Exploring Long-Term Changes in Happiness and its Predictors. A Latent Class Analysis.

Lina Braun

S2123967

1st Supervisor: Sander de Vos

2nd Supervisor: Marijke Schotanus-Dijkstra

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Abstract

Objective: In the past, changes in long-term happiness have often been investigated on an average level showing incongruent findings in change pattern as well as predictors. To get a more elaborate insight into changes in long-term happiness, the aim of this study was to investigate whether there are multiple participants with similar happiness change trajectories that can be modelled into classes within the sample of the Dutch population. And, if certain characteristics predict following a specific trajectory. **Method:** Every year from 2008 to 2022, data was gathered from 1340 participants. The construct of happiness was the dependent variable and age, as well as personality traits neuroticism and agreeableness, were used as independent variables. Multiple latent growth mixture models were employed to model the trajectories of change in happiness. **Results:** Three latent classes were found describing different happiness trajectories. Most people (68%) had a stable and high level of happiness over time. Another class (17%) showed an overall decrease in happiness which was lowest in 2016 depicting a U-shaped change pattern. The third class (15%) increased in happiness generally but had a peak in 2016 creating an inverted U-shaped pattern. The trait neuroticism as well as age were predictive of class membership. Scoring high in neuroticism was predictive for being assigned to class 2 or 3 and being younger was predictive for being assigned to class 2. **Conclusions:** The study presented multiple different happiness trajectories. Certain individuals' characteristics were predictive for being assigned to a specific class which allows creating adjusted interventions for subgroups to increase their level of happiness. Future research should include a more heterogenic sample regarding background characteristics like age.

Keywords: Long-term Happiness, Change Trajectories, Personality Traits, Age

EXPLORING LONG-TERM CHANGES IN HAPPINESS AND ITS PREDICTORS.
A LATENT CLASS ANALYSIS.

Most people strive for happiness in life. In a ranking on the most important life goals, being happy was voted for the most often (Dillinger, 2020). However, people have different understandings and approaches on what makes them happy and how to reach happiness. Some people say happiness is being rich, some say starting a family and some others expect to become happy as soon as they retire (Layous & Lyubomirsky, 2014).

Happiness is part of subjective well-being and plays an important role in reaching and maintaining mental health. Happiness can overall be defined as experiencing more positive than negative affect such as high satisfaction in life and high enjoyment (Argyle, 2001; Lyubomirsky, 2001; Tkach & Lyubomirsky, 2006). Generally, there are two different kinds of happiness: short-term and long-term happiness. The difference between short-term and long-term happiness is the duration that these positive emotions are experienced. Short-term happiness describes momentary positive emotions whereas long-term happiness is about a satisfaction that persists from the past into the future (Biswas-Diener & Wiese, 2018).

When considering that long-term happiness is satisfaction that lasts from the past to the future, it could either mean that the level of happiness is stable and does not change over time or that the level of happiness can still fluctuate. In a longitudinal study review by Yap et al. (2014), it was investigated that there actually is a change in happiness meaning that the level of happiness is not constant throughout life. The review included multiple study results across countries that have revealed that one-third of the variance remained stable, one-third changed slowly and the last third was occasion-specific and therefore not stable. A longitudinal study conducted in the Netherlands that lasted decades investigated long-term happiness of the Dutch population (De Jonge et al., 2016). Generally, people living in the Netherlands are stably happy and have high life satisfaction which even increased slightly over the last forty years (Boelhouwer & van Campen, 2013; De Jonge et al., 2016). This indicates that the mean level of happiness in the Dutch population is rather constant over time.

When comparing the findings from two longitudinal studies (Yap et al., 2014; De Jonge et al., 2016), the deviating results indicate that the construct of long-term happiness is complex and that multiple factors might have an impact on the level of happiness of individuals (Lyubomirsky, 2001; Tkach & Lyubomirsky, 2006; Yap et al., 2014). Researchers have investigated that there are numerous influencing factors for long-term happiness such as personality, sex, age, and life events which can include financial changes, social support, and health (Eddington & Shuman, 2005; Helliwell et al., 2012).

One factor that supports change in long-term happiness is age as studies show that over the years happiness changes in a pattern. In one study, Vera-Villarroel et al. (2012) describe a downward trend of happiness in a sample of 18- to 29-year-olds. In a different longitudinal study, an upward trend from early adulthood to midlife was investigated (Galambos et al., 2015). These insights seem contradictory at first, however, the target group represents a slightly different timespan in life. The first study observes a downward trend in young adults and the second study focuses on people in midlife that seem to become happier over the years. This is in line with a common idea that happiness has a U-shaped trend over a lifetime, describing that middle-aged people are the least happy (Helliwell et al., 2012). Recently, Galambos et al. (2020) have explored this further and concluded that not everyone will experience U-shape happiness in life. Hence, there is a lot of evidence that happiness does change with age, but there is not one universal trajectory as multiple factors seem to have an impact on the level of happiness.

Next to the predictor age, which displayed incongruent findings on the impact on happiness so far, the factor personality has been shown to be strongly related to happiness (Schotanus-Dijkstra et al., 2016; Anglim et al., 2020). To be concrete, Hentschel et al. (2017)

found that about 20% of the level of happiness is predicted by personality traits. Every individual has a unique personality, which has a genetic basis and is relatively stable and consistent in adult life (Cummins, 2014; Hentschel et al., 2017). One widely accepted personality theory, called the Big Five (Costa Jr & McCrae, 1992), declares that personality can be clustered into five main factors, namely conscientiousness, agreeableness, neuroticism, openness to experience, and extraversion. Everyone scores higher or lower on each factor and thus, taken together, the scale indicates a spectrum of a person's personality. The trait conscientiousness ranges from impulsive and disorganized on the low end to careful and disciplined on the high end. People scoring low on agreeableness tend to be suspicious and uncooperative whereas scoring high on this scale indicates high trust and being helpful. Neuroticism ranges from calm and confident to anxious and pessimistic. Next, scoring low on openness to experience could describe someone who prefers routines and is practical while scoring high indicates imagination and spontaneity. The last trait, extraversion, ranges from being reversed and thoughtful on the low end and to being sociable and fun-loving on the high end (Costa Jr & McCrae, 1992).

Previous studies mainly focused on the personality traits extraversion and neuroticism and whether they predict the level of happiness. Specifically, extraversion shows a positive and neuroticism a negative effect on the level of happiness (DeNeve, & Cooper, 1998; Diener, 1998; Hentschel et al., 2017; McCrae, & Costa Jr, 1991). Nevertheless, there is not much research on the personality traits conscientiousness, agreeableness, and openness and their effect on happiness even though it seems that they can also have an impact to some extent (Diener, 1998; McCrae & Costa Jr, 1991). Generally, people who are agreeable can more easily connect to others compared to less agreeable people ("Big 5 personality traits", n.d.). This entails being friendly, to comply, and to socialize (Costa Jr & McCrae, 1992). Overall, people scoring high in agreeableness display more prosocial behaviours than others.

Interestingly, Segrin and Taylor (2007) investigated that people with high social skills and thereby positive interpersonal relationships are happier than people with no social skills. This might consequently indicate that individuals scoring high on agreeableness tend to be happier.

Next to personality traits, also life events appeared to impact long-term happiness. Especially events that are long-lasting and influence daily life like financial problems had a negative effect on people's happiness (Hentschel et al., 2017). One recent major life event that impacted the daily life of the entire population was the COVID-19 pandemic. One study conducted in the Netherlands found that the level of subjective happiness declined by about four per cent during the first year of the pandemic (Veenhoven et al., 2021). This shows that life events seem to have an impact on the general level of happiness.

Overall, it is not clear if and how happiness changes over time since there are multiple factors influencing the level of happiness and studies show inconsistent results. Given the multiple factors, people may show different trajectories of change or stability over time. This cannot be examined with only two measurements no matter whether it compared weeks, months or years (Yap et al., 2014), because it is not informative enough to draw conclusions about long-term changes as it does not give insight into the change pattern. Conclusively, it has been shown that at least four waves stretching over multiple months or years are necessary to receive valid results in determining changes or stability in long-term happiness considering a variety of possible influencing factors (Yap et al., 2014). Moreover, most longitudinal studies with multiple measurements used analyses of average mean scores and did not examine potential between-subject differences in trajectories of change (e.g. Vera-Villarroel et al., 2012; Galambos et al., 2015; De Jonge et al., 2016). To investigate long-term happiness and possible predictors, an exploratory latent class mixture analysis is useful because it can detect latent classes of individuals with similar trajectories over time. Thereby changes in the population and possibly multiple trajectories for specific subgroups can be identified. This information can then be used to develop interventions to promote mental health specifically for these latent groups.

Based on the previous literature, the aim of the current study is to investigate (a) whether and how happiness has changed in terms of the average trend and shape in the Dutch population over a decade. Moreover, (b) if heterogeneous patterns of change can be exploratively explained with latent classes of people with similar trajectories of change, and (c) if age, agreeableness, and neuroticism are systematically associated with long-term happiness.

Methods

Design and Participants

A panel study design was used with the data from the LISS Panel (Scherpenzeel & Das, 2010). The LISS Panel stands for Longitudinal Internet studies for the Social Sciences and invites households in the Netherlands to fill out questionnaires regularly. Overall, about 5000 Dutch households are taking part in the LISS Panel by completing questionnaires once a year, starting in 2008 until today. The sample is a true probability sample from the population. The questionnaires were separated into different modules that contained one overall topic and they were sent to the participants every month. It took them about 15 to 30 minutes to accomplish each questionnaire. Every completed questionnaire was rewarded with 10 euros. For this analysis, the modules “Background Variables” and “Personality” were used. The module “Background Variables” was only asked to be answered once because it contained information that did not change over time, such as date of birth. The module “Personality” was always sent to the participants in May and June every year except for the years 2014 and 2015 in which the months changed to November and December.

In total, 16,275 participants were present in the LISS panel. First, 9,479 participants were excluded because they did not fill out the questionnaire in the first wave in 2008. Second, of the 6,796 remaining participants, 5,456 did not fill in all the waves from 2008 to 2022 and were also excluded. Moreover, one inclusion criterion was being at least 16 years old at baseline in 2008. The youngest participant of all participants was one year old which is due to the questions being posed to the households and parents were able to fill it out for them. Since it can be assumed that children did not fill out the investigated questionnaires, they have been excluded. Thus, the overall number of included participants was 1340.

As can be seen in Table 1, the background characteristics of the included participants were different to the ones from the excluded sample. The excluded group scored lower on happiness, higher on neuroticism, was younger and included a higher proportion of women.

Table 1
Descriptives of the Excluded Sample Compared to the Included Sample

	Excluded Sample (N = 5456)		Included Sample (N = 1340)		Statistic
	Mean	SD	Mean	SD	
Happiness	5.07	.96	5.16	.93	F =10.02*
Age in 2008	41.61	16.65	50.92	12.51	F=133.68**
Agreeableness	3.88	.45	3.87	.43	F=.16
Neuroticism	2.58	.62	2.44	.60	F=58.18**
	N (%)		N (%)		
Gender					χ =11.38**
Female	3009 (55.24)		670 (50.00)		
Male	2438 (44.75)		667 (50.00)		

Note. Age 2008 = Age at baseline, Gender had 12 missing values (9 for excluded sample, 3 for included sample), F = Oneway ANOVA, χ = Chi-square test, * = p<.005, ** = p<.001.

Materials

From the two longitudinal study modules of the LISS Data Panel archive, the module "Background Variables" provided information about the participants' years of birth and the module "Personality" was needed for the following characteristics.

To measure happiness, the participants were asked to complete the five-item Satisfaction with Life Scale from Diener et al. (1985) with a seven-point Likert scale ranging from 1 (*strongly disagree*) to 7 *(strongly agree*). A higher mean score indicates a higher level of happiness. One example of the questions is: "I am satisfied with my life". The Satisfaction with Life Scale was used because happiness and satisfaction are describing a similar construct and have been shown to be interrelated wherefore it can be used interchangeably in this analysis (Bieda et al., 2019). Additionally, a scale shows more reliable results than a single item (Diener et al., 2002) and since the LISS Panel only included a single item for exploring happiness, the Satisfaction with Life Scale was chosen. A meta-analysis of 60 studies using the Satisfaction with Life Scale showed an acceptable average reliability of .78 and a correlation coefficient of a minimum of .50 was found which represents a strong correlation (Corrigan et al., 2013). In the present study, Cronbach's alpha had a minimum reliability score of .88 for the years 2008 and 2010 which is good and a maximum reliability score of .91 for the years 2019, 2021, and 2022 which is excellent.

For the variable agreeableness, Goldberg's (1992) Big-Five Factor Markers consisting of ten questions was part of the personality questionnaire. On a five-point Likert scale questions like "Am interested in people" were answered ranging from 1 (*very inaccurate*) to 5 (*very accurate*). The higher the mean score, the higher the level of agreeableness. A previous study by Ypofanti et al. (2015) found good reliability with Cronbach's alpha of .76

which is comparable to the minimum score of .77 for the year 2010 and a maximum score of .83 for the years 2015, and from 2020 to 2022 in this analysis.

Also for the personality trait neuroticism, Goldberg's (1992) Big-Five Factor Markers were used. It consisted of ten questions that were answered on a five-point Likert scale ranging from 1 (*very inaccurate*) to 5 (*very accurate*). The questions were recoded because a high score would have indicated a low level of neuroticism due to the factor originally being Emotional Stability. Hence, after recoding a higher mean score indicates a higher the level of neuroticism. One example question is "Seldom feel blue". In a study determining the reliability and validity of the Big Five Factor Marker with ten items per trait, a good convergent validity with a score of .86 and a good internal consistency of .85 was shown (Donnellan et al., 2006). This is in line with Cronbach's alpha of the present study which has good reliability with a minimum score of .86 for year 2010 and a maximum score of .90 for the years 2015 and from 2019 to 2022.

Analysis

Pearson correlations for happiness and agreeableness as well as happiness and neuroticism were estimated to check the relationship between the variables.

Exploring for Latent Classes

The data were edited and analysed with the statistical software IBM SPSS statistics (Version 28) and by the computer programme R (Version 2022.07.2) using the package latent class mixed models (LCMM, Version 2.0.0). With this package, subjective measures can be analysed, and longitudinal outcomes as well as a model fit can be estimated (Proust-Lima et al., 2017).

The data was checked for normal distribution by examining the skewness and kurtosis. The scores showed an overall normal distribution. First, baseline models were estimated to understand average change over time. Four models were tested with different restrictions. Models with fixed effects are easier to estimate and interpret because the coefficients show the average trend of the data. Models with random effects are more flexible because they consider distributed variances around the fixed effects (Wardenaar, 2020). The first estimated baseline model had a fixed intercept and slope. Second, a model with a random intercept and a fixed slope was modelled. And third, a baseline model with a random intercept and random slope was modelled. Last, to the model with random intercept and random slope, a quadratic effect was added, to test whether this non-linear model fits the data better than a linear model.

The following fit indices were used for selecting the most optimal baseline model. The Akaike Information Criterion (AIC) shows a lack of fit of the data to the model and considers the complexity of the model which is why a smaller value of the AIC is preferred. The Bayesian Information Criterion (BIC) is also a criterion for model selection and just like the AIC, the lower the value, the better (Chakrabarti & Ghosh, 2011). Both are likelihood-based methods, but AIC rather chooses more complex models whereas the BIC selects simpler models (Brownlee, 2020). For selecting the best model with n classes, the entropy and Integrated Complete Data Likelihood (ICL) were used as primary indicators. The entropy determines the quality of the classification in which a number closer to one indicates better quality (Yeşilyaprak, & Boysan, 2015). The ICL considers the BIC while correcting for the entropy. It has been shown to perform better than the BIC alone in estimating latent classes (Biernacki et al., 2000). As an additional indicator, the percentage of class distribution was considered. Small classes (e.g. less than 5%) are not desired because they do not represent the sample (Nasserinejad et al., 2017). Class membership probability is related to the entropy and indicates the probabilities of individuals being assigned to the class which is most closely related to the individual’s trajectory. The higher the probability, the better the model (Kamp Dush et al., 2008).

After estimating the most optimal baseline model, a new model was sequentially tested by adding an extra class to the baseline model and comparing the fit to the previous model. First, two classes were tested on model fit compared to the baseline model. Then, three classes were tested and the process of adding additional classes to the previous model was continued until the most optimal fit was reached. This comparison ensured finding the most parsimonious model explaining between-subject variability in within-subject trajectories of change.

Participant Characteristics and Class membership

A multinomial logistic regression with two steps was used to determine the predictive value for being assigned to a class with a certain characteristic. The assumptions for a multinomial regression were checked by linearity, outliers, independence, and no multicollinearity. The odds ratio and 95% confidence interval were calculated as well. In the first step, the determinants age, agreeableness, and neuroticism were added. In the next step, the intercept of the baseline score of every participant was added to the previous regression with the participants' characteristics to examine whether adding this led to changes in the model fit and different findings for the predictors.

Results

Data from the included sample with 1340 participants showed different background characteristics than the excluded sample. The included sample was older, happier, less neurotic, and more evenly distributed in regard to gender compared to the excluded sample. The level of agreeableness was not significantly different (Table 1).

Pearson correlations between happiness and agreeableness were lowest in wave ten .07, $p = .041$, and highest in the last wave .19, $p<.01$. Pearson correlations for happiness and neuroticism were lowest in wave eleven -.45, $p<.01$ and highest in the third wave -.34, $p<.01$.

Model Fit

To decide which model is the most optimal baseline model explaining the average trajectories of happiness, fixed and random intercept and slope models were compared. Comparing the four baseline models displayed lowest fit indices (AIC=37326.70, BIC=37357.90) for the random intercept and random slope baseline model. As can be seen in Table 2, adding a quadratic effect to the model with random intercept and random slope presents the lowest fit indices (AIC=37301.43, BIC= 37337.83). This means that a non-linear model with random coefficients describes the happiness trajectory best compared to the other models tested. Even if the difference in the fit indices is small, it makes the squared model the best performing latent growth baseline model. The intercept of the chosen baseline model was $M = 5.23$, $SE = .03$, $p < .001$ and had a small negative slope $M = -.02$, $SE = .005$, $p < .001$. This means that the average trajectory of happiness decreased slightly over time and is therefore changing to a small extent.

Next, to the baseline model with random intercept and slope with a quadratic effect, an additional class was added and the fit indices of the model with two classes were compared to the baseline model (Table 2). The two-class model performed better evaluating the ICL (34283.49) compared to the baseline model (ICL = 37337.83). To check for the best fitting number of classes, another class was added, and the three-class model (ICL = 34080.89) was compared to the model with two classes (ICL = 34283.49). Due to the improved fit indices, a four-class model was added and checked for fit indices afterwards. The increased ICL value (34123.99) as well as the small percentage of participants being represented in one trajectory of the four-class model (2.09%) led to deciding for the three-class model which had the most optimal fit indices.

Table 2

Fitness Statistics of Possible Baseline Model and Latent Class Analysis

	Loglik	AIC	BIC	entropy	ICL	%class1	%class2	%class3	%class4
Fixed effects	-28245.02	56496.04	56511.64						
Random intercept	-19371.29	38750.59	38771.39						
Random intercept&slope	-18657.35	37326.70	37357.90						
Random.intercept&slope_Q	-18643.71	37301.43	37337.83	1.00000	37337.83	100.00			
Class 2	-18337.17	36698.34	36760.74	0.71694	34283.49	18.28	81.72		
Class 3	**-18142.68**	**36319.37**	**36407.78**	**0.68646**	**34080.89**	**68.06**	**17.39**	**14.55**	
Class 4	-18104.39	36252.78	36367.19	0.69199	34123.99	65.97	17.16	14.78	2.09

Note. Loglik = log likelihood, AIC = Akaike Information Criterion, BIC = Bayesian Information Criterion, ICL = Integrated Complete Data Likelihood, entropy = measure for classification quality, %class = percentage of participants assigned to the class.

Change trajectory classes

As can be seen in Table 3, the three classes showed a good average class membership probability (>.80). The first class (68.06%), *stable high happiness*, had a high level of happiness in 2008 (intercept) which is the first wave (*M*= 5.60, *SE* = 0.03, *p* = .001), no significant slope (*M* = -0.00, *SE* = 0.01, *p* = 0.87) and no quadratic effect (*M* = 0.00, *SE* = 0.00, *p* = .47). This means that the majority of the sample reported relatively high levels of happiness which remained stable over 14 years of waves.

The second class (17.39%), *happiness decrease,* started moderately compared to the other two classes (*M* = 5.08, *SE* = 0.09, *p* = .00), showed a small negative slope (*M* = -0.29, *SE* = 0.02, *p* = .001) and a small quadratic effect (*M* = 0.02, *SE* = 0.00, *p* = .001). This means that some participants generally experienced a decrease in happiness over the 14 years. But the trajectory is not linear, meaning that participants became happier again in the last few waves which is represented in a U-shaped change pattern (Figure 1).

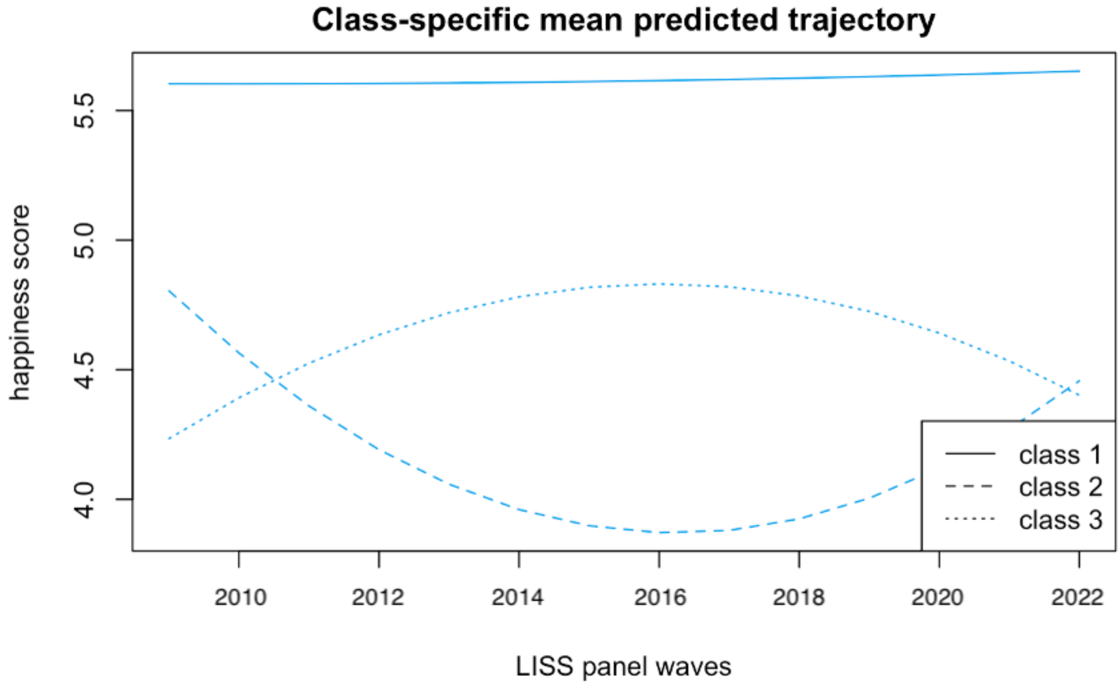
Class three (14.55%), *happiness increase,* had the lowest level of happiness in the beginning compared to the other two classes (*M* = 4.05, *SE* = 0.13, *p* = .00), a low positive slope (*M* = 0.19, *SE* = 0.02, *p* = .001) and a small quadratic effect (*M* = -0.01, *SE* = 0.00, *p* = .001). In other terms, some participants reported being less happy in the first waves which increased over time but decreased again, not following a linear trajectory and depicting an inverted U-shaped pattern.

Table 3
Latent class characteristics for happiness

class	number N (%)	class prob	intercept M (SE)	slope M (SE)	quadratic M (SE)
1 stable high happiness	912 (68.06)	.88	5.60 (.03)*	-.00 (.01)	.00 (.00)
2 happiness decrease	233 (17.39)	.87	5.08 (.09)*	-.29 (.02)*	.02 (.00)*
3 happiness increase	195 (14.55)	.81	4.05 (.13)*	.19 (.02)*	-.01 (.00)*

Note. * = p< .000, sig. = significant, class prob. = average class membership probability.

Figure 1
Plot of Mean Predicted Trajectory of Three Classes



Predicting Class Membership

The first class with *stable high happiness* was used as a reference category for the multinomial regression analysis (Table 4).

Including the predictor variables to a model intercept only benefited the fit between the model and data significantly, χ^2 (6, N = 1337) = 225.71, Nagelkerke R^2 = .19, p <.001.

Participants assigned to class 2 *happiness decrease* are more likely to be younger (β = .02, *SE* = 0.01, *p* = .005, OR = 1.02, 95% CI [1.01, 1.03]) and to score higher on neuroticism (β = 1.67, *SE* = 0.14, *p* < .001, OR = 5.33, 95% CI [4.02, 7.06]) compared to the reference class *stable high happiness*. Participants assigned to class 3 *happiness increase* are also more likely to score higher on neuroticism (β = 1.35, *SE* = 0.15, *p* < .001, OR = 3.86, 95% CI [2.89, 5.14]) compared to the reference class.

In a second regression, when adding the participants' class intercepts to the predictor variables, the model fit increases even more, χ^2 (8, N = 1340) = 639.36, Nagelkerke R^2 = .47, p < .001. It shows that this model can explain more variation than the previous model.

Participants assigned to class 2 *happiness decrease* are more likely to be younger (β = .02, *SE* =.01, *p* = .003, OR = 1.02, 95% CI [1.01, 1.03]) and to score higher on neuroticism (β = 1.38, *SE* = .16, *p* <.001, OR = 3.99, 95% CI [2.94, 5.43]) and less likely to score high on satisfaction at baseline (β = -1.19, *SE* =.11, *p* <.001, OR = .30, 95% CI [0.25, 0.38]) compared to the reference group. Participants assigned to class 3 *happiness increase* are more likely to score higher on neuroticism (β = .66, *SE* = .18, *p* <.001, OR = 1.93, 95% CI [1.35, 2.76]) and less likely to score high on satisfaction at baseline (β = -2.01, *SE* =.13, *p* <.001, OR = .14, 95% CI [0.10, 0.17]) compared to the *stable high happiness* class.

Table 4
Overview of Class Membership Prediction of Two Regressions

		B	SE	Sig	OR	95% Confidence interval Lower Bound	Upper Bound
Regression 1							
Class 2							
	Intercept	-37.99	11.99	.002			
	Age	.017	.01	.005	1.02	1.01	1.03
	Agreeableness	-.30	.18	.089	.74	.52	1.05
	Neuroticism	1.67	.14	<.001	5.33	4.02	7.06
Class 3							
	Intercept	-4.61	12.87	.72			
	Age	.00	.01	.975	1.00	.99	1.01
	Agreeableness	-.18	.19	.341	.84	.58	1.21
	Neuroticism	1.35	.15	<.001	3.86	2.89	5.14
Regression 2							
Class 2							
	Intercept	-37.41	12.88	.004			
	Age	.02	.01	.003	1.02	1.01	1.03
	Agreeableness	.01	.20	.981	1.01	.69	1.47
	Neuroticism	1.38	.16	<.001	3.99	2.94	5.43
	Class intercept	-1.19	.11	<.001	.30	.25	.38
Class 3							
	Intercept	-6.81	15.96	.670			
	Age	.01	.01	.420	1.01	.99	1.02
	Agreeableness	.18	.23	.433	1.19	.77	1.86
	Neuroticism	.66	.18	<.001	1.93	1.35	2.76
	Class intercept	-2.01	.13	<.001	.13	.10	.172

Note. Class 1 as reference group, B = regression coefficient, SE = standard error, df = degrees of freedom, Sig. = significance, OR = Odds Ratio, Regression 1 = regression without class intercept, Regression 2 = regression with class intercept.

Discussion

The purpose of the study was to gain a better understanding of long-term changes in happiness in the Dutch population and its’ possible predictors. The stability of happiness is a long-investigated topic with varying results over the years (De Jonge et al., 2016; Lucas & Donnellan, 2007; Yap et al., 2014). In the present study, average change trajectories of happiness within and between persons were modelled. The differences in change trajectories between participants could be explained with three separate classes. One class remained stable whereas the other two classes displayed changes in happiness over time. The classes further differentiated on neuroticism, and age, but not on agreeableness.

Understanding the Change Trajectories of Happiness and Predicting Class Membership

The happiness of the overall sample in the present study decreased slightly over the period of 14 years. Findings from a previous longitudinal study of the Dutch population also show small changes in happiness by means of a rise in happiness (De Jonge et al., 2016). Even though the trend is not the same, the happiness trajectory from both studies is displayed as being relatively stable, with no significant fluctuations. When comparing the mean score of happiness of the present study to previous studies of the Dutch population in which the Satisfaction with Life Scale was used, this sample had a higher average score of 5.2 instead of the average score of about 4.7 from the study of Lehmann et al. (2015). To explain the difference, it should be considered that the majority of the sample in this study followed a *high stable happiness* trajectory whereas there were two lower-scoring classes. The mean score of the high-scoring class is above 5.0 whereas the other two classes score below 5.0. Therefore, it can be assumed that the Dutch population is not per se happier than investigated before, but the majority of high-scoring people raised the average score. Nevertheless, the scores of the class probability are high with a score of above .80 which confirms that the classes are valid and supports the stability of the results.

One underlying reason for the imbalance in class distribution in the present study might be participants' characteristics: age, as well as the personality trait neuroticism, have been shown to predict following a specific change trajectory. Participants in this sample with lower age had an increased likelihood of being assigned to the *happiness decrease* class which means that younger people rather show a reduced level of happiness and a U-shaped change pattern. This subsequently means that in early adulthood they experience a lower level of happiness which increases again after some years. A decrease in happiness of 18 to 29 years old was observed in a previous study (Vera-Villaroel et al., 2012) and supports this investigation. Looking back at the research that described a low level of happiness in middle-aged people (Helliwell et al., 2012), our findings seem to move up the U-shaped pattern to younger people. Even though the findings can be explained by literature and the class membership probability is significant, the odds ratio being around one implies that effects of age being a predictor for the *happiness decrease* class are not strong. Since the mean age of the included sample was 51 years compared to the mean age of the excluded sample, which was 42 years, a smaller number of young participants was included in the analysis subsequently leading to a smaller percentage of participants being assigned to the *happiness decrease* class.

In regard to neuroticism, the study results are in line with previous literature stating that scoring high on neuroticism predicts scoring lower on happiness (DeNeve & Cooper, 1998; Diener, 1998; Hentschel et al., 2017; McCrae & Costa Jr, 1991). In this context, it might be that neurotic people are not assigned to the *stable high happiness* class, but to the *happiness decrease* class or *happiness increase* class because having anxious and pessimistic traits, which is common for people with a neurotic tendency (Costa Jr & McCrae, 1992), seem to inhibit scoring high on happiness. Nevertheless, the two lower scoring classes have two different trajectories of change, and neurotic people can be assigned to either of them which indicates that there seems to be an additional factor impacting the level of happiness. Besides the participants' characteristics, literature has described that life events make a difference in the level of happiness (Hentschel et al., 2017). Especially events that have an impact on daily life seemed to make a difference in the level of happiness. Sheldon and Lucas (2014) concluded that there is an interaction between life events and genetic factors. More concretely, genetic factors create some kind of stability in long-term happiness which interacts with environmental conditions. Therefore, depending on genetics, environmental conditions and the interplay, happiness can be stable or changing. This subsequently means for neurotic people that life events could have an impact on either following the *happiness decrease* trajectory or the *happiness increase* trajectory.

The most mentionable life event affecting everyone's life during the data collection of the present study was the COVID-19 pandemic (Pancholi, 2020). It caused restrictions in daily life as well as worries about health and finances ("Zwischen Lockdown und Lockerung*:"*, 2021). Therefore, a decrease in happiness in every participant could be expected from 2020 onwards. This was also observed in a study by Veenhoven et al. (2021) in which happiness declined in the Netherlands after 2020. Against expectations, the data of this study did not show a downward trend which could be explained by the pandemic. The only decrease in happiness was observed in the *happiness increase* class from 2016 onwards which does not correspond to the time when the pandemic started. A possible reason for the life event to not impact the level of happiness could be the time of the year when the data was collected. The questionnaires were always (except for 2014 and 2015) sent to the participants in the summer. The summers in the Netherlands were mostly restriction free whereas in winter the regulations were stricter ("Restriction free summers, lockdown winters in Cabinet's long-term Covid Plan: Report", 2021). This would explain why the pandemic did not have a significant impact on the level of happiness in the Dutch population at the point of measurement.

Strengths and Limitations

Previous studies that investigated long-term happiness examined the population as one class and the overall changes of this class. The benefit of the present study is that differences within and between participants were explored. This allows a better insight into the stability of happiness as well as possible underlying predictors determining the changes. Additionally, data from 14 years were used, which gives elaborate insights into the changes in happiness over more than a decade. Having multiple measurements over several years generates valid results in terms of determining changes in happiness (Yap et al., 2014). Besides the strengths of a long period, the large sample size of 1340 included participants seems at first to be a good representation of the population.

However, even though the sample size was large, the results cannot be generalized to the entire population of the Netherlands because the participants' characteristics deviate from the participants that were excluded before the analysis. When considering the score of happiness, for example, it is higher in the included sample compared to the excluded participants which might mean that the sample is biased. Choosing only participants that completed all waves might indicate that the group has differences in characteristics or differences in health. People with mental illnesses are less perseverant than mentally healthy people (Fernández-Mondragón & Adan, 2015) which makes it less likely that people with mental illnesses filled out all questionnaires over the time span of 14 years. Hence, if the other participants were included in the analysis, the happiness trajectories as well as the level of happiness might have changed. Another limitation is that there might have been better models to display the change as only the linear and quadratic models were compared in this analysis. Non-linear effects can be explained by more complex alternative models like the Gompertz model which has been shown to perform best in a previous study in which eleven models were compared (Narinc et al., 2010).

Directions for Future Research and Implications

In order to be able to generalize the findings to the Dutch population it is necessary to make a data imputation procedure to receive more reliable results in the analysis (Zhang, 2016). In the current study, the excluded sample was different from the included sample in terms of background characteristics. In the future, additional participants could be included in the analysis by adding participants that have only missed completing a small number of waves. Based on the differences between excluded and included participants, it can be assumed that considering more participants from the LISS panel might have led to a more heterogeneous sample which is more representative of the Dutch population. An alternative idea to increase the number of participants for upcoming waves would be to keep participants motivated to take part. This could be done by increasing the reward every time they have completed a questionnaire, for example, receiving 5€ for the first and 7€ for the second questionnaire and so on (Moss, 2022).

Even though these directions can be followed in the future for extending the findings from the present study, the current results also lead to practical implications that can be tackled from now on. The present study showed that having a neurotic tendency increases the likelihood of being less happy and following an unstable trajectory. This insight can be used to create a programme which is adjusted to the subgroup of people scoring high on neuroticism. Creating an intervention specifically focussing on neuroticism is most effective to elicit improvements in psychological therapy for neurotic people (Sauer-Zavala et al., 2017). A concrete intervention which has been shown to be effective to increase happiness in long-term for high-scoring neurotics is continuously writing about the best possible self (Ng, 2016). It could be considered to contact participants who scored high in neuroticism and offer them a psychological intervention programme. Targeting this subgroup might lead to an increased level of happiness in people scoring high on neuroticism which might be influential for their happiness change trajectory.

Conclusion

Despite the limitations, the results of the present study suggest that there is not one universal happiness trajectory, but multiple. The personality trait neuroticism and age seem to predict the change trajectory of happiness. Hence, subgroups of the population should be considered in the future when creating happiness interventions.

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