Can Money Buy National Happiness? Comparing Economic and Non-Economic Factors on Happiness

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Introduction

Happiness is a complex interdisciplinary construct with a vital role in human life (Bila and Hoian, 2022; Stanislavova and Solovyova, 2023). Despite no strict definition, happiness generally refers to positive emotions (e.g., joy, satisfaction, fulfilment) that shape individual behaviour and societal development (Goetz and Weisfeld, 2024; Grigorieva, 2022; Raul and Velásquez, 2024). Research on happiness is gaining momentum with increasing support for its use as a guide for public policy (e.g., Stiglitz, 2009). However, ongoing debate remains about whether economic or non-economic factors better explain national happiness. Some studies suggest that GDP per capita correlates more strongly with happiness than other factors (Kula et al., 2010). Meanwhile, other research suggests that economic factors alone cannot fully explain happiness, highlighting the need to explore non-economic influences (Gupta, 2023). Thus, this report compares economic and non-economic factors in predicting happiness and argues that happiness, as a multifaceted construct, cannot rely on a few explanatory factors even with high predictive powers.

Data & Analysis Methodology

The data for this report is sourced from the World Happiness Report (WHR), a publication by the University of Oxford in partnership with Gallup and the UN Sustainable Development Solutions Network, examining global and national happiness (Helliwell et al., 2024). The report is based on survey data from over 100,000 people from 165 countries over 19 years. The dataset contains eleven variables, six of which the report's researchers deem explanatory happiness factors: GDP per capita, social support, life expectancy, freedom, generosity, and corruption.

The WHR dataset includes a large representative sample. For example, with data from 165 countries, this dataset can be considered non-WEIRD, thereby minimising the risk of sampling bias. A representative sample enhances the validity of potential analyses by providing a more comprehensive understanding of the complex phenomenon of happiness across different countries and cultures (Ghai, 2021). However, due to the focus of the organisations managing this dataset, only a limited number of variables related to happiness were collected. For instance, the author can investigate only one economic factor (GDP) using six core non-economic variables. This narrow scope limits the author's ability to investigate happiness from an economic perspective.

As noted earlier, economic and non-economic factors influence happiness, yet much research is limited to correlational studies that primarily emphasise economic factors. Therefore, this report aims to answer the core research question: Do non-economic factors predict greater happiness than traditional economic factors? This dataset includes one economic factor, log GDP per capita and eight non-economic factors. The non-economic focus will be on social support, which has significantly influenced national happiness (Helliwell et al., 2024; Liu, 2024).

Hence, a further sub-question for this report is: Does 'social support' predict a higher happiness (i.e., 'life ladder') score than 'GDP per capita'? Two linear regression models will be created to answer this research question:

Model 1: GDP per capita as a predictor of Life Ladder

Model 2: Social support as a predictor of Life Ladder

Data Processing

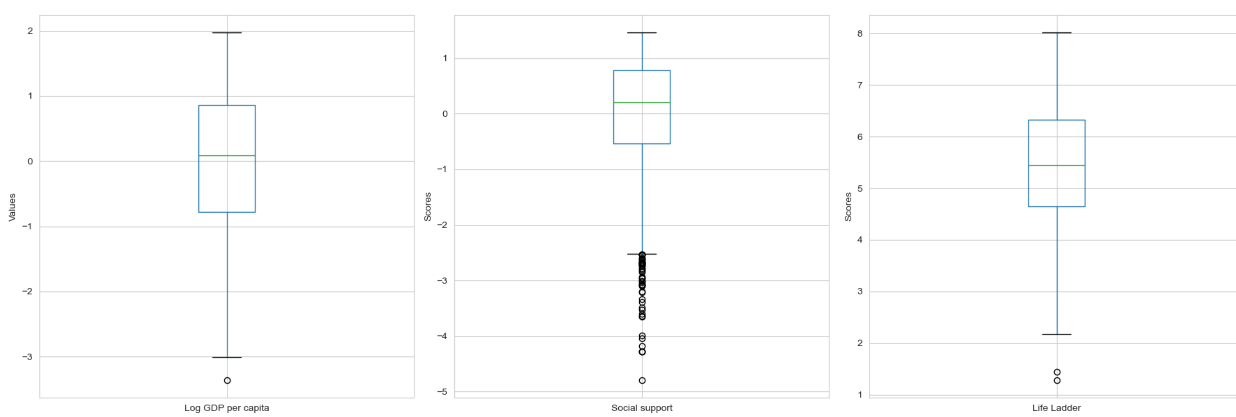
Before analysis, the dataset was checked for missing data, revealing 28 missing instances for GDP per capita and 13 for social support. Mean substitution was used, whereby missing values were replaced with the mean score for each country. After this, countries with missing data (e.g., Cuba, Oman, Somaliland, and South Sudan) were removed (implying no data was present for a variable), reducing the dataset from 2,363 observations from 165 countries to 2,353 observations from 161 countries. Mean substitution was used for its data processing efficiency and ability to retain the sample size to preserve statistical power (Cheung et al., 2024). However, this method reduces data variability as the exact value is applied to multiple observations within each country, potentially introducing bias by making results appear more consistent than they are (Dodeen, 2003). Nevertheless, mean substitution was applied to only 28 out of 2,353 observations, posing a minimal risk of bias.

Descriptive Statistics

The life ladder refers to an individual's evaluation of one's life on a scale from 0 (worst possible life) to 10 (best possible life). All subsequent references to happiness scores relate to this measure. The average happiness score was 5.48 (SD = 1.13), indicating that participants generally rated their lives as neither the best nor the worst. Log GDP per capita is the natural logarithm of a country's GDP per capita, adjusted for population size. The average GDP was 9.40 (SD = 1.15), suggesting this sample of countries has relatively higher economic performance. Social support indicates whether participants believe someone would care for them in their time of need. The average score was 0.81 (SD = 0.12), suggesting this sample of countries reported relatively higher social support. The distribution of responses for all variables can be seen in the boxplots below (Figure 1). To mitigate the sensitivity of linear regression to different scaling, predictor variables were standardised (i.e., $M = 0$, $SD = 1$). Thus, following regression analyses will be based on these new standardised values.

Figure 1

Boxplots of Log GDP per capita (left), Social Support (middle) and Life ladder (happiness; right)



Inferential Statistics

Regression model 1 explored the predictive relationship between GDP per capita and happiness scores. The regression equation was $y = 0.879x + 5.48$. The beta coefficient indicates that for every 1-unit increase in GDP, the happiness score increases by 0.879 units. R^2 posits that this economic factor can explain 61.4% ($R^2 = .614$) of the variance in happiness scores.

Regression model 2 explored the predictive relationship between social support and happiness scores. The regression equation was $y = 0.814x + 5.48$. The beta coefficient indicates that for every 1-unit increase in social support, the happiness score increases by 0.814 units. R^2 posits that this economic factor can explain 52.1% ($R^2 = .521$) of the variance in happiness scores.

Both predictive models were significant ($p < .001$) and thus were used to predict happiness based on new GDP/social support values. Happiness scores of 7.68 and 7.52 were predicted for GDP and social support, respectively, when both standardised predictor values were 2.5. This prediction helps answer the core and sub-research question where the economic factor, GDP, predicted higher happiness scores than the non-economic factor, social support. The predictive relationships and predicted values for GDP and social support are shown in Figures 2 and 3, respectively.

Figure 2

Scatterplot of standardised Log GDP per capita plotted against Happiness scores with a line of best fit and the predicted happiness score (purple cross)

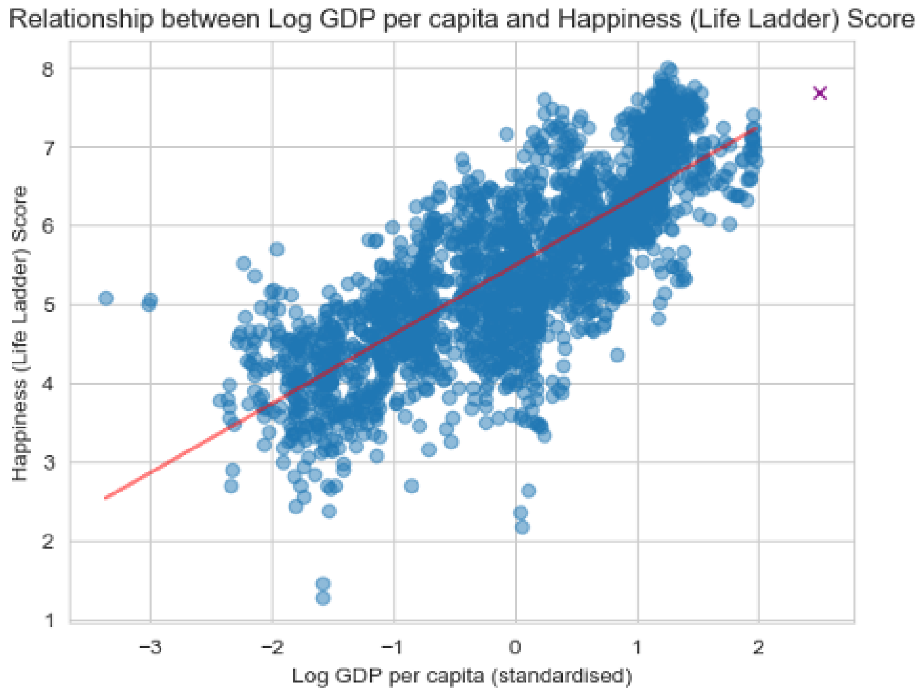
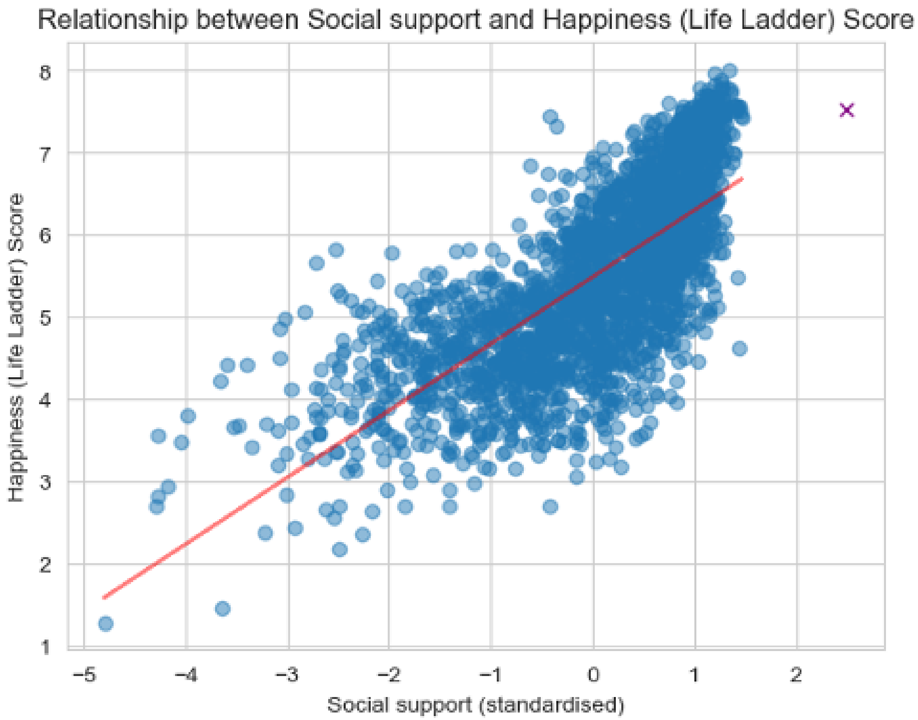


Figure 3

Scatterplot of standardised Social support plotted against Happiness scores with a line of best fit and the predicted happiness score (purple cross)



Reflections

Based on the regression models above, the economic factor, GDP per capita, remains slightly more influential than the non-economic factor, social support, in this analysis. Even though both models were significant, the economic model had a larger beta coefficient than the non-economic model, suggesting a more significant proportion of happiness is gained per unit of the predictor variable. This finding aligns with previous literature, which has reported significant increases in happiness linked to GDP, particularly in low-income countries (Kula et al., 2010; Proto and Rustichini, 2013). However, the latter remained unexplored here due to an absence of information about the national income level in the dataset. Therefore, a future data science project could build on the economic model by comparing countries and using income level as a moderator to assess its impact on happiness predictions. This new model will improve the current model by highlighting additional economic factors beyond the traditional use of GDP (as it was the only available economic factor in the dataset) that may influence happiness. The author's initial exploration of Finland and Malaysia provides a starting point for this project, particularly for data processing (Appendix B).

However, given that the non-economic model also had a significant positive relationship, it further evidenced that GDP is not the sole determinant of happiness. This more nuanced understanding aligns with previous correlational research that also utilised the WHR dataset and found that happiness is a multifaceted phenomenon that cannot be solely attributed to one factor (e.g., Gupta, 2023). This single predictor factor is a limitation of the current model but was employed to isolate the factor to ease the interpretation and comparison of predictive relationships. Hence, a future data science project could implement a multiple regression analysis of multiple non-economic factors within the WHR dataset to provide a more holistic understanding of their collective role in predicting happiness.

This report concludes that while the economic model predicted higher happiness scores, it should not be considered the primary explanatory factor due to the complexity of happiness, especially since the non-economic model was also significant and predicted similar happiness scores. Moreover, since each model explored only one factor for each construct, these results should not be seen as definitive answers to the core question but rather as a partial understanding. Nevertheless, future research should build on these models and explore additional factors to provide a more comprehensive understanding of happiness prediction.

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Appendix A

Core Jupyter Notebook

Appendix B

Additional Jupyter Notebook