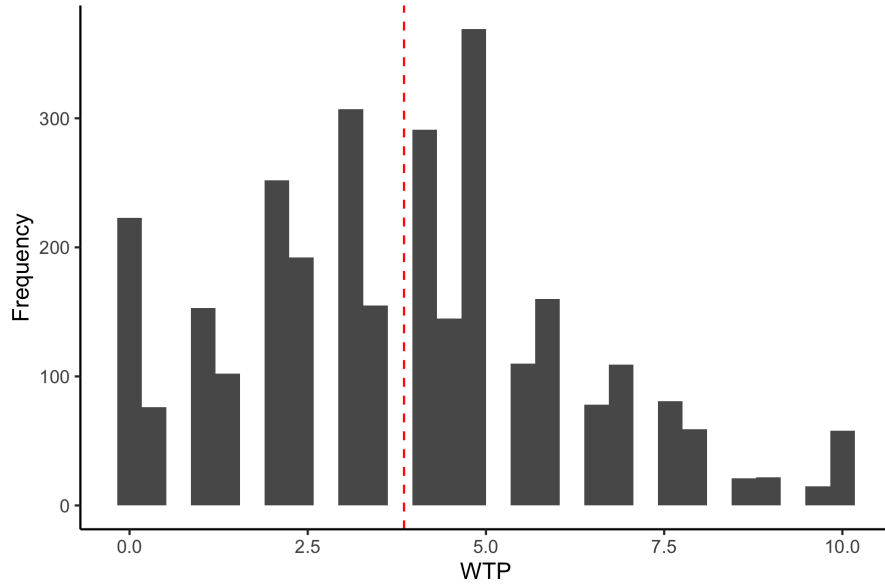


Figure A.2: WTP distribution

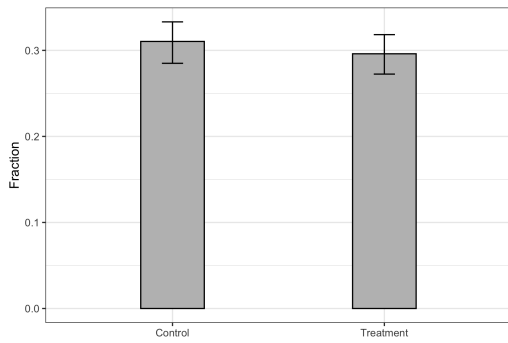


Figure A.3: No Information

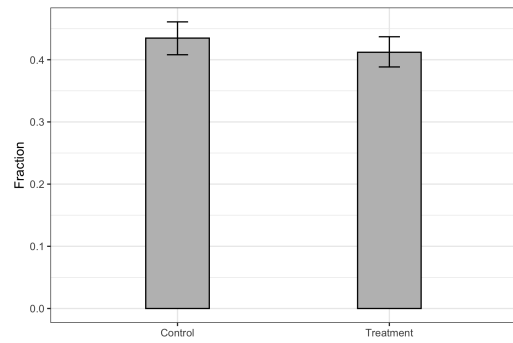


Figure A.4: University Psychologist

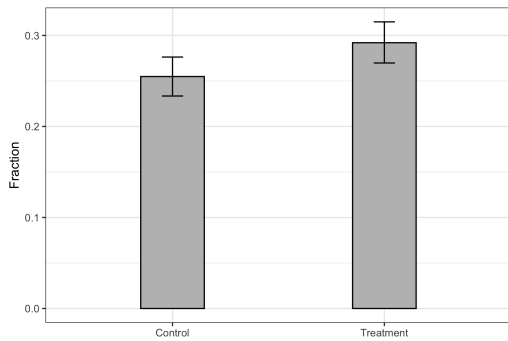


Figure A.5: Coaching Service

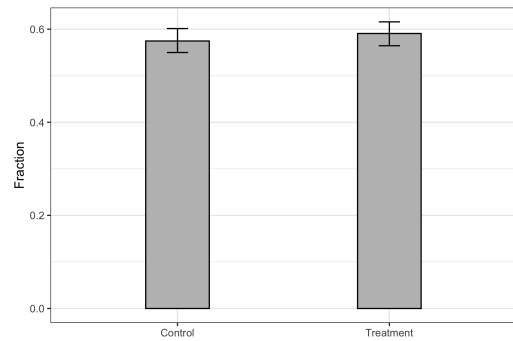


Figure A.6: Any Information

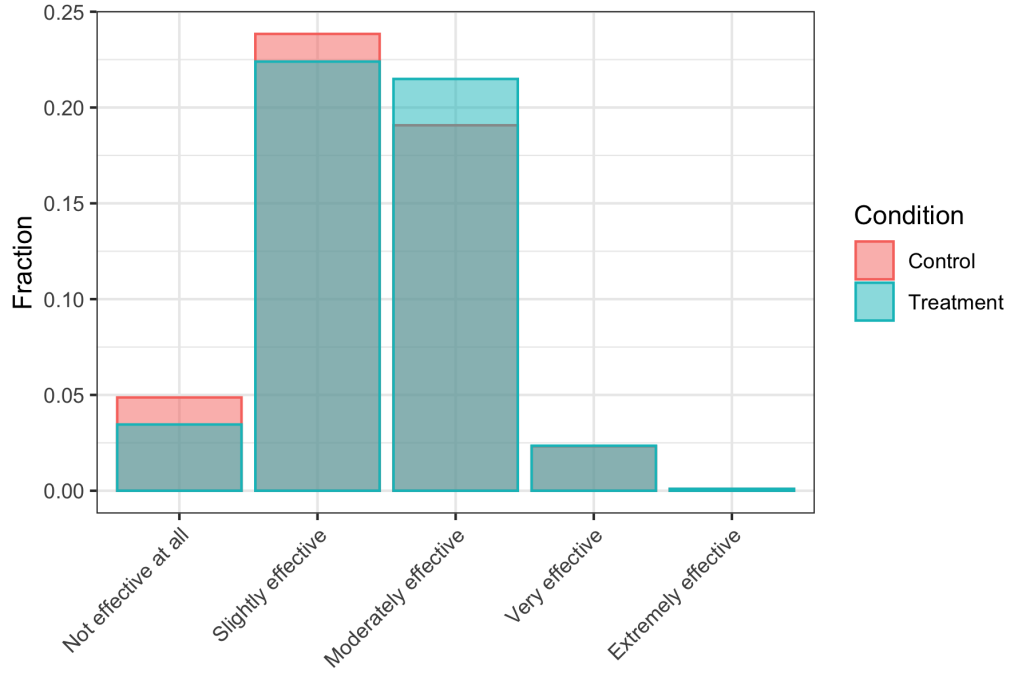


Figure A.7: Beliefs about the effectiveness of the mental health app

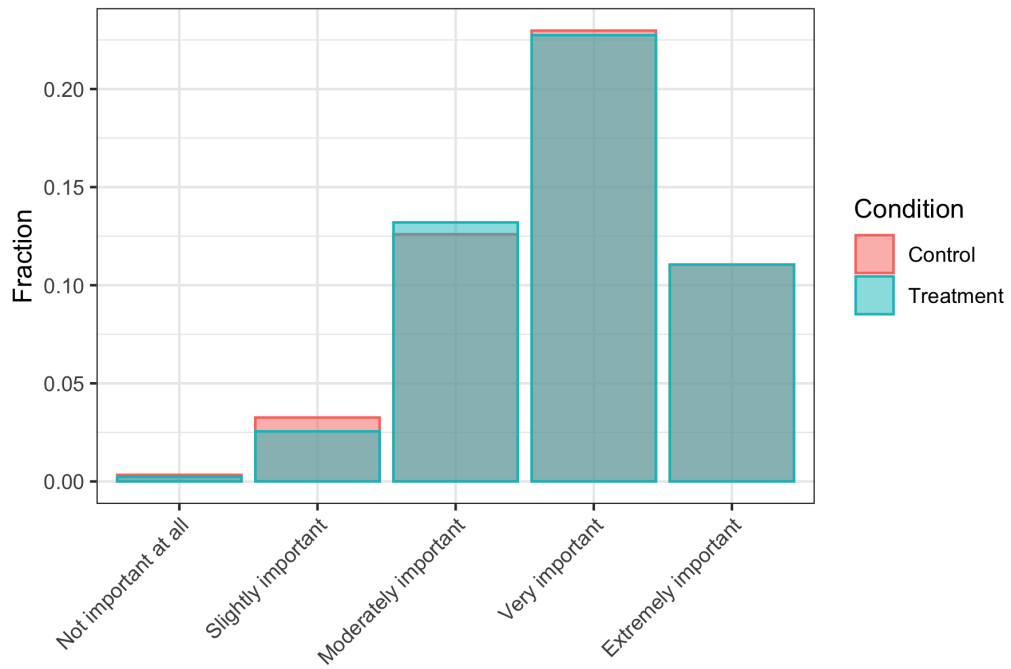


Figure A.8: Beliefs about the labor market returns of mental health

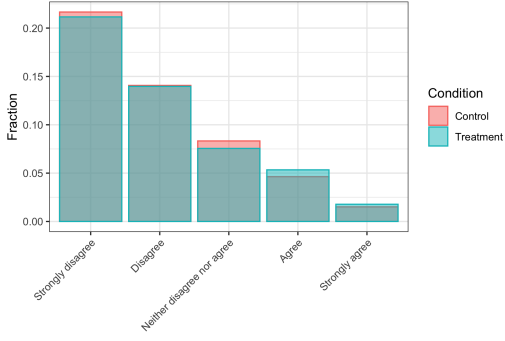


Figure A.10: Feeling inadequate

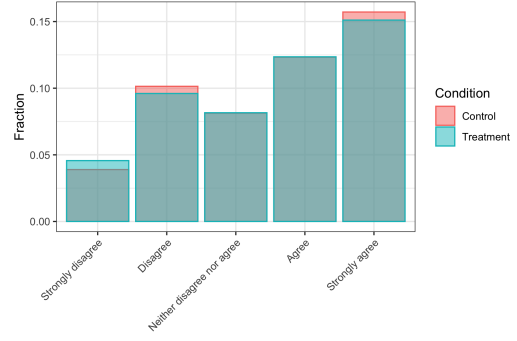


Figure A.11: Self-Confidence

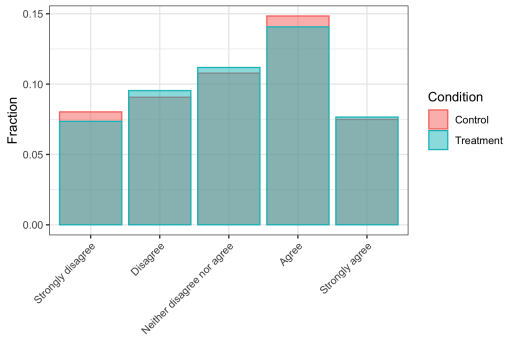


Figure A.12: Feeling worse

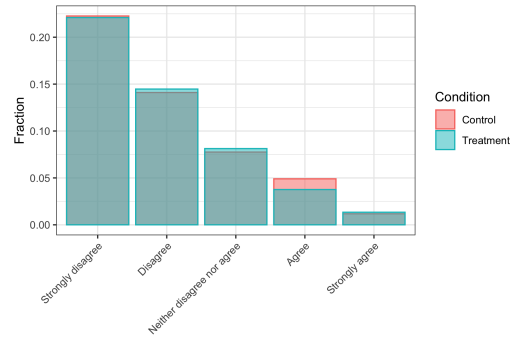


Figure A.13: Feeling less

Figure A.14: Self-Stigma components

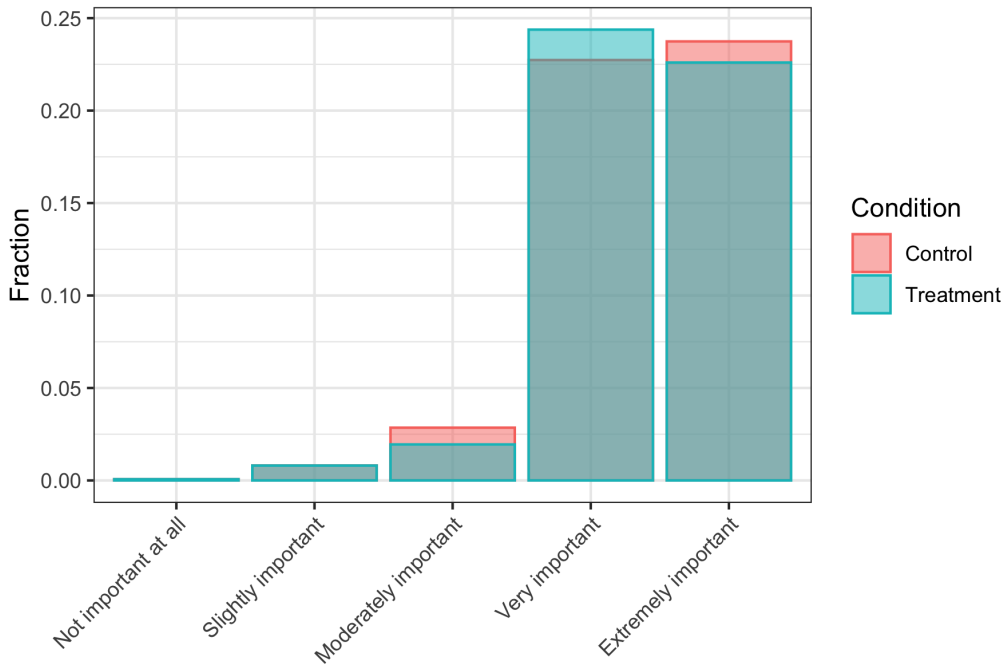


Figure A.9: Beliefs about the academic returns of mental health

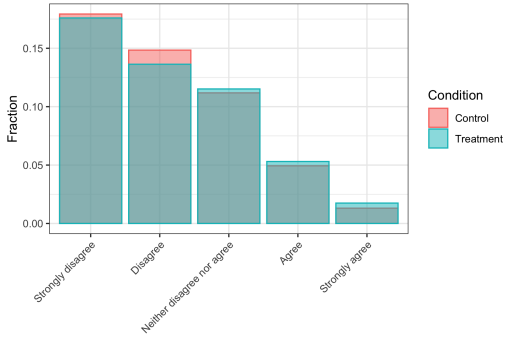


Figure A.15: Perceived discrimination

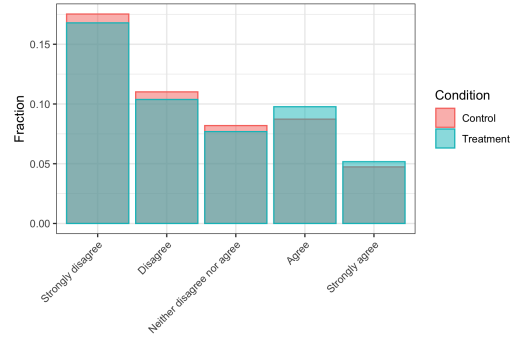


Figure A.16: Worried about Family

Figure A.17: Social Stigma components

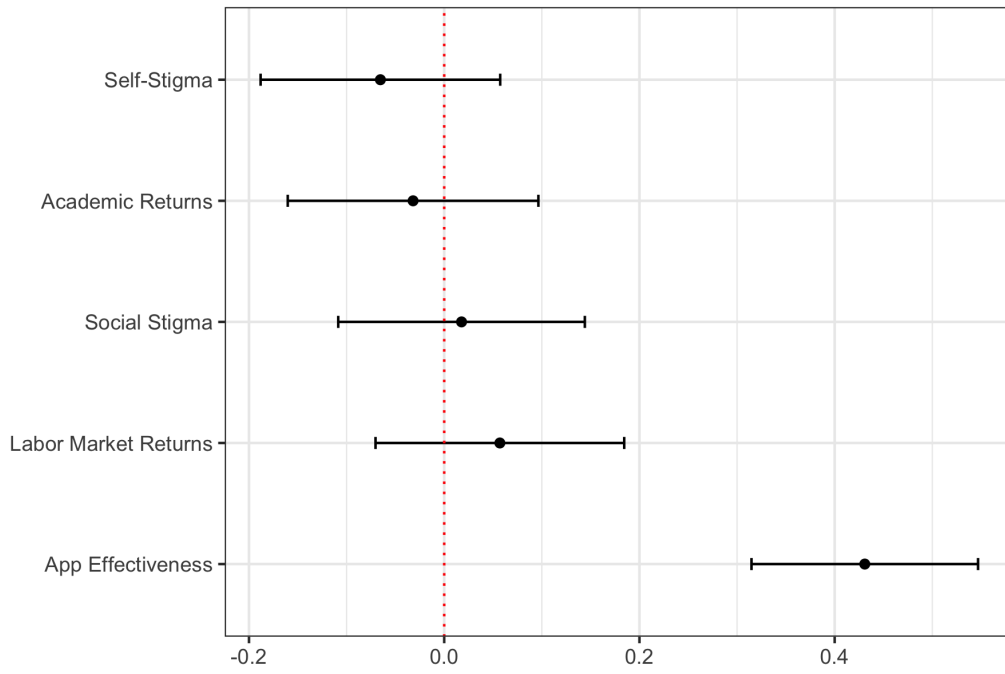


Figure A.18: Drivers of the WTP for mental health app

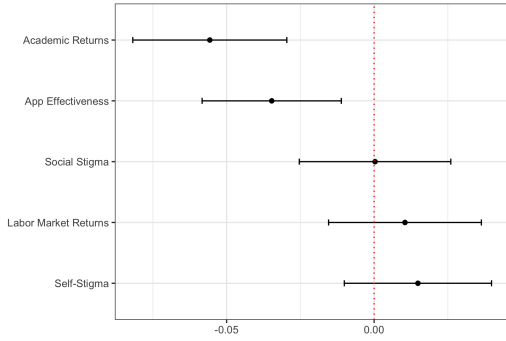


Figure A.19: No Information

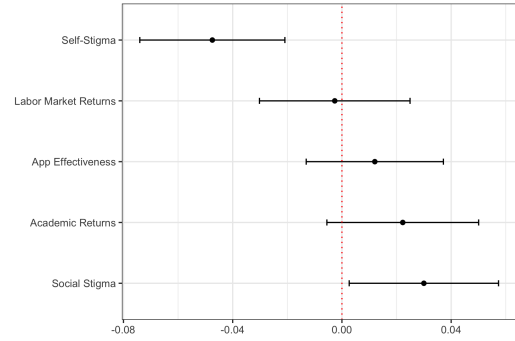


Figure A.20: University Psychologist

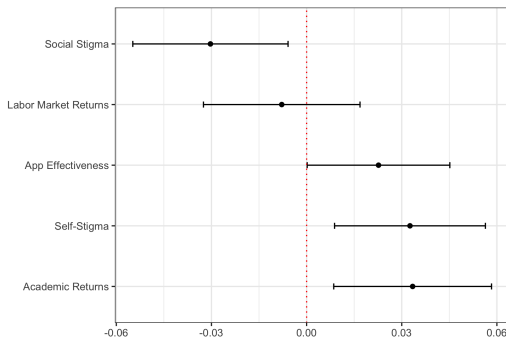


Figure A.21: Coaching Service

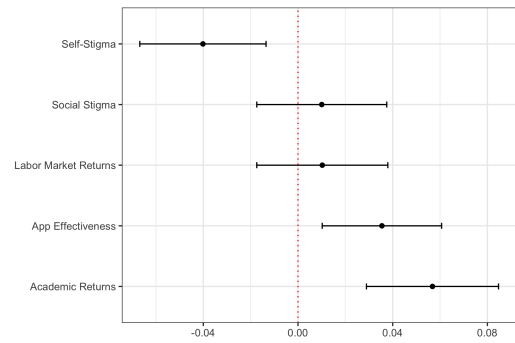


Figure A.22: Any Information

Figure A.23: Drivers of the demand for Information

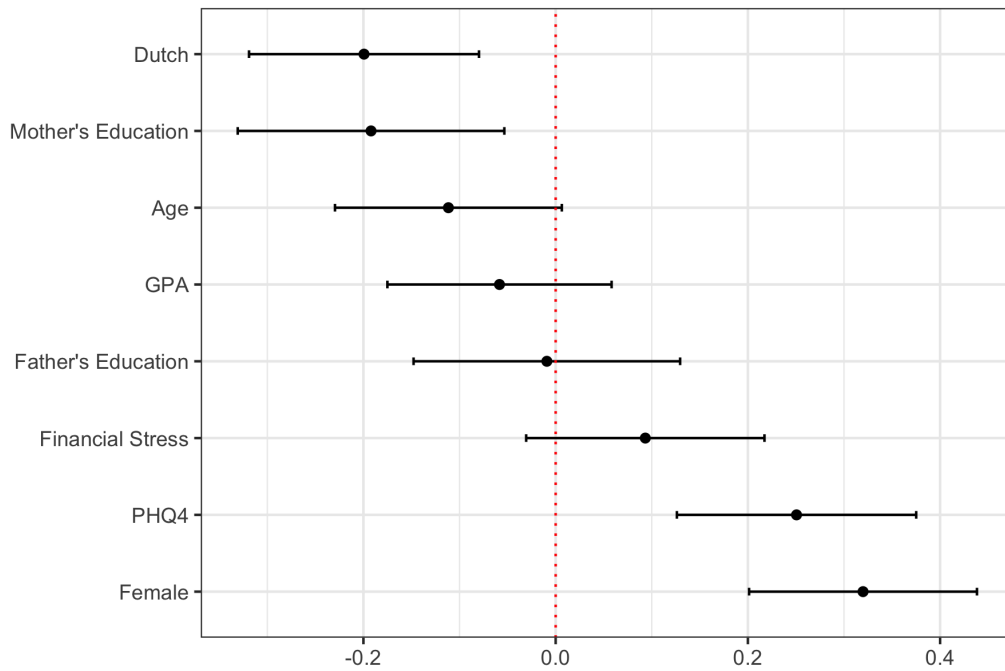


Figure A.24: Correlations between WTP for mental health app and control variables

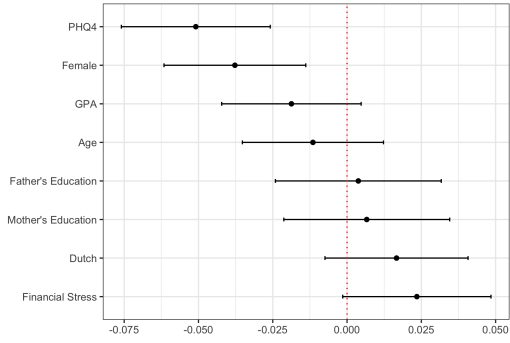


Figure A.25: No Information

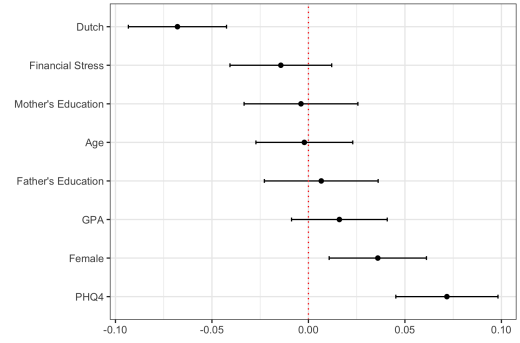


Figure A.26: University Psychologist

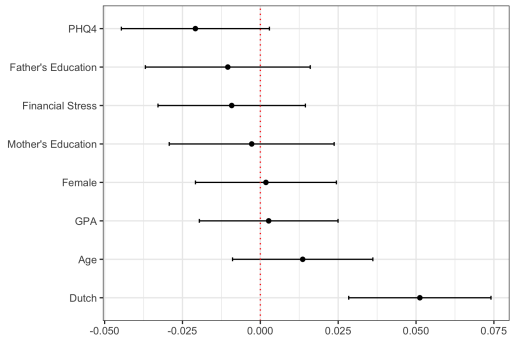


Figure A.27: Coaching Service

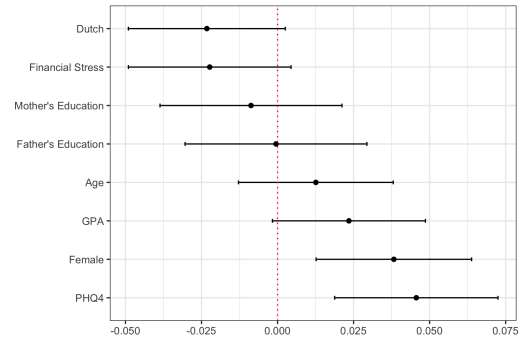


Figure A.28: Any Information

Figure A.29: Correlations between Demand for information and control variables

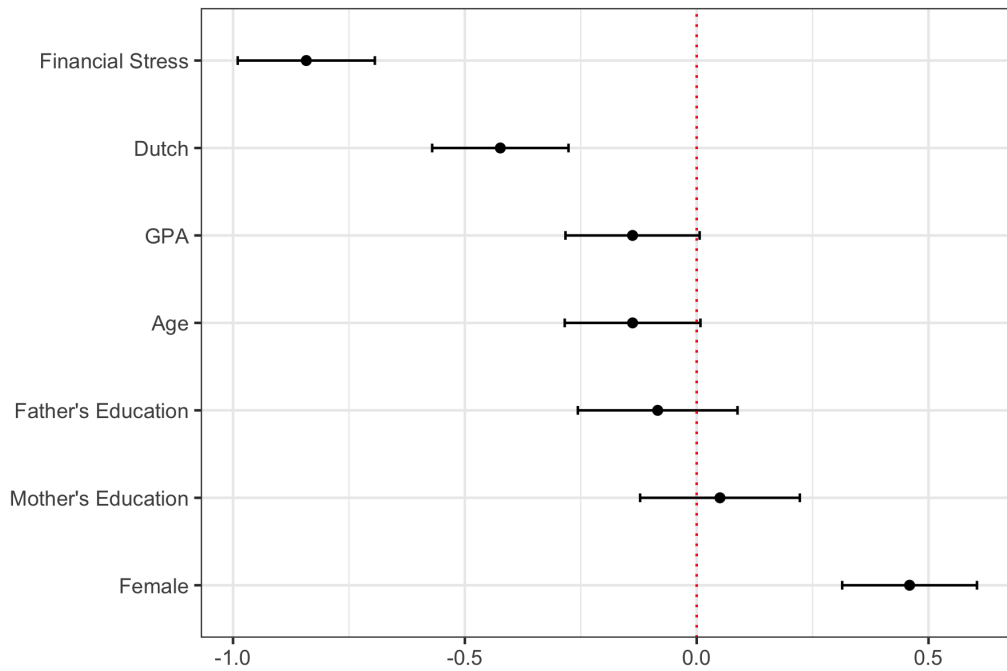


Figure A.30: Correlations between PHQ4 and control variables

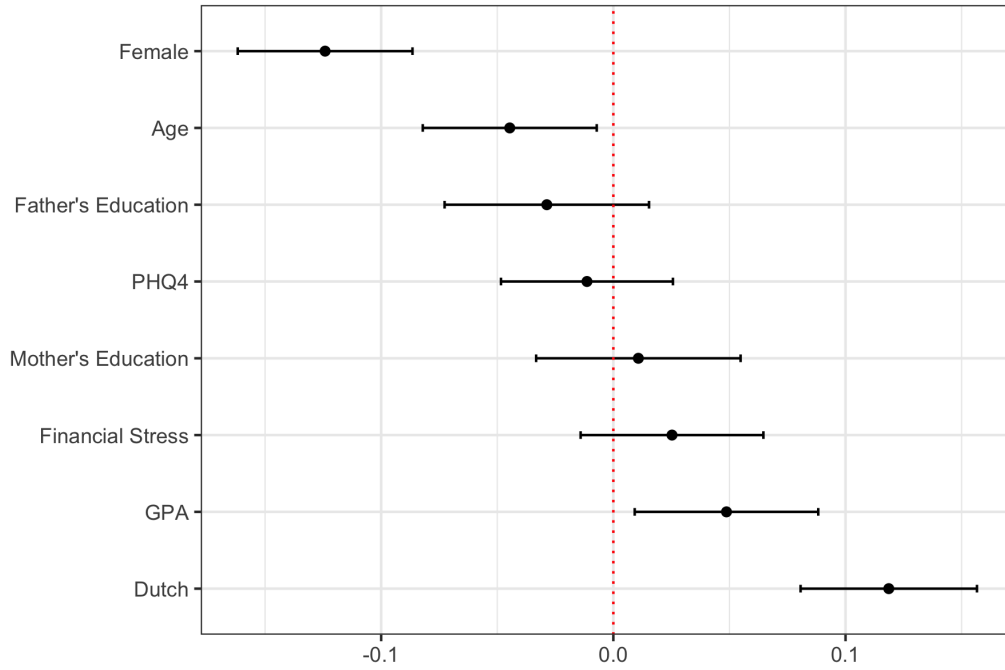


Figure A.31: Correlations between Self-Stigma index and control variables

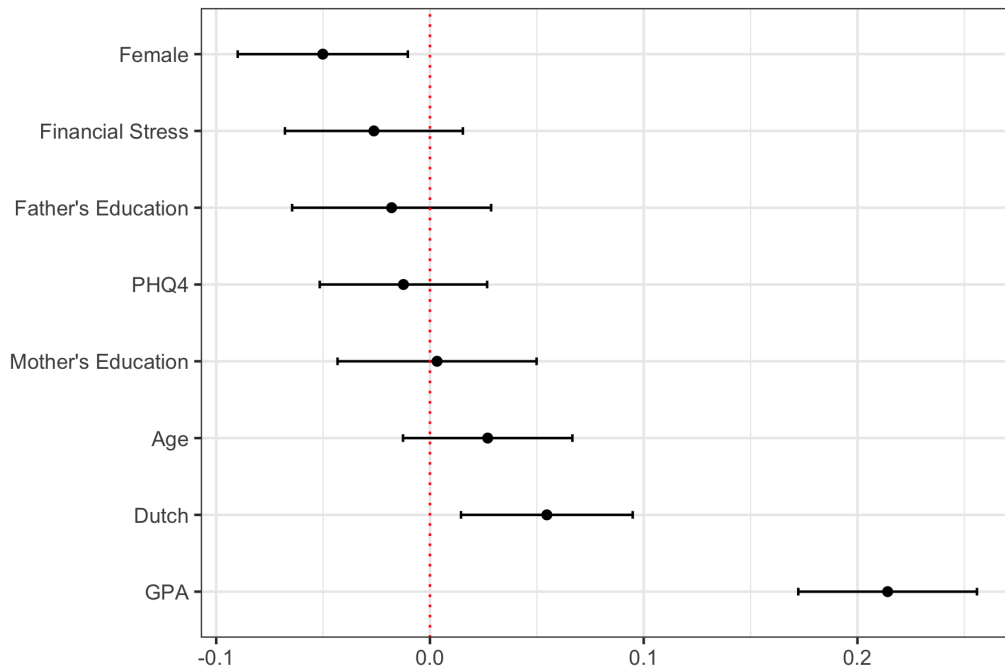


Figure A.32: Correlations between Social stigma and control variables

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

	<i>Dependent variable:</i>	
	Finished	Finished
	(1)	(2)
Treatment	-0.0072 (0.010)	-0.0099 (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

	<i>Dependent variable:</i>				
	WTP	No Information	University Psychologist	Coaching Service	Any Informa- tion
	(1)	(2)	(3)	(4)	(5)
Treatment	0.121 (0.086)	-0.014 (0.017)	-0.023 (0.018)	0.037** (0.016)	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

Table E1: Heterogeneous Treatment Effects - Gender

	<i>Dependent variable:</i>				
	WTP	No Informa- tion	University Psychologist	Coaching Service	Any Informa- tion
	(1)	(2)	(3)	(4)	(5)
Treatment	0.344** (0.139)	0.010 (0.027)	-0.020 (0.029)	0.010 (0.027)	-0.008 (0.029)
Female	0.738*** (0.124)	-0.074*** (0.024)	0.063** (0.026)	0.011 (0.024)	0.081*** (0.026)
Treatment x Female	-0.429** (0.175)	-0.023 (0.034)	-0.021 (0.037)	0.043 (0.034)	0.019 (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

	<i>Dependent variable:</i>				
	WTP	No Informa- tion	University Psychologist	Coaching Service	Any Informa- tion
	(1)	(2)	(3)	(4)	(5)
Treatment	0.335** (0.143)	0.012 (0.029)	-0.023 (0.029)	0.011 (0.027)	-0.009 (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

	<i>Dependent variable:</i>				
	WTP	No Informa- tion	University Psychologist	Coaching Service	Any Informa- tion
	(1)	(2)	(3)	(4)	(5)
Treatment	-0.093 (0.106)	-0.015 (0.020)	-0.042* (0.023)	0.057*** (0.021)	0.012 (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: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

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 F1 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 F1: CATE for the main outcome variables

Variables	ATE	CI 95%	Differences in ATE	CI 95% Differences in ATE
WTP	0.077	± 0.166	0.194	± 0.331
NoInfo	-0.008	± 0.032	0.027	± 0.065
Psychologist	-0.034	± 0.035	-0.117	± 0.069
Coaching Service	0.041	± 0.032	0.006	± 0.063
AnyInfo	0.011	± 0.035	0.072	± 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 F1 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".

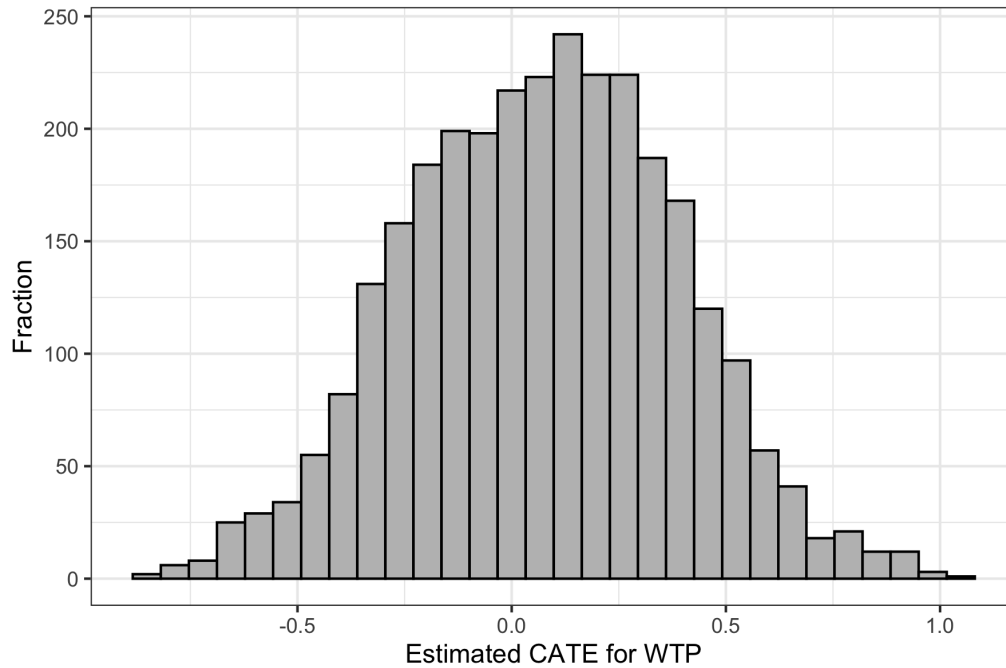


Figure F.1: Estimated CATE for WTP

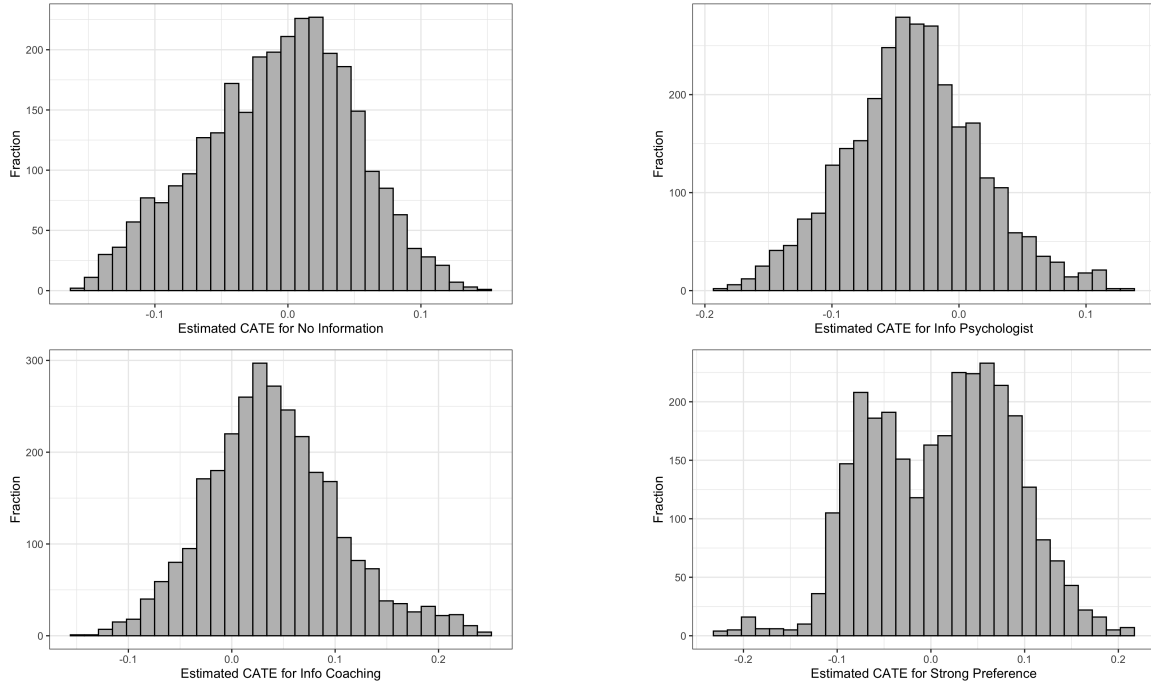


Figure F.2: Estimated CATE for Information Demand

G Mechanisms

Table G1: Mechanisms by Gender

(a) Mechanisms - Male

	<i>Dependent variable:</i>				
	Academic returns	Labor returns	App effectiveness	Self- Stigma	Social Stigma
	(1)	(2)	(3)	(4)	(5)
Treatment	0.008 (0.010)	0.040 (0.060)	0.198*** (0.062)	0.037 (0.044)	0.077 (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

	<i>Dependent variable:</i>				
	Academic returns	Labor returns	App effectiveness	Self- Stigma	Social Stigma
	(1)	(2)	(3)	(4)	(5)
Treatment	-0.010 (0.007)	-0.024 (0.044)	0.055 (0.045)	0.043 (0.033)	0.043 (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

	<i>Dependent variable:</i>					
	Self-Stigma Index	Feeling inadequate	inade-	Self-Confidence	Feeling worse	Feeling less
	(1)	(2)		(3)	(4)	(5)
Treatment	0.154 (0.105)	0.071* (0.037)		0.053 (0.037)	0.028 (0.036)	0.003 (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

	<i>Dependent variable:</i>		
	Social Stigma In- dex	Perceived dis- crimination University	Telling Family Psychologist
	(1)	(2)	(3)
Treatment	0.117** (0.057)	0.049 (0.037)	0.067* (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

	<i>Dependent variable:</i>
	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	1121	

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

	<i>Dependent variable:</i>		
	Did seek care	Plan seek care	Improved PHQ4
	(1)	(2)	(3)
Treatment	0.003 (0.019)	0.022 (0.020)	0.047* (0.028)
Observations	1,121	1,121	1,121
Controls	YES	YES	YES
Control group means	0.132	0.151	0.416
Adjusted R ²	0.132	0.171	0.115

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; Improved MH gets value 1 if the respondent reports a lower PHQ4 score in the follow-up than in the first wave. *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

	<i>Dependent variable:</i>		
	Did seek care (1)	Plan seek care (2)	Improved MH (3)
Treatment	-0.033 (0.021)	-0.006 (0.025)	-0.056 (0.047)
Observations	399	399	399
Controls	YES	YES	YES
Control group means	0.132	0.151	0.411
Adjusted R ²	0.072	0.104	0.121

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; Improved MH gets value 1 if the respondent reports a lower PHQ4 score in the follow-up than in the first wave. *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

	<i>Dependent variable:</i>		
	Did seek care (1)	Plan seek care (2)	Improved MH (3)
Treatment	0.033 (0.028)	0.039 (0.029)	0.111*** (0.036)
Observations	710	710	710
Controls	YES	YES	YES
Control group means	0.132	0.151	0.425
Adjusted R ²	0.127	0.166	0.123

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; Improved MH gets value 1 if the respondent reports a lower PHQ4 score in the follow-up than in the first wave. *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

	<i>Dependent variable:</i>			
	Psychologist past 2 weeks (1)	Coaching past 2 weeks (2)	Psychologist next 2 weeks (3)	Coaching next 2 weeks (4)
Info Psychologist	0.024 (0.018)		0.065*** (0.020)	
Info Coach		0.030*** (0.011)		0.030** (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

	<i>Dependent variable:</i>
	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: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

I Robustness Checks

Table I1: Robustness Checks - Awareness

	<i>Dependent variable:</i>				
	WTP	No Information	University Psychologist	Coaching Service	Any Informa- tion
	(1)	(2)	(3)	(4)	(5)
Treatment	0.083 (0.085)	-0.002 (0.017)	-0.034* (0.018)	0.036** (0.016)	0.003 (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

	<i>Dependent variable:</i>			
	No Information	University Psychologist	Coaching Service	Any Informa- tion
	(1)	(2)	(3)	(4)
Treatment	-0.016 (0.082)	-0.147* (0.077)	0.191** (0.084)	0.014 (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

	<i>Dependent variable:</i>			
	No Information	University Psychologist	Coaching Service	Any Informa- tion
	(1)	(2)	(3)	(4)
Treatment	0.984 (0.082)	0.863* (0.066)	1.209** (0.101)	1.014 (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

	<i>Dependent variable:</i>				
	WTP	No Information	University Psychologist	Coaching Service	Any Informa- tion
	(1)	(2)	(3)	(4)	(5)
Treatment	0.089 (0.086)	-0.002 (0.017)	-0.036** (0.018)	0.038** (0.016)	0.004 (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: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Table I5: Main Effect among "Readers"

	<i>Dependent variable:</i>			
	WTP	No Information	University Psychologist	Coaching Service
	(1)	(2)	(3)	(4)
Treatment	0.104 (0.087)	-0.012 (0.017)	-0.031* (0.018)	0.043** (0.017)
Observations	2,836	2,836	2,836	2,836
Controls YES	YES	YES	YES	YES
Control group mean 0.574	3.789	0.310	0.434	0.254
Adjusted R ²	0.045	0.043	0.061	0.021

Note: All specifications are OLS models. Robust standard errors are reported in parentheses. We focus on the respondents from the Control group and the respondents from the Treatment group from at least the 10th percentile of the distribution of the time spent on the mental health literacy intervention page. *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 I6: Mental Health Follow up among "Readers"

	<i>Dependent variable:</i>		
	Improved MH (1)	Improved MH (Male) (2)	Improved MH (Female) (3)
Treatment	0.052* (0.029)	-0.050 (0.048)	0.115*** (0.036)
Observations	1,087	385	690
Controls	YES	YES	YES
Control group means	0.416	0.411	0.425
Adjusted R ²	0.120	0.121	0.130

Note: The specification is an OLS model. Robust standard errors are reported in parentheses. We focus on the respondents from the Control group and the respondents from the Treatment group from at least the 10th percentile of the distribution of the time spent on the mental health literacy intervention page. 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; Improved MH gets value 1 if the respondent reports a lower PHQ4 score in the follow-up than in the first wave. *Control* variables are: Age, Dutch, Female, GPA, Financial Stress, Father's Education, Mother's Education, PHQ4 from the main study. Significance code: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

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](#)

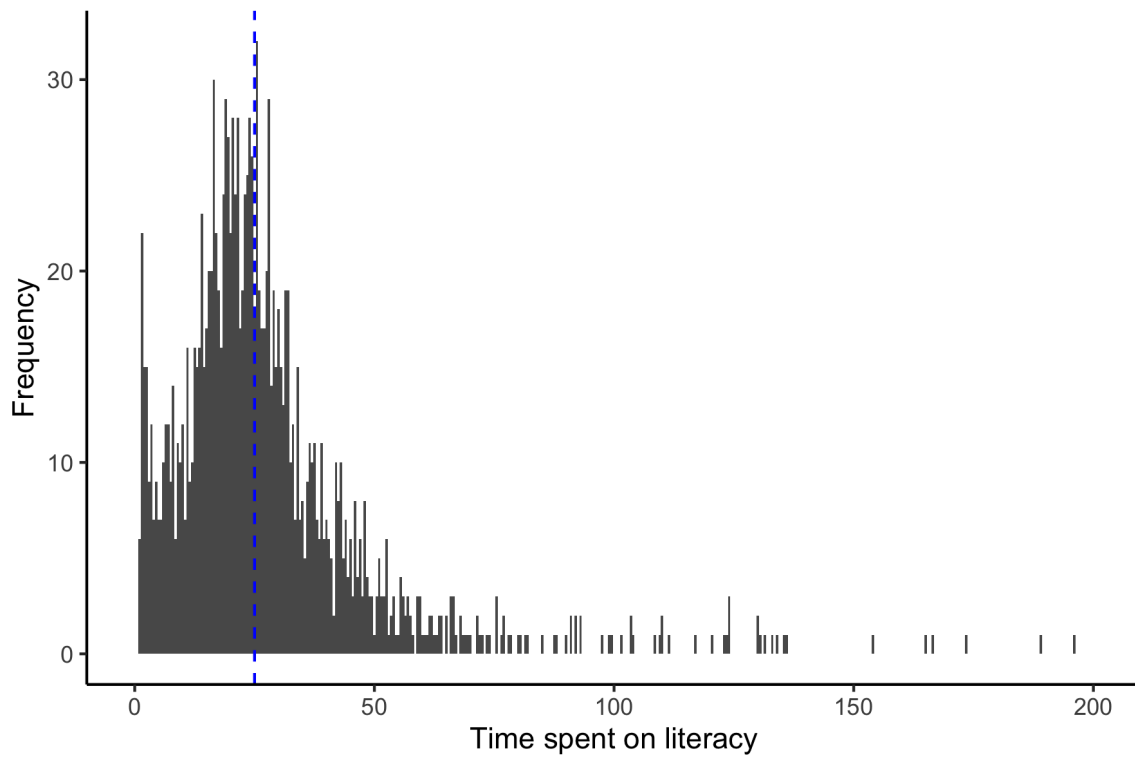
Thanks a lot for your time and your collaboration!

Warm regards,

Vahid Moghani

K Time spent on reading the literacy intervention

This graph shows the amount of time that the respondents from the Treatment Group have spent on reading the information of the mental health literacy intervention. The dotted blue line represents the average time spent on the page, which is roughly 25 seconds.



L 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	<input type="radio"/>
Bol.com	<input type="radio"/>
I do not wish to participate in the lottery	<input type="radio"/>

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	<input type="radio"/>
Male	<input type="radio"/>
Other	<input type="radio"/>
Prefer not to say	<input type="radio"/>

Were you born in the Netherlands?

Yes	<input type="radio"/>
No	<input type="radio"/>

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., LL.M., Medical Training)

What is your overall GPA?

Below 5.5	<input type="radio"/>
5.5-6.5	<input type="radio"/>
6.5-7.5	<input type="radio"/>
7.5-8.5	<input type="radio"/>
Above 8.5	<input type="radio"/>
Prefer not to say	<input type="radio"/>

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

Elementary education or lower	<input type="radio"/>
Secondary education	<input type="radio"/>
Vocational education/MBO	<input type="radio"/>
Higher education (below Master's level)	<input type="radio"/>
Master's	<input type="radio"/>
PhD	<input type="radio"/>
Not applicable	<input type="radio"/>

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

Elementary education or lower	<input type="radio"/>
Secondary education	<input type="radio"/>
Vocational education/MBO	<input type="radio"/>
Higher education (below Master's level)	<input type="radio"/>
Master's	<input type="radio"/>
PhD	<input type="radio"/>
Not applicable	<input type="radio"/>

How would you describe your mental health currently?

Very Good	<input type="radio"/>
Good	<input type="radio"/>
Fair	<input type="radio"/>
Bad	<input type="radio"/>
Very Bad	<input type="radio"/>

How would you describe your current financial situation?

Always stressful	<input type="radio"/>
Somewhat stressful	<input type="radio"/>
Sometimes stressful	<input type="radio"/>
Rarely stressful	<input type="radio"/>
Never stressful	<input type="radio"/>

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.

0 0.5 1 1.5 2 2.5 3 3.5 4 4.5 5 € 5.5 6 6.5 7 7.5 8 8.5 9 9.5 10
State your price



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	<input type="radio"/>
Slightly important	<input type="radio"/>
Moderately important	<input type="radio"/>
Very important	<input type="radio"/>
Extremely important	<input type="radio"/>

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	<input type="radio"/>
Slightly important	<input type="radio"/>
Moderately important	<input type="radio"/>
Very important	<input type="radio"/>
Extremely important	<input type="radio"/>

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

Professional support (i.e. visiting a general practitioner, praktijkondersteuner, psychologist, psychotherapist, or counselor)	<input type="checkbox"/>
Coaching services	<input type="checkbox"/>
Digital apps (e.g., meditation or self-care apps)	<input type="checkbox"/>
Peer-to-peer support	<input type="checkbox"/>
Support from family or friends	<input type="checkbox"/>
None	<input type="checkbox"/>

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

Very effective	<input type="radio"/>
Somewhat effective	<input type="radio"/>
Sometimes effective	<input type="radio"/>
Rarely effective	<input type="radio"/>
Never effective	<input type="radio"/>

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	<input type="radio"/>
Several days	<input type="radio"/>
More than half days	<input type="radio"/>
Nearly every day	<input type="radio"/>

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

Not at all	<input type="radio"/>
Several days	<input type="radio"/>
More than half days	<input type="radio"/>
Nearly every day	<input type="radio"/>

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

Not at all	<input type="radio"/>
Several days	<input type="radio"/>
More than half days	<input type="radio"/>
Nearly every day	<input type="radio"/>

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

Not at all	<input checked="" type="radio"/>
Several days	<input type="radio"/>
More than half days	<input type="radio"/>
Nearly every day	<input type="radio"/>

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.

M 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	<input type="radio"/>
Bol.com	<input type="radio"/>
I do not want to participate in the lottery	<input type="radio"/>

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)	<input type="radio"/>
Australia and Oceania	<input type="radio"/>
Europe (Northern Europe, Southern Europe, Eastern Europe, Western Europe)	<input type="radio"/>
Middle East/Africa (Middle East, Northern Africa, Southern Africa)	<input type="radio"/>
North America	<input type="radio"/>
South America, Central America, Caribbean	<input type="radio"/>

In what degree program are you currently enrolled?

Bachelor's	<input type="radio"/>
Pre-Master's	<input type="radio"/>
Master's (including MSc., MPhil., LL.M., Medical Training)	<input type="radio"/>

How would you describe your current financial situation?

Always stressful	<input type="radio"/>
Somewhat stressful	<input type="radio"/>
Sometimes stressful	<input type="radio"/>
Rarely stressful	<input type="radio"/>
Never stressful	<input type="radio"/>

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	<input type="radio"/>
Slightly effective	<input type="radio"/>
Moderately effective	<input type="radio"/>
Very effective	<input type="radio"/>
Extremely effective	<input type="radio"/>

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

Not effective at all	<input type="radio"/>
Slightly effective	<input type="radio"/>
Moderately effective	<input type="radio"/>
Very effective	<input type="radio"/>
Extremely effective	<input type="radio"/>

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

Not effective at all	<input type="radio"/>
Slightly effective	<input type="radio"/>
Moderately effective	<input type="radio"/>
Very effective	<input type="radio"/>
Extremely effective	<input type="radio"/>

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

Yes	<input type="radio"/>
No	<input type="radio"/>

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

General Practitioner	<input type="checkbox"/>
Praktijkondersteuner	<input type="checkbox"/>
Psychologist	<input type="checkbox"/>
Psychotherapist	<input type="checkbox"/>
Coach	<input type="checkbox"/>
Counselor	<input type="checkbox"/>
Mental health app/online platform	<input type="checkbox"/>
Other	<input type="checkbox"/>

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

Yes	<input type="radio"/>
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No	<input type="radio"/>
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From which source are you planning to receive mental health support? You can choose as many options as you want.

General Practitioner	<input type="checkbox"/>
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Praktijkondersteuner	<input type="checkbox"/>
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Psychologist	<input type="checkbox"/>
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Psychotherapist	<input type="checkbox"/>
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Coach	<input type="checkbox"/>
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Counselor	<input type="checkbox"/>
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Mental health app/online platform	<input type="checkbox"/>
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Other	<input type="checkbox"/>
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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	<input type="checkbox"/>
The distress that I am experiencing is temporary/not serious	<input type="checkbox"/>
I use app/online platform to receive support	<input type="checkbox"/>
The waiting time to access support is too long	<input type="checkbox"/>
I do not know how or where to seek support	<input type="checkbox"/>
Support is too expensive	<input type="checkbox"/>
I do not have time to seek support	<input type="checkbox"/>
Other	<input type="checkbox"/>

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

Not at all	<input type="radio"/>
Several days	<input type="radio"/>
More than half days	<input type="radio"/>
Nearly every day	<input type="radio"/>

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

Not at all	<input type="radio"/>
Several days	<input type="radio"/>
More than half days	<input type="radio"/>
Nearly every day	<input type="radio"/>

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

Not at all	<input type="radio"/>
Several days	<input type="radio"/>
More than half days	<input type="radio"/>
Nearly every day	<input type="radio"/>

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

Not at all	<input checked="" type="radio"/>
Several days	<input type="radio"/>
More than half days	<input type="radio"/>
Nearly every day	<input type="radio"/>

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

I have read the information above.