Development of the Mental Health of Teenagers and Young Adults after the COVID-19 Pandemic: a Longitudinal Study

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Management summary

The COVID-19 pandemic has affected the mental health of the Dutch population, especially among the youth. The Integrated Health Monitor COVID-19 showed an increase in the prevalence of psychological complaints among youth from 25% before the lockdown in December 2021 to 39% during this lockdown. When all COVID-19 restrictions were relaxed, the prevalence of psychological complaints dropped to an approximately steady 33%. These findings suggest the possible existence of a distinct subgroup among Dutch teenagers and young adults who have not yet experienced complete recovery from the psychological repercussions triggered by the preceding lockdown measures. Therefore, this study aimed to identify different classes of youth with similar mental health trajectories after the COVID-19 pandemic and to explore the correlates of trajectory class membership.

Data were obtained from five quarterly survey waves set out among youth (aged 12-25 years) between March 2022 and March 2023. Participants who completed the survey during at least three of the five survey waves were included in the analysis (n = 936). Mental health was assessed with the Mental Health Inventory 5 (MHI-5). To identify the different classes of mental health trajectories among teenagers and adolescents, latent class growth analysis (LCGA) and growth mixture modelling (GMM) were applied. Various fit statistics were used to determine the optimal number of classes. Multinomial logistic regression was applied to examine the correlates of class membership.

Four latent classes were identified that best describe the mental health trajectories among youth based on the MHI-5 scores: a class of participants with constant low MHI-5 scores (n = 29), a class of participants with deteriorating MHI-5 scores (n = 44), a class of participants with constant high MHI-5 scores (n = 408), and a class of participants with slightly recovering MHI-5 scores (n = 455). Compared to the class with constant high MHI-5 scores, the participants in the other classes were more likely to experience stress due to school and work, have less faith in the future, and feel irritable. Based on the estimated odds ratios from the multinomial regression, the most important correlate for class membership seems to be the faith one has in the future. A low educational level was the main risk factor for participants with deteriorating MHI-5 scores compared to recovering participants.

The mental health of the vast majority of Dutch youth appears to be unaffected or in recovery after the last COVID-19 lockdown. Nonetheless, there seems to be a small group with deteriorating mental health or chronic psychological complaints. The characteristics defined in this study could guide public health policymaking to improve mental health among youth. However, since the most important predictor for the trajectory seems to be the faith one has in the future, which is very intrinsic, it is difficult to translate this into policy. However, faith in the future might improve when future goals are established and ways to realise those goals are found.

Acknowledgements

Hereby, I present my master's thesis *'Development of the Mental Health of Teenagers and Young Adults after the COVID-19 Pandemic: a Longitudinal Study'*, on which I have worked since March 2023. This is the last hurdle I had to take before obtaining my master's degree in Industrial Engineering and Management. With this thesis, I completed my life as a student at the University of Twente, which lasted six years and a few months. I completed my bachelor's study in Technical Medicine during the first three years. For the last three years, I followed the master's study in Industrial Engineering and Management with the track in Healthcare Technology and Management.

Although this thesis concludes my life as a student, I could not have done this entirely on my own. And therefore, I would like to thank some people who have been involved.

First of all, I would like to thank everyone at the RIVM. I have always enjoyed being in Bilthoven on Mondays! Furthermore, I would like to thank Imme and Elske, in particular, who were my supervisors at the RIVM. They were really involved during the whole process and guided me towards this final product I am very proud of. Also, when I lost my motivation, it helped me a lot when they showed how interesting they found the research I was doing.

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Now, all that lasts me to say is: I wish you an enjoyable read!

Hans Hazelzet,
Enschede, December 2023

Contents

List of Acronyms

AIC	-	Akaike's information criterion
BIC	-	Bayesian information criterion
GMM	-	Growth mixture model
GOR	-	Health research in disasters
LCGA	-	Latent class growth analysis
MHI-5	-	Mental health inventory 5
RIVM	-	National Institute for Public Health and the Environment
SABIC	-	Sample-size adjusted Bayesian information criterion

Chapter 1

Introduction

At the end of February 2020, the first COVID-19 patient was diagnosed in the Netherlands. Since the number of COVID-19 infections increased rapidly, the government decided to take measures in the weeks after. On March 15 2020, the so-called intelligent lockdown was proclaimed in the Netherlands (Rijksoverheid, 2020). The intelligent lockdown consisted of several measures to control the spread of the virus by reducing the number of potential social contacts. However, it was not a complete lockdown. After the intelligent lockdown, two other lockdowns and social distancing measures followed. The last lockdown was the Omicron lockdown, which started in December 2021 (Rijksoverheid, 2021). The virus and the measures to control the virus resulted in all kinds of physical and mental health effects (Bosmans et al., 2022; Pfefferbaum & North, 2020).

1.1 Mental health during the COVID-19 pandemic in the Netherlands

Previous studies have examined the effect of the COVID-19 pandemic on the mental health in the Netherlands. Some of these studies aimed to give an overview of existing studies regarding the mental health and well-being of youth during the COVID-19 pandemic (Rijksinstituut voor Volksgezondheid en Milieu, 2022a; Sociaal en Cultureel Planbureau, 2021; Nederlandse Organisatie voor toegepast-natuurwetenschappelijk onderzoek, 2021; Nederlands Centrum Jeugdgezondheid, 2021; Nederlands Jeugdinstituut, 2021; Gezondheidsraad, 2022). In all those literature reviews, researchers conclude that the mental health of children, teenagers and young adults deteriorated during the COVID-19 pandemic and the corresponding lockdowns.

Furthermore, Statistics Netherlands (CBS) found that a larger part of the teenagers and young adults in the Netherlands experienced psychological complaints in 2021 than in 2019 and 2020 (Centraal Bureau voor de Statistiek, 2022). Although they do not directly relate this deterioration of the mental health to the COVID-19 pandemic, they acknowledge that the decline in mental health occurred concurrently with the implementation of various COVID-19 measures, such as school closures and lockdowns. In addition, GGD-GHOR (2023) concludes that more than half of the young adults (16-25 years old) were experiencing mental health problems in 2022. Although it cannot be inferred with certainty that these problems are a result of the COVID-19 pandemic, a part of these problems is likely a result of the COVID-19 period.

However, it also looks like the mental well-being deteriorated during lockdowns but partly recovered when measurements became less strict (Rijksinstituut voor Volksgezondheid en Milieu, 2022a). Furthermore, the Nederlands Centrum Jeugdgezondheid (2021) states that a large group of young people is quite resilient, but there needs to be a focus on helping the most vulnerable groups within the population of young people. However, more research is required to identify those vulnerable groups.

In addition, some longitudinal studies have been performed in the general Dutch population (Van der Velden et al., 2021; Van der Velden, Marchand, et al., 2022) and young adults of the general population (Van der Velden, van Bakel, & Das, 2022). Furthermore, Luijten et al. (2021) performed a cross-sectional study based on two representative samples of Dutch children and teenagers before the COVID-19 outbreak (2018) and during the first lockdown (April 2020).

Findings of Van der Velden et al. (2021) suggested that, based on the MHI-5 scores, the COVID-19 outbreak did not negatively impact the prevalence of depression and anxiety symptoms, but emotional loneliness increased between October 2019 and June 2020. Van der Velden, Marchand, et al. (2022) drew a similar conclusion based on a longitudinal study performed on the general population, stating that, in general, the Dutch adult population has been relatively resilient in the first nine months after the COVID-19 outbreak.

However, this holds for the total adult Dutch population. Van der Velden, van Bakel, & Das (2022) showed that in Dutch young adults (16-20 year-olds), the prevalence and incidence of moderate depression and anxiety symptoms increased and that the utilisation of mental health services was higher in 2020 than in 2012 and 2016. Their findings suggest that the COVID-19 pandemic had a limited but negative effect on the mental health of Dutch young adults.

Luijten et al. (2021) compared two representative samples of Dutch children and teenagers (8-18 years) before (2018) and during (2020) the first COVID-19 lockdown based on the Patient-Reported Outcomes Measurements Information System (PROMIS) domains of physical, social and mental health. Participants reported worse health in all domains during the lockdown. Also, most participants experienced a negative impact of the COVID-19 regulations on their daily lives.

The mentioned studies indicate that the mental health of Dutch teenagers and young adults deteriorated during the COVID-19 pandemic. To limit the mental health consequences of the COVID-19 pandemic, information that can guide policymaking is needed. Therefore, the Network for Health Research in Disasters (GOR Network) aims to monitor the physical and mental health of the population of the Netherlands.

1.2 GOR Network

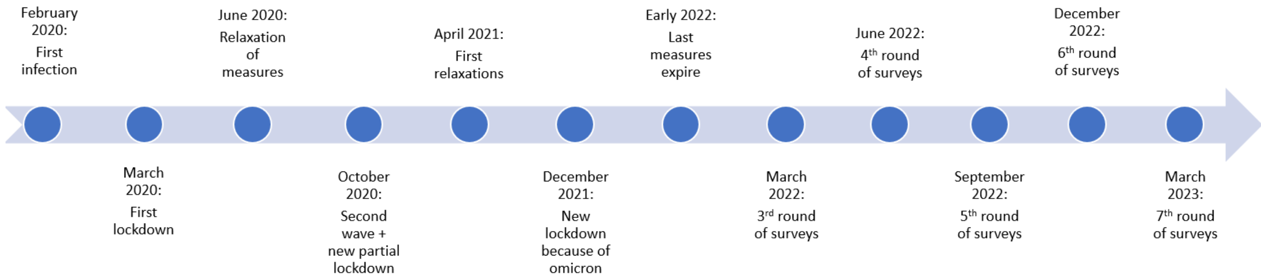
The GOR Network consists of the following organisations: the National Institute for Public Health and the Environment (RIVM), GGD GHOR Netherlands (representing the municipal health services), NIVEL Netherlands Institute for Health Services Research, and ARQ National Psychotrauma Centre. The GOR Network assesses the impact of the COVID-19 crisis on the physical and mental health in the Netherlands in the Integrated Health Monitor COVID-19 (Rijksinstituut voor Volksgezondheid en Milieu, 2022b; Bosmans et al., 2022). By conducting the Integrated Health Monitor COVID-19, the GOR Network aims to monitor the effects of the COVID-19 pandemic on the physical and mental health of the Dutch population so that policymakers can establish care and support corresponding with the demand.

1.2.1 Integrated Health Monitor COVID-19

In the Integrated Health Monitor COVID-19, two types of monitoring are used: short-cycle and long-cycle monitoring (Bosmans et al., 2022). The short-cycle monitoring aims to provide insight into the extent to which physical and mental health problems occur within the Dutch population. The results from the short-cycle monitoring ensure that information regarding physical and mental health can be provided to policymakers. This way, policy can be quickly adjusted to the population's needs if necessary. The data used for the short-cycle monitoring emanates from healthcare registration data from general practitioners in the Netherlands and quarterly surveys. The goal of the long-cycle monitoring is to provide insight into the course of the physical and mental health problems and the healthcare utilisation over time. In addition, a yearly systematic literature review of ongoing and completed studies in the Netherlands and international research findings regarding the health consequences of the COVID-19 pandemic is performed. The results from the systematic literature review can be used to better interpret the results of short- and long-cycle monitoring.

1.2.2 Short-cycle quarterly surveys

As part of the Integrated Health Monitor COVID-19, the RIVM sends out a survey every three months to monitor physical and mental health. I&O Research distributes this survey on behalf of the RIVM. I&O Research is a research agency in the Netherlands that helps the government and other public organisations conduct their research. I&O Research contacts its panel members to ask if they want to participate in the study by filling out the survey. Panel members above 16 can decide if they would like to participate. In addition, I&O Research also contacts panel members with children between 12 and 16 and asks if they would like to join with their children. This is done because, for this age category, consent of both the children and parents is needed to fill in the survey. So far, there have been seven survey waves: the first in September 2021 and the last in March 2023. In the first two waves, Kantar Research distributed the surveys. The GOR Network chose I&O Research to distribute the surveys from the third wave. Therefore, a longitudinal dataset is available from the third survey wave onwards. To get an overview of when the data collection occurred relative to the most important events during the COVID-19 pandemic, Figure 1.1 shows the events and the data collection from March 2022 to March 2023. The first two survey waves (September and December 2021) were not included in this timeline since another organisation distributed the surveys in those waves.



Note: The dates of the important COVID-19 events are retrieved from `https://www.rijksoverheid.nl/onderwerpen/coronavirus-tijdlijn`.

Figure 1.1: Timeline of important COVID-19 events and data collection rounds

1.3 Research motivation

Figure 1.2 shows the results of the short-cycle monitoring regarding the mental health of teenagers and young adults (Rijksinstituut voor Volksgezondheid en Milieu, 2023b). By conducting the short-cycle monitoring, the GOR Network found that the percentage of teenagers and young adults (aged between 12 and 25 years old) that experienced mental health issues, measured with the Mental Health Inventory 5 (MHI-5), increased during the lockdown at the end of 2021 (the Omicron lockdown), up to around 40%, and decreased again after this lockdown. However, this decreasing trend did not continue but appeared to stagnate in December 2022, at a higher level (around 33%) than before the lockdown at the end of 2021 (25%). The prevalence of psychological complaints is higher among teenagers and young adults than among adults. For adults, the prevalence of psychological complaints since March 2022 has stabilised around 20% (Rijksinstituut voor Volksgezondheid en Milieu, 2023c).

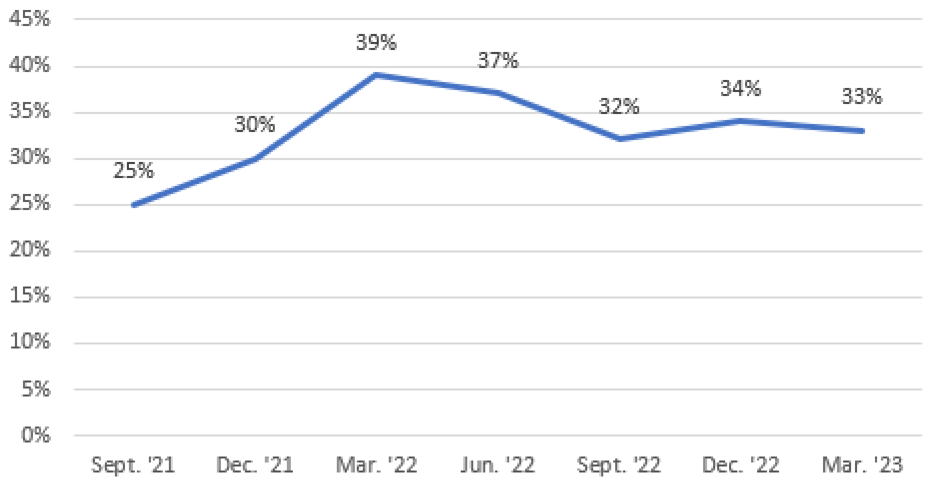


Figure 1.2: Trend line of the percentage of teenagers and young adults experiencing mental health issues

The percentages shown in Figure 1.2 are obtained by a cross-sectional analysis of representative samples, which means that the data is analysed at a specific point in time for a sample representative of the Dutch population of teenagers and young adults in terms of age, sex and education level. The percentages suggest that some of the teenagers and young adults have not recovered from the psychological complaints they experienced during the last lockdown.

In conclusion, previous research has pointed out that young people appeared to experience a more significant impact of the COVID-19 pandemic on their mental health and that additional research is needed to identify vulnerable groups within this population. Furthermore, it looks like the recovery of the mental health of teenagers and young adults stagnated in December 2022, with a higher proportion of teenagers and young adults experiencing poor mental health than before the last lockdown. These findings suggest the existence of a distinct subgroup among teenagers and young adults who have not yet experienced complete recovery from the psychological repercussions triggered by the preceding lockdown measures. Therefore, it can be expected that distinct mental health trajectories exist.

1.4 Previous studies on mental health trajectories during the COVID-19 pandemic

The existence of distinct mental health trajectories during the COVID-19 pandemic has been explored in previous studies worldwide.

Kimhi et al. (2021) examined the trajectories of anxiety and depression symptoms and correlates of those trajectories during COVID-19 in Israel for the Israeli population older than 18. For their analysis, they used latent growth mixture modelling. For both anxiety and depression symptoms, they identified four trajectories that best described the development of the symptoms: a group with consistently low levels of symptoms, a group with consistently high levels of symptoms, a group with emerging symptoms and a group with decreasing symptoms. Furthermore, they tested whether gender, age, family income, education, number of children, family status and political attitude were correlates of trajectory membership and found that participants with consistently low levels of symptoms experienced less financial difficulties due to the COVID-19 pandemic, had a greater income and were more likely to be religious.

McPherson et al. (2021) performed a similar study in which they aimed to identify distinct trajectories of anxiety, depression and COVID-19-related traumatic stress in the first twelve-week period after the first national lockdown in the United Kingdom. In addition, they explored risk and protective factors associated with the identified mental health trajectories. For all three mental health outcomes (anxiety, depression and COVID-19-related traumatic stress) they found similar trajectories as Kimhi et al. (2021) found in their research, which are classes of low and stable symptomatology, high and stable symptomatology, decreasing symptomatology and increasing symptomatology. They found that participants with high and stable symptomatology and increasing symptomatology were more likely to experience COVID-19-related traumatic stress. Also, participants with higher meaning-in-life scores were less likely to be in the high and stable symptomatology class.

Another study, performed by Li et al. (2023), aimed to identify distinct depression trajectories among adolescents during the COVID-19 pandemic and the impact of parental style in China. Therefore, they used group-based trajectory modelling and multivariate logistic regression. They identified the same four distinct depression trajectories.

Although different studies have established the existence of distinct mental health trajectories, no study to identify distinct mental health trajectories among Dutch teenagers and young adults has been found.

1.5 Research questions

Based on the described previous studies, the following research questions were identified:

- What different groups among teenagers and young adults in the Netherlands can be identified based on distinct mental health trajectories between March 2022 and March 2023?
- What are the correlates of the distinct mental health trajectories?

The research objective is to provide policymakers insight into the development of mental health among young people so that they can take targeted interventions to enhance their mental health.

1.6 Thesis outline

The remainder of this thesis is structured as follows. Chapter 2 describes the methods for answering the research questions. In Chapter 3, the results of the performed analyses are presented. These results are discussed in Chapter 4. Lastly, Chapter 5 finalises this thesis by drawing the conclusions.

Chapter 2

Methods

This chapter describes the methods used to answer the research questions. Section 2.1 describes the research population. Next, Section 2.2 provides more information regarding the quarterly surveys. The last section, Section 2.3, sets out the statistical analyses used to analyse the data.

2.1 Research population

In Section 1.2, it is described that, as of the third survey wave (March 2022), the last five surveys were distributed by the same organisation (I&O Research). Therefore, participants who completed the survey in multiple survey waves since March 2022 can be merged into a longitudinal dataset. Thus, the data used in the analyses were collected after the last lockdown expired. To be more specific, the last social distancing measures were relaxed on the 25th of February 2022, while the data from the third survey wave was collected between the 1st and 17th of March 2022.

The complete longitudinal dataset consisted of 2426 participants who completed the surveys twice or more since March 2022. All the participants who completed the survey at least three out of five timepoints were included in the analyses. This choice was made because proper longitudinal data analysis requires at least three measurements, and four or five repeated measurements are preferred (Nguena Nguefack et al., 2020; Hetherington et al., 2020). In total, 936 individuals aged between 12 and 25 who completed the survey at least three times were included in the analysis. This means that 1490 participants were excluded because they completed the survey only two times. Table 2.1 shows the number of participants that completed the survey per round. Additionally, Table 2.2 shows that the vast majority of the participants (78%) completed the survey at three different timepoints, while 205 participants (22%) completed the survey at four different timepoints. Only four participants (0.4%) completed the survey at all the timepoints.

Table 2.1: Number of responses per survey wave

Survey wave	**Number of responses,** N = 936[1]
3 (Mar. '22)	386 (41%)
4 (Jun. '22)	510 (54%)
5 (Sept. '22)	893 (95%)
6 (Dec. '22)	727 (78%)
7 (Mar. '23)	505 (54%)

[1] n (%)

Table 2.2: Number of waves that participants completed the survey

Number of surveys completed	**Number of participants,** N = 936[1]
3	727 (78%)
4	205 (22%)
5	4 (0.4%)

[1] n (%)

2.2 Surveys

In this section, the quarterly surveys are further discussed. Section 2.2.1 explains the topics for which questions are posed in the surveys. Section 2.2.2 further explains the scale used to quantify mental health.

2.2.1 Questions in survey

A survey is distributed every three months to monitor the mental and physical health of Dutch teenagers and young adults (aged between 12-25 years). In this survey, questions regarding the following subjects are asked:

- Education and work
  It is asked if one is currently following education or if one is working. If one is not following education, one is asked what the highest degree is one earned.
- Living situation
  It is asked how one lives and with whom.
- General health
  It is asked if one can indicate how their health is in general. There are five answer options: very good, good, not good or bad, bad, and very bad.
- Faith in the future
  It is asked if one has faith in the future. This is scaled from 1 to 10, where 1 equals no faith, and 10 equals a lot of faith.
- Mental health
  More information regarding the questions on this subject can be found in Section 2.2.2.
- Experienced loneliness
  To measure experienced loneliness, the 6-item De Jong Gierveld Loneliness Scale (DJGLS) is used (De Jong Gierveld & van Tilburg, 2006). This is a reliable and valid measurement to determine overall, emotional and social loneliness.
- Experienced stress
  It is asked if one has experienced stress regarding certain aspects in the last four weeks. These aspects are school and work, the situation at home, personal problems, what others think of them, everything one has to do, corona, and miscellaneous.
- Suicidal thoughts
  It is asked if one seriously considered committing suicide in the last three months.
- Somatically unexplained physical complaints
  It is asked if one experienced somatically unexplained physical complaints in the last four weeks.
- Social support and activities
  It is asked what kind of (social) activities one undertook the past week.
- The need for extra support
  It was asked if one needed extra support during the COVID-19 pandemic regarding certain aspects. These aspects are that they needed support because they were not feeling well, had physical complaints and pain, had to take care of sick loved ones, had problems at home, needed guidance with schoolwork, needed financial help, had trouble combining school and work with their private life and miscellaneous. If one did not need extra help or support regarding one of those aspects, there is also an option to answer 'I did not need extra help or support'.
- COVID-19-related experience
  It is asked what kind of COVID-19-related events one experienced. It is asked if one experienced a COVID-19 infection, had been in the hospital due to a COVID-19 infection, had a loved one who was in the hospital due to a COVID-19 infection, had a loved one who died due to a COVID-19 infection, was afraid a loved one would get COVID-19, has seen many people who were seriously ill due or died due to a COVID-19 infection during work, was unable to provide support to a loved one due to the measures, was unable to say goodbye to a loved one that passed away during the COVID-19 pandemic due to the measures, faced threats or violence due to discussion about the COVID-19 measures or missed an important event due to a COVID-19 infection or the COVID-19 measures. One can choose multiple answers. If one did not experience one of the COVID-19-related events, one can choose 'None of the above'. If one experienced a COVID-19-related event, it is also asked if one still suffers from this event.
- Participated in (social) activities
- Experienced trauma
  For experienced trauma, the Post-traumatic Stress Disorder Checklist for DSM-5 (PCL-5) scale is used. It is a 20-item questionnaire that reflects the diagnostic criteria for post-traumatic stress disorder (PTSD) (Weathers et al., 2013). An evaluation of the PCL-5 indicated that the questionnaire is a sound

measure for the DSM-5 symptoms criteria of PTSD (Blevins et al., 2015). A participant only had to fill in the PCL-5 if one still suffers from a COVID-19-related experience.

Specific demographics of the participants, such as age, gender and in which region in the Netherlands one lives, were not asked in the survey but are also included in the dataset since the panel agency, I&O Research, collects those data regularly.

Throughout the study period, the questions sometimes differed slightly in their formulation. For example, first, it was asked if one needed extra support during the COVID-19 pandemic. Later, the formulation was changed to: *Did you need help or support in the past three months?*. In addition, some questions have not been asked in every round but have been added to get more information regarding the physical and mental health of the Dutch population. Also, some questions have been removed from the survey over time because they were irrelevant.

2.2.2 Mental Health Inventory 5

The Mental Health Inventory 5 (MHI-5) was used to measure the participants' mental health. The MHI-5 is a 5-item Short Form 36-item Health Survey (SF-36) subscale. Table 2.3 gives the questions for the MHI-5. Berwick et al. (1991) showed that the MHI-5 questionnaire is a good measure of mental health problems such as anxiety disorders and major depression, with an area under the curve (AUC) of 0.739 and 0.892, respectively. Similar results were found by Rumpf et al. (2001). They found an AUC of 0.88 for mood disorders, such as major depression and bipolar disorders, and an AUC of 0.71 for anxiety disorders. These findings suggest that the MHI-5 can distinguish individuals with anxiety disorders or depression from those without these conditions quite well.

Table 2.3: Questions MHI-5

How much of the time during the last four weeks ...
... have you been a very nervous person? (1)
... have you felt calm and peaceful? (2)
... have you felt happy? (3)
... have you felt so down nothing could cheer you up? (4)
... have you felt downhearted and blue? (5)

Table 2.4: Response options and score per option per question of the MHI-5

Response option	**Score Q1, 4 &5**	**Score Q2 & 3**
All the time	1	6
Most of the time	2	5
A good bit of the time	3	4
Some of the time	4	3
A little of the time	5	2
None of the time	6	1

Table 2.4 shows the answer options and the scores correlated with an answer option per question. Based on the answers, a score between 5 and 30 can be determined (Theunissen et al., 2011). This can be linearly transformed into a score between 0 and 100 with the following formula:

$$Score = 100 * \frac{(\sum \text{Score per question}) - 5}{25}$$

This score reflects the mental health status of a participant. Perenboom et al. (2000) determined a cut-off to divide mentally healthy and unhealthy people. Based on their results, they advised a cut-off score of 60, which indicates that people with an MHI-5 score between 61-100 have good mental health, while people with a score of 60 and lower are mentally unhealthy. This cut-off point corresponds with a cut-off point found by Kelly et al. (2008). Rumpf et al. (2001) also suggest a cut-off point of 60 for the MHI-5, but only for mood disorders. In correspondence with these studies, a cut-off score of 60 was used in this research.

2.3 Statistical analyses

The statistical analyses performed to answer the research questions are described in this section. Section 2.3.1 explains the analyses to identify the different groups in the research population. Section 2.3.2 describes the analyses to determine the correlates of class membership.

2.3.1 Trajectory modelling techniques

To explore the existence of distinct mental health trajectories among teenagers and adolescents after March 2022, trajectory modelling techniques were applied to the repeatedly measured MHI-5 score. For longitudinal data, a trajectory describes the evolution of some repeated measure over time (Elmer et al., 2018). Nguena Nguefack et al. (2020) describe different kinds of trajectory modelling techniques. Trajectory modelling techniques can distinguish data-driven classes within a population of individuals who show similar trajectories. The trajectory modelling techniques reviewed in their paper are the latent class modelling approaches growth mixture modelling (GMM), latent class growth analysis (LCGA), latent transition analysis (LTA) and latent class analysis (LCA). In latent class modelling approaches individuals with relatively similar observed outcomes over time are assigned to the same trajectory subgroup. Based on the observed outcome over time, posterior probabilities of belonging to each subgroup are estimated, and an individual is placed in the class for which they have the highest probability (Reinecke & Seddig, 2011). The first three mentioned methods (GMM, LCGA and LTA) were developed to handle longitudinal data, while the latter (LCA) was developed to analyse cross-sectional data. Since longitudinal data was used in this study, this section only elaborates on the methods developed to handle longitudinal data. For longitudinal data, latent class modelling approaches are used to identify subgroups within a population that have a similar outcome pattern over the study period.

In addition, trajectory modelling techniques to examine subgroups within a population can roughly be divided into three categories: nonparametric, semi-parametric, and parametric (Nguena Nguefack et al., 2020). The difference is that no assumptions about how the data are distributed are made for nonparametric models. At the same time, semi-parametric and parametric approaches assume a finite mixture of distributions in the data. Therefore, classifying individuals into a certain subgroup is based on a conditional probability of group membership.

Growth mixture modelling

GMM is a parametric technique primarily developed for modelling longitudinal continuous data (Nguena Nguefack et al., 2020). Generalisations of the model have been developed to handle other types of data, such as count and categorical data. The GMM is a finite mixture model, which means that it assumes that any given population consists of unobserved subgroups consisting of individuals with comparable trajectories. For each identified subgroup, an average growth trajectory is estimated. For this growth trajectory, an intercept and a slope are estimated. The intercept of a class is the estimated value of the outcome measure at the first timepoint. The slope of a subgroup represents the change (increase or decrease) of the outcome measure within that particular subgroup over time. The intercept and the slope are the fixed effects for a subgroup. They are often called the growth parameters. In addition, GMM allows for differences between individuals in the same class by introducing random effects in the model. These random effects represent the difference between individuals' growth trajectories and the fixed effects of the average growth trajectory of the subgroup in which the individual is classified. Based on the observed data, the posterior group probability for each subgroup is calculated for each individual and individuals are assigned to the subgroup for which they have the highest probability. Once class membership (based on the posterior probability) is established, the assigned class of individuals can be used as a dependent or independent variable to explore correlates of trajectories (Nguena Nguefack et al., 2020).

Latent class growth analysis

LCGA is also a finite mixture model, just like GMM. However, unlike GMM, LCGA assumes that there is no difference between individuals classified into the same subgroup of the population. For each estimated subgroup, the fixed effects (intercept and slope) are estimated, but not the random effects. Therefore, LCGA can be considered a simplified version of GMM (Nguena Nguefack et al., 2020). In LCGA, the classification of individuals into a subgroup happens in the same manner as in GMM, based on the highest posterior group probability. Furthermore, LCGA can handle the same types of data as GMM: continuous, count, and categorical data. Like with GMM, the trajectory class can be used as the dependent or an independent variable in further analysis.

Latent transition analysis

With LTA the changes in multiple categorical variables over time can be analysed. From a set of categorical variables, a latent variable at each timepoint is defined. In this model, individuals can change their class membership over time. The goal of LTA is to study the probability of transitioning from one class at one timepoint to another at the next timepoint (Nguena Nguefack et al., 2020). A matrix of transition probabilities quantifies the change between consecutive timepoints. The following parameters are estimated in LTA: class membership probability at the first measurement, the proportion of the total population in each class at each timepoint, the transition probabilities over time and the posterior probability of being in a certain class at a given timepoint (similar to the posterior group probability in GMM and LCGA). LTA shows a resemblance to Markov modelling. In fact, LTA is a latent Markov model, in which the states are unobserved (latent), but estimated on a set of observed categorical variables (Chung et al., 2008).

In this study, we aimed to identify different classes concerning mental health trajectories and not the transitions between the latent classes. Therefore, GMM and LCGA were considered and not LTA.

Statistical background of the LCMM package

According to Nguena Nguefack et al. (2020), the latent class mixed models (LCMM) package in R can be used to estimate both GMMs and LCGAs. The LCMM package is based on linear mixed models theory (Proust-Lima et al., 2017). A linear mixed model is defined as:

$$Y_{ij} = X_{Li}(t_{ij})^T \beta + Z_{Li}(t_{ij})^T u_i + \epsilon_{ij} \tag{2.1}$$

Where:

- Y_{ij} is the outcome of subject i at occasion j measured at t_{ij}
- $X_{Li}(t_{ij})$ and $Z_{Li}(t_{ij})$ are vectors of covariates at t_{ij}
- β is the vector of fixed effects
- u_i is the vector of random effects
- ϵ_{ij} is the measurement error

Because the time of measurement t_{ij} is seen separately from occasion j it is possible that the total number of measurements can vary between the subjects. This makes it possible to include individuals in the study with intermittent missing data or who have dropped out (Proust-Lima et al., 2017).

In a linear mixed model, it is assumed that a population is homogeneous. However, this is not always the case. Therefore, introducing latent classes can extend Equation 2.1. The linear mixed model for latent class g becomes:

$$Y_{ij}|_{c_i=g} = X_{L1i}(t_{ij})^T \beta + X_{L2i}(t_{ij})^T v_g + Z_{Li}(t_{ij})^T u_{ig} + \epsilon_{ij} \tag{2.2}$$

The vector $X_{Li}(t_{ij})$ from Equation 2.1 is now split into $X_{L1i}(t_{ij})$ associated with the common fixed effects over classes β and $X_{L2i}(t_{ij})$ associated with the class-specific fixed effect v_g. By this extension, different subgroups in a heterogeneous population can be identified (Proust-Lima et al., 2017).

In the LCMM package, the posterior probabilities used for the classification of individuals into a latent class are computed with Bayes' theorem (Proust-Lima et al., 2017). This means that the probability of belonging to a certain class is calculated given the information that is already collected. This means that the posterior probabilities are based on the observed outcomes and the estimated parameters in the model (e.g., the intercept and the slope of the different subgroups). Therefore, class membership can be determined based on the posterior probability because a higher posterior probability indicates that an individual is more likely to belong to a certain class given the observed outcomes and the estimated parameters.

Furthermore, in the LCMM package, the extended mixed models are estimated within the maximum likelihood framework Proust-Lima et al. (2017). In the maximum likelihood framework, the set of parameters is identified that maximises the likelihood of a model, given the observed data. Therefore, the most likely model given the observed data is identified.

Fitted models

Six models with different restrictions were estimated with the *hlme()*-function from the LCMM package (version 2.0.2) in R (version 4.3.0). The dependent variable for the analysis was the MHI-5 score, while the independent variable was the time of the survey waves in months.

Table 2.5 summarises the six different models. First, a linear LCGA with a fixed intercept at the first measurement and a fixed slope over time was estimated. Second, the LCGA was extended by adding a quadratic effect to the model. This allows the identification of non-linear trajectories over time. For example, when this quadratic term is added, a class can be estimated with participants whose MHI-5 score first decreases and then increases again. Third, a growth mixture model (GMM) with a random intercept but a fixed slope was estimated. With a random intercept, the MHI-5 score of the participants can vary within a class at the first available survey wave, but the change in the MHI-5 score over time is fixed for the participants within that class. The fourth model was estimated by extending the third model with a fixed quadratic effect. Fifth, a GMM with a random intercept and a random slope was estimated. The last estimated model is GMM with a random intercept, a random slope and a random quadratic effect. The quadratic effects were added to test if a non-linear model fits the data better than a linear model.

Table 2.5: Summary of fitted models

Kind of model	Random intercept	Random slope	Quadratic effect
LCGA	No	No	No
LCGA	No	No	Yes
GMM	Yes	No	No
GMM	Yes	No	Yes
GMM	Yes	Yes	No
GMM	Yes	Yes	Yes

For all these models, first, a growth model for the entire population was estimated. This means that no subgroups are estimated. An extra class was iteratively added to the models until the optimal number of classes was identified. To identify the model and the number of classes that best fit the data, the Bayesian information criterion (BIC), the sample-size adjusted BIC (SABIC), Akaike's information criterion (AIC) and the entropy were used (Tofighi & Enders, 2008; Ram & Grimm, 2009; Nguena Nguefack et al., 2020). These fit statistics are calculated in the LCMM package in the following ways:

$$BIC = -2LL + p \cdot ln(N) \tag{2.3}$$

$$SABIC = -2LL + p \cdot ln\left(\frac{N+2}{24}\right) \tag{2.4}$$

$$AIC = -2LL + 2p \tag{2.5}$$

$$Entropy = 1 + \frac{\sum_{i=1}^{N}\sum_{g=1}^{G}\pi_{ig} \cdot ln(\pi_{ig})}{N \cdot ln(G)} \quad \text{where } \sum_{g=1}^{G}\pi_{ig} = 1 \text{ for every } i \text{ in } i = 1, ..., N \tag{2.6}$$

In Equations 2.3, 2.4, and 2.5, LL is the log-likelihood of a model, p is the number of parameters estimated in the model, and N is the sample size. In Equation 2.6 π_{ig} is the posterior probability of participant i being classified in class g, N is the sample size, and G is the number of classes.

The BIC, SABIC and AIC are information-based indices. Information-based indices generally favour models with a high log-likelihood and fewer parameters (Tofighi & Enders, 2008). However, the indices differ from each other in how they penalise the complexity of the model, as can be seen in equations 2.3, 2.4 and 2.5. All information-based indices are scaled such that a lower value of the fit statistic implies a better fit of the model to the data. The values of the information-based indices can only be compared to each other. A single value of the indices does not convey the goodness of fit.

The entropy is a statistic that reflects the confidence with which the model classifies individuals as belonging to a class (Ram & Grimm, 2009). As implemented in the LCMM package, the entropy takes a value between

0 and 1. An entropy closer to 1 means that identified classes are better separated, which indicates a better model fit (Nguena Nguefack et al., 2020). Ram & Grimm (2009) state that models with a high value of the entropy (> 0.80) can adequately separate between the estimated latent classes. However, clear cut-off criteria for the entropy do not exist (Nguena Nguefack et al., 2020). Furthermore, Ram & Grimm (2009) suggest that models with a higher entropy should be favoured when selecting the best model if other fit indices are relatively similar among models.

Besides statistical fit, the model's interpretability was considered when choosing the optimal number of classes. A model with more classes is often more complex to interpret than one with fewer classes. In addition, a model with fixed effects is easier to interpret but often shows a suboptimal fit to the data. Conversely, a in which random effects are included is much more flexible and offers a better statistical fit to real-life data but is often more complex to interpret and fit because more parameters have to be estimated (Wardenaar, 2020; Nguena Nguefack et al., 2020). Furthermore, the class size was considered. A rule of thumb was applied that an additional class must include at least 25 observations (numerically), or 1% of the observations (proportionally) (Berlin et al., 2014a,b).

To select the optimal number of classes, firstly, the number of observations in the smallest class was considered. When classes become too small, more classes have to be estimated, which will result in a model that is more complex to interpret. Therefore, the class size was considered for the model's interpretability. Secondly, the information-based indices were consulted. If all the information-based indices were the lowest for the same model, this model was selected as the best model. Lastly, if the information indices did not unequivocally appoint the best model, the model with the highest entropy was chosen among models with similar values for the information-based indices.

LCGA and GMM were estimated with the full information maximum likelihood (FIML) procedure (Wardenaar, 2020). Through this mechanism, the LCMM package inherently handles missing data on the outcome measure. This is important because, as mentioned in Section 2.1, many of the included participants from the longitudinal dataset did not participate in all the survey waves. When the model is estimated through FIML, missing values on the outcome measure do not have to be replaced or imputed, but the model parameters are estimated based on all the available data (Iris Eekhout, 2023).

When a model with more than one class is estimated, the estimation of the model might converge to a local instead of a global solution (Hipp & Bauer, 2006). The *gridsearch()*-function was used to prevent obtaining a local solution. This function allows one to run the estimation function for a maximum of m iterations with B sets of initial values drawn from an asymptotic distribution of the parameters from the model with one class (Proust-Lima et al., 2017). After m iterations, the parameter values corresponding to the most likely model are used as initial values in the final estimation. In this research, B was set to 30 and m was set to 15.

2.3.2 Identifying the correlates of class membership

Multinomial logistic regression was used to determine the correlates of class membership. Multinomial logistic regression is an extension of binary logistic regression in which the outcome variable can have more than two levels (James et al., 2021). For the estimation, the *multinom()*-function from the NNET package (version 7.3-18) in R (version 4.3.0) was used. For the analysis, the first available observation for each variable of interest of each participant was included.

Variable selection

For the multinomial regression, the following variables were considered a-priori:

1. A categorical variable that reflects the age of the participants (12-17 years old or 18-25 years old);
2. A variable that reflects the gender of the participants;
3. A variable that reflects the current education level (if one is following education) or the highest degree one earned (if one is not following education);
4. A categorical variable that indicates the first survey wave (3, 4 or 5) in which one completed the survey;
5. Variables that reflect if one experienced stress due to school and work, personal problems, everything one has to do, the situation at home, and COVID-19;
6. A variable that reflects if one still suffers from a COVID-19-related experience.

The variables that reflect if one experienced stress due to one of the mentioned aspects were recoded into binary variables. In the survey, it is asked if one experienced stress due to these aspects in the last four weeks and a participant has five response options: never, rarely, sometimes, often, or very often. Based on these response options, two categories are created, namely 'Yes, I experienced stress' and 'No, I did not experience stress'. One is classified in the first category if the participant has answered often or very often. In the latter category, everyone has answered never, rarely, or sometimes. The variable that reflects whether one still suffers from a COVID-19-related experience is also a binary variable. One category consists of all the participants who do not suffer from or did not experience a COVID-19-related event and the other of all the participants who answered that they still suffer from a COVID-19-related event.

The first three variables were included to investigate the relationship between demographic characteristics (age, gender, and education level) and class membership. The fourth variable was included as a control variable to check whether it matters that not every participant completed their first questionnaire in the same survey wave. The variables that reflect if one experienced stress were included because experienced stress is a significant correlate for the mental health status in the cross-sectional analysis performed by the GOR Network. Lastly, the variable that reflects whether one suffers from a COVID-19-related experience was included to link this study to the COVID-19 pandemic.

To check if any other potentially relevant variables that could explain the class membership were missed, variable importance plots (VIPs) were made using random forest regression. We chose this method to identify important variables to keep consistency with previously performed cross-sectional analyses of the surveys (Rijksinstituut voor Volksgezondheid en Milieu, 2023a). In VIPs, the contribution a feature has to a model's prediction is quantified (Greenwell & Boehmke, 2020). The mean decrease accuracy (MDA) was computed to determine a variable's importance. The computed variable importance plots are given in Appendix A.

Based on those VIPs, five more variables were included for the multinomial regression:

1. A categorical variable that reflects whether one has faith in the future or not;
2. Variables that reflect if one experienced one of the following somatically unexplained physical complaints: feeling irritable, palpitations, sleep problems, feeling tired.

In the end, a total of 15 variables were considered. How the questions that were used to create the variables have been posed in the survey can be found in Appendix B.1. The questions used to make the variables were the same throughout all the survey waves included in this research. The variables that indicate the age, gender, educational level and the first survey wave in which one completed the survey are not asked out in the questionnaire and are not mentioned in this Appendix. Furthermore, Appendix B.2 elaborates on the considered variables.

Model-building process

First, a univariable multinomial analysis was performed for each considered independent variable. All of the independent variables were also included in a multivariable model. Each estimated regression coefficient in the multivariable model was compared to the regression coefficient of the univariable model of the corresponding independent variable. This was done to check the stability of the regression models. If one of the regression coefficients would change the direction of its effect on the dependent variable, this could indicate an unstable model. Therefore, if this happens for a variable, that variable has to be excluded from the multivariable model. The estimated regression coefficients and standard errors of the multivariable regression were used to calculate the odds ratios and the corresponding 95% confidence intervals. These 95% confidence intervals were used to determine the significance of correlates. There was no correction for multiple testing.

A common problem in multivariable regression models is multicollinearity. Multicollinearity exists when multiple independent variables in a regression model are correlated. To test for potential multicollinearity of the independent variables, the generalised variance inflation factor (GVIF) for each independent variable was calculated because terms are included with more than one degree of freedom (e.g., variables with more than two levels) (Fox & Monette, 1992). The GVIF reflects how much correlations with other independent variables in the model influence the variance of the regression coefficient of an independent variable. If a regressor has one degree of freedom, the GVIF reduces to the usual VIF (Fox & Weisberg, 2011). Furthermore, if there are p regressors in a term, the GVIF$^{1/2p}$ was computed. The GVIF$^{1/2p}$ is a one-dimensional expression of the decrease in estimation precision due to collinearity. It is analogous to taking the square root of the usual VIF (Fox & Weisberg, 2011). Therefore, the GVIF and GVIF$^{1/2p}$ can be interpreted as the normal VIF value. A VIF value > 10 suggests a high correlation between an independent variable and other independent variables (Steyerberg, 2019). This means that the GVIF$^{1/2p}$ cannot be higher than $\sqrt{10} \approx 3.16$. If GVIF and GVIF$^{1/2p}$ values were larger than 10 or $\sqrt{10}$, the variable with the largest values was removed from the multivariable regression model. The values of the GVIF and the GVIF$^{1/2p}$ for the multivariable regression models for the first observation can be found in Appendix C.1. Based on these values, no variables were excluded from the multivariable regression model.

2.3.3 Correlates of class membership at last observation

An alternative multinomial regression analysis was performed to determine if the predictors for class membership remained stable over time. For this alternative analysis, the multinomial regression was performed again with the last observation of each participant instead of the first observation. The same independent variables were included. No new variable importance plots were made, but new values for the GVIF and the GVIF$^{1/2p}$ were calculated. The values of the GVIF and the GVIF$^{1/2p}$ for the multivariable regression models for the last observation can be found in Appendix C.2. Based on these values, no variables were excluded from the multivariable regression model.

The approach followed in this study is a commonly used three-step approach (Herle et al., 2020; Vermunt, 2010). In this three-step approach, the first step is to identify the best-fitting trajectory. In the second step, subjects are assigned to a latent class based on the computed posterior probabilities of class membership. In the third and final step, the classifications are used as the dependent variable in a relevant statistical model, such as a multinomial regression model. This approach was also used by McPherson et al. (2021) in their research on distinct mental health trajectories.

Chapter 3

Results

This chapter presents the results of the performed research. In Section 3.1, the descriptive statistics of the research population are given. Section 3.2 presents the results for the different estimated trajectory models. Finally, Section 3.3 presents the results from the multivariable multinomial regression models.

3.1 Descriptive statistics

In this section, some descriptive statistics of the population are given. In Section 3.1.1, the characteristics of the included participants regarding the considered variables are shown. Section 3.1.2 discusses the prevalence of psychological complaints for the included participants. Lastly, Section 3.1.3 gives the individual trajectories of the MHI-5 score for each included participant.

3.1.1 Characteristics of participants

In total, 936 participants were included in the analysis, all of whom completed the survey at least thrice starting from March 2022. Table 3.1 shows an overview of the characteristics of the participants the first time they completed a survey, stratified the MHI-5 score with a cut-off point of ≤ 60 indicating psychological complaints. For example, if a participant completed the survey in March 2022, September 2022, December 2022, and March 2023, Table 3.1 shows the characteristics of this participant in March 2022.

Table 3.1: Sample descriptive statistics for population stratified by MHI-5 score

Characteristic	**Overall** N = 936[1]	**MHI-5 $>$ 60** N = 556[1]	**MHI-5 $\leq$ 60** N = 380[1]	**p-value** [2]
Age (yrs.)				$>$ 0.9
	22.0 (5.0)	22.0 (5.0)	22.0 (5.0)	
Age (cat.)				0.2
12 - 17 years	137 (15%)	88 (16%)	49 (16%)	
18 - 25 years	799 (85%)	468 (84%)	331 (87%)	
Gender				$<$ 0.001
Male	305 (33%)	219 (40%)	86 (23%)	
Female	615 (67%)	335 (60%)	280 (77%)	
Educational level				0.8
High	659 (71%)	388 (70%)	271 (72%)	
Middle	239 (26%)	147 (26%)	92 (24%)	
Low	33 (3.5%)	20 (3.6%)	13 (3.5%)	
First round of participation				0.036
Round 3	386 (41%)	213 (38%)	173 (46%)	
Round 4	162 (17%)	94 (17%)	68 (18%)	
Round 5	388 (41%)	249 (45%)	139 (37%)	
Stress due to school and work				$<$ 0.001
Yes	358 (38%)	111 (20%)	247 (65%)	
No	578 (62%)	445 (80%)	133 (35%)	
Stress due to personal problems				$<$ 0.001
Yes	173 (18%)	33 (5.9%)	140 (37%)	
No	763 (82%)	523 (94%)	240 (63%)	

Characteristic	Overall N = 936[1]	MHI-5 > 60 N = 556[1]	MHI-5 ≤ 60 N = 380[1]	p-value [2]
Stress due to everything one has to do				< 0.001
Yes	348 (37%)	105 (19%)	243 (64%)	
No	588 (63%)	451 (81%)	137 (36%)	
Stress due to situation at home				< 0.001
Yes	83 (8.9%)	16 (2.9%)	67 (18%)	
No	853 (91%)	540 (97%)	313 (82%)	
Stress due to corona				< 0.001
Yes	125 (13%)	36 (6.5%)	89 (23%)	
No	811 (87%)	520 (94%)	291 (77%)	
Suffers from COVID-19-related experience				< 0.001
Yes	259 (28%)	113 (20%)	146 (38%)	
No	677 (72%)	443 (80%)	234 (62%)	
Faith in the future				< 0.001
Moderate to yes	839 (90%)	546 (98%)	293 (77%)	
Little to no	97 (10%)	10 (1.8%)	87 (23%)	
Irritable				< 0.001
Yes	204 (22%)	42 (7.6%)	162 (43%)	
No	732 (78%)	514 (92%)	218 (57%)	
Palpitations				< 0.001
Yes	49 (5.2%)	9 (1.6%)	40 (11%)	
No	887 (95%)	547 (98%)	340 (89%)	
Sleep problems				< 0.001
Yes	201 (21%)	49 (8.8%)	152 (40%)	
No	735 (79%)	507 (91%)	228 (60%)	
Tiredness				< 0.001
Yes	422 (45%)	149 (27%)	273 (72%)	
No	514 (55%)	407 (73%)	107 (28%)	

[1] Median (IQR); n (%)
[2] Wilcoxon rank sum test; Pearson's Chi-squared test

3.1.2 Psychological complaints

Table 3.2 shows the prevalence rates of psychological complaints among adolescents across different survey waves. As mentioned in Section 2.2.2, a participant is considered to have psychological complaints if their MHI-5 score is equal to or below 60. Furthermore, Table 3.2 presents the average MHI-5 scores of participants per survey round, categorised into two groups: those experiencing psychological complaints and those not experiencing psychological complaints. This table shows the difference between those groups regarding the mean MHI-5 score is quite large.

Table 3.2: Sample descriptive statistics for population stratified by MHI-5 score

Characteristic	Survey wave 3 N = 386[1]	Survey wave 4 N = 510[1]	Survey wave 5 N = 893[1]	Survey wave 6 N = 727[1]	Survey wave 7 N = 505[1]
MHI-5 category					
MHI-5 > 60	213 (55%)	289 (57%)	569 (64%)	442 (61%)	326 (65%)
MHI-5 ≤ 60	173 (45%)	221 (43%)	324 (36%)	285 (39%)	179 (35%)
MHI-5 score					
MHI-5 > 60	74.2 (8.2)	75.6 (8.9)	76.9 (8.7)	76.3 (8.2)	76.0 (8.5)
MHI-5 ≤ 60	48.5 (11.0)	47.0 (11.6)	48.4 (11.8)	47.8 (12.3)	47.6 (12.5)

[1] n (%); Mean (SD)

A comparison between the prevalence rates of psychological complaints in Table 3.2 and the corresponding percentages in Figure 1.2 reveals a similar pattern in the prevalence rates for the longitudinal sample used in the current study and the cross-sectional samples since March 2022. Figure 3.1 displays this pattern. Additionally, Figure 3.1 shows that the prevalence of psychological complaints per survey wave is consistently higher in the longitudinal sample compared to the cross-sectional sample.

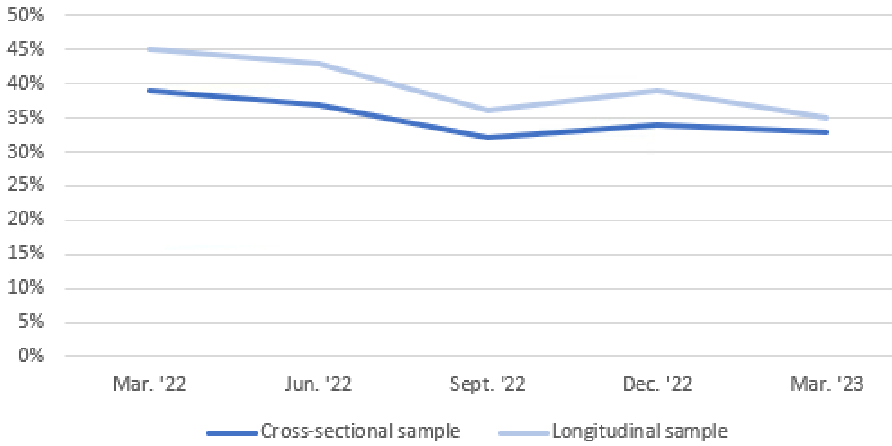


Figure 3.1: Prevalence of psychological complaints since March 2022 in the cross-sectional and longitudinal samples

3.1.3 Individual trajectories

Figure 3.2 shows the development of the MHI-5 score of each participant over time since March 2022. However, since this figure shows 936 trajectories, it appears visually cluttered, limiting its usefulness in identifying meaningful patterns or trends in the participants' mental health development. Therefore, trajectory modelling techniques were used to identify latent classes consisting of participants with similar mental health trajectories.

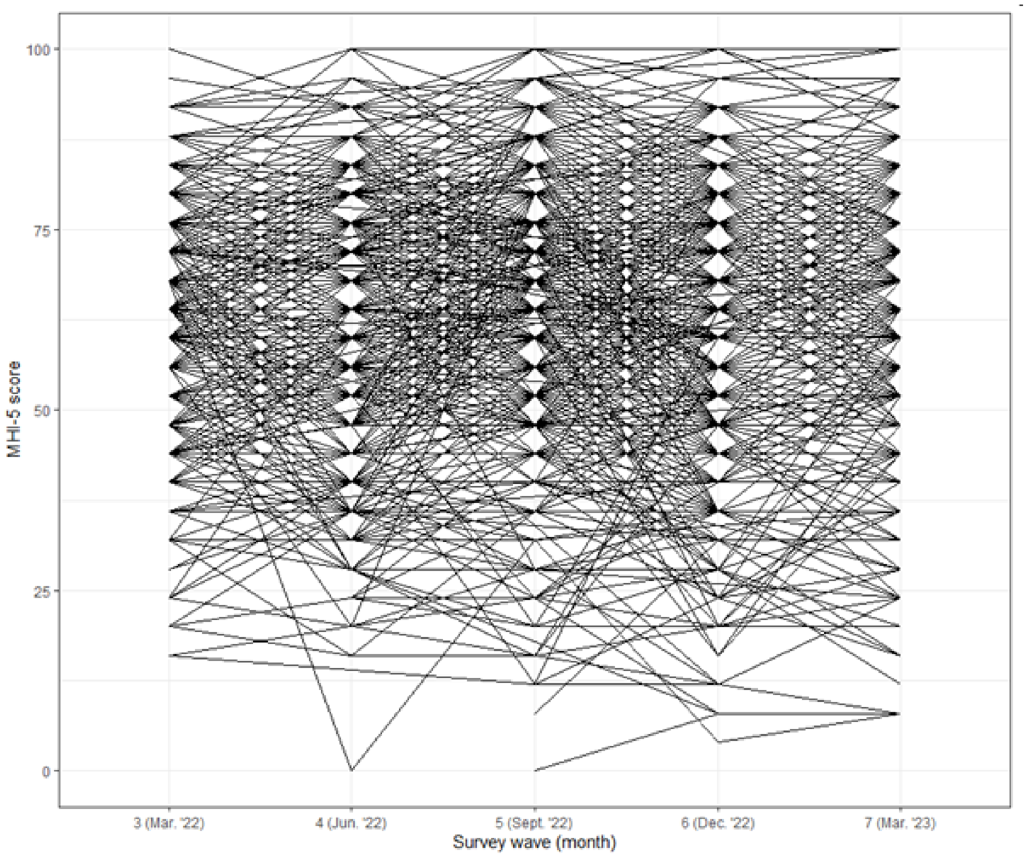


Figure 3.2: Individual trajectories of the MHI-5 scores of all participants

3.2 Trajectory models

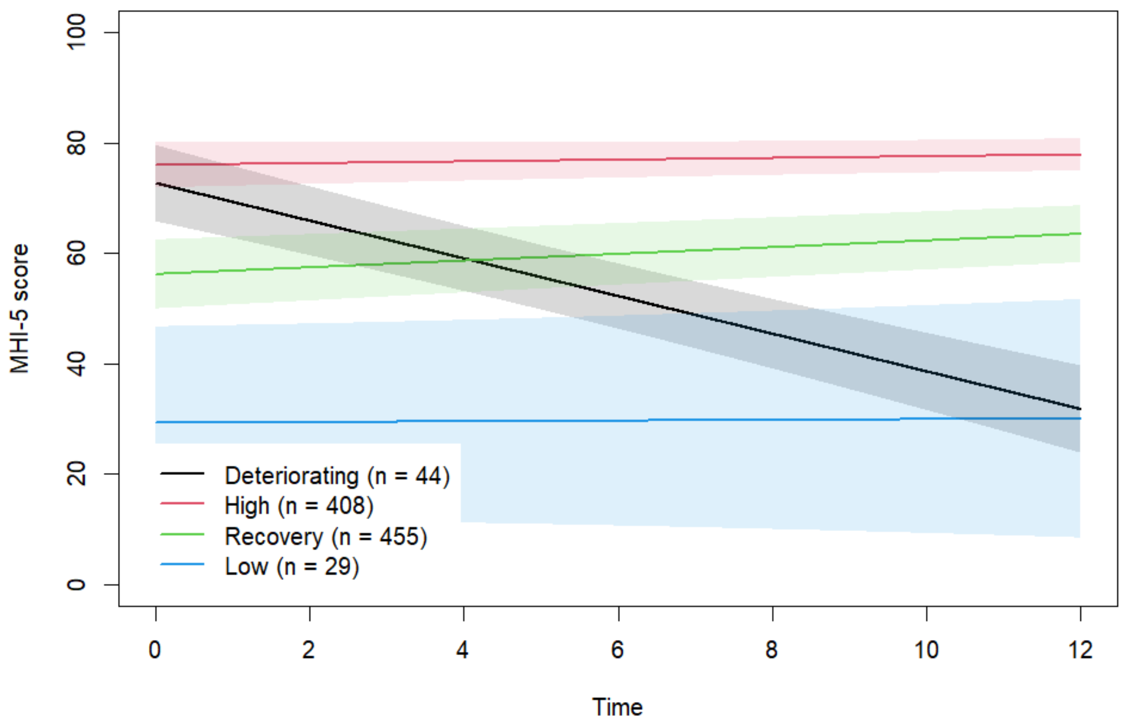
This section presents the results of the fitted trajectory models. Section 3.2.1 compares the different models based on their model fit. Section 3.2.2 elaborates on the model identified as the best-fitting model.

3.2.1 Comparison of estimated trajectory models

Table 3.3 shows the values of the fit statistics described in Section 3.2.1 and the size of the smallest class, numerically and proportionally, for all the estimated models. In general, the information-based indices (BIC, SABIC, AIC) improved when additional classes were added to the model, while the entropy decreased with an increasing number of classes. Furthermore, Table 3.3 shows that models estimating a greater number of classes yielded smaller classes that failed to meet the minimum amount of observations requirement in a class. Additionally, models for which more parameters had to be estimated in terms of random effects or an added quadratic term failed to converge. Table 3.3 also shows that adding a quadratic term or allowing the slope to vary between individuals within a class did not necessarily improve the model's fit, based on the fit statistics. However, by allowing the intercept to vary between individuals within a class, the model's fit improved. The models with the best fit statistics that fulfilled the requirement regarding class size and showed convergence are highlighted in green in Table 3.3. For all the models, the sizes of the estimated classes can be found in Appendix D.

3.2.2 Best model

Based on the fit statistics and the interpretability of the model, the linear growth mixture model with four classes and a random intercept but a fixed slope was identified as the model that best represents the data. As Table 3.3 shows, the linear 4-class GMM with a random intercept is among the models with the lowest information-based indices but has higher entropy than other models with the lowest information-based indices. Figure 3.3 shows the estimated mean trajectories of the MHI-5 score over time for the estimated classes with the corresponding 95% confidence intervals.



Notes: The shaded areas around the trajectories represent the 95% confidence intervals.

Figure 3.3: Estimated mean trajectories of MHI-5 score over time

The biggest group is the one in which, on average, the MHI-5 score of the participants increased slightly but significantly over time as indicated by a significant positive slope over time. This group is labelled as the

Table 3.3: Fit statistics per model

Number of classes	BIC	SABIC	AIC	Entropy	Size smallest class (n, (%))
Linear LCGA					
1	25703.25	25693.72	25688.73	1.00	936 (100)
2	24563.24	24544.19	24534.19	0.82	286 (30.6)
3	24073.84	24045.26	24030.27	0.84	94 (10.0)
4	23912.06	23873.95	23853.96	0.83	33 (3.5)
5	23845.41	23797.77	23772.79	0.79	28 (3.0)
6	23823.21	23766.05	23736.06	0.79	25 (2.7)
7	23850.49	23783.80	23748.82	0.72	17 (1.8)
Quadratic LCGA					
1	25705.75	25693.05	25686.38	1.00	936 (100)
2	24568.58	24543.17	24529.85	0.82	286 (30.6)
3	24082.34	24044.23	24024.24	0.84	95 (10.1)
4	23926.59	23875.78	23849.12	0.83	34 (3.6)
5	23913.28	23849.76	23816.45	0.82	30 (3.2)
6	23844.37	23768.15	23728.18	0.79	29 (3.1)
7	23832.22	23743.30	23696.66	0.78	22 (2.4)
8	23840.81	23739.18	23685.88	0.76	7 (0.7)
Linear GMM with random intercept					
1	23836.15	23823.44	23816.78	1.00	936 (100)
2	23776.72	23751.31	23737.98	0.88	37 (4.0)
3	23739.27	23701.15	23681.17	0.52	40 (4.3)
4	23749.77	23698.96	23672.31	0.64	29 (3.1)
5	23774.31	23710.79	23677.48	0.54	4 (0.4)
6[1]	23796.58	23720.36	23680.38	0.62	23 (2.5)
Quadratic GMM with random intercept					
1	23831.73	23815.85	23807.52	1.00	936 (100)
2	23768.57	23736.81	23720.16	0.87	41 (4.4)
3	23738.31	23690.67	23665.69	0.53	46 (4.9)
4	23755.44	23691.92	23658.60	0.60	54 (5.8)
5	23748.60	23669.21	23627.56	0.70	7 (0.7)
6[1]	23811.52	23716.25	23666.27	0.53	53 (5.7)
Linear GMM with random intercept and slope					
1	23831.98	23812.92	23802.93	1.00	936 (100)
2	23764.46	23732.71	23716.05	0.72	103 (11.0)
3	23754.27	23709.81	23686.49	0.56	86 (9.2)
4	23774.95	23717.78	23687.80	0.65	48 (5.1)
5[1]	23784.76	23714.89	23678.25	0.57	46 (4.9)
6[1]	23812.22	23729.64	23686.34	0.51	0 (0)
Quadratic GMM with random intercept and slope					
1	23836.32	23804.56	23787.91	1.00	936 (100)
2	23773.35	23725.72	23700.73	0.71	104 (11.1)
3	23768.03	23704.52	23671.20	0.56	85 (9.1)
4[1]	23795.02	23715.63	23673.98	0.65	52 (5.6)
5	23809.06	23713.78	23663.81	0.61	20 (2.1)
6[1]	23849.30	23738.14	23679.84	0.41	0 (0)

[1] No convergence

recovery group. Almost half of the participants (n = 455, 48.6%) were classified in this group. The second largest group is the one in which participants with a high and stable MHI-5 score were classified. This group's slope is not significant, indicating that the MHI-5 score did not change over time. This group did not experience psychological complaints after the COVID-19 pandemic. The third group consists of participants with a strongly decreasing MHI-5 score over time. This group had a deteriorating mental health after the COVID-19 pandemic. The smallest group consists of participants with a low MHI-5 score over time. This group was consistently experiencing psychological complaints. Table 3.4 gives a numerical description of the linear 4-class GMM with random intercept with the sizes, intercepts and slopes of the different classes.

Table 3.4: Numerical description of classes

Class	**Size** *(N (%))*	**Intercept** *(95% CI)*	**Slope** *(95% CI)*
Recovery	455 (48.6)	56.22 (49.96 - 62.48)	0.61 (0.39 - 0.83)
High	408 (43.6)	76.01 (71.90 - 80.11)	0.16 (-0.09 - 0.40)
Deteriorating	44 (4.7)	72.70 (65.79 - 79.61)	-3.41 (-4.16 - -2.66)
Low	29 (3.1)	29.24 (11.77 - 46.71)	0.07 (-0.75 - 0.88)

The characteristics presented in Table 3.1 but then stratified by class are given in Appendix E.

3.3 Correlates of class membership

This section presents the results of the multinomial regression models. Section 3.3.1 presents the results when the first available observation of each participant was included, while Section 3.3.2 presents the results when the last available observation was included.

3.3.1 First observation

Table 3.5 shows the results of the multivariable multinomial logistic regression when the first available observation of each participant was included. The results of the univariable models for the first observation can be found in Appendix F.1. The two biggest groups (recovery and high) were used as the reference groups for the multinomial regression.

Table 3.5: Odds ratios and confidence intervals (95% CI) for the multivariable multinomial logistic regressions for first observation

Predictor variable	Deteriorating versus high*	Recovery versus high*	Low versus high*	Deteriorating versus recovery**	Low versus recovery**
Age (category) *(Ref = 12 – 17 years old)*					
18-25 years old	0.88 (0.27 – 2.87)	1.07 (0.53 – 2.14)	0.64 (0.09 – 4.80)	0.82 (0.26 – 2.56)	0.60 (0.09 – 4.09)
Gender *(Ref = Male)*					
Female	1.44 (0.64 – 3.25)	1.26 (0.87 – 1.82)	0.32 (0.09 – 1.08)	1.15 (0.51 – 2.56)	**0.25 (0.08 – 0.82)**
Education *(Ref = High)*					
Low	**5.82 (1.18 – 28.60)**	0.59 (0.17 – 2.02)	0.38 (0.01 – 13.92)	**9.89 (2.22 – 44.09)**	0.65 (0.02 – 19.98)
Middle	1.30 (0.50 – 3.39)	0.62 (0.37 – 1.05)	1.39 (0.35 – 5.56)	2.11 (0.84 – 5.28)	2.24 (0.61 – 8.26)
First round of participation *(Ref = Round 3)*					
Round 4	0.75 (0.25 – 2.24)	1.08 (0.65 – 1.79)	3.90 (0.81 – 18.77)	0.70 (0.24 – 2.03)	3.62 (0.80 – 16.32)
Round 5	0.85 (0.41 – 1.95)	0.96 (0.66 – 1.41)	0.99 (0.25 – 3.85)	0.93 (0.43 – 1.98)	1.02 (0.27 – 3.82)
Experienced stress due to... *(Ref = No)*					
School and work	**2.43 (1.02 – 5.75)**	**4.13 (2.68 – 6.35)**	**6.19 (1.71 – 22.42)**	0.59 (0.26 – 1.33)	1.50 (0.44 – 5.10)
Personal problems	1.30 (0.40 – 4.27)	**4.38 (2.32 – 8.30)**	**14.09 (3.66 – 54.24)**	**0.30 (0.10 – 0.85)**	3.21 (0.96 – 10.71)
Everything one has to do	1.29 (0.52 – 3.16)	1.45 (0.93 – 2.26)	2.05 (0.47 – 8.97)	0.89 (0.38 – 2.08)	1.42 (0.34 – 5.85)
Situation at home	**4.60 (1.18 – 17.89)**	**3.75 (1.43 – 9.84)**	3.48 (0.71 – 17.14)	1.23 (0.42 – 3.60)	0.93 (0.26 – 3.36)
Corona	1.44 (0.50 – 4.11)	1.45 (0.78 – 2.69)	**12.72 (3.41 – 47.47)**	0.99 (0.38 – 2.57)	**8.75 (2.67 – 28.67)**
Suffers from COVID-19 related experience *(Ref = No)*					
Yes	**2.15 (1.01 – 4.56)**	1.18 (0.78 – 1.80)	0.46 (0.13 – 1.62)	1.82 (0.88 – 3.73)	0.39 (0.12 – 1.28)
Faith in the future *(Ref = Moderate to yes)*					
Little to no	**5.37 (1.31 – 21.95)**	**5.90 (2.07 – 16.87)**	**105.36 (21.58 – 514.47)**	0.91 (0.31 – 2.67)	**17.86 (5.22 – 61.13)**
Experienced somatically unexplained physical complaints *(Ref = No)*					
Irritable	**4.17 (1.69 – 10.31)**	**3.10 (1.73 – 5.55)**	**9.44 (2.46 – 36.21)**	1.35 (0.61 – 2.96)	3.05 (0.89 – 10.43)
Palpitations	0.97 (0.15 – 6.38)	1.90 (0.58 – 6.27)	5.24 (0.91 – 30.17)	0.51 (0.10 – 2.54)	2.75 (0.74 – 10.28)
Sleep problems	**2.78 (1.11 – 6.97)**	**2.48 (1.45 – 4.27)**	1.55 (0.40 – 6.04)	1.12 (0.49 – 2.58)	0.62 (0.18 – 2.20)
Tiredness	1.64 (0.72 – 3.73)	**1.88 (1.27 – 2.78)**	4.86 (0.91 – 25.90)	0.87 (0.39 – 1.94)	2.59 (0.50 – 13.34)

Notes: Two models were run, with high (*) and recovery (**) as the reference groups. Statistically significant associations are given in bold.

Table 3.5 shows that, in comparison with the participants with a high and stable MHI-5 score, all the other groups were more likely to experience stress due to school and work, have less faith in the future, and be more irritable.

When considering different classes separately compared to the participants with a high and stable MHI-5 score, participants with deteriorating mental health were also more likely to be lowly educated, experience more stress at home, suffer from a COVID-19-related experience and have problems with sleeping. Participants with an increasing MHI-5 score over time were more likely to experience stress due to personal problems, experience stress at home, have problems with sleeping and feel tired. Participants with chronic psychological complaints, indicated by a consistently low MHI-5 score over time, were more likely to experience stress due to personal problems and COVID-19.

Furthermore, the group of participants with an increasing MHI-5 score was compared with the class consisting of participants with a deteriorating mental health and the class consisting of participants with a low mental health. Participants with a deteriorating mental health were likelier to be lowly educated but they were less likely to experience stress due to personal problems than participants with a recovering mental health. Participants with a low mental health were less likely to be female and to have faith in the future, but they were more likely to experience stress due to COVID-19 than participants with a recovering mental health.

3.3.2 Last observation

Table 3.6 shows the multivariable multinomial logistic regression results when the last available observation was included. The results of the univariable models for the last observation can be found in Appendix F.2. The two biggest groups (recovery and high) were used as the reference groups for the multinomial regression.

Table 3.6: Odds ratios and confidence intervals (95% CI) for the multivariable multinomial logistic regressions for last observation

Predictor variable	Deteriorating versus high*	Recovery versus high*	Low versus high*	Deteriorating versus recovery**	Low versus recovery**
Age (category) *(Ref = 12 – 17 years old)*					
18-25 years old	0.72 (0.21 – 2.43)	1.43 (0.77 – 2.69)	0.88 (0.15 – 5.08)	0.50 (0.16 – 1.54)	0.61 (0.11 – 3.30)
Gender *(Ref = Male)*					
Female	1.39 (0.57 – 3.38)	**1.56 (1.10 – 2.20)**	0.75 (0.22 – 2.55)	0.89 (0.38 – 2.10)	0.48 (0.15 – 1.58)
Education *(Ref = High)*					
Low	2.19 (0.30 – 15.81)	0.57 (0.15 – 2.22)	0.73 (0.05 – 9.80)	3.83 (0.71 – 20.53)	1.28 (0.12 – 13.37)
Middle	0.83 (0.28 – 2.49)	0.68 (0.42 – 1.12)	1.23 (0.29 – 5.26)	1.22 (0.44 – 3.41)	1.80 (0.45 – 7.25)
First round of participation *(Ref = Round 3)*					
Round 4	0.78 (0.25 – 2.46)	1.05 (0.65 – 1.67)	2.39 (0.57 – 10.04)	0.74 (0.25 – 2.21)	2.28 (0.58 – 9.07)
Round 5	0.78 (0.34 – 1.79)	0.86 (0.60 – 1.22)	0.64 (0.19 – 2.22)	0.91 (0.42 – 2.00)	0.75 (0.23 – 2.50)
Experienced stress due to... *(Ref = No)*					
School and work	**3.78 (1.43 – 9.99)**	**2.53 (1.66 – 3.87)**	**4.97 (1.15 – 21.54)**	1.49 (0.60 – 3.72)	1.96 (0.47 – 8.11)
Personal problems	**7.47 (2.79 – 19.99)**	**3.94 (1.99 – 7.78)**	**9.55 (2.56 – 35.60)**	1.90 (0.88 – 4.10)	2.43 (0.77 – 7.70)
Everything one has to do	1.63 (0.60 – 4.44)	1.48 (0.97 – 2.27)	2.82 (0.56 – 14.12)	1.10 (0.43 – 2.83)	1.90 (0.40 – 9.16)
Situation at home	1.70 (0.49 – 5.97)	1.20 (0.50 – 2.90)	1.99 (0.43 – 9.26)	1.42 (0.54 – 3.71)	1.65 (0.45 – 6.03)
Corona	5.42 (0.95 – 30.80)	3.08 (0.88 – 10.83)	4.18 (0.49 – 35.81)	1.76 (0.48 – 6.42)	1.36 (0.22 – 8.32)
Suffers from COVID-19 related experience *(Ref = No)*					
Yes	1.07 (0.43 – 2.62)	**1.59 (1.03 – 2.46)**	0.57 (0.15 – 2.14)	0.67 (0.30 – 1.51)	0.36 (0.10 – 1.27)
Faith in the future *(Ref = Moderate to yes)*					
Little to no	**6.76 (2.09 – 21.85)**	**3.70 (1.53 – 8.96)**	**152.28 (29.04 – 798.67)**	1.82 (0.78 – 4.27)	**41.09 (9.51 – 177.57)**
Experienced somatically unexplained physical complaints *(Ref = No)*					
Irritable	**7.47 (2.96 – 18.86)**	**3.71 (2.05 – 6.70)**	**3.92 (1.06 – 14.56)**	2.02 (0.94 – 4.35)	1.06 (0.32 – 3.48)
Palpitations	1.85 (0.39 – 8.74)	1.18 (0.36 – 3.91)	**6.17 (1.04 – 36.58)**	1.56 (0.51 – 4.83)	**5.21 (1.29 – 21.09)**
Sleep problems	1.88 (0.74 – 4.79)	1.38 (0.79 – 2.43)	1.95 (0.53 – 7.21)	1.36 (0.61 – 3.02)	1.41 (0.42 – 4.70)
Tiredness	2.61 (0.98 – 6.98)	**2.19 (1.51 – 3.18)**	1.36 (0.30 – 6.12)	1.19 (0.46 – 3.08)	0.62 (0.14 – 2.72)

Notes: Two models were run, with high (*) and recovery (**) as the reference groups. Statistically significant associations are given in bold.

Again, participants in all the other groups were more likely to experience stress due to school and work, have less faith in the future and be more irritable compared with the participants with a high and stable MHI-5 score. Furthermore, participants in all the other groups were more likely to experience stress due to personal problems than participants with a high and stable MHI-5 score.

In addition, participants with an increasing MHI-5 score over time were more likely to be female and to suffer from a COVID-19-related experience than participants with a high MHI-5 score. They were also more likely to feel tired. Participants with a consistently low MHI-5 score were more likely to experience palpitations than those with a high MHI-5 score.

This regression model also shows that if the results of the last completed survey of each participant were included in the multinomial regression, there was no statistically significant difference in the considered correlates between the recovering and deteriorating groups. This indicates that either participants with a recovering mental health were experiencing less stress due to personal problems or that participants with a deteriorating mental health were experiencing more stress due to personal problems over time.

Lastly, participants with chronic psychological complaints tend to have less faith in the future, and they experience palpitations more often than participants with improved mental health.

Chapter 4

Discussion

This chapter discusses the results of this research. Section 4.1 interprets the results presented in Chapter 3. Section 4.2 discusses certain research limitations. Section 4.3 discusses the directions for future research. Section 4.4 finalises this chapter by discussing the implications of this research for public health policy.

4.1 Interpretation of the results and comparison of the results to literature

The current study provides insight into the distinct mental health trajectories of Dutch teenagers and young adults after the last COVID-19 (Omicron) lockdown and determines the correlates of these different mental health trajectories. The identification of distinct mental health trajectories is important because it allows for a better understanding of the variability and patterns of mental health outcomes over time (Nguena Nguefack et al., 2020). It is useful to identify more vulnerable subpopulations and, therefore, to optimise healthcare on the needs of these subpopulations.

Mental health trajectories

The development of the mental health of young individuals included in this study could best be explained by classifying them into four distinct trajectory classes. Based on the participants' MHI-5 scores, those classes were the following: constant high MHI-5 scores, recovering MHI-5 scores, deteriorating MHI-5 scores, and constant low MHI-5 scores. The identified classes in this study correspond to the most commonly observed classes Galatzer-Levy et al. (2018) found following potentially traumatic events (PTEs), as which the COVID-19 pandemic can also be interpreted (Bridgland et al., 2021). However, where Galatzer-Levy et al. (2018) found that the most common response to PTEs was resilience (e.g., the capacity to withstand or to recover quickly from difficulties), while the largest class identified in the current study was a slowly recovering class. A possible explanation for the difference was also presented in the systematic literature review by Galatzer-Levy et al. (2018). In their review, they state that prospective studies (with data from before and the PTE) were found to underestimate the resilience rate, indicating a selection bias in longitudinal studies. Since the data used in this research was collected after the COVID-19 pandemic (as of March 2022), data from before the PTE is lacking. Furthermore, the mentioned selection bias in longitudinal studies could explain the difference in the prevalence of psychological complaints between the cross-sectional and longitudinal samples as presented in Figure 3.1, which suggests that people with more psychological complaints were more likely to complete the survey at different survey waves than people with less psychological complaints.

Recently, Schäfer et al. (2022) performed a literature review to summarise what is known about the mental health consequences of the COVID-19 pandemic and to explore if the most common mental health trajectories identified by Galatzer-Levy et al. (2018) also exist for macro-stressors, such as the COVID-19 pandemic. Overall, they found that mental distress increased in the general population in response to the COVID-19 pandemic. Furthermore, in comparison with the study of Galatzer-Levy et al. (2018), Schäfer et al. (2022) found the same global types of trajectories, but the recovery trajectory seemed to be less prevalent. This contradicts the results of this study, in which the recovery trajectory was the most prevalent. However, Schäfer et al. (2022) also conclude that some trajectories are more prevalent in younger samples, such as the recovery trajectory.

If the findings of the current study are related to the findings of the studies described in Section 1.4 the same four distinct trajectories have been identified in the current study as in the previous trajectory studies (Kimhi et al., 2021; McPherson et al., 2021; Li et al., 2023). However, in all the previous studies, the class without psychological complaints over time was identified as the largest class instead of the class with improving mental health over time. It must be noted that Kimhi et al. (2021) and McPherson et al. (2021) used growth mixture modelling, while Li et al. (2023) used latent class growth analysis. The best-fitting LCGA model identified in this study consisted of six classes instead of four, as found by Li et al. (2023).

Correlates of class membership

The identified trajectory classes differed from each other concerning certain correlates of class membership. However, there also seem to be some consistent correlates over time when the groups are compared to the group of individuals with constant high MHI-5 scores. Teenagers and adolescents in all trajectories other than the constant high MHI-5 score trajectory reported less faith in the future, experienced more stress due to school and work and were more irritable. A comparison of the estimated odds ratios regarding the faith one has in the future in Table 3.5 and Table 3.6 suggests that the class with constantly low MHI-5 scores lose their faith in the future even more over time. Meanwhile, the group with recovering MHI-5 scores seem to have more faith in their future over time. Although the confidence intervals for the odds ratios at the different timepoints are quite overlapping, these results suggest that having faith in one's future is an important determinant of recovering from psychological complaints after the COVID-19 pandemic. However, based on the current study, it is impossible to determine the cause and the effect. The effect of the faith one has in the future on the mental health was also found by Thartori et al. (2021) in a cross-sectional study. Their findings suggest that individuals who positively evaluated their future were less likely to experience anxiety and depressive symptoms during the COVID-19 pandemic.

Some correlates of class membership in the current study were not stable over time. A remarkable observation is that participants with recovering MHI-5 scores were more likely to suffer from a COVID-19-related experience longer after the COVID-19 pandemic than the participants with constantly high MHI-5 scores. The opposite was observed for the class with deteriorating mental health, which was, compared to the class with participants with high MHI-5 scores, less likely to suffer from a COVID-19-related experience over time. This can be explained by the fact that throughout 2022, the impact of the COVID-19 crisis became less significant in daily life when considering the number of infections and the measures to control the virus (Rijksoverheid, 2022). Therefore, it is likely that fewer COVID-19-related events occurred. Also, the COVID-19-related events that one experienced occurred further in the past, so participants may be less affected by these events. There were other significant correlates at the first observation that were no longer significant when using the last observation of the participants for the multinomial logistic regression, which the decreasing seriousness of the COVID-19 pandemic over time can explain. These correlates are the experienced stress due to corona and the experienced stress due to the situation at home. Lastly, the odds ratios for the stress experienced due to personal problems suggest that the participants with deteriorating mental health are experiencing more stress due to personal problems over time compared to the classes with participants with constantly high and recovering MHI-5 scores.

When comparing the groups with deteriorating and recovering MHI-5 scores over time, slight differences can be observed in the correlates of these groups. The most important correlate for deteriorating mental health seems to be a low educational level. This was also found by Liang et al. (2020) in a cross-sectional study, which concluded that less educated youth were more likely to experience psychological complaints during the COVID-19 pandemic. Furthermore, when comparing participants' first observations, participants with increasing MHI-5 scores over time were more likely to experience stress due to personal problems. This finding is unexpected because one could argue that experiencing stress due to personal problems might hinder mental health recovery. However, at the first observation, the participants in the recovering group had, on average, a lower MHI-5 score than those classified in the groups with deteriorating MHI-5 scores. Their poorer mental health status at the start of the study period could explain why participants in the class with recovering MHI-5 scores experience more stress due to personal problems. Nonetheless, the question remains why some youth's mental health deteriorates while the mental health of others recovers within a year after the Omicron lockdown remains.

Resilience factors

The question of why some youth's mental health deteriorates while the mental health of others recovers might be answered in a review by Doom et al. (2023). This review discusses resilience factors that promote more positive mental health outcomes among children and adolescents during the COVID-19 pandemic. They distinguish between individual and social resilience factors. Individual psychological resilience factors associated with mental health outcomes are better emotional regulation skills, better ability to recover from adverse events or negative emotional states, and higher self-efficacy, self-esteem and life satisfaction. Individual behavioural resilience factors protective of adolescents' mental health include engaging in physical activities, spending more time in nature, and less on passive screentime (Doom et al., 2023). Furthermore, some social resilience factors associated with better mental health are parental support and warmth, peer support and closeness and school connectedness. However, it must be mentioned that some of these resilience factors have been asked out in the surveys. In the survey, it is asked whether one participated in physical activities in the past week. Also, the De Jong-Gierveld Loneliness Scale reflects social loneliness, which indicates whether a participant has a social network to rely on. This can be explained as parental and peer support. However, the variables reflecting those aspects of the survey did not seem to be important correlates of the different identified mental health trajectories since they do not come up in the variable importance plots. Therefore, it is probable that not the behavioural resilience factors but the individual resilience factor are more important for the mental health trajectories. Unfortunately, those were not asked out in the surveys. Furthermore, those individual resilience factors are more intrinsic than the behavioural resilience factors, just like the faith in the future one has is a more intrinsic factor. Therefore, they might be more difficult to target.

In addition, Schäfer et al. (2022) reviewed 16 trajectory studies that investigated resilience factors as correlates of mental health trajectories. They found that self-reported resilience and optimism were associated with more favourable mental health trajectories.

Earlier mental health diagnosis

Furthermore, the dataset used for the analysis did not contain information regarding participants' earlier mental health diagnoses. In other words, whether participants have been diagnosed with psychiatric disorders before completing the surveys is unknown. However, previous research has shown that children and adolescents with a mental illness are at an increased risk of suffering from pandemic-associated psychological distress (Gilsbach et al., 2021). This suggests that children and adolescents with existing mental health disorders may be less resilient to the impact that the COVID-19 pandemic had on their mental health than their peers without diagnosed mental disorders. Therefore, earlier mental health diagnosis might also be a correlate of class membership. However, the relation between earlier mental health diagnosis and class membership could not be investigated.

Mental health trends during the past decades

The findings of this study cannot be seen separately from the trends in mental health over the past few decades. Boer et al. (2022) discuss the development of the mental health of Dutch teenagers (aged 11-16) since 2001. They conclude that over the past 20 years, mental well-being has deteriorated among Dutch teenagers, predominantly among girls. Furthermore, a significant increase in psychological complaints was seen between 2017 and 2021, which suggests that the COVID-19 pandemic may have accelerated the already existing trend in the development of mental health problems (Boer et al., 2022). They indicate the decline in mental health may be related to the increased pressure that young people experience due to school. This finding was supported in this study as results suggest that participants with constant high MHI-5 scores were less likely to experience stress due to school and work than participants classified in the other trajectory classes.

In addition, Yang et al. (2023) found that, from 1990-2019, the depression incidence rates decreased globally, but in high socio-demographic index (SDI) regions, the incidence rate increased, especially in younger generations. The SDI is a combined measure of a country's average income, educational level, and fertility rates. Most Western European countries are high SDI countries. The findings of Yang et al. (2023) support the conclusions of Boer et al. (2022).

4.2 Limitations of this research

This research comes with certain limitations, which are addressed in this section. Section 4.2.1 describes why this research is limited by missing data, Section 4.2.2 describes the limitation of the relatively low entropy, and Section 4.2.3 describes why the choice to model the continuous MHI-5 score is a limitation.

4.2.1 Missing data

This research is subject to missing data. For this study, missing data can be divided into two components: the lack of data from before March 2022 and the missing information on participants at different survey waves.

Lack of data from before March 2022

As mentioned in Section 4.1, the lack of data from before the potentially traumatic event (e.g., the COVID-19 pandemic and the Omicron lockdown) can lead to a selection bias. This selection bias can result in the underestimation of the group that was resilient to the impact the COVID-19 pandemic had on their mental health. Furthermore, due to the lack of data from before March 2022, claims regarding the causality between the identified mental health trajectories and the COVID-19 pandemic should be made cautiously, even though an association seems plausible.

The lack of data from before March 2022 is due to two different research agencies distributing the surveys: Kantar Research during the first two waves and I&O Research during the last five waves. Therefore, the data of the first two and last five rounds cannot be combined into a more extensive longitudinal dataset.

Loss to follow-up

Although the estimated trajectory models inherently deal with missing data on the outcome through the FIML mechanism, it is not desirable to have missing data on the outcome measure. However, this research is subject to missing data because not all the included participants completed the survey at every available wave. To be more specific, only 0.4% of the included participants from the longitudinal dataset completed the survey a maximum of five times. If more participants had completed the survey at more timepoints, this could have led to the identification of different trajectories. However, a trade-off exists between the number of survey waves one participated in and the sample size because fewer participants have completed the surveys at multiple survey waves. Therefore, the choice was to include participants who completed the survey three times or more. This made it possible to estimate non-linear trajectories by adding the quadratic term.

4.2.2 Low entropy

As discussed, the fit statistic entropy was computed as one of the statistics to determine the fit of the estimated models to the data. For the best model, the linear GMM with four classes, the entropy was 0.64. This is lower than 0.80, which is suggested as an adequate entropy value (Ram & Grimm, 2009). Although some models were estimated with an entropy higher than 0.80, those models showed a worse fit to the data based on the information-based indices (BIC, SABIC, and AIC). Therefore, the linear GMM with four classes was favoured. However, a higher entropy would be better because it would mean a better separation of the identified classes. In addition, the lower entropy might also have consequences on the results of the multinomial regression. In the three-step approach, the relationship between class membership and its correlates tends to be underestimated when classification into a class is less certain because it does not take the uncertainty of the posterior probability of class membership into account (Vermunt, 2010). This also implies that a higher entropy would be better when the class membership is used as the dependent variable in further analysis.

4.2.3 Definition of mental health recovery

A last limitation of this research is how mental health recovery was operationalised. For this study, mental health recovery was operationalised through the MHI-5 score. However, mental health recovery has more aspects than only a MHI-5 score above or below 60. Hence, the continuous MHI-5 score was chosen as the dependent variable for the trajectory models at the beginning of this study. The downside is that not every participant classified in the class with increasing MHI-5 scores has recovered from psychological complaints they experienced at the end of the study period as defined by the MHI-5 cutoff point. You can only state that, on average, participants in this class feel slightly better over time.

4.3 Future research

The findings of the current study can be extended with future research. Since the quarterly surveys of the Integrated Health Monitor COVID-19 will still be distributed until 2025, the longitudinal dataset used for the analysis can only grow with new participants who completed the survey in multiple survey waves. In addition, further information regarding the participants included in this study can be gathered through the surveys. Therefore, the presented method in this study can help to monitor the development of the mental health among Dutch teenagers and adolescents in the future. However, the inclusion criteria for this study cannot be adopted blindly in future research. A new inclusion criterion needs to be introduced that ensures that the first round of participation of the participants is not too late after the COVID-19 pandemic (e.g., after the Omicron lockdown). For example, this criterion can be that one must have completed the questionnaire for the first time during the third, fourth or fifth survey wave. However, it cannot be assumed that the same model, the 4-class linear GMM with random intercept, will be the best if the analysis is performed again, but with an extra round added to the dataset. To determine the best model, all the models must be estimated again. Based on the described criteria, a new best model for the mental health trajectories can be chosen.

In addition, certain resilience factors can be included in the multinomial regression model to investigate the effect of those factors on the mental health trajectories. However, one should be careful when introducing new variables into the model because too many variables might lead to instability of the regression model due to a relatively small size of identified groups. A solution for this problem might be replacing some currently considered variables that do not seem relevant as correlates for class membership with resilience factors. Another solution might be to use forward or backward feature selection for the considered variables to end up with a more parsimonious multinomial regression model. Although the resilience factors available in the current dataset did not appear to be important correlates of the identified trajectories, it might be worthwhile to investigate an association between the resilience factors and the mental health trajectories, based on the already existing literature. Another option to explore the concept of resilience among adolescents is to include questions regarding resilience factors in the survey. This can be done by implementing scales in the survey that reflect self-efficacy, life satisfaction or resilience (Muris, 2001; Smith et al., 2008; Diener et al., 1985). However, not all these scales have been translated or validated for Dutch teenagers and young adults, so one should be cautious when implementing these scales. In addition, making the survey too long might also not be beneficial for the number of participants completing the survey. Therefore, when new questions are introduced, other questions might have to be removed from the survey.

A last direction for future research is to investigate the influence of loneliness on experienced mental health problems. As can be seen in the importance plots in Appendix A, loneliness is an important correlate of class membership. Yet, for this research, a variable for loneliness was not included in the analysis because of the plausible bidirectional interplay between the mental health outcome and loneliness (Pitman et al., 2018). A similar study can be conducted to determine the influence of experienced loneliness, in which the trajectories of the loneliness scores, instead of the MHI-5 scores, are modelled over time. Then, a multinomial regression can be made for the same variables considered in this study to explore if the same correlates are significant. It is also worthwhile to investigate how certain mental health outcomes from the survey affect each other to better understand the concept of mental health in its totality.

4.4 Implications for public health policy

Based on this research, the most important correlate for experiencing psychological complaints after the COVID-19 pandemic seems to be having little faith in the future. So, when policy can be implemented to improve faith in the future, the mental health of teenagers and adolescents may also improve. The faith one has in the future can be interpreted as hope. According to Snyder's hope theory, hope is the ability to reach desired goals and motivate oneself to reach those goals (Snyder, 2002). Therefore, establishing future goals for adolescents and finding ways to realise those goals might improve their mental health and help them with their mental health recovery. Policymakers can try this, for example, by implementing this in schools as part of the curriculum. However, one must be cautious that this does not add to the school-related stress that is experienced because then it could have an adverse effect since higher levels of school-related stress are associated with poorer mental health trajectories. In addition, higher hope seems to positively affect coping when confronted with stressors (Rand & Cheavens, 2009). Therefore, promoting hope might be beneficial when teenagers and young adults are confronted with stressors in the future.

Another way to improve mental well-being is through positive psychology interventions (PPIs) (Carr et al., 2021). PPIs are interventions based on positive psychology, which is the scientific study of what makes life worth living (Ackerman, 2018). For children and young adults, especially the effect of PPIs on the experienced quality of life seemed large, but PPIs were also found to improve well-being and reduce depressive and anxiety symptoms among children and young adults (Carr et al., 2021). In addition, PPIs can be used in clinical as well as in non-clinical settings. Therefore, they can be implemented in for example schools to promote the well-being of youths.

Chapter 5

Conclusion

This research was performed to get a better insight into the development of the mental health of youth in the Netherlands. The Integrated Health Monitor COVID-19 showed an increase in the prevalence of psychological complaints during the Omicron lockdown and decreased after this lockdown. However, the prevalence of psychological complaints was higher after the Omicron lockdown than before. This suggests that there are youths who recover from their psychological complaints but also youths who do not recover. Therefore, one can assume the existence of different classes within the Dutch youth regarding the mental health trajectories.

The presented research findings imply that these different classes do indeed exist in the population of Dutch teenagers, adolescents and young adults. The largest ones are those associated with positive mental health outcomes (e.g., a better or constant high MHI-5 score over time). However, classes associated with negative mental health outcomes were also identified, namely a class with deteriorating MHI-5 scores and a class with a constant low MHI-5 score, indicating chronic psychological complaints.

In addition, this study showed that the identified groups differ concerning certain correlates. Compared to the participants in the class with high and stable MHI-5 scores, all other participants were more likely to experience stress due to school and work, have less faith in the future, and feel irritable. However, causality between a correlate and class membership cannot be assumed. The most important correlate of mental health trajectories other than the trajectory of constant high MHI-5 scores seems to be the faith that one has in the future.

In the future, the presented method can be used to keep monitoring the development of the mental health among Dutch teenagers and adolescents, as a part of the Integrated Health Monitor COVID-19. Additionally, new variables, especially those associated with resilience, can be included in the regression models to explain the differences in the identified mental health trajectories.

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Appendix A

Variable importance plots

This appendix gives the variable importance plots used to identify important variables for class membership. Figure A.1 shows the importance plots for the high and the deteriorating class. Figure A.2 shows the importance plots for the high and the recovery class. Figure A.3 shows the importance plots for the high and the low class. Based on these variable importance plots a variable that reflects one's faith in the future and the variables indicating whether one experienced a specific somatically unexplained physical complaint were included for the analysis.

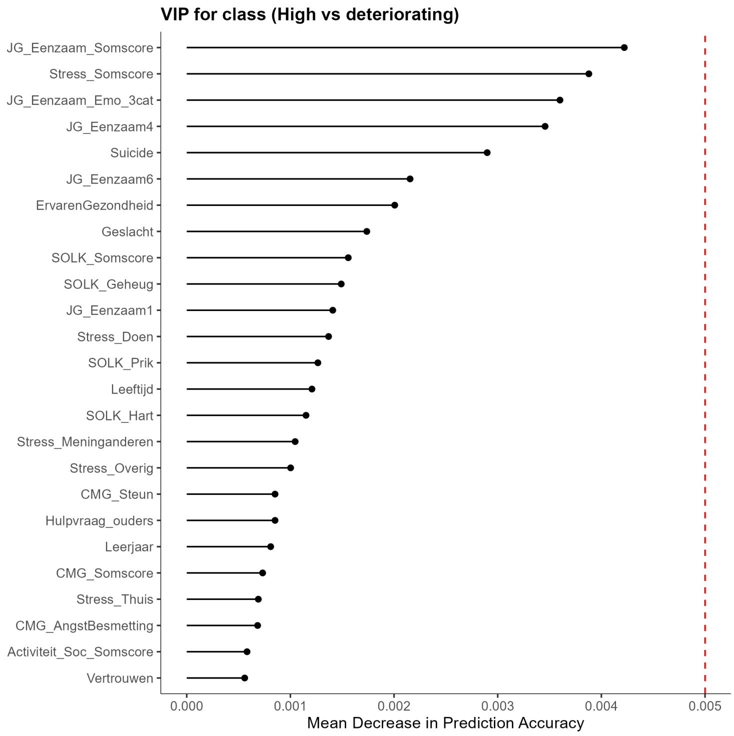

Figure A.1: Variable importance plot for classes high and deteriorating

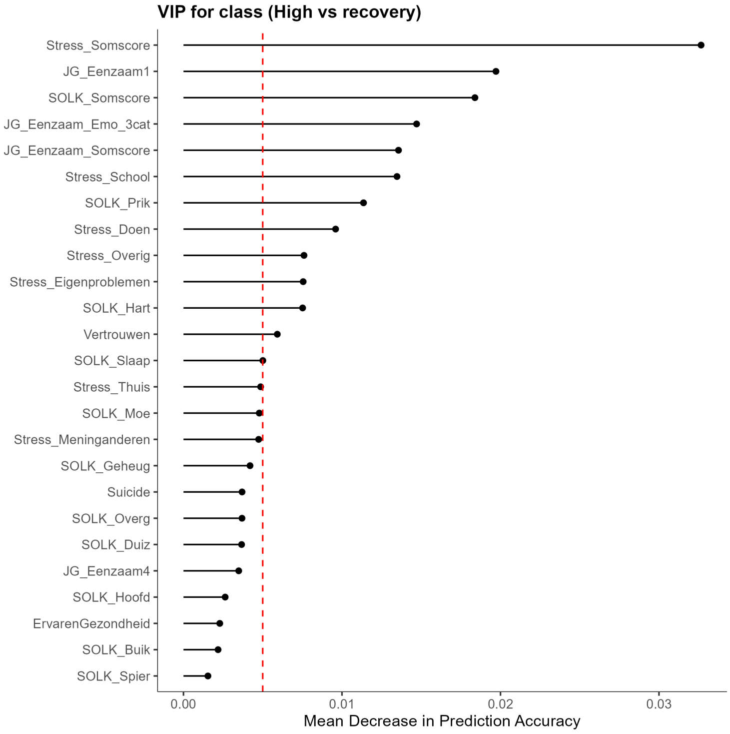

Figure A.2: Variable importance plot for classes high and deteriorating

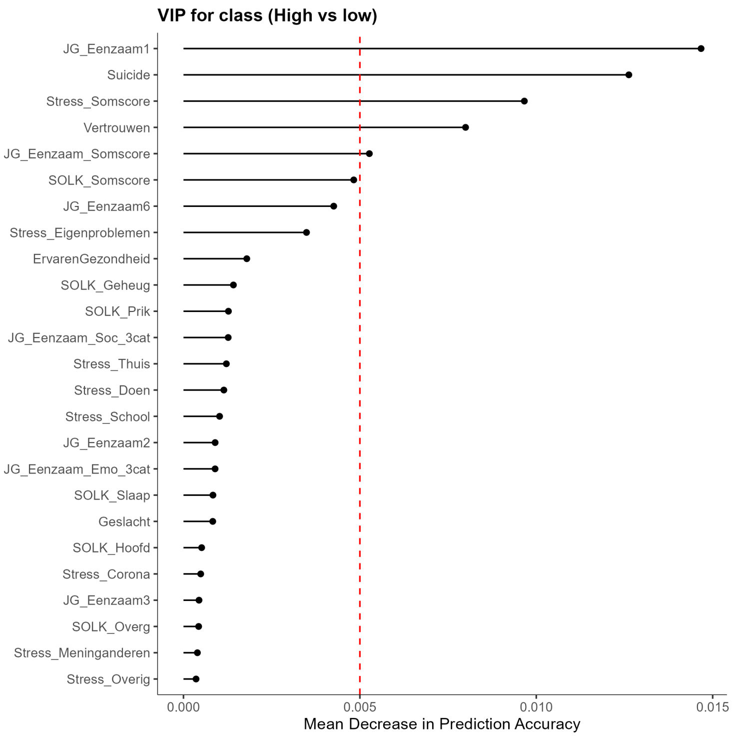

Figure A.3: Variable importance plot for classes high and deteriorating

Appendix B

Description of considered variables

This appendix provides information on the questions from the survey that were used to compute the considered variables (appendix B.1). Furthermore, appendix B.2 gives a more elaborate description of the considered variables.

B.1 Posed questions for considered variables

The considered variables in the multinomial regression models that are asked out in the survey are the ones regarding the participants' education, experienced stress, experienced somatically unexplained physical complaints, suffering from a COVID-19-related experience and faith in the future. Since the questions are posed in Dutch, each question is briefly explained.

Education

The variable that gives the participants' educational level is based on three questions. First, it is asked whether the participant follows education. If the answer to this question is 'Yes', one is asked what the current educational level is one follows. If the answer to the first question was 'No', it is asked what the highest educational level is one completed. These questions are combined into a categorical education variable with three categories: high, middle, and low. All participants who currently study at an HBO or university or earned their degree at an HBO or university are labelled 'High'. Everyone who currently follows HAVO or VWO at high school or does a level 2-4 MBO study, or has one of those as the highest degree is labelled as 'Middle'. The rest was labelled as 'Low'. If one filled in 'Different kind of education', one was labelled 'NA'.

[Onderwijs (F1.0)]
Vraag 1. Volg je onderwijs?
[1] ❑ Ja → *ga naar vraag 2*
[2] ❑ Nee → *ga naar vraag 4*

Routing: indien Onderwijs = 1 (Ja)
Vraag 2. Welk soort onderwijs volg je?
Je mag meerdere antwoorden aankruisen
[Onderwijssoort_Basisschool (F1.0)] ❑ Basisschool onderwijs → *ga naar vraag 5*
[Onderwijssoort_Praktijk (F1.0)] ❑ Praktijkonderwijs → *ga naar vraag 5*
[MBOKK332 (F1.0)] ❑ Vmbo-b (basis) -> *ga naar vraag 3*
[MBOKK333 (F1.0)] ❑ Vmbo-k (kader) -> *ga naar vraag 3*
[MBOKK334 (F1.0)] ❑ Vmbo-g (gemengd) -> *ga naar vraag 3*
[MBOKK335 (F1.0)] ❑ Vmbo-t (theoretisch, mavo) -> *ga naar vraag 3*
[MBOKK336 (F1.0)] ❑ Havo-> *ga naar vraag 3*
[MBOKK337 (F1.0)] ❑ Vwo (atheneum, gymnasium) -> *ga naar vraag 3*
[MBOKK338 (F1.0)] ❑ Mbo niveau 1 -> *ga naar vraag 5*
[MBOKK339 (F1.0)] ❑ Mbo niveau 2 t/m 4 -> *ga naar vraag 5*
[MBOKK3310 (F1.0)] ❑ Hbo -> *ga naar vraag 5*
[MBOKK3311 (F1.0)] ❑ Universiteit -> *ga naar vraag 5*
[MBOKK3312 (F1.0)] ❑ Ander soort onderwijs-> *ga naar vraag 4*
[1 = aangekruist; 2 = niet aangekruist]
[9 = missing]

Routing: indien Onderwijs = 2 (Nee) OR MBOKK3312 = 1 (aangekruist)
[Opleidingsniveau (F2.0)]
[als vraag 1= nee] Vraag 4. Wat is de hoogste opleiding die je hebt afgemaakt?
[1] ❑ Basisschool
[2] ❑ Praktijkonderwijs
[3] ❑ Vmbo
[4] ❑ Havo
[5] ❑ Vwo
[6] ❑ Mbo niveau 1
[7] ❑ Mbo niveau 2 t/m 4
[8] ❑ Hbo
[9] ❑ Universiteit
[10] ❑ Andere opleiding
[11] ❑ Ik heb geen opleiding afgemaakt
[99 = missing]

Experienced stress

For various aspects, it is asked if one experienced stress in the past four weeks. These aspects are school and work, the situation at home, personal problems, the opinions of others, everything one has to do, and COVID-19. One can also fill in miscellaneous. Answer options are never, rarely, sometimes, often, and very often.

Vraag 15. Hoe vaak voelde je je gestrest in de laatste 4 weken?
Geef op elke regel één antwoord.

	[1] Nooit	[2] Bijna nooit	[3] Soms	[4] Vaak	[5] Zeer vaak
[SBSSK301 (F1.0)] Ik voel me gestrest door school of huiswerk / werk	❑	❑	❑	❑	❑
[SBSSK302 (F1.0)] Ik voel me gestrest door mijn situatie thuis *(zoals zorgen, problemen of ruzies thuis)*	❑	❑	❑	❑	❑
[SBSSK303 (F1.0)] Ik voel me gestrest door eigen problemen *(zoals mijn gezondheid, ruzies met anderen, geheimen of schulden)*	❑	❑	❑	❑	❑
[SBSSK304 (F1.0)] Ik voel me gestrest over wat anderen van me vinden	❑	❑	❑	❑	❑
[SBSSK305 (F1.0)] Ik voel me gestrest door alles wat ik moet doen (school/huiswerk, werk, social media, bijbaantje, sporten etc.)	❑	❑	❑	❑	❑
[Stress_Corona (F1.0)] Ik voel mij gestrest door de coronaperiode en/of coronamaatregelen	❑	❑	❑	❑	❑
[Stress_Overig (F1.0)] Ik voel mij gestrest door overige zaken	❑	❑	❑	❑	❑

[9 = missing]

Experienced somatically unexplained physical complaints

It is asked if one experienced a somatically unexplained physical complaint in the past four weeks. The complaints that are asked out are abdominal pain, palpitations, headache, dizziness or light-headedness, muscle and joint complaints, throat complaints, feeling irritable, memory and concentration problems, sleeping problems and fatigue.

Vraag 17. Hoe vaak heb je in de laatste 4 weken last gehad van de volgende klacht(en)?
Geef op elke regel één antwoord.

	[1] Nooit	[2] Bijna nooit	[3] Soms	[4] Vaak	[5] Zeer vaak
[LBSOK301 (F1.0)] Buik- of maagklachten	❑	❑	❑	❑	❑
[LBSOK302 (F1.0)] Hartkloppingen	❑	❑	❑	❑	❑
[LBSOK303 (F1.0)] Hoofdpijn	❑	❑	❑	❑	❑
[LBSOK304 (F1.0)] Duizeligheid of licht in het hoofd	❑	❑	❑	❑	❑
[LBSOK305 (F1.0)] Overgevoeligheid voor licht of geluid	❑	❑	❑	❑	❑
[LBSOK306 (F1.0)] Spier- of gewrichtsklachten	❑	❑	❑	❑	❑
[LBSOK307 (F1.0)] Hoesten of keelklachten	❑	❑	❑	❑	❑
[LBSOK308 (F1.0)] Prikkelbaar of irritatie	❑	❑	❑	❑	❑
[LBSOK309 (F1.0)] Geheugen- of concentratieproblemen	❑	❑	❑	❑	❑
[LBSOK310 (F1.0)] Slaapproblemen	❑	❑	❑	❑	❑
[LBSOK311 (F1.0)] Moeheid	❑	❑	❑	❑	❑

[9 = missing]

Suffer from COVID-19-related experience

First, it was asked if participants experienced a COVID-19-related event. In total, ten different COVID-19-related experiences are asked out. Participants can choose multiple experiences. For the experiences that the participants endured, it is asked if they still suffer from these experiences. Again, participants can indicate for multiple experiences that they still suffer from them.

Vraag 26. Wat heb je tijdens de coronaperiode meegemaakt?
Je mag meer dan één antwoord geven.
[CMG_Besmetting] ❑ Ik heb corona gehad
[CMG_ZelfZiekenhuis] ❑ Ik heb in het ziekenhuis gelegen door corona
[CMG_AnderZiekenhuis] ❑ Iemand die belangrijk voor mij is, heeft in het ziekenhuis gelegen door corona
[CMG_AnderOverleden] ❑ Iemand die belangrijk voor mij is, is overleden aan corona
[CMG_AngstBesmetting] ❑ Ik was bang dat ik of iemand die belangrijk voor mij is corona zou krijgen
[CMG_Werk] ❑ Ik heb in mijn werk veel mensen gezien die ernstig ziek waren of zijn overleden aan corona
[CMG_Steun] ❑ Door de coronamaatregelen kon ik geen steun of zorg bieden aan iemand die belangrijk voor mij is
[CMG_Afscheid] ❑ Door de coronamaatregelen kon ik geen afscheid nemen van iemand die is overleden
[CMG_Bedreiging] ❑ Ik had te maken met bedreiging en/of geweld door discussie over coronamaatregelen
[CMG_Evenement (F1.0)] ❑ Ik heb een belangrijke gebeurtenis/evenement niet kunnen meemaken door het coronavirus/de maatregelen
❑ Geen van deze antwoorden -> **ga naar vraag 32**
[1 = aangekruist; 2 = niet aangekruist]
[9 = missing]

Routing: Bij vraag 27 alleen de antwoordopties tonen die bij vraag 26 zijn aangekruist
Vraag 27. Van welke gebeurtenissen heb je nu nog last?
Je mag meer dan één antwoord geven.
[CMG_Last_Besmetting] ❑ Ik heb corona gehad
[CMG_Last_ZelfZiekenhuis] ❑ Ik heb in het ziekenhuis gelegen door corona
[CMG_Last_AnderZiekenhuis] ❑ Iemand die belangrijk voor mij is, heeft in het ziekenhuis gelegen door corona
[CMG_Last_AnderOverleden] ❑ Iemand die belangrijk voor mij is, is overleden aan corona
[CMG_Last_AngstBesmetting] ❑ Ik was bang dat ik of iemand die belangrijk voor mij is corona zou krijgen
[CMG_Last_Werk] ❑ Ik heb in mijn werk veel mensen gezien die ernstig ziek waren of zijn overleden aan corona
[CMG_Last_Steun] ❑ Door de coronamaatregelen kon ik geen steun of zorg bieden aan iemand die belangrijk voor mij is
[CMG_Last_Afscheid] ❑ Door de coronamaatregelen kon ik geen afscheid nemen van iemand die is overleden
[CMG_Last_Bedreiging] ❑ Ik had te maken met bedreiging en/of geweld door discussie over coronamaatregelen
[CMG_Last_Evenement (F1.0)] ❑ Dat ik een belangrijke gebeurtenis/evenement niet heb kunnen meemaken door het coronavirus/de maatregelen
❑ Geen van deze antwoorden -> **ga naar vraag 32**
[1 = aangekruist; 2 = niet aangekruist]
[8 = nvt]
[9 = missing]

Faith in the future

It is asked how much faith the participant has in the future. The participant can give a rating on a scale from 1 to 10, where 1 means no faith in the future and 10 means a lot of faith in the future.

[PBVTK301 (F2.0)]
Vraag 12. Hoeveel vertrouwen heb je in je toekomst?

[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
1	2	3	4	5	6	7	8	9	10

Geen vertrouwen — Heel veel vertrouwen
[99 = missing]

B.2 Original variable names and description

Table B.1 presents the original variable names, a short description, the datatype and the different levels of the considered variables.

Table B.1: Description of the variables considered in the multinomial logistic regression

Original variable name	Description	Datatype	Levels
Leeftijd_2cat	Age of participant	Binary	0: 12-17 years 1: 18-25 years 9: Missing
Geslacht_2cat	Gender of participant	Binary	0: Male 1: Female 8: Different/does not want to say 9: Missing
Onderwijs_Huidig_Voltooid	Current or highest completed education level	Categorical	0: High 1: Middle 2: Low
T_Start	First survey wave of participation	Categorical	0: Round 3 1: Round 4 2: Round 5
Stress_School_2cat	Experienced stress due to school/work the past 4 weeks	Binary	0: No (never to sometimes) 1: Yes, (often to a lot)
Stress_Eigenproblemen_2cat	Experienced stress due to personal problems the past 4 weeks	Binary	0: No (never to sometimes) 1: Yes, (often to a lot)
Stress_Doen_2cat	Experiences stress due to everything one had to do the past 4 weeks	Binary	0: No (never to sometimes) 1: Yes, (often to a lot)
Stress_Thuis_2cat	Experiences stress due to the situation at home the past 4 weeks	Binary	0: No (never to sometimes) 1: Yes, (often to a lot)
Stress_Corona_2cat	Experiences stress due to corona the past 4 weeks	Binary	0: No (never to sometimes) 1: Yes, (often to a lot)
CMG_Last_Somscore_2cat	If one suffers from an experience that is related to the COVID-19 pandemic	Binary	0: No, does not suffer from or did not endure a COVID-19-related experience 1: Yes, suffers from at least one COVID-19-related experience
Vertrouwen_2catneg	If one has faith in the future	Binary	0: No, moderate to a lot (6 or higher) 1: Yes, little to no (5 or lower)
SOLK_Prik_2catvaak	If one felt irritable the past 4 weeks	Binary	0: No (never to sometimes) 1: Yes, (often to a lot)
SOLK_Hart_2catvaak	If one had palpitations the past 4 weeks	Binary	0: No (never to sometimes) 1: Yes, (often to a lot)
SOLK_Slaap_2catvaak	If one had sleep problems the past 4 weeks	Binary	0: No (never to sometimes) 1: Yes, (often to a lot)
SOLK_Moe_2catvaak	If one felt tired the past 4 weeks	Binary	0: No (never to sometimes) 1: Yes, (often to a lot)

Appendix C

VIF-values

The tables in Section C.1 and C.2 show the VIF-values of the multivariable multinomial regression models. As can be seen in those tables, none of the considered variables exceeded the value of 10 or $\sqrt{10}$.

C.1 First observation

Table C.1: GVIF and GVIF$^{1/2p}$ values multivariable multinomial regression model for first observation with 'High' as reference category

Variable	GVIF	DF	GVIF$^{1/2p}$
T_Start	2.83	2	1.29
Leeftijd_2cat	9.82	1	3.13
Geslacht_2cat	4.44	1	2.11
Onderwijs_Huidig_Voltooid	5.48	2	1.53
Stress_School_2cat	2.86	1	1.69
Stress_Eigenproblemen_2cat	1.71	1	1.31
Stress_Doen_2cat	3.08	1	1.76
Stress_Thuis_2cat	2.06	1	1.44
Stress_Corona_2cat	1.78	1	1.33
CMG_Last_Somscore_2cat	2.21	1	1.49
Vertrouwen_2catneg	2.20	1	1.48
SOLK_Prik_2cat	2.52	1	1.59
SOLK_Hart_2cat	1.59	1	1.26
SOLK_Slaap_2cat	2.11	1	1.45
SOLK_Moe_2cat	3.22	1	1.79

Table C.2: GVIF and GVIF$^{1/2p}$ values multivariable multinomial regression model for first observation with 'Recovery' as reference category

Variable	GVIF	DF	GVIF$^{1/2p}$
T_Start	2.57	2	1.27
Leeftijd_2cat	9.02	1	3.00
Geslacht_2cat	4.36	1	2.09
Onderwijs_Huidig_Voltooid	4.69	2	1.47
Stress_School_2cat	2.56	1	1.60
Stress_Eigenproblemen_2cat	1.85	1	1.16
Stress_Doen_2cat	2.77	1	1.66
Stress_Thuis_2cat	1.29	1	1.14
Stress_Corona_2cat	1.47	1	1.21
CMG_Last_Somscore_2cat	2.02	1	1.42
Vertrouwen_2catneg	1.28	1	1.13
SOLK_Prik_2cat	1.91	1	1.38
SOLK_Hart_2cat	1.16	1	1.08
SOLK_Slaap_2cat	1.74	1	1.32
SOLK_Moe_2cat	3.04	1	1.74

C.2 Last observation

Table C.3: GVIF and GVIF$^{1/2p}$ values multivariable multinomial regression model for last observation with 'High' as reference category

Variable	GVIF	DF	GVIF$^{1/2p}$
T_Start	3.44	2	1.36
Leeftijd_2cat	9.90	1	3.15
Geslacht_2cat	5.31	1	2.31
Onderwijs_Huidig_Voltooid	7.75	2	1.67
Stress_School_2cat	5.34	1	2.31
Stress_Eigenproblemen_2cat	4.11	1	2.03
Stress_Doen_2cat	5.66	1	2.38
Stress_Thuis_2cat	2.57	1	1.60
Stress_Corona_2cat	2.45	1	1.57
CMG_Last_Somscore_2cat	1.96	1	1.40
Vertrouwen_2catneg	3.65	1	1.91
SOLK_Prik_2cat	4.27	1	2.07
SOLK_Hart_2cat	2.54	1	1.59
SOLK_Slaap_2cat	3.45	1	1.86
SOLK_Moe_2cat	6.71	1	2.59

Table C.4: GVIF and GVIF$^{1/2p}$ values multivariable multinomial regression model for last observation with 'Recovery' as reference category

Variable	GVIF	DF	GVIF$^{1/2p}$
T_Start	2.76	2	1.29
Leeftijd_2cat	8.37	1	2.89
Geslacht_2cat	4.93	1	2.22
Onderwijs_Huidig_Voltooid	4.85	2	1.48
Stress_School_2cat	4.73	1	2.18
Stress_Eigenproblemen_2cat	2.52	1	1.59
Stress_Doen_2cat	5.05	1	2.25
Stress_Thuis_2cat	1.51	1	1.23
Stress_Corona_2cat	1.36	1	1.17
CMG_Last_Somscore_2cat	1.61	1	1.27
Vertrouwen_2catneg	1.91	1	1.38
SOLK_Prik_2cat	2.94	1	1.72
SOLK_Hart_2cat	1.34	1	1.16
SOLK_Slaap_2cat	2.52	1	1.59
SOLK_Moe_2cat	6.25	1	2.50

Appendix D

Class sizes

In this appendix, the class sizes for all the identified classes of the different estimated models can be found.

Table D.1: Class size of classes estimated for linear LCGA models

Number of classes	**Class sizes (n (%))** Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7
1	936 (100)						
2	286 (30.6)	650 (69.4)					
3	389 (41.6)	94 (10.0)	453 (48.4)				
4	365 (39.0)	162 (17.3)	376 (40.2)	33 (3.5)			
5	99 (10.6)	302 (32.3)	28 (3.0)	133 (14.2)	374 (40.0)		
6	25 (2.7)	27 (2.9)	99 (10.6)	294 (31.4)	365 (39.0)	126 (13.5)	
7	261 (27.9)	17 (1.8)	23 (2.5)	191 (20.4)	266 (28.4)	124 (13.2)	54 (5.8)

Table D.2: Class size of classes estimated for quadratic LCGA models

Number of classes	**Class sizes (n (%))** Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Class 8
1	936 (100)							
2	286 (30.6)	650 (69.4)						
3	458 (48.9)	95 (10.1)	383 (40.9)					
4	34 (3.6)	363 (38.8)	377 (40.3)	162 (17.3)				
5	146 (15.6)	30 (3.2)	359 (38.4)	38 (4.1)	363 (38.8)			
6	117 (12.5)	29 (3.1)	367 (39.2)	292 (31.2)	101 (10.8)	30 (3.2)		
7	34 (3.6)	115 (12.3)	354 (37.8)	45 (4.8)	22 (2.4)	83 (8.9)	283 (30.2)	
8	7 (0.7)	28 (3.0)	34 (3.6)	222 (23.7)	265 (28.3)	106 (11.3)	248 (26.5)	26 (2.8)

Table D.3: Class size of classes estimated for linear GMM models with a random intercept

Number of classes	**Class sizes (n (%))** Class 1	Class 2	Class 3	Class 4	Class 5	Class 6
1	936 (100)					
2	37 (4.0)	899 (96.0)				
3	576 (61.5)	40 (4.3)	320 (34.2)			
4	44 (4.7)	408 (43.6)	455 (48.6)	29 (3.1)		
5	4 (0.4)	31 (3.3)	459 (49.0)	44 (4.7)	398 (42.5)	
6	45 (4.8)	266 (28.4)	86 (9.2)	25 (2.7)	491 (52.5)	23 (2.5)

Table D.4: Class size of classes estimated for quadratic GMM models with a random intercept

Number of classes	**Class sizes (n (%))** Class 1	Class 2	Class 3	Class 4	Class 5	Class 6
1	936 (100)					
2	895 (95.6)	41 (4.4)				
3	46 (4.9)	601 (64.2)	289 (30.9)			
4	449 (48.0)	54 (5.8)	55 (5.9)	378 (40.4)		
5	422 (45.1)	35 (3.7)	430 (45.9)	7 (0.7)	42 (4.5)	
6	53 (5.7)	53 (5.7)	431 (46.0)	196 (20.9)	147 (15.7)	56 (6.0)

Table D.5: Class size of classes estimated for linear GMM models with a random intercept and random slope

Number of classes	**Class sizes (n (%))** Class 1	Class 2	Class 3	Class 4	Class 5	Class 6
1	936 (100)					
2	833 (89.0)	103 (11.0)				
3	86 (9.2)	446 (47.6)	404 (43.2)			
4	69 (7.4)	435 (46.5)	48 (5.1)	384 (41.0)		
5	46 (4.9)	66 (7.1)	58 (6.2)	491 (52.5)	275 (29.4)	
6	73 (7.8)	490 (52.4)	46 (4.9)	265 (28.3)	62 (6.6)	0 (0)

Table D.6: Class size of classes estimated for quadratic GMM models with a random intercept and random slope

Number of classes	**Class sizes (n (%))** Class 1	Class 2	Class 3	Class 4	Class 5	Class 6
1	936 (100)					
2	104 (11.1)	832 (88.9)				
3	85 (9.1)	442 (47.2)	409 (43.7)			
4	75 (8.0)	435 (46.5)	52 (5.6)	374 (40.0)		
5	53 (5.7)	349 (37.3)	468 (50.0)	20 (2.1)	46 (4.9)	
6	34 (3.6)	45 (4.8)	369 (39.4)	82 (8.8)	406 (43.4)	0 (0)

Appendix E

Descriptive statistics per class

This appendix presents the descriptive statistics of the variables considered in the multinomial logistic regression per class at the first observation (Appendix E.1) and the last observation (Appendix E.2).

E.1 First observation

Table E.1: Descriptive statistics per class at first observation

Characteristic	**Deteriorating**, N = 44[1]	**High**, N = 408[1]	**Recovery**, N = 455[1]	**Low**, N = 29[1]	**p-value**[2]
Age (yrs.)					0.026
	20.0 (7.3)	22.0 (4.0)	22.0 (4.0)	21.0 (5.0)	
Age (cat)					0.007
12-17 years	12 (27%)	70 (17%)	51 (11%)	4 (14%)	
18-25 years	32 (73%)	338 (83%)	404 (89%)	25 (86%)	
Gender					<0.001
Male	10 (26%)	174 (43%)	111 (25%)	10 (42%)	
Female	29 (74%)	234 (57%)	338 (75%)	14 (58%)	
Education					
High	24 (55%)	276 (68%)	345 (76%)	14 (50%)	
Middle	14 (32%)	116 (29%)	97 (21%)	12 (43%)	
Low	6 (14%)	15 (3.7%)	10 (2.2%)	2 (7.1%)	
First round of participation					0.7
3	19 (43%)	160 (39%)	195 (43%)	12 (41%)	
4	6 (14%)	67 (16%)	82 (18%)	7 (24%)	
5	19 (43%)	181 (44%)	178 (39%)	10 (34%)	
Stress due to school and work					<0.001
Yes	19 (43%)	58 (14%)	261 (57%)	20 (69%)	
No	25 (57%)	350 (86%)	194 (43%)	9 (31%)	
Stress due to personal problems					<0.001
Yes	7 (16%)	16 (3.9%)	130 (29%)	20 (69%)	
No	37 (84%)	392 (96%)	325 (71%)	9 (31%)	
Stress due to everything one has to do					<0.001
Yes	18 (41%)	62 (15%)	246 (54%)	22 (76%)	
No	26 (59%)	346 (85%)	209 (46%)	7 (24%)	
Stress due to situation at home					<0.001
Yes	6 (14%)	6 (1.5%)	62 (14%)	9 (31%)	
No	38 (86%)	402 (99%)	393 (86%)	20 (69%)	
Stress due to corona					<0.001
Yes	7 (16%)	25 (6.1%)	78 (17%)	15 (52%)	
No	37 (84%)	383 (94%)	377 (83%)	14 (48%)	
Suffers from COVID-19-related experience					<0.001
Yes	19 (43%)	75 (18%)	155 (34%)	10 (34%)	
No	25 (57%)	333 (82%)	300 (66%)	19 (66%)	
Faith in the future					<0.001
Moderate to yes	35 (80%)	403 (99%)	393 (86%)	8 (28%)	
Little to no	9 (20%)	5 (1.2%)	62 (14%)	21 (72%)	

Characteristic	Deteriorating, N = 44[1]	High, N = 408[1]	Recovery, N = 455[1]	Low, N = 29[1]	p-value[2]
Irritable					<0.001
Yes	17 (39%)	19 (4.7%)	147 (32%)	21 (72%)	
No	27 (61%)	389 (95%)	308 (68%)	8 (28%)	
Palpitations					<0.001
Yes	2 (4.5%)	4 (1.0%)	37 (8.1%)	6 (21%)	
No	42 (95%)	404 (99%)	418 (92%)	23 (79%)	
Sleep problems					<0.001
Yes	13 (30%)	28 (6.9%)	143 (31%)	17 (59%)	
No	31 (70%)	380 (93%)	312 (69%)	12 (41%)	
Tiredness					<0.001
Yes	23 (52%)	89 (22%)	284 (62%)	26 (90%)	
No	21 (48%)	319 (78%)	171 (38%)	3 (10%)	

[1] Median (IQR); n (%)
[2] Kruskal-Wallis rank sum test; Pearson's Chi-squared test; Fisher's exact test

E.2 Last observation

Table E.2: Descriptive statistics per class at last observation

Characteristic	Deteriorating, N = 44[1]	High, N = 408[1]	Recovery, N = 455[1]	Low, N = 29[1]	p-value[2]
Age (yrs.)					0.026
	20.0 (7.3)	22.0 (4.0)	22.0 (4.0)	21.0 (5.0)	
Age (cat)					0.007
12-17 years	12 (27%)	70 (17%)	51 (11%)	4 (14%)	
18-25 years	32 (73%)	338 (83%)	404 (89%)	25 (86%)	
Gender					<0.001
Male	10 (25%)	175 (43%)	111 (25%)	11 (42%)	
Female	30 (75%)	233 (57%)	337 (75%)	15 (58%)	
Education					
High	27 (61%)	286 (70%)	361 (80%)	16 (57%)	
Middle	12 (27%)	109 (27%)	84 (19%)	10 (36%)	
Low	5 (11%)	12 (2.9%)	7 (1.5%)	2 (7.1%)	
First round of participation					0.7
3	19 (43%)	160 (39%)	195 (43%)	12 (41%)	
4	6 (14%)	67 (16%)	82 (18%)	7 (24%)	
5	19 (43%)	181 (44%)	178 (39%)	10 (34%)	
Stress due to school and work					<0.001
Yes	30 (68%)	62 (15%)	224 (49%)	21 (72%)	
No	14 (32%)	346 (85%)	231 (51%)	8 (28%)	
Stress due to personal problems					<0.001
Yes	24 (55%)	12 (2.9%)	105 (23%)	19 (66%)	
No	20 (45%)	396 (97%)	350 (77%)	10 (34%)	
Stress due to everything one has to do					<0.001
Yes	29 (66%)	70 (17%)	224 (49%)	22 (76%)	
No	15 (34%)	338 (83%)	231 (51%)	7 (24%)	
Stress due to situation at home					<0.001
Yes	9 (20%)	9 (2.2%)	43 (9.5%)	10 (34%)	
No	35 (80%)	399 (98%)	412 (91%)	19 (66%)	
Stress due to corona					<0.001
Yes	4 (9.1%)	4 (1.0%)	21 (4.6%)	3 (10%)	
No	40 (91%)	404 (99%)	434 (95%)	26 (90%)	

Characteristic	**Deteriorating**, N = 44[1]	**High**, N = 408[1]	**Recovery**, N = 455[1]	**Low**, N = 29[1]	**p-value**[2]
Suffers from COVID-19-related experience					<0.001
Yes	13 (30%)	51 (13%)	125 (27%)	9 (31%)	
No	31 (70%)	357 (88%)	330 (73%)	20 (69%)	
Faith in the future					<0.001
Moderate to yes	29 (66%)	400 (98%)	398 (87%)	3 (10%)	
Little to no	15 (34%)	8 (2.0%)	57 (13%)	26 (90%)	
Irritable					<0.001
Yes	28 (64%)	17 (4.2%)	135 (30%)	19 (66%)	
No	16 (36%)	391 (96%)	320 (70%)	10 (34%)	
Palpitations					<0.001
Yes	5 (11%)	4 (1.0%)	23 (5.1%)	8 (28%)	
No	39 (89%)	404 (99%)	432 (95%)	21 (72%)	
Sleep problems					<0.001
Yes	21 (48%)	26 (6.4%)	110 (24%)	20 (69%)	
No	23 (52%)	382 (94%)	345 (76%)	9 (31%)	
Tiredness					<0.001
Yes	35 (80%)	91 (22%)	282 (62%)	24 (83%)	
No	9 (20%)	317 (78%)	173 (38%)	5 (17%)	

[1] Median (IQR); n (%)
[2] Kruskal-Wallis rank sum test; Pearson's Chi-squared test; Fisher's exact test

Appendix F

ORs univariable multinomial logistic regression

This appendix presents the odds ratios for the different univariable multinomial regression models that were estimated.

F.1 First observation

Table F.1: Odds ratios and confidence intervals (95% CI) for the univariable multinomial logistic regressions for first observation

Predictor variable	Deteriorating versus high*	Recovery versus high*	Low versus high*	Deteriorating versus recovery**	Low versus recovery**
Age (category) *(Ref = 12 – 17 years old)*					
18-25 years old	0.55 (0.27 -1.13)	**1.64 (1.11 – 2.42)**	1.29 (0.44 – 3.84)	**0.34 (0.16 – 0.69)**	0.79 (0.26 – 2.36)
Gender *(Ref = Male)*					
Female	**2.16 (1.03 – 4.56)**	**2.27 (1.69 – 3.03)**	1.04 (0.45 – 2.40)	0.95 (0.45 – 2.02)	0.46 (0.20 – 1.07)
Education *(Ref = High)*					
Low	**4.60 (1.63 – 12.94)**	0.53 (0.24 – 1.21)	2.63 (0.55 – 12.64)	**8.63 (2.89 – 25.74)**	4.93 (0.99 – 24.64)
Middle	1.39 (0.69 – 2.78)	**0.67 (0.49 – 0.91)**	2.04 (0.92 – 4.54)	**2.07 (1.03 – 4.16)**	**3.05 (1.37 – 6.81)**
First round of participation *(Ref = Round 3)*					
Round 4	0.75 (0.29 – 1.97)	1.00 (0.68 – 1.48)	1.39 (0.53 – 3.69)	0.75 (0.29 – 1.95)	1.39 (0.53 – 3.65)
Round 5	0.88 (0.45 – 1.73)	0.81 (0.60 – 1.08)	0.74 (0.31 – 1.75)	1.10 (0.56 – 2.14)	0.91 (0.38 – 2.16)
Experienced stress due to… *(Ref = No)*					
School and work	**4.59 (2.37 – 8.86)**	**8.12 (5.81 – 11.34)**	**13.41 (5.82 – 30.89)**	0.56 (0.30 – 1.06)	1.65 (0.74 – 3.71)
Personal problems	**4.64 (1.79 – 11.98)**	**9.80 (5.71 – 16.81)**	**54.45 (21.44 – 138.29)**	0.47 (0.21 – 1.09)	**5.55 (2.46 – 12.51)**
Everything one has to do	**3.86 (2.00 – 7.47)**	**6.57 (4.74 – 9.11)**	**17.54 (7.18 – 42.81)**	0.59 (0.31 – 1.10)	**2.67 (1.12 – 6.37)**
Situation at home	**10.58 (3.25 – 34.42)**	**10.57 (4.52 – 24.72)**	**30.15 (9.78 – 93.01)**	1.00 (0.41 – 2.47)	**2.85 (1.24 – 6.55)**
Corona	**2.90 (1.17 – 7.15)**	**3.17 (1.98 – 5.08)**	**16.42 (7.14 – 37.78)**	0.91 (0.39 – 2.13)	**5.18 (2.40 – 11.17)**
Suffers from COVID-19 related experience *(Ref = No)*					
Yes	**3.38 (1.77 – 6.46)**	**2.29 (1.67 – 3.15)**	**2.33 (1.04 – 5.23)**	1.47 (0.79 – 2.76)	1.02 (0.46 – 2.24)
Faith in the future *(Ref = Moderate to yes)*					
Little to no	**20.73 (6.59 – 65.22)**	**12.72 (5.06 – 31.96)**	**211.57 (63.70 – 702.70)**	1.63 (0.75 – 3.56)	**16.64 (7.06 – 39.21)**
Experienced somatically unexplained physical complaints *(Ref = No)*					
Irritable	**12.89 (6.02 – 27.61)**	**9.77 (5.92 – 16.12)**	**53.74 (21.09 – 136.96)**	1.32 (0.70 – 2.50)	**5.50 (2.38 – 12.72)**
Palpitations	4.81 (0.85 – 27.05)	**8.94 (3.16 – 25.32)**	**26.37 (6.95 – 100.02)**	0.54 (0.13 – 2.31)	**2.95 (1.13 – 7.69)**
Sleep problems	**5.70 (2.68 – 12.09)**	**6.22 (4.04 – 9.58)**	**19.17 (8.34 – 44.08)**	0.91 (0.46 – 1.80)	**3.09 (1.44 – 6.65)**
Tiredness	**3.93 (2.08 – 7.42)**	**5.95 (4.40 – 8.05)**	**31.07 (9.19 – 105.02)**	0.66 (0.35 – 1.23)	**5.22 (1.56 – 17.50)**

Notes: Two models were run, with high (*) and recovery (**) as the reference groups. Statistically significant associations are given in bold.

F.2 Last observation

Table F.2: Odds ratios and confidence intervals (95% CI) for the univariable multinomial logistic regressions for first observation

Predictor variable	Deteriorating versus high*	Recovery versus high*	Low versus high*	Deteriorating versus recovery**	Low versus recovery**
Age (category) *(Ref = 12 – 17 years old)*					
18-25 years old	0.55 (0.27 -1.13)	**1.64 (1.11 – 2.42)**	1.29 (0.44 – 3.84)	**0.34 (0.16 – 0.69)**	0.79 (0.26 – 2.36)
Gender *(Ref = Male)*					
Female	**2.26 (1.07 – 4.75)**	**2.28 (1.71 – 3.05)**	1.02 (0.46 – 2.28)	0.99 (0.47 – 2.09)	0.45 (0.20 – 1.01)
Education *(Ref = High)*					
Low	**4.41 (1.45 – 13.47)**	0.46 (0.18 – 1.19)	2.98 (0.61 – 14.45)	**9.55 (2.84 – 32.11)**	**6.45 (1.24 – 33.54)**
Middle	1.17 (0.57 – 2.38)	**0.61 (0.44 – 0.84)**	1.64 (0.72 – 3.72)	1.91 (0.93 – 3.93)	**2.69 (1.18 – 6.13)**
First round of participation *(Ref = Round 3)*					
Round 4	0.75 (0.29 – 1.97)	1.00 (0.68 – 1.48)	1.39 (0.53 – 3.69)	0.75 (0.29 – 1.95)	1.39 (0.53 – 3.65)
Round 5	0.88 (0.45 – 1.73)	0.81 (0.60 – 1.08)	0.74 (0.31 – 1.75)	1.10 (0.56 – 2.14)	0.91 (0.38 – 2.16)
Experienced stress due to... *(Ref = No)*					
School and work	**11.96 (6.00 – 23.83)**	**5.41 (3.90 – 7.50)**	**14.65 (6.21 – 34.55)**	**2.21 (1.14 – 4.28)**	**2.71 (1.17 – 6.24)**
Personal problems	**39.60 (17.34 – 90.42)**	**9.90 (5.36 – 18.30)**	**62.64 (24.06 – 163.11)**	**4.02 (2.14 – 7.56)**	**6.38 (2.87 – 14.19)**
Everything one has to do	**9.34 (4.76 – 18.32)**	**4.68 (3.41 – 6.42)**	**15.18 (6.24 – 36.90)**	**1.99 (1.04 – 3.82)**	**3.24 (1.36 – 7.73)**
Situation at home	**11.40 (4.25 – 30.58)**	**4.63 (2.23 – 9.61)**	**23.32 (8.48 – 64.09)**	**2.46 (1.11 – 5.47)**	**5.04 (2.20 – 11.54)**
Corona	**10.10 (2.43 – 41.95)**	**4.89 (1.66 – 14.37)**	**11.64 (2.47 – 54.78)**	2.07 (0.68 – 6.33)	2.39 (0.67 – 8.53)
Suffers from COVID-19 related experience *(Ref = No)*					
Yes	**2.94 (1.44 – 5.98)**	**2.65 (1.85 – 3.79)**	**3.16 (1.36 – 7.31)**	1.11 (0.56 – 2.18)	1.19 (0.53 – 2.68)
Faith in the future *(Ref = Moderate to yes)*					
Little to no	**25.84 (10.12 – 65.98)**	**7.16 (3.37 – 15.21)**	**434.50 (108.66 – 1737.53)**	**3.61 (1.83 – 7.15)**	**60.51 (17.74 – 206.39)**
Experienced somatically unexplained physical complaints *(Ref = No)*					
Irritable	**40.25 (18.40 – 88.07)**	**9.70 (5.74 – 16.41)**	**43.70 (17.65 – 108.22)**	**4.15 (2.17 – 7.92)**	**4.50 (2.04 – 9.94)**
Palpitations	**12.95 (3.34 – 50.21)**	**5.38 (1.84 – 15.68)**	**38.48 (10.72 – 138.09)**	2.41 (0.87 – 6.69)	**7.16 (2.86 – 17.88)**
Sleep problems	**13.40 (6.57 – 27.33)**	**4.68 (2.98 – 7.35)**	**32.64 (13.52 – 78.80)**	**2.86 (1.53 – 5.37)**	**6.97 (3.08 – 15.75)**
Tiredness	**13.54 (6.28 – 29.21)**	**5.68 (4.21 – 7.67)**	**16.73 (6.21 – 45.10)**	**2.38 (1.12 – 5.08)**	**2.94 (1.10 – 7.86)**

Notes: Two models were run, with high (*) and recovery (**) as the reference groups. Statistically significant associations are given in bold.