# Exploring Happiness Trajectories in the Dutch Population: Latent Class Analysis and the Impact of Demographic Factors

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## Abstract

*Background:* Researchers have long been interested in the topic of happiness, yet there is a research gap in understanding long-term happiness changes and trends among the Dutch population. Given the focus on quality of life and mental health in the Netherlands, understanding longitudinal happiness changes and their influencing factors is crucial. *Objective:* This paper examines 14-year happiness trends within the Dutch population, identifies latent classes, and investigates the influence of age, income, gender, and education on these classes at a subgroup level. *Method:* Using LISS panel happiness survey data from 2008 to 2022, repeated ANOVA tests were conducted to analyze happiness change trends. Latent Growth Modeling was employed to explore class trajectories, and a two-step Multinomial Regression Analysis assessed the influence of age, gender, income, and education on class membership. *Results:* The findings indicate a slight decline in happiness over time, year accounting for 0.4% of the observed variance. Four distinct classes emerged: Stable High, U-shaped, Stable Medium, and Inverted U-shaped. Age, gender, income, and education each played a role in determining class categorization. *Discussion:* This study provides insights into happiness changes over time, and the influence of age, income, gender, and education on happiness classifications. Understanding these classes informs targeted policies and programs to reduce happiness disparities among different groups. These findings contribute to existing happiness literature and support evidence-based strategies for improving the happiness of these subgroups and the overall population's happiness.


Key words: Happiness; Latent Growth Model Analysis; LISS Panel; Dutch.

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## Introduction

While discussions on what brings happiness have existed since ancient Greek times (Ryan & Deci, 2001), there is still much to explore regarding long-term changes in happiness specifically within the Dutch context. There is still a big study gap when it comes to knowing how happiness changes over time in the Netherlands (Smith & Easterbrook, 2020). The Netherlands consistently ranks high in the World Happiness Report, making it intriguing to understand their high levels of happiness and its trends (Helliwell et al., 2022). Studying happiness trends in the Netherlands helps the cross-cultural understanding of happiness by identifying happiness fluctuations during a period of time and their underlying reasons (Headey et al., 2010; Smith & Johnson, 2021).

In addition to investigating happiness trends, exploring latent classifications of happiness is an interesting field of research. Latent classes are groups or categories of individuals or items within a larger population characterized by shared patterns of responses or characteristics (Lazarsfeld & Henry, 1968). Previous studies have investigated happiness latent classes, but little is known about the specific classes that could emerge within the Dutch population over an extended period (Bergman et al., 2019). Studying latent classes of happiness in the Dutch population enables the identification of distinct groups of individuals with similar happiness experiences and trajectories, and understanding the unique challenges and needs of different classes (Clark et al., 2008). Longitudinal happiness studies enable researchers to investigate both the stability, change, and influencing factors of happiness across time (Headey et al., 2021).

Moving from the population level to sub-group level, while factors such as personality traits (DeNeve & Cooper, 1998), self-esteem (Baumeister et al., 2003; Orth & Widaman, 2012), socioeconomic status (Pinquart & Sörensen, 2001), age (Stone et al., 2010; Diener & Chan, 2011), income (Aknin et al., 2012; Bonicatto et al., 2021), gender (Huang & Yang, 2022), and education (Nikolaev & Rusakov, 2015) have been extensively studied in relation to happiness, less attention has been given to examining how these factors interact within the context of latent classes and their implications for happiness. It is vital to investigate how age, gender, income, and education affect membership in distinct happiness classes to address this research gap and shed light on the relationship between demographic characteristics and happiness classes. This understanding can provide useful insights into the intersectionality of these aspects and their impact on overall happiness outcomes (Luhmann et al., 2012). It could aid in determining if certain age groups, genders, income brackets, or levels of education are more likely to fall into certain happiness classes (Weller et al., 2020). This can reveal the vulnerability and strength of the different classes (Moreno-Agostino et al., 2020). With these insights, targeted interventions, policies, and support systems may be developed to fulfill the specific needs of different groups, hence improving the welfare of society (Weller et al., 2020).

*Happiness Change Over Time*

When examining the happiness change over time, it is crucial to differentiate between population-level happiness and subgroup-level happiness. Nationally, the Dutch population ranks fifth in overall happiness among 156 countries (Helliwell et al., 2022). Longitudinal studies utilizing data from the Dutch Household Panel Survey and the Dutch General Social Survey suggest that happiness fluctuates in the short term but generally remains stable in the long term (Huijts et al., 2014; Huinink &

Schneider, 2019). Additionally, research has highlighted the positive impact of factors such as economic growth, social support, and freedom on national happiness levels (Helliwell et al., 2020; Deaton & Kahneman, 2010). In the pursuit of enhancing happiness, researchers aim to uncover factors that could elevate happiness at both the population and sub-group levels (Diener, 2000). However, this pursuit operates under the assumption that happiness can be improved (Lucas & Donnellan, 2007). Studying how happiness changes over time in the Dutch population is essential because it assists policymakers in evaluating the effectiveness of their policies and the overall happiness of the population (Oswald et al., 2010; Clark et al., 2018).

The data used in this study spans from 2008 to 2022, encompassing a substantial period marked by worldwide and local occurrences, economic fluctuations, and sociocultural changes. First, the 2008-2009 global financial crisis hit economies globally, including the Netherlands. This economic downturn affected employment, income, and financial well-being (Edey, 2009). Economic recessions can cause stress, instability, and job loss, which can affect happiness levels in the population level (Di Tella et al., 2010). Secondly, technology has advanced rapidly in the previous decade. Tech advancements have changed social connectivity, job relations, and information availability (Brynjolfsson, 2009). Technology and well-being research shows that these changes can affect happiness (Brynjolfsson & McAfee, 2014). Finally, the study period includes the COVID-19 pandemic in 2020. The pandemic has altered daily routines, mental and physical health, economic instability, and social interactions (Brooks et al., 2020). Studies have demonstrated that the pandemic negatively impacts well-being, in turn can affect Dutch populational happiness (Wang et al., 2021).

In conclusion, the overall happiness within a population usually exhibits stability. Fluctuations in happiness could potentially be linked to external macro-level events. As a result, the anticipation of changes in Dutch population happiness levels gains support when the data timeframe is considered alongside the significant events that have happened during that period.

*Exploring Latent Classes*

Beyond predicting overall happiness changes in the Dutch population, exploring latent classifications of happiness offers a way to uncover and understand distinct patterns and variations in individuals' experiences at a more specific subgroup level (Weller et al., 2020). Latent class analysis (LCA) identifies hidden population subgroups based on shared traits or patterns (Clogg, 1988). Grouping people into classes deepens population understanding and uncovers characteristics of each group (Schreibe, 2017). The study by Han and Hong (2011) utilized data from the Korean Retirement and Income Study to investigate happiness classifications among Korean adults aged 50 and above. Through Latent Class Analysis, the study identified three classes of happiness (low, moderate, and high). Specifically, one class with consistently high happiness (stable high class), one with consistently low happiness (stable low class), and one with moderately stable satisfaction (Han & Hong, 2011).

*Class Membership Prediction*

While a lot of research has been done on the relationship between demographics and happiness, less attention has been dedicated to understanding the factors that lead to class membership within identified latent classes, as well as what those factors mean for overall happiness. Age, gender, income, and education are some of the most important demographic factors that influence happiness (Diener and Oishi, 2005; Lucas, 2007; Clark et al. 2008). However, the findings from these studies show mixed results, requiring careful interpretations. Building on this notion, research uncovered a U-shaped age-happiness relationship, characterized by high happiness in early adulthood, a dip in mid-life, and a rise in late adulthood (Blanchflower et al., 2023). However, some studies suggest consistent levels of happiness throughout life (Deaton et al., 2010; Chan & Diener, 2011). Transitioning to gender differences, research yields mixed results. While some studies indicate higher reported happiness among women, others find no significant differences or even a recent decline in female happiness relative to males (Stevenson & Wolfers, 2009; Hori & Kamo, 2018). The relationship between income and happiness is also complicated. The renowned Easterlin Paradox suggests that increasing income does not proportionally raise happiness. (Easterlin & O'Connor, 2020). However, other research has indicated a positive relationship between income and happiness (Deaton, 2008; Stevenson and Wolfers, 2008; Sacks, Stevenson, and Wolfers, 2013). On the other hand, some studies argue that while an increase in income initially boosts happiness, once income surpasses a threshold of $75,000, its impact becomes less significant (Deaton and Kahneman, 2010). Regarding education, there is a consensus that individuals with higher levels of education tend to report higher levels of happiness (Helliwell et al., 2020). However, there are also contradictory findings suggesting either a negative or insignificant correlation between education and happiness (Clark & Oswald, 1996; Green et al., 2011).

In summary, understanding how demographic factors, such as age and income, influence the happiness classifications enhances our comprehension of societal well-being and dynamics. This understanding helps policymakers, researchers, and social welfare professionals to strategically target interventions and allocate resources effectively, thereby contributing to improve happiness in the societal level.

*Current Study*

Building on the literature review, this study aims to investigate happiness changes in the Netherlands from 2008 to 2022, with a focus on addressing several important questions. Firstly, is there a change in the happiness levels of the Dutch population during this 14-year span? This question essentially explores how people's happiness has evolved over time. Furthermore, are there distinct patterns of happiness classes that might exist within the Dutch population? This question aims to reveal subgroups representing different happiness experiences. Lastly, do age, gender, income, and education influence an individual's likelihood of belonging to specific happiness classes? This investigation helps understand the connection between these demographic traits and happiness classifications.

## Method

### *LISS Panel*

The Longitudinal Internet Studies for the Social Sciences (LISS) Panel is a long-term socioeconomic data gathering project that aims to observe changes in participants' lives and provide insights into Dutch families and society. Demographics, personality, mental health, physical health, income, and other data areas are included in the project.

### *Participants*

Recruitment process involved random selection of 10,150 Dutch addresses, followed by mailing letters and informational brochures about the study. A 10-minute phone call or a brief in-person interview was done to determine the appropriateness of participation, and the procedure included an evaluation of internet connectivity. Those who consented to participate confirm their participation either online or by a confirmation card. It is worth noting that the figure 10,150 refers to residential addresses rather than the number of participants; multiple people living at the same home may participate as different participants. In the end, a total of 20043 participants were recruited.

Participants received monthly module questionnaires, which took between 15 and 30 minutes to complete and they had a three-month timeframe to complete each module. Completion of each module resulted in a 10-euro incentive. Personality and background variables datasets from 2008 to 2022 were downloaded for this study from the LISS Panel website (https://www.lissdata.nl/).

*Exclusion criteria*

Participants under the age of 16 in the first wave in 2008 were excluded, as well as those who did not complete the happiness survey item at the first wave in 2008 were excluded.

The Longitudinal Internet Studies for the Social Sciences (LISS) Panel is a comprehensive long-term socioeconomic data collection project aimed at tracking changes in the lives of participants and providing insights into Dutch families and society. The project encompasses a wide range of data domains, including Demographics, Personality, Mental Health, Physical Health, Income, and more.

*Measurement*

Happiness was measured using a single survey question: "On the whole, how happy would you say you are?" This question was taken from the European Social Survey, which used a 10-point scale ranging from 0 (totally unhappy) to 10 (totally happy).

*Demographic variables:*

Age was calculated by subtracting participants' year of birth from the year of the first wave of data collection (2008). Gender information was self-reported, with participants selecting from three categories: 1) Male, 2) Female, and 3) Other. Income data were collected through participants' self-reports of their total gross monthly income in Euros. Education level was collected based on participants' responses indicating their highest educational diploma.

*Data Analysis*

Data analysis was conducted using both SPSS and R-studio. To explore the change in happiness over time, the data set was prepared with only "ID" variable and 14 waves of happiness scores. A repeated ANOVA was done to assess overall changes in happiness over time.

For the second research question, exploring latent class in the data set, Latent Class Analysis was performed using the LCMM package (Proust-Lima et al., 2017) in R-studio. Firstly, four baseline models were tested: (1) models with fixed intercept and slope, (2) models with random intercept, (3) models with random intercept and slope, and (4) models with random intercept and slope with a quadratic effect. The best baseline model was chosen based on the AIC (Akaike Information Criterion), BIC (Bayesian Information Criterion), Loglik (log-likelihood) and ICL (Integrated Completed Likelihood) values. AIC and BIC are measures that balance model complexity and goodness of fit, with lower values suggesting a better fit (Schreiber, 2017). Loglik value shows how well the model explains the data, with higher values indicating a better fit (Schreiber, 2017). ICL is a latent class analysis fit indicator that considers both model fit and classification accuracy, with lower ICL value suggests better model fit (Bertoletti et al., 2015). Once the optimal baseline model was established, an additional class was added to the baseline model, and the fit of each subsequent model was compared to the previous one. This process repeated until seven classes were generated. When interpreting results, comparing ICL, entropy, and BIC values is important.  Entropy is a measure that indicates whether or not people are correctly assigned to latent classes (Bergman, 2019). Higher values of entropy suggest a more accurate overall class classification (Bergman et al., 2019). The ICL indicator is the BIC corrected for entropy, lower values suggest a better match for ICL indicator (Wang et al., 2017).

Lastly, a two-step Multinomial Logistic Regression analysis was conducted to explore associations between independent variables (age, gender, income, and education) and happiness class membership over a 14-year period. In the initial step, the assumptions of linearity, independence, and absence of multicollinearity were checked. The VIFs were computed to evaluate multicollinearity, with all values found to be within acceptable range. The first step of multinomial logistic regression, the independent variables (age, gender, income, and education) were regressed against happiness classes without including the happiness intercepts. In the second step of multinomial regression, the intercept representing the happiness score in 2008 was added because a two-step approach allows for a more structured and in-depth exploration of these complex research questions.

## Results

### *Happiness Trends*

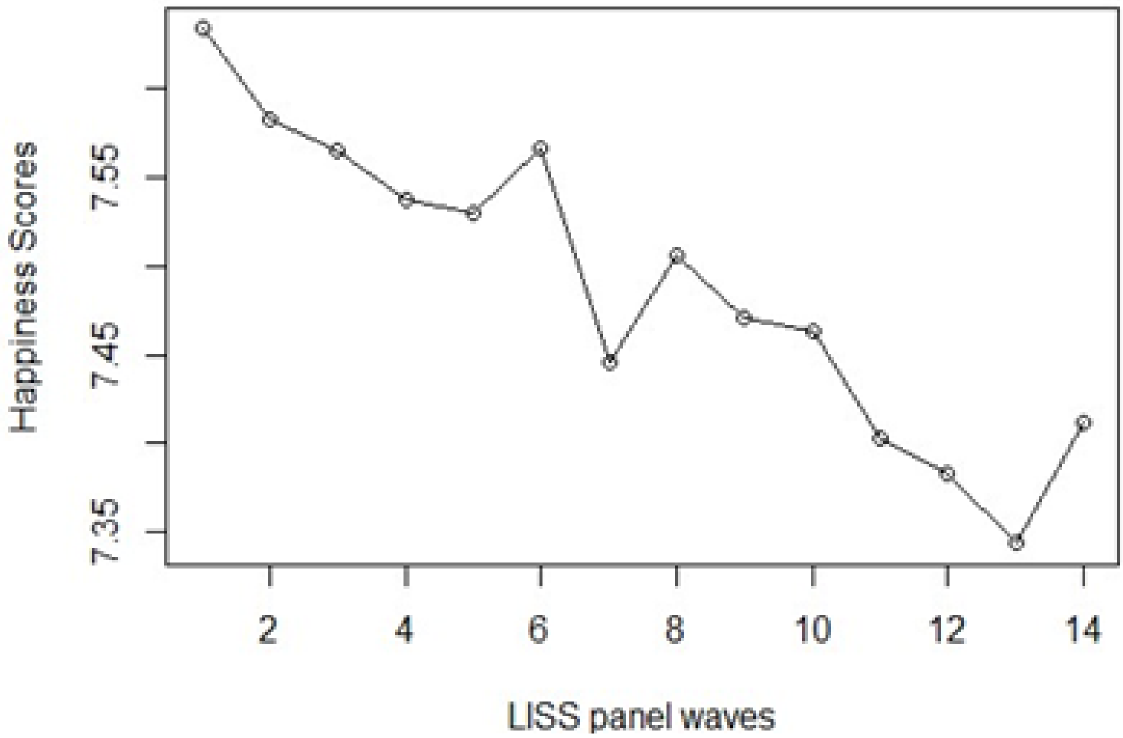
The repeated ANOVA test demonstrated a significant effect of year on happiness levels ($F$ (9.08) = 12.778, $p < .001$). However, the effect size is small, the generalized eta-squared of 0.004 suggests that year explains only a small proportion of happiness scores. Figure 1 depicts the overall change in happiness from 2008 to 2022.

### *Latent Class Analysis*

Among the four baseline models, model 4 (Random intercept and slope with quadratic effect) is the best fit baseline model. It demonstrates the lowest values for AIC, BIC, ICL1 and ICL2. Table 1 shows the baseline model fit indices. Figure 2 shows the happiness means per year alongside the predicted values from the quadratic model. The plot demonstrates that the model predicts the observed data points well, suggesting it is a good fit in terms of prediction accuracy. This further supports the selection of the quadratic model as the optimal model for analyzing the link between time and happiness levels.

***Figure 1***

*Overall change in Happiness in 14 years from 2008 to 2022*




Latent Class Analysis indicated that the improvement in the ICL value stopped at the four classes (gm4), indicating that further additional classes did not contribute significantly to explaining the data. Moreover, the four class model exhibited a satisfactory entropy value of 0.70, indicating a relatively high degree of classification certainty. Further, the AIC and BIC values displayed similar patterns across the different models. This suggests that the complexity added by including more classes does not necessarily lead to substantial improvements in model fit. Based on these considerations, a Latent Class Analysis model comprising four distinct classes was deemed to be the most suitable fit for the given data. Figure 3 depicts predicted trajectory based on happiness scores between 2008 to 2022.

***Table 1***

*Baseline model fit indices for fixed intercept and slope, random intercept, fixed slope, random intercept, random slope, and random intercept, random slope, quadratic effect*

| Model | Loglik | AIC | BIC | ICL1 | ICL2 |
|---|---|---|---|---|---|
| 1 | -152744.7 | 305495.5 | 305518.6 | 305518.6 | 305518.6 |
| 2 | -141150.3 | 282308.7 | 282339.4 | 282339.4 | 282339.4 |
| 3 | -140784.9 | 281581.7 | 281627.9 | 281627.9 | 281627.9 |
| **4** | **-140751.4** | **281516.8** | **281570.7** | **281570.7** | **281570.7** |

***Figure 2***

*Predicted vs observed scores of happiness in the quadratic model*

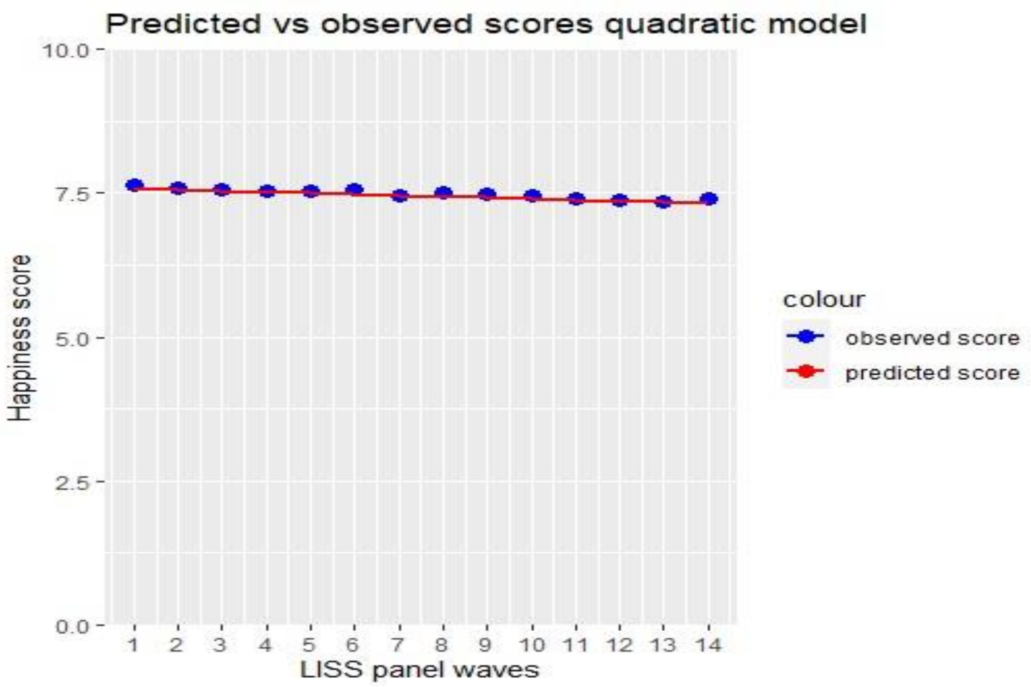



**Figure 3**

*Class specific mean trajectory for Happiness between 2008 and 2021*

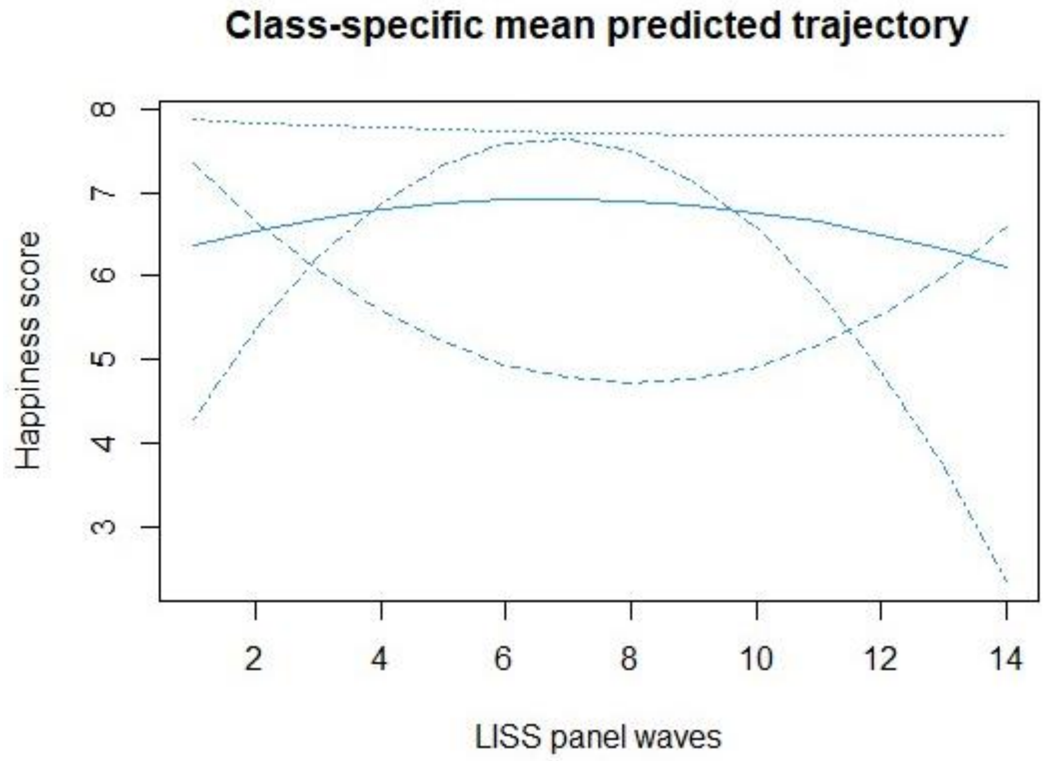



Table 2 summarizes information on the specifics of the happiness trajectories for each class. In the four-class model, Class 1, further referred to as "*Stable High*" is the largest class with 972 individuals, comprising 88.67% of the cases. The class probability for this group is 0.89, indicating a very high likelihood of belonging to this class. This class shows a significant baseline happiness level (Intercept = 7.81, p < .001) with a negative linear trend (β1 = -0.02, $p < .001$) over time, accompanied by a curvilinear pattern (β2 = -0.07, $p < .001$).

Class 2, further referred to as "*U-Shaped*" class. It comprises 74 individuals, representing 6.95% of the total valid cases. The class probability for this group is 0.77, indicating a good chance of belonging to this class. This class shows an elevated initial happiness level (Intercept = 7.10, p < .001), followed by a significant decrease (β1 = -0.05, $p < .003$) and an upward curve (β2 = -0.02, $p < .009$).

Class 3, "*Stable Medium*", consists of 35 individuals, accounting for 3.24% of the total population. The class probably is .82 indicating participants has a strong probably belonging to this class. This class has a starting happiness score of (Intercept = 6.27, p < .001), and while the slope (β1 = 0.002, *p* < .68) showed minimal change, the quadratic effect (β2 = -0.007, *p* < .14) was not statistically significant.

Class 4, "*Invert U-Shaped*" has the smallest sample size, with only 12 individuals accounting for 1.12% of the total population. The class probability for this group is 0.65. This class exhibits a lower baseline happiness (Intercept = 4.33, p < .001), a non-significant downward trend (β1 = -0.09, *p* < .23), and non-significant curvature (β2 = -0.12, *p* < .32).

***Table 2***

*Information on the specifics of the happiness trajectories for each class*

| Class | N | Prob | Intercept | Slope (β1) | Quadratic (β2) |
|---|---|---|---|---|---|
| 1 Stable High | 972 (88.67%) | .89 | 7.81(<.001) * | - .02(<.001) * | - .07 (<.001) * |
| 2 U Shaped | 74(6.95%) | .77 | 7.10(< .001) * | - .05 (.003) * | - .02 (.009) |
| 3 Stable Medium | 35(3.24%) | .82 | 6.27(<.001) * | .002(.68) | - .007 (.14) |
| 4 Invert U-Shaped | 12 (1.12% ) | .65 | 4.33(<.001) * | - .09(.23) | - .12 (.32) |

*Two step multinomial Regression*

The two-step multinomial logistic regression analyses were conducted to examine the factors influencing happiness within three different classes: Stable Medium, U-shaped, and Invert U-shaped. The reference category for comparison was the Stable High class.

*First step Multinomial Logistic Regression (Without happiness intercept):*

Compared to the reference group, age (OR = 0.099, B = -.008, p < .01, 95% CI [0.982, 0.997]) in stable medium class showed a significant negative effect. This means that for every one-unit increase in age, the odds of belonging to the stable medium class decreased by 0.8%. In other words, as individuals in this class get older, they are less likely to belong to the stable medium class. Income (OR = .517, B = -

.66, *p* <.001, 95% CI [1.000, 1,000]) demonstrated a negative relationship between income and belonging to this class. However, the CI of 1.000 - 1.000 suggests that there is no meaningful variability in the effect estimate, meaning income has no impact on the class membership prediction in the stable medium class. Although gender (OR = 1, B = .00, p < .001, 95% CI [0.421, 0.634]) indicates that there is no statistically significant association between gender and belonging to the stable medium class. The CI suggests the odds of belonging to this class are not significantly different for male or female. Education (OR = 0.848, B = -0.165, p < .001, 95% CI [0.786, 0.915]). This indicates that a one-unit increase in education was associated with a 16.5% decrease in the odds of belonging to the Stable Medium class.

Compared to the reference group, age in the U-shaped class (OR = 0.982, B = 0.018, p < .001, 95% CI [0.974, 0.967]) was significantly associated with this class. A one-unit increase in age was linked to a 1.8% decrease in the odds of belonging to this class, indicating that as individuals get older, they are less likely to be classified in this group. Income (OR = 1.000, B = 0.000, p < .001, 95% CI [1.000, 1.000]) implies that there is no association between income and likelihood of belonging to the U-shaped class. An odds ratio of 1 indicates that the odds of the outcome occurring are equal across different levels of income. The confidence interval [1.000 - 1.000] further suggests that the estimated effect size is not statistically significant. This outcome indicates that income is unlikely to be a significant determinant of the U-shaped class. Gender did not show a significant impact on class membership in the U-shaped class (OR = 0.435, B = -0.832, p > .05, 95% CI [0.326, 0.581]). Education demonstrated a notable association with class membership (OR = 0.908, B = -0.033, p < .001, 95% CI [0.823, 1.002]). For each unit increase in education, individuals experienced a 3% decrease in the odds of belonging to this class.

**Table3**

*Multinomial logistic regression analyses on variables that potentially influence happiness*

| | Stable Medium | | | U-Shaped Class | | | Invert U- Shapped class | | |
|---|---|---|---|---|---|---|---|---|---|
| Variables | OR | B | CI | OR | B | CI | OR | B | CI |
| *MNLR without happiness intercept* | | | | | | | | | |
| Age | .099 | -.008** | 0.986-0.997 | 0.982 | -0.018*** | 0.974-0.991 | 0.967 | -0.033*** | 0.952-0.982 |
| Income | .517 | -0.660*** | 1.000-1.000 | 1.000 | 0.000*** | 1.000-1.000 | 1.000 | 0.000** | 1.000-1.000 |
| Gender | 1.000 | 0.000*** | 0.421-0.634 | 0.435 | -0.832 | 0.326-0.581 | .458 | -.723** | .307-.768 |
| Education | 0.848 | -0.165*** | 0.786-0.915 | 0.908 | -0.033*** | 0.823-1.002 | .768 | -.264** | .644-.916 |
| *MNLR with happiness intercept* | | | | | | | | | |
| Age | .999 | -.001 | 0.993 - 1.006 | .994 | -.006 | 0.984 - 1.003 | .974 | -.009 | 0.974 - 1.008 |
| Income | 1.000 | .000*** | 1.000 - 1.000 | 1.000 | .000*** | 1.000 - 1.000 | 1.000 | -.009* | 1.000 - 1.000 |
| Gender | .720 | -.329* | 0.553 - 0.936 | .754 | -.283 | 0.516 - 1.101 | .861 | -.009 | 0.861 - 3.449 |
| Education | .924 | -.079 | 0.846 - 1.010 | 1.048 | .047 | 0.931 - 1.179 | .835 | -.009 | 0.835 - 1.271 |

*CI = 95% confidence interval, OR = odds ratio, MNLR = multinominal logistic regression analysis.*

*The reference category is Class 3 Stable high class.*

**=p<.05, **=p<.01, ***=p<.001*

Compared to the reference group, age in the Invert U-shaped class (OR = 0.967, B = -0.033, $p < .001$, CI: 0.952 - 0.982) showed a significant negative effect. This indicates that as individuals within this class age, their likelihood of belonging to this class decreases. The influence of income (OR = 1.000, B = 0.000, $p < .01$, CI: 1-1) was not statistically significant in determining membership in the Invert U-shaped class for happiness. Additionally, gender displayed a noteworthy negative effect (OR = 0.458, B = -0.723, $p < .01$, CI: 0.307 - 0.768), indicating that being female is associated with a higher probability of belonging to this class compared to the Stable High class.

*Second step Multinomial Logistic Regression (With happiness intercept):*

Age, income, and education are not significantly associated with class membership across all three classes after adding the happiness intercept. Gender (OR

= 0.720, B = -0.329, $p < .05$, CI: 0.553 - 0.936) shows a significant influence on class membership with being female is associated with a lower probability of belonging to stable medium class compared to males.

**Discussion**

The first research question was to examine happiness changes, and the results indicate that year has a significant but small effect on happiness levels. The second research question was to identify possible latent classes, results revealed four distinct classes based on participants' happiness trajectories over time. The third research question investigated the influence of age, income, education, and gender on class membership, with findings suggesting that age, income, and education initially impact class membership but lose significance when adding the happiness intercept. Notably, gender remains a significant factor, with females showing a lower likelihood of belonging to the stable medium class compared to males when compared to the reference class.

*Happiness Changes*

This study explored changes and trends in Dutch happiness at both the population and sub-group levels from 2008 to 2022. The results indicated the lowest happiness score observed in 2021, accompanied by a slight decline in happiness levels within the Dutch population. The year alone explained only 0.4% of the variance in happiness levels. One possible reason for this minor decline over the 14-year period could be attributed to the data collection timeframe. The first data wave labeled as 2008 was actually completed in the third or fourth quarter of 2007 and transcribed onto the internet in 2008, hence the label. The same applies to the data labeled for the year 2021, representing people's happiness levels in 2020. Figure 1 visually shows that the happiness score in 2008 was slightly lower than in 2007 yet remained high at above 7. This observation could be due to the Dutch economy's resilience through its flexible labor market and low unemployment (Masselink & van den Noord, 2009). This finding echoes Diener's systematic review (2015), indicating that overall population happiness generally remains stable, with minor fluctuations linked to macroeconomic factors like unemployment rates. Additionally, the lowest happiness score among the 14 waves was noted in 2021, reflecting the happiness scores in 2020, the year of the Covid-19 outbreak. The COVID-19 pandemic might have impacted people's happiness levels due to restrictions, uncertainties, and health concerns, which increased stress, anxiety, and disrupted daily routines (Mohring et al., 2020). Moreover, results indicated the year alone explaining only 0.4% of the variance in happiness levels. This suggests that factors beyond the year alone influence the minor decline in happiness levels. Building on these interpretations, future research could comprehensively explore the underlying reasons for the slight fluctuations in Dutch population happiness, such as societal dynamics or lifestyle shifts. Furthermore, a more in-depth investigation of the effects of COVID-19 on happiness could provide valuable insights.

The second aim of this study was to explore if distinct class trajectories exist within the gathered happiness data. The results revealed that four classes exist in the data set, namely, stable high levels of happiness trajectory, U-shaped happiness trajectory, stable medium level of happiness trajectory, and lastly invert U-shaped happiness trajectory. The identification of four distinct classes reveals that not all Dutch individuals experience consistently high happiness levels over time. Each trajectory represents unique patterns of change. The stable high happiness trajectory encompasses nearly 89% of cases, reflecting a sustained high happiness level over the 14-year period. Consistent with previous findings, the people in the Netherlands tend to be generally happy (Helliwell et al., 2022; Boelhouwer, 2021). Economic research suggests link between high happiness levels may be linked to the country's sustained high GDP (Boelhouwer & van Campen, 2013), which is further supported by the consistent economic growth since 1974, ranking 17th globally (Economic Forum, 2020). Additionally, factors such as low corruption, quality governance, and freedoms contribute to elevated population happiness levels (Clark et al., 2019). Building on this, the "happiness pie" model developed by Lyubomirsky et al. (2005), which attributes variance in happiness to a set point (50%), deliberate activity (40%), and circumstances (10%), suggests that people on different happiness trajectories may adopt different strategies in response to life events and engage in different life activities within the same macroenvironment. The observed classes and associated trajectories give helpful insights into the population's different well-being profiles, displaying different trends in happiness experienced by individuals over time. These diverse patterns indicate the presence of subpopulations with unique well-being patterns, which has crucial implications for developing tailored interventions that cater to the individual needs of these groups while taking their unique happiness trajectories into consideration. For instance, for the stable high trajectory group, strategies to maintain and enhance existing sources of happiness might be beneficial. On the other hand, for the U-shaped and inverted U-shaped groups, interventions could focus on assisting individuals during transitions or providing support during challenging periods.

The third research question was to explore how age, gender, income, and education affect the above-mentioned class membership. Using the stable high class as reference class, the Multinomial Regression Analysis without intercept revealed that age has a significant effect on all three classes, as individuals age, their probability of belonging to all three classes decreases compared with the reference class. This suggests that advancing in age is associated with a decreased likelihood of following these three happiness trajectories. This finding is in line with findings from Moreno-Agostino et al.'s study (2020), which suggest that there are no unitary trajectories for older population. Future studies might examine how happiness trajectories evolve and develop over even longer periods of time. Additionally, investigating how people move between different classes of happiness trajectories and if there are certain turning points or life events that affect these transitions. Gender is not significantly associated with class membership in both the stable medium and U-shaped classes. However, females are more likely to belong to the invert U-shaped class. This suggests that women in this class experience a low initial level of happiness, followed by an improvement and then a decline. These findings align with Stevenson & Wolfers (2009), highlighting a potential gender-specific pattern within this trajectory. It shows the unique life transitions and challenges commonly faced by women. On a positive note, gender differences are only observed in the smallest class, indicating good overall gender equality within Dutch society. Research on gender and happiness indicates substantial improvements in women's happiness over the years (Audette, 2019). Moreover, gender equality positively affects both men and women, as enhancing women's happiness does not reduce men's happiness (Audette, 2019). In other words, gender equality elevates societal happiness.  Future research can focus on investigating the specific life transitions or challenges that contribute to the observed happiness trajectory among women in the invert U-shaped class. For example, future research could investigate how marriage and marital changes influence the happiness trajectory of women in the invert U-shaped class. Specifically, how getting married, going through divorce, or experiencing changes in marital status affect the happiness trajectories among women in this group. Identifying and addressing these factors could lead to targeted interventions that support women during challenging periods and improve their well-being. Additionally, utilizing qualitative methods such as interviews or focus groups on future research could provide deeper insights into the subjective experiences and perceptions of individuals belonging to the invert U-shaped classes. Exploring these research directions could potentially uncover underlying factors and mechanisms that contribute to the gender differences observed in happiness trajectories within the invert U-shaped class.

Regarding education, higher levels of education are associated with a decreased probability of being assigned to all three classes compared with reference class, indicating that higher education is linked to lower likelihood of following a U-shaped, invert U-shaped and stable medium happiness trajectory. Building on previous research, higher education has been found to be associated with higher levels of self-reported happiness scores (Araki, 2021; Jongbloed, 2018). This relationship could be associated with better career opportunities, financial stability, or access to resources and support systems (Chen, 2012). It suggests that improving educational opportunities and attainment levels have positive implications for overall happiness and life satisfaction (Nikolaev & Rusakov, 2015). Future research could explore the mediating factors, such as self-efficacy and job satisfaction. that potentially mediate the relationship between education and happiness.

The second step Multinomial Regression Analysis found that, after adding the 2008 intercept happiness score, age, income, and education did not have an impact on class membership across all three classes. Which means the baseline level of happiness in 2008 is a stronger predictor for group classification compared to age, income, and education. This suggests that, the baseline happiness level in 2008 has a lasting influence on their class membership, potentially overshadowing the effects of age, income, and education. However, gender did show a significant effect, indicating that females had a lower probability of belonging to the stable medium class compared to males. It suggests that there is a significant difference in happiness trajectories between males and females, even when controlling for the initial level of happiness in 2008. To gain a deeper understanding of gender and happiness, future research could investigate how different gender roles and social expectations contribute to the gender differences in happiness levels. For example, by adding a questionnaire that explores caregiving responsibilities for children or the elderly within families, comparing the experiences of men and women, and compare how these responsibilities influence their levels and trajectories of happiness.

*Strengths and Limitations*

One strength of the study was its use of longitudinal data from the Dutch population over a 14-year period, allowing for the identification of changes in happiness patterns over time (Tomaszewski et al., 2020; Charles & Carstensen, 2010). Additionally, the research included individuals of various ages, enabling the investigation of age-related happiness and developmental patterns impacting happiness at different life stages (Franssen et al., 2020). The large sample size of 1093 cases enhanced the generalizability of the results and statistical power to detect changes and associations (Johnson et al., 2014). Using data obtained from Dutch households provided representative insights into the specific Dutch population and facilitated comparisons with similar studies in cultural settings. Finally, by employing latent growth modeling, the study accounted for the layered structure of the data, allowing the exploration of background variables influencing happiness (Singer & Willett, 2003) and enhancing the accuracy and reliability of the outcomes.

However, the study had limitations. Firstly, a single self-reported question was used to assess happiness scores, which may be influenced by assumptions, reaction styles, and situational factors when participants answered the question (Diener et al., 2013). Thus, the findings may not fully capture the complexity and multidimensionality of happiness, potentially affecting the reliability of the scores. Secondly, the study only considered age, gender, income, and education as predictors of happiness, neglecting other important factors such as marital status, health, and social support (Lyubomirsky et al., 2005; Diener et al., 1999). Including a broader range of predictors could provide a more comprehensive understanding of the factors influencing happiness. Thirdly, potential confounding variables, including life events and policy changes occurring during the 14-year period, were not considered in the analysis (Lucas & Donnellan, 2011), which could have affected the observed relationships.

## Conclusion

This study provides a comprehensive assessment of changes and trends in Dutch happiness from 2008 to 2022. The result helps our understanding of happiness. While there is a significant effect of year on happiness levels, the effect size is relatively small, emphasizing the need to consider other factors influencing happiness. Furthermore, the identification of four distinct classes provides a deeper understanding of happiness trajectories over time for different groups of individuals. Lastly, the significant influence of gender on happiness trajectories over time emphasizes the importance of considering gender-related factors in understanding happiness differences. This detailed knowledge provides an opportunity for personalized treatments and policies aimed at sustaining and improving happiness based on people's unique trajectories. The findings could aid policymakers and mental health professionals, as they may use this information to develop targeted treatments and strategies that address the unique well-being requirements of different subgroups.

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