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Using machine learning to predict UK and Japanese secondary students' life satisfaction in PISA 2018

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Abstract

Background: Life satisfaction is a key component of students' subjective well-being due to its impact on academic achievement and lifelong health. Although previous studies have investigated life satisfaction through different lenses, few of them employed machine learning (ML) approaches.

Objective: Using ML algorithms, the current study predicts secondary students' life satisfaction from individual-level variables.

Method: Two supervised ML models, random forest (RF) and k-nearest neighbours (KNN), were developed based on the UK data and the Japan data in PISA 2018.

Results: Findings show that (1) both models yielded better performance on the UK data than on the Japanese data; (2) the RF model outperformed the KNN model in predicting students' life satisfaction; (3) meaning in life, student competition, teacher support, exposure to bullying and ICT resources at home and at school played important roles in predicting students' life satisfaction.

Conclusions: Theoretically, this study highlights the multidimensional nature of life satisfaction and identifies several key predictors. Methodologically, this study is the first to use ML to explore the predictors of life satisfaction. Practically, it serves as a reference for improving secondary students' life satisfaction.

KEYWORDS

k-nearest neighbours, life satisfaction, machine learning, PISA, random forest

INTRODUCTION

Well-being and life satisfaction

The multi-dimensional construct of subjective well-being (Llamas-Díaz et al., 2022; Steinmayr et al., 2022) encapsulates the extent to which individuals perceive their lives as desirable, fulfilling, and rewarding (Diener, 1984; Diener et al., 2003). A key component of subjective well-being across countries and cultures is life satisfaction, which represents individuals' overall evaluation of their lives (Antaramian et al., 2008; Diener, 2006).

Importance of well-being

The reason researchers have examined well-being is because life satisfaction serves as an important indicator of individuals' functioning across academic achievement, interpersonal connectedness, and physical health. First, the positive relationship between life satisfaction and health outcomes has been supported by empirical evidence. For example, a 20-year prospective study of Finnish individuals aged between 18 and 64 years revealed a significant correlation between life satisfaction and all-cause mortality (Koivumaa-Honkanen, 2000). In a cross-cultural study sampling 17,246 young adults aged between 17 and 30 years, the association between life satisfaction and health-promoting behaviours appeared to be bidirectional, partly accounting for the relationship between positive subjective well-being and good health (Grant et al., 2009). Robust and reciprocal associations were also found between life satisfaction and a series of mental health problems, such as depression, anxiety disorder, suicidality, alcohol dependence, and substance dependence in a study involving individuals aged 18–35 years (Fergusson et al., 2015).

Well-being and secondary students: Academic achievement

The subjective well-being of secondary school students is particularly crucial to delve into, as this stage is characterized by significant change and flexibility in human development (Steinberg, 2005). Specifically, secondary students' subjective well-being not only shapes their academic outcomes but also has far-reaching implications for their long-term health trajectories (Ng & Huebner, 2015; Patton et al., 2011). Additionally, the secondary school period serves as a pivotal phase in terms of subjective well-being, as this period witnesses the emergence of half of all lifetime mental health problems (Belfer, 2008).

Life satisfaction is a robust predictor of the presence or absence of clinical symptoms and comorbidity. For instance, in secondary students aged around 12.68 years, a significant reciprocal relationship between life satisfaction and cognitive engagement has been evidenced longitudinally (Heffner & Antaramian, 2016). This finding is further corroborated by a study conducted by Lewis et al. (2011), where participants with an average age of 12.64 years demonstrated similar trends. Additionally, life satisfaction has been shown to influence the cumulative Grade Point Average (GPA) and assessment centre exercise ratings of students with a mean age of 20.7 years, even when considering typical predictors of academic achievement like gender and cognitive aptitude (Rode et al., 2005). Furthermore, research with participants aged around 13.07 years underscores that students' life satisfaction is not only intertwined with their academic achievement but also has lasting implications for their health in later life (Ng & Huebner, 2015). This connection was also identified in a study with students aged between 12 and 14 years (Patton et al., 2011).

Most of the previous work regarding the relationship between life satisfaction and variables related to academic outcomes has been based on small and medium sample sizes and looked at a small subset of variables. In the current study, we used a larger data set and a large subset of variables that require techniques that are scalable and yet provide both prediction and explanation of the results. This way, the results could be used to inform both research and practice.

Machine learning techniques: Prediction versus explanation

Integrating predictive and explanatory approaches to scientific inquiry has always been a concern in social science and educational research (Hofman et al., 2021). Historically, most researchers in these fields preferred explanatory methods over predictive methods that focus on forecasting (Yarkoni & Westfall, 2017). In recent years, the application of machine learning (ML) techniques has allowed researchers to focus more on the predictive power of algorithms, while, in some cases, maintaining the explanatory capability of such algorithms. Although the potential of ML for prediction has been unlocked, explaining its operational processes and results in specific domain knowledge contexts remains a challenge. ML is a subfield of artificial intelligence that enables computers to learn automatically from large quantities of data without being explicitly programmed (Kersting, 2018). In the presence of unlimited data, ML algorithms are typically trained and tested on different, large datasets. However, given the typically small sample size employed in most social science and educational studies, ML techniques train different algorithms on a larger partition of the original dataset and compare their predictive performance on a different, smaller partition of the same original dataset. Most ML studies have compared the performance of different algorithms, but few have considered the effect of dataset selection on prediction results.

Statement of purpose

The purpose of this study is to predict secondary students' life satisfaction from individual-level variables using ML algorithms. Specifically, a tree-based model (i.e., random forest) and an instance-based model (i.e., k-nearest neighbours) are developed to predict students' life satisfaction based on data from two countries. The predictive performance of the ML models is explained based on domain knowledge from two perspectives: the operational processes of the algorithms and the characteristics of the datasets. The study poses the following research questions:

1. How well can the two ML models predict secondary students' life satisfaction from individual-level variables?
2. Does the feature importance of predictive variables vary across the countries examined?

CONCEPTUAL FRAMEWORK

Theory-based approach to life satisfaction

In PISA 2018, life satisfaction is defined as an overall evaluation of one's perceived quality of life (Marquez & Long, 2021; Shin & Johnson, 1978). In this regard, life satisfaction serves as a cognitive component of subjective well-being as well as a self-avowal of happiness (Chen et al., 2020; Diener, 1984; Proctor et al., 2009). The bottom-up and top-down approaches have traditionally been the two theoretical approaches to study life satisfaction (Busseri & Mise, 2020; Lance et al., 1989). The bottom-up approach implies that individuals' life satisfaction is dependent upon their experiences and situations in various life domains, whereas the top-down approach regards life satisfaction as an individual difference which is shaped by one's personality (Headey et al., 1991; Steel et al., 2008).

Data-Driven approach to life satisfaction

This study adopted a data-driven approach, which examines students' life satisfaction based on the patterns and relationships emerging from the data. Specifically, the individual-level variables considered include factors related to material resources, social relations, and psychological factors. Following Maslow's hierarchy of needs (Maslow, 1943), material resources are postulated to meet students' physiological and safety needs, social relations cater to their needs for love and belonging, and psychological factors fulfil their needs for esteem and self-actualization. It is important to note that these categories are used solely for organizing and presenting the included individual-level variables in a structured manner, and the analysis is driven by the data rather than preconceived hypotheses or assumptions.

LITERATURE REVIEW

Life satisfaction

Previous research has identified a variety of factors influencing life satisfaction, which span across diverse areas of an individual's life, as highlighted in this section. While the relationship between material resources, including socio-economic and ICT resources, and life satisfaction may seem equivocal (Gilman & Huebner, 1997; Huebner, 1991), certain studies suggest that students with more resources tend to report higher life satisfaction (Ash & Huebner, 2001; Neto, 1993). Notably, ICT resources contribute to positive emotional experiences and support goal pursuit, subsequently leading to higher life satisfaction (Kushlev, 2018).

Social relations, or interactions between individuals, also significantly affect life satisfaction. The quality of relationships with parents, teachers, and peers plays a crucial role in shaping students' life satisfaction. Students with supportive parents and teachers, as well as those experiencing a sense of belonging within their classrooms, often report higher life satisfaction (Dunleavy & Burke, 2019; Gilman et al., 2006; Ortman, 1988). However, it is important to note that negative experiences, such as peer victimization, can considerably decrease life satisfaction (Huang, 2020).

Psychological dispositions, which denote relatively stable inner states, form another significant component that influences life satisfaction. The presence of positive feelings and a sense of meaning in life are tightly connected to higher life satisfaction (Govorova et al., 2020). Moreover, life satisfaction associates with a range of psychological characteristics such as self-efficacy, motivation, achievement goals, attitudes towards competition, and fear (Diseth et al., 2012; Grasseni & Origo, 2018; Moksnes et al., 2019; Salinas-Jiménez et al., 2010; Yılmaz, 2018). For instance, growth mindset interventions could improve life satisfaction among perfectionist students, suggesting a positive relationship between growth mindset and life satisfaction (Chan, 2012).

As mentioned before, relevant studies only examined small or medium samples, with a reduced set of possible predictors of life satisfaction. However, the current study is based on a large publicly available data set with a wide range of variables that have not been examined before in relation with life satisfaction. This required more robust methods that could examine at once a large number of records and a large number of variables, without the theoretical and technical barriers encountered by conventional statistics.

Machine learning

As a subfield of artificial intelligence, machine learning (ML) enables computers to learn automatically from data without being explicitly programmed (Kersting, 2018). ML models are generally more data-driven and unbiased than more classical statistics approaches (Gorostiaga & Rojo-Álvarez, 2016), and they can usually handle missing data without further customization. Supervised ML models make predictions based on labelled data. In recent years, ML models, especially supervised models, have attracted attention in social science and educational research for two main reasons.

First, ML algorithms can achieve high predictive performance, especially when working with large-scale and high-dimensional datasets. For example, Saarela et al. (2016) used an ML approach to predict students' mathematics performance on the Programme for International Student Assessment (PISA) 2012 data. Through training supervised learning models with 53 initial features, their algorithm achieved a classification accuracy of over 95% in identifying the top performers (Saarela et al., 2016). With regard to social cognition, regression-based supervised models exhibited higher accuracy and validity in predicting the personality of 17,622 participants compared to human judgements (Youyou et al., 2015).

Second, some supervised models can also provide information regarding the importance of their input features (i.e., independent or predictor variables) in predicting the response (i.e., dependent) variable. Using sparse regression models, Brow (2019) successfully identified the significant predictors of mathematical literacy for six countries in PISA 2012. Through boosted regression trees, Gabriel et al. (2018) investigated the educational effects of mathematical dispositions using data from the Australian subset of PISA 2012; they further ranked the input features by their relative importance and identified the self-efficacy item as the most influential predictor.

Although ML models have shown great potential in predicting students' cognitive and affective outcomes, most of the existing studies focused on students' academic achievement and career choice, with little attention to their subjective well-being (Dong & Hu, 2019; Mandalapu & Gong, 2019; Puah, 2021; Yeung & Yeung, 2019). Although several studies paid attention to subjective well-being, few of them investigated the effects of student-related variables, such as the teacher support and learning goals (Kaiser et al., 2021; Morrone et al., 2019; You, 2021). Typically, studies sampling students focused on a few specific factors without examining their synergetic effect on well-being (Jaques et al., 2015; Sahdra et al., 2021). To address this gap, the present study employs ML techniques to investigate the synergetic effect of individual-level variables on students' life satisfaction. The term "synergetic effect" denotes the combined impact of two or more variables on an outcome that differs from the sum of their separate impacts. For instance, the combined influence of high self-efficacy and a growth mindset might exceed their separate effects on life satisfaction, suggesting a potential reinforcing interaction between the two variables.

METHODS

Dataset

The Programme for International Student Assessment (PISA) is a triennial survey of 15-year-old students around the world (OECD, 2019) aiming to evaluate students' academic achievement. It also collects extensive data regarding students' demographics, social life, and psychological well-being. The PISA 2018 assessment (2018) includes a well-being questionnaire administered to students for the first time as part of the student questionnaire (OECD, 2019).

Participants

Students from the United Kingdom and Japan were selected as samples of interest for the following reasons. First, the United Kingdom and Japan are geographically different, representing two distinct global regions. The inherent cultural and social differences offered by these separate regions provide a rich comparative backdrop for our analyses. Second, an examination of country-level indices reveals a convergence between the United Kingdom and Japan on several dimensions. As shown in Table 1, some key metrics related to student life and economic development—namely students' academic performance scores, Human Development Index (HDI), and Gross Domestic Product (GDP) per capita—exhibit

TABLE 1 Basic information for the United Kingdom and Japan.

Index	UK	Japan
Country Abbreviation in PISA	GBR	JPN
Average of Students' Academic Test Scores	504	504
Human Development Index (HDI)	0.93	0.92
Gross Domestic Product (GDP) per Capita (in US Dollars)	40,285	39,539

similar averages in both nations. This similarity in fundamental indices, coupled with the geographical and cultural diversity, enhances the analytical potential of the current study. Hence, the selection of these two countries as samples of interest not only enriches the scope of the study but also bolsters the robustness of the analyses and subsequent findings.

As no significant relationship was found between the missingness of the data and any values, it was assumed that the missing values in the sample occurred randomly. In the present study, missing data (<10%) were handled by imputing the series mean. Overall, 13,818 students from the United Kingdom and 6109 students from Japan were included in the analysis. Additional information regarding the missing patterns (Table A1) can be found in Appendix A.

Variables

Life satisfaction

The response variable (i.e., dependent variable) was *Life Satisfaction* derived from the PISA 2018 student questionnaire (OECD, 2018a), representing students' overall evaluation of their perceived quality of life. In PISA 2018, its value was determined by students' self-reported scores ranging from 0 to 10 on the life satisfaction scale (*sample item: overall, how satisfied are you with your life as a whole these days?*).

Individual-level features

The features (i.e., independent variables) were 26 individual-level variables extracted from the PISA 2018 student questionnaire (OECD, 2018a) and well-being questionnaire (OECD, 2018b). Information regarding the included variables is displayed in Table 2. A comprehensive description of these variables, complemented by basic statistics, is available in Tables A2 and A3 in Appendix A.

Although this study emphasizes modelling students' life satisfaction using individual-level variables (i.e., different scores for different students) and there was no explicit intention to prioritize variables associated with either school life or family life during the variable selection phase, it was found that most variables included in this study are pertinent to students' experiences within the school environment. This unintentional concentration on school-related variables resonates with the extensive literature on educational outcomes, frequently highlighting the profound influence of school and district-level factors on student well-being and achievement (e.g., Downey & Condron, 2016).

ML algorithms

Random forest

Random forest (RF) is a non-linear, non-parametric supervised learning technique that utilizes ensemble learning methods to make predictions (Breiman, 1996; Ho, 1995). In brief, the ensemble learning

TABLE 2 Overview of the included variables.

Variable name	Description
Dependent variable	
ST016Q01NA	Life satisfaction
Independent variables	
AGE	Age
ST004D01T	Gender
ESCS	Index of economic, social, and cultural status
ICTRES	ICT resources at home and at school
BEINGBULLIED	Exposure to bullying
EMOSUPS	Parents' emotional support
TEACHSUP	Teacher support
ADAPTIVITY	Adaptation of instruction
BELONG	Sense of belonging
PERFEED	Perceived feedback
TEACHINT	Perceived teacher's interest
PERCOOP	Student cooperation
PERCOMP	Student competition
COMPETE	Attitudes towards competition
ST185Q01HA	Growth mindset
MASTGOAL	Learning goals
WORKMAST	Motivation to master tasks
ATTLNACT	Attitudes towards learning
JOYREAD	Joy/Like reading
RESILIENCE	Self-efficacy
GFOFAIL	Fear of failure
EUDMO	Meaning in life
SWBP	Positive feelings
DISCLIMA	Disciplinary climate
DIRINS	Teacher-directed instruction
STIMREAD	Teacher's stimulation of reading engagement perceived by student

approach combines the outcomes from several ML algorithms to generate a better prediction. The random forest not only outperforms a single decision tree in terms of prediction metrics but also provides information about the feature importance (Grömping, 2009; Sathyadevan & Nair, 2015). The random forest regression algorithm (1) constructs randomized decision trees (i.e., regression trees, as the response variable is continuous) based on the training data; (2) aggregates the performances of a multitude of decision trees (i.e., it takes the average of the individual predictions); and (3) outputs the optimal decision.

K-nearest neighbours

K-nearest neighbours (KNN) is an instance-based learning model that makes predictions based on the similarity measure (Fix & Hodges, 1989). It is also non-linear and non-parametric, and it usually yields good predictive performances (Rajaguru & Chakravarthy, 2019). As a supervised learning algorithm, the KNN regression stores the training instances verbatim and averages the values of k-nearest neighbours (Altman, 1992). It is easy to implement and requires no training time. In this study, KNN is used to solve a regression task (i.e., predicting a continuous response variable).

Rationale behind utilizing two different ML approaches

The two ML approaches in this study, RF and KNN, represent two different non-linear and non-parametric algorithms to predict life satisfaction. RF is an ensemble learning method that combines multiple decision trees. It takes into account complex interactions between variables, making it suitable for capturing the interplay of various factors influencing life satisfaction. Additionally, RF provides measures of feature importance, enabling the identification of key predictors and facilitating result interpretation. On the other hand, KNN excels at capturing localized patterns and is conceptually based on similarity. While it does not explicitly consider interactions between variables, it still offers valuable insights into the similarities among students and their shared characteristics.

In the fields of education and psychology, interpretability plays a significant role when selecting ML algorithms. RF and KNN provide more interpretability compared to other algorithms like neural networks, which are often considered black-box approaches. RF offers interpretability by providing measures of feature importance. This allows researchers to identify the key predictors that contribute to students' life satisfaction. Understanding the relative importance of different variables can help inform decision-making and intervention strategies. KNN offers a straightforward visual interpretation based on similarity. By identifying groups of students with similar individual-level features, researchers may have a better idea of the homogeneity within the dataset, which may further inform targeted interventions and support systems for students. Comparing the two methods allows for an exploration of their respective strengths and weaknesses in capturing the complexity of students' life satisfaction. While prediction accuracy is important, the interpretability of the algorithms allows researchers to look beyond predictions and gain insights into the mechanisms and processes underlying students' well-being. It aligns with the goals of advancing knowledge in the specific domain and improving the transparency of ML studies.

Data preparation

The data preparation procedure was conducted using the IBM SPSS (Version 27) software (2020). First, the student questionnaire data file was downloaded from the PISA 2018 database (OECD, 2019). Second, the data for the UK and Japanese samples were extracted from the SPSS file. Third, the scores for the variables of interest were normalized and the instances with missing values were imputed using series mean. Data normalization is only required by KNN, but both algorithms are trained and tested on the same data; thus, this step needs to be performed on the entire dataset before model training. Then, the pre-processed dataset was exported as comma-separated values (CSV) file and placed in the working directory.

Model development

Both the RF and KNN algorithms were implemented using the *scikit-learn* package (Pedregosa et al., 2011) in *Python* (Van Rossum & Drake Jr, 1995).

Performance metrics

The Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and coefficient of determination (R^2) were used as the performance metrics.

Hyperparameter tuning

Hyperparameter tuning is a process of determining the optimal values of parameters that define the model architecture. In this study, a grid search was used as the hyperparameter tuning method. Grid search is one of the most widely used strategies for hyperparameter tuning (Sanchez et al., 2021). A grid of hyperparameter values was created followed by a series of iterations over each possible combination of specified hyperparameters to build models for the two algorithms. The summaries of the hyperparameters included in the grid search are shown in Tables 3.1 and 3.2.

Feature importance

For RF models, every node in a decision tree represents a condition that tests a particular feature, with the goal of splitting the dataset into two groups with comparable response values. Impurity, a measure of variance, is the criterion by which the optimal split is determined. Thus, it is possible to calculate how much each feature reduces the weighted impurity in a tree while training the model. In a random forest with multiple decision trees, the impurity decrease from each feature is averaged and the feature importance is ranked according to this metric. In this study, the feature importance for each individual-level variable was computed and ranked from high to low. For KNN, all the features are assumed to contribute equally to the prediction.

Nested cross-validation

Nested cross-validation is an enhanced technique utilized in the ML domain to evaluate the model's performance in a more robust manner, particularly when hyperparameter tuning is involved. Cross-validation ensures that the performance evaluation is not biased by the model's exposure to the test data during the tuning process (Kohavi & John, 1995). In a typical k-fold cross-validation procedure, the dataset is partitioned into k equal-sized subsets. One subset is held out as the test set, while the model is trained on the remaining k-1 subsets. This process is repeated k times, ensuring each subset serves as the test set once. The performance measures from these k iterations are then averaged to derive a more comprehensive evaluation of the model's performance. However, when hyperparameter tuning is involved, the k-fold cross-validation approach may inadvertently introduce bias as the hyperparameters may overfit the validation set (Varma & Simon, 2006). To avoid the potential overfitting, nested cross-validation, which involves an outer cross-validation loop for model evaluation and an inner cross-validation loop for hyperparameter tuning, is introduced (Cawley & Talbot, 2010).

TABLE 3.1 Summary of the hyperparameters and their range of values for RF.

Hyperparameter	Description	Values
n_estimators	The number of trees in the forest	10, 50, 100
max_depth	The maximum depth of the tree	None, 10, 20
min_samples_split	The minimum number of samples required to split an internal node	2, 5, 10

TABLE 3.2 Summary of the hyperparameters and their range of values for KNN.

Hyperparameter	Description	Values
n_neighbors	The number of neighbours	3, 5, 7, 9, 11
weights	The weight given to each neighbour	'uniform', 'distance'
p	The power parameter for the Minkowski metric	1: equivalent to using the Manhattan distance
		2: equivalent to using the Euclidean distance

In this study, a nested cross-validation with five outer folds and five inner folds was employed. First, the dataset is split into five outer folds. Subsequently, one of these outer folds is held out as a test set. The inner cross-validation is a standard five-fold cross-validation on the combined remaining four outer folds. This involves partitioning the combined four outer folds into five inner folds, training models on four of these inner folds, and validating the model on the remaining one inner fold. This inner loop is repeated five times, with each inner fold serving as the validation set once. The average performance of these five iterations serves as a performance indicator for a specific set of hyperparameters. This process is conducted iteratively for varying hyperparameter configurations to identify the optimal set that maximizes the model's performance.

Upon determination of the optimal hyperparameters, the model is trained with these settings on all four outer training folds and subsequently validated on the outer test fold that was initially held out. This entire process, encapsulating the inner loop for hyperparameter tuning and the outer loop for model evaluation, is repeated five times, once for each outer fold. The performance measures are then averaged to obtain a more robust estimation of the model's predictive performance. The supporting information including data and code can be found in our Github Code repository.

RESULTS

Model prediction

Random forest (RF)

The results obtained from the RF regression are presented in this section. The mean validation and mean test performance across all five outer folds are reported in Table 4.

K-nearest neighbours (KNN)

The results obtained from the KNN are presented in this section. The mean validation and mean test performance across all five outer folds are reported in Table 5.

In summary, based on the obtained metrics, the results suggest that both the RF regression model and the KNN regression model performed slightly better on the UK dataset compared to the Japan dataset. However, in both cases, there is room for improving the model's ability to account for the variance in the dependent variable. The nested cross-validation process was beneficial in providing a more robust estimation of the model's performance and helped in identifying optimal hyperparameters for the model. A more detailed comparison of the model performances on the data from the two countries can be found in Tables A4 and A5 in Appendix A.

TABLE 4 Mean validation and test performance across five outer folds (RF).

Metrics	Validation					Test
UK						
Outer	1	2	3	4	5	Mean
MSE	0.203	0.205	0.203	0.202	0.203	0.203
RMSE	0.450	0.452	0.451	0.450	0.450	0.451
MAE	0.408	0.411	0.409	0.407	0.409	0.408
R^2	0.189	0.181	0.186	0.190	0.188	0.187
Japan						
Outer	1	2	3	4	5	Mean
MSE	0.213	0.215	0.215	0.215	0.212	0.215
RMSE	0.461	0.463	0.463	0.463	0.461	0.464
MAE	0.430	0.433	0.433	0.434	0.431	0.434
R^2	0.148	0.140	0.141	0.140	0.150	0.138

TABLE 5 Mean validation and test performance across five outer folds (KNN).

Metrics	Validation					Test
UK						
Outer	1	2	3	4	5	Mean
MSE	0.225	0.227	0.225	0.223	0.225	0.224
RMSE	0.474	0.477	0.474	0.473	0.474	0.474
MAE	0.433	0.437	0.433	0.431	0.433	0.433
R^2	0.101	0.091	0.101	0.106	0.100	0.103
Japan						
Outer	1	2	3	4	5	Mean
MSE	0.232	0.234	0.237	0.240	0.233	0.236
RMSE	0.481	0.483	0.486	0.490	0.483	0.486
MAE	0.446	0.448	0.450	0.456	0.447	0.451
R^2	0.072	0.064	0.053	0.039	0.066	0.055

Feature importance

Table 6 displays the top 10 most important features in the United Kingdom and Japan. The highlighted variables, including meaning in life, student competition, ICT resources at home and at school, exposure to bullying, and teacher support, represent shared key features in both countries. Graphical illustrations of the ranking for feature importance are shown in Appendix A (see Figure A1 for the United Kingdom and Figure A2 for Japan).

DISCUSSION

Model prediction

The current study adopted supervised ML techniques to examine the effect of individual-level variables in predicting secondary students' life satisfaction in the United Kingdom and Japan. Compared with the RF model, the KNN model performed worse on the samples from both countries. In

TABLE 6 Top 10 most important features.

Rank	Variable	Description	Variable	Description
	UK		Japan	
1	**EUDMO**	Meaning in life	PERCOOP	Student cooperation
2	WORKMAST	Motivation to master tasks	RESILIENCE	Self-efficacy
3	**PERCOMP**	Student competition	**EUDMO**	Meaning in life
4	**ICTRES**	ICT resources at home and at school	**PERCOMP**	Student competition
5	MASTGOAL	Learning goals	**TEACHSUP**	Teacher support
6	**BEINGBULLIED**	Exposure to bullying	**ICTRES**	ICT resources at home and at school
7	PERFEED	Perceived feedback	**STIMREAD**	Teacher's stimulation of reading engagement perceived by student
8	GFOFAIL	Fear of failure	DISCLIMA	Disciplinary climate
9	BELONG	Sense of belonging	EMOSUPS	Parents' emotional support
10	**TEACHSUP**	Teacher support	**BEINGBULLIED**	Exposure to bullying

Note: Shared key features in both countries are highlighted in light grey. The text marked in bold denotes the top 10 most important features for both countries.

summary, the RF model outperformed the KNN model in predicting secondary students' life satisfaction.

There are several possible explanations. First, the RF model involved a procedure of feature weighting, whereas the KNN model weighed each feature equally when making the prediction. It is always the case that different features contribute differently to the final output. For instance, through investigating the effects of 40 developmental variables, Soares et al. (2019) identified nine significant predictors of life satisfaction in a sample of 503 Portuguese students, within which the overall self-esteem made the largest contribution. In the current study, the RF model calculated feature importance as the mean and standard deviation of impurity reduction accumulating inside each tree. For a particular feature, the higher the feature importance score, the greater the predictive power. In contrast, the KNN model assumed all the features were equally important, which was inconsistent with reality. When making a prediction using the KNN algorithm, the contribution of some of the most important features such as student cooperation and self-efficacy may be underestimated, whereas the contribution of some of the least important features such as age and attitudes towards competition may likely be overestimated. As a result, the KNN model performed worse than the RF model.

Another difference in the two types of models was that the RF model considered the interaction between predictive features, whereas the KNN model treated each feature independently. Students' life satisfaction can be influenced by either a single factor or a combination of several factors (Eid et al., 2008). For example, Aldridge et al. (2020) reported resilience and bullying as mediating factors in the association between school climate and life satisfaction among 6120 Australian students. As the tree-based RF model considered the features sequentially, it is likely to capture some important interactions between features (Denisko & Hoffman, 2018). In contrast, the KNN model computed the similarity measure with all the input features concomitantly, without accounting for the potential interactions between features, consequently leading to lower performance.

In this study, separate ML models were developed based on the data from the United Kingdom and Japan, respectively. Both models performed better on the UK data than on the Japan data, suggesting that the life satisfaction of the UK students may be explained by their individual-level variables to a larger extent than the life satisfaction of the Japanese students.

Cultural orientation may serve as a possible explanation for the difference in prediction performance. Although the concept of cultural orientation is difficult to define precisely, it is often regarded as a critical factor that shapes the content and distribution of individuals' values, beliefs, and behaviours (Gelfand et al., 2007; Schwartz, 2009) and it is intertwined with recurring situations and experiences in human society (Oyserman, 2011). The manifestation of cultural orientation usually takes the form of cognitive orientation or tendency. Among the components of cultural orientation, the most prominent dimension is individualism versus collectivism (Hamamura, 2012). By definition, individualism highlights independence and personal achievement, whereas collectivism emphasizes interdependence and group goals (Triandis, 1995). According to a country-level survey conducted by Hofstede (1980), Western countries (e.g., the United Kingdom, Canada, and Finland) are generally considered more individualistic than Eastern countries (e.g., Japan, China, and Thailand).

Cultural orientation is likely to influence students' life satisfaction in several ways. First, students with different cultural orientations may have different mental representations of life satisfaction. Once students adopt an analytic view towards life satisfaction, they focus more on their unique situations and experiences (Suh, 2000). Therefore, the predictive power of individual-level variables may be stronger for students with an individualistic orientation. Second, culture may influence how students value aspects of their lives when evaluating their overall satisfaction. Students with an individualistic orientation place more importance on personal feelings and goals, whereas students with a collectivistic focus pay more attention to the support system and social norms (Diener & Diener, 1995; Suh et al., 1998). As individuals with different cultural orientations were likely to have different attribution and reasoning styles (Markus & Kitayama, 1991; Nisbett et al., 2001), students from the United Kingdom may pay more attention to the features related to their own lives, whereas students from Japan may think more about the macro-level variables when evaluating their life satisfaction.

An alternative explanation was that there were more available instances in the UK sample than in the Japanese sample. The predictive performance of ML models has shown to be influenced by the sample size (García et al., 2020; Ng et al., 2020). With a larger sample size, the model may be more likely to capture the complex patterns embedded in data. Therefore, the ML models developed from the UK data outperformed those developed from the Japanese data.

Feature importance

This study revealed that the feature importance of predictive variables varied across the countries examined. The difference in the patterns of feature importance has several potential explanations. First, individuals may view life satisfaction differently according to their cultural orientations. In PISA 2018, life satisfaction was defined as individuals' overall evaluation of the perceived quality of life based on their chosen criteria (Shin & Johnson, 1978). In this sense, the conceptualization of life satisfaction may vary across different cultural contexts. For example, the UK students may consider life satisfaction as a state, which was decided by multiple aspects of one's life, whereas the Japanese students may regard life satisfaction as a dimension of mental health (Haybron, 2007; Maddux, 2018). As a result, the features vary in terms of relative importance, consequently influencing the structure and performance of the regression models.

Second, individuals with different cultural orientations may emphasize different aspects of their lives when evaluating the overall satisfaction. For example, students with an individualistic cultural orientation may give more importance on personal initiative, whereas students with a collectivistic cultural orientation may focus more on environment and adaptivity (Diener & Diener, 1995; Suh et al., 1998). As a consequence, some self-oriented features, such as meaning in life and motivation to master tasks, were more predictive in the UK data. In contrast, some environmental-oriented features, such as student cooperation and teacher support, were more predictive in the Japanese data.

Third, individuals' sensitivity to specific features may vary across different cultural orientations. According to the self-determination theory (Ryan & Deci, 2000), students' life satisfaction would be enhanced by fulfilling three major needs: competence, autonomy, and relatedness. Given that individualism highlighted independence and collectivism emphasized interdependence (Triandis, 1995), the UK students may be more sensitive to their needs of autonomy, whereas the Japanese students may be more sensitive to their needs of relatedness. As a result, the UK students weighed meaning in life and motivation to master tasks more, whereas the Japanese students attached more importance to student cooperation and competition.

Limitations

The inability to account for racial and ethnic diversity in the United Kingdom and Japan presents a limitation in this study. Given the lack of such information in the dataset, the findings may not uniformly apply to all racial and ethnic groups within these countries. Therefore, the generalizability of the results may be compromised. Future research should consider incorporating demographic data, such as race and ethnicity, to enhance the depth and applicability of the findings. Additionally, this study examined individual-level variables, which were included in the PISA 2018 survey, without considering the school-level and country-level factors. To gain a comprehensive understanding of students' life satisfaction, future studies could include more types of variables. Another significant limitation of this study arises from its cross-sectional design, which precludes the inference of causal relationships. Although this study identifies several predictors of life satisfaction using ML models, it is important to note that these models illustrate correlations, not cause-and-effect relationships. Moreover, all the data used in this study were collected through questionnaire surveys. Therefore, self-reported measures may be prone to social desirability bias and response bias (Demetriou et al., 2015), consequently impairing the reliability and validity of data. Thus, future research could focus on more diverse populations and employ complementary measures to provide convergent evidence.

Contributions and implications

The current study offers insights into educational psychology research from a theoretical, methodological, and practical perspective.

From a theoretical perspective, this study contributes to the research on students' subjective well-being, expanding knowledge and enhancing the understanding of life satisfaction among secondary students through the use of ML methodologies. Using ML models has underscored the multi-dimensional nature of life satisfaction, demonstrating that it is influenced by a wide range of individual-level factors such as meaning in life, ICT resources, and teacher support. Therefore, future theoretical models of life satisfaction among secondary students could be enriched by incorporating these diverse factors for a holistic understanding of the subject. Specifically, this study acknowledges the role of culture as a vital lens for interpreting life satisfaction (Oishi, 2006; Oishi et al., 2009). Although empirical research has brought to light substantial differences in life satisfaction across cultures (Jebb et al., 2020; Senik, 2014; Suh & Choi, 2018), these studies have predominantly focused on adult participants and macro-level factors such as national income level (Diener & Biswas-Diener, 2002). In contrast, while individual-level variables associated with students' life satisfaction have been explored (Gilman & Huebner, 2003; Proctor et al., 2009), these studies seldom consider the potential interactions among these variables. This study samples students in secondary school, which is a crucial phase for establishing the foundations of lifelong well-being (Salmela-Aro & Tynkkynen, 2010), and it investigates the impact and interplay of various individual-level variables on students' life satisfaction. In particular, this study emphasizes the importance of diversity among students in ML research.

From a methodological perspective, this study highlights a gap in the literature and it is the first to use ML methods to investigate students' life satisfaction. The use of ML models in this study represents a significant shift towards more data-driven methods in the field of psychological research. This study shifts the focus of ML-based prediction from academic achievement to subjective well-being, which is a critical antecedent of individuals' lifelong health and career success. This approach allows for a richer understanding of the intricate patterns in the relationship between predictors and the response variable, life satisfaction. As such, the study compares and contrasts two ML models aiming to predict secondary students' life satisfaction using two different datasets of PISA 2018. In addition, it examines the predictive performance of two ML models based on domain knowledge from two perspectives: the operational processes of algorithms and the characteristics of datasets. These models have the potential to illuminate the importance of different predictors and their complex interrelationships, thus paving the way for more nuanced and complex analyses. In addition, the use of both RF and KNN regression models allows for the comparison of different ML algorithms, contributing to the ongoing methodological dialogue in the field. Thus, this innovative approach not only deepens our understanding of students' life satisfaction but also offers a valuable demonstration of how to incorporate ML models into subjective well-being research.

From a practical perspective, the findings from this study provide useful insights for practitioners working in fields related to students' subjective well-being. The identified predictors of life satisfaction could guide school administrations in observing and nurturing students' subjective well-being. Additionally, understanding the key predictors of life satisfaction can inform the design of targeted interventions and programmes. For instance, initiatives that focus on enhancing individuals' sense of meaning in life, improving ICT resources, or facilitating teacher support could potentially enhance life satisfaction. During this process, some social–psychological interventions can be conducted according to the actual needs of students (Brady et al., 2018; Cohen, 2006; Kizilcec & Cohen, 2017).

Furthermore, the insights gained from this research could inform educational policies that aim to create a more conducive learning environment to enhance students' life satisfaction.

CONCLUSIONS

This study showed that both ML models yielded better performance on the UK data than on the Japan data, with RF outperforming KNN for both countries. Notably, several factors were identified as significant predictors of secondary students' life satisfaction, including meaning in life, student competition, teacher support, exposure to bullying, and ICT resources. Using ML techniques, the findings of this study contribute to the understanding of life satisfaction, providing practical insights for improving secondary students' subjective well-being.

AUTHOR CONTRIBUTIONS

EP contributed to the conceptualization, investigation, methodology, data analyses, software, writing original draft, and writing—critical review and editing; MC contributed to the conceptualization, funding acquisition, supervision, investigation, methodology, and writing—critical review and editing.

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CONFLICT OF INTEREST STATEMENT

The authors have no conflict of interest to report.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available in PISA 2018 database at https://www.oecd.org/pisa/data/2018database/. The code can be found in a GitHub repository at https://github.com/echozpan/Using-ML-to-Predict-Life-Satisfaction (2023).

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APPENDIX A

TABLE A1 Number and per cent of missing cases.

Country	UK		Japan	
Variable name	**Missing case**	**Missing per cent**	**Missing case**	**Missing per cent**
ST016Q01NA	887	6.4%	79	1.3%
AGE	0	0	0	0
ST004D01T	0	0	0	0
ESCS	925	6.7%	54	0.9%
ICTRES	474	3.4%	20	0.3%
BEINGBULLIED	1669	12.1%	195	3.2%
EMOSUPS	1290	9.3%	148	2.4%
TEACHSUP	582	4.2%	45	0.7%
ADAPTIVITY	857	6.2%	94	1.4%
BELONG	1127	8.2%	117	1.9%
PERFEED	751	5.4%	92	1.5%
TEACHINT	751	5.4%	80	1.3%
PERCOOP	2026	14.7%	258	4.2%
PERCOMP	1606	11.6%	187	3.1%
COMPETE	904	6.5%	89	1.5%
ST185Q01HA	855	6.2%	92	1.5%
MASTGOAL	1089	7.9%	113	1.8%
WORKMAST	1197	8.7%	110	1.8%
ATTLNACT	796	5.8%	72	1.2%
JOYREAD	710	5.1%	46	0.8%
RESILIENCE	1103	8%	100	1.6%
GFOFAIL	980	7.1%	101	1.7%
EUDMO	1245	9.0%	117	1.9%
SWBP	1116	8.1%	135	2.2%
DISCLIMA	557	4.0%	35	0.6%
DIRINS	621	4.5%	38	0.6%
STIMREAD	829	6.0%	64	1.0%

TABLE A2 Descriptive statistics of variables (UK).

Country	UK			
Variable Name	**Mean**	**Standard Deviation**	**Skewness**	**Kurtosis**
ST016Q01NA	6.31	2.647	−0.618	−0.398
AGE	15.764	0.283	0.024	−1.137
ST004D01T	50.6% Female, 49.4% Male			
ESCS	0.243	0.886	−0.259	−0.232
ICTRES	0.455	1.090	0.805	1.078
BEINGBULLIED	0.225	1.054	0.789	0.185
EMOSUPS	0.096	0.987	−0.633	−0.690
TEACHSUP	0.265	0.964	−0.711	0.020
ADAPTIVITY	0.163	1.000	−0.057	−0.008
BELONG	−0.213	0.867	1.015	2.997
PERFEED	0.456	0.957	−0.115	−0.450
TEACHINT	0.181	0.990	−0.095	−0.410
PERCOOP	−0.121	0.919	−0.003	−0.666
PERCOMP	0.317	0.926	−0.011	−0.251
COMPETE	0.129	0.996	0.078	−0.029
ST185Q01HA	2.610	0.859	−0.207	−0.584
MASTGOAL	−0.109	0.997	0.074	−0.156
WORKMAST	−0.174	0.946	0.258	0.050
ATTLNACT	0.209	0.971	−0.786	0.271
JOYREAD	−0.280	1.101	0.115	0.292
RESILIENCE	−0.159	0.938	0.643	1.063
GFOFAIL	0.281	1.030	−0.110	−0.554
EUDMO	−0.225	0.999	0.093	−0.320
SWBP	−0.275	0.967	−0.007	−0.552
DISCLIMA	0.064	1.126	−0.255	−0.042
DIRINS	0.002	1.017	−0.060	0.074
STIMREAD	0.090	0.952	0.024	0.151

TABLE A3 Descriptive statistics of variables (Japan).

Country	Japan			
Variable Name	**Mean**	**Standard Deviation**	**Skewness**	**Kurtosis**
ST016Q01NA	6.190	2.599	−0.458	−0.480
AGE	15.781	0.289	−0.040	−1.156
ST004D01T	51.1% Female, 48.9% Male			
ESCS	−0.107	0.730	−0.168	−0.038
ICTRES	−0.525	0.831	0.799	3.541
BEINGBULLIED	−0.287	0.863	1.734	2.803
EMOSUPS	−0.265	1.024	−0.090	−1.056
TEACHSUP	0.070	0.966	−0.568	0.227
ADAPTIVITY	−0.097	0.940	−0.047	0.454
BELONG	0.013	0.932	1.050	1.968
PERFEED	−3.000	0.977	0.484	−0.439
TEACHINT	−0.235	0.988	0.211	−0.195
PERCOOP	0.113	1.051	−0.197	−0.867
PERCOMP	−0.364	1.002	0.383	−0.011
COMPETE	−0.198	1.016	0.048	0.127
ST185Q01HA	2.610	0.859	−0.207	−0.584
MASTGOAL	−0.304	0.974	0.218	0.147
WORKMAST	−0.114	1.051	0.143	−0.238
ATTLNACT	0.177	0.960	−0.648	−0.466
JOYREAD	0.298	1.084	0.044	0.202
RESILIENCE	−0.618	0.950	0.832	1.914
GFOFAIL	0.380	0.957	−0.216	−0.232
EUDMO	−0.401	0.981	0.470	−0.086
SWBP	−0.132	0.956	−0.247	−0.403
DISCLIMA	0.785	0.970	−0.517	−0.074
DIRINS	0.166	1.014	−0.180	0.296
STIMREAD	0.131	1.014	−0.039	0.013

TABLE A4 Mean validation and test performance across five outer folds (UK).

Metrics	Validation					Test
RF						
Outer	1	2	3	4	5	Mean
MSE	0.203	0.205	0.203	0.202	0.203	0.203
RMSE	0.450	0.452	0.451	0.450	0.450	0.451
MAE	0.408	0.411	0.409	0.407	0.409	0.408
R^2	0.189	0.181	0.186	0.190	0.188	0.187
KNN						
Outer	1	2	3	4	5	Mean
MSE	0.225	0.227	0.225	0.223	0.225	0.224
RMSE	0.474	0.477	0.474	0.473	0.474	0.474
MAE	0.433	0.437	0.433	0.431	0.433	0.433
R^2	0.101	0.091	0.101	0.106	0.100	0.103

TABLE A5 Mean validation and test performance across five outer folds (Japan).

Metrics	Validation					Test
RF						
Outer	1	2	3	4	5	Mean
MSE	0.213	0.215	0.215	0.215	0.212	0.215
RMSE	0.461	0.463	0.463	0.463	0.461	0.464
MAE	0.430	0.433	0.433	0.434	0.431	0.434
R^2	0.148	0.140	0.141	0.140	0.150	0.138
KNN						
Outer	1	2	3	4	5	Mean
MSE	0.232	0.234	0.237	0.240	0.233	0.236
RMSE	0.481	0.483	0.486	0.490	0.483	0.486
MAE	0.446	0.448	0.450	0.456	0.447	0.451
R^2	0.072	0.064	0.053	0.039	0.066	0.055

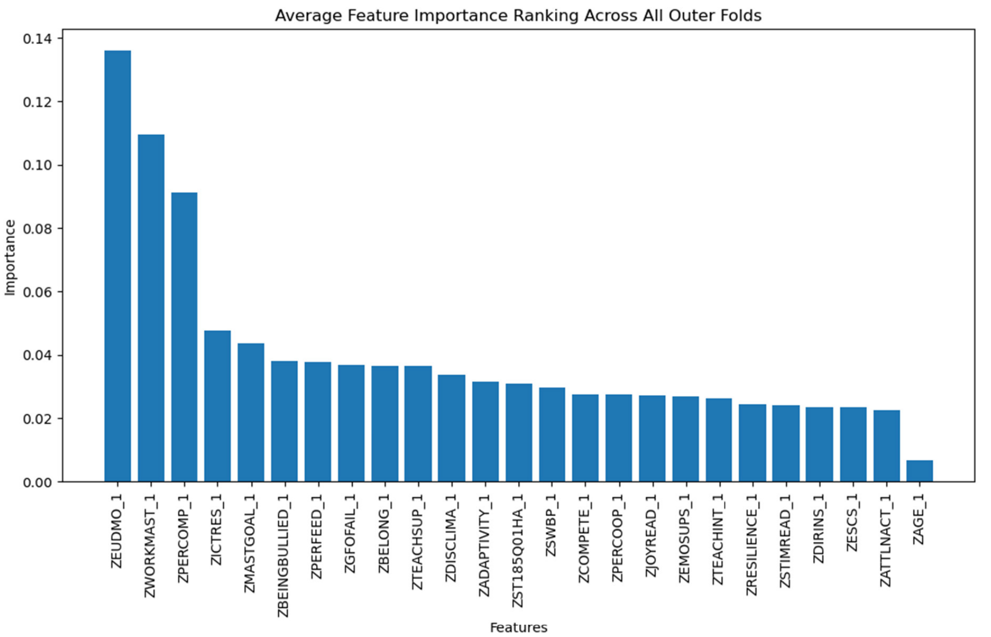

FIGURE A1 Ranking for feature importance (UK).

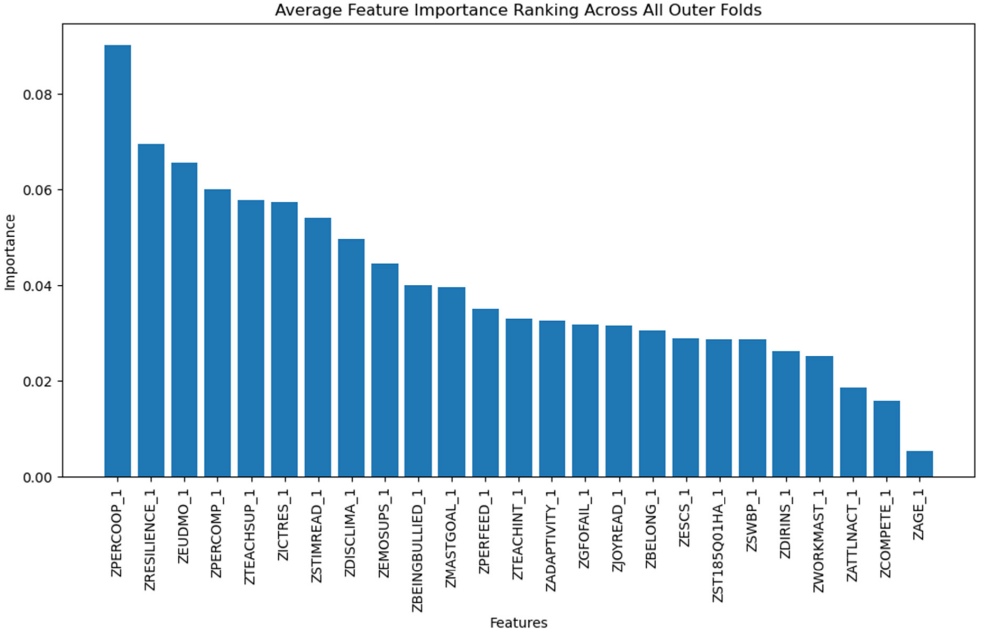

FIGURE A2 Ranking for feature importance (Japan).