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ORIGINAL RESEARCH

A Machine Learning Approach to Well-Being in Late Childhood and Early Adolescence: The Children's Worlds Data Case

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Abstract

Explaining what leads to higher or lower levels of subjective well-being (SWB) in childhood and adolescence is one of the cornerstones within this field of studies, since it can lead to the development of more focused preventive and promotion actions. Although many indicators of SWB have been identified, selecting one over the other to obtain a reasonably short list poses a challenge, given that models are particularly sensitive to the indicators considered.Two Machine Learning (ML) algorithms, one based on Extreme Gradient Boosting and Random Forest and the other on Lineal Regression, were applied to 77 indicators included in the 3rd wave of the Children's Worlds project and then compared. ExtremeGradient Boosting outperforms the other two, while Lineal Regression outperforms Random Forest. Moreover, the Extreme Gradient Boosting algorithm was used to compare models for each of the 35 participating countries with that of the pooled sample on the basis of responses from 93,349 children and adolescents collected through a representative sampling and belonging to the 10 and 12-year-olds age groups. Large differences were detected by country with regard to the importance of these 77 indicators in explaining the scores for the five-item-version of the CWSWBS5 (Children's Worlds Subjective Well-Being Scale). The process followed highlights the greater capacity of some ML techniques in providing models with higher explanatory power and less error, and in more clearly differentiating between the contributions of the different indicators to explain children's and adolescents' SWB. This finding is useful when it comes to designing shorter but more reliable questionnaires (a selection of 29 indicators were used in this case).

Keywords Subjective well-being · Psychological well-being · Childhood · Adolescence · Children's Worlds · Machine Learning (ML)

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1 Introduction

Subjective well-being (SWB) has been conceptualized as the way in which people evaluate their lives, regardless of age, both in general and in relation to specific life domains (family, friends, leisure time, etc.) (Campbell et al., 1976). It comprises a cognitive component (life satisfaction), but also an affective component with two dimensions (positive and negative affect), reflecting the so-called tripartite structure theory of SWB (Arthaud-Day et al., 2005; Diener, 1984; Metler & Busseri, 2017), which has been taken as a reference for many years. As for SWB measurement instruments, according to Holte et al. (2014), they can be classified into the following: 1) Single-item scales based on the response to a global or generic question; 2) One-dimensional multiple-item scales, based on the assumption that all items load onto a single component. The latter can be of two types: *context-free*, which include generic items on overall life satisfaction, and *scales based on satisfaction domains*; and 3) Multidimensional multiple-item scales that refer to different components of the SWB construct. The contribution made by each of these scales in explaining the overall SWB construct has yet to be fully elucidated, however. More research is therefore needed in this direction.

Being able to explain what leads to a higher or lower SWB in childhood and adolescence has become one of the cornerstones within this field of studies, insofar as it can lead to the development of better preventive and promotion actions. In recent years, numerous attempts have been made to explain children's and adolescents' SWB globally. Different indicators have been used to this end, including the aforementioned satisfaction with specific life domains, and affect (both positive and negative) indicators, but also perception of control, self-esteem and values, among many other psychosocial constructs (Casas et al., 2007, 2015).

Over time, a notable number of factors determining child and adolescent SWB have been identified – such as safety and social participation, for example – although most studies have focused on only a few (Marjanen et al., 2017; Moore, 2020), and commonly indicators from the cognitive dimension, such as satisfaction with life domains. We agree with the aforementioned authors that a broader range of factors needs to be taken into account through the use of large-scale surveys. In parallel, several debates have emerged in relation to which determining factors should be considered, these including the role of objective *versus* subjective indicators (see Voukelatou et al., 2021), the convenience of using more generic *versus* more specific indicators, and variations in these determining factors according to age, gender and sociocultural context.

Although these debates remain open, the scientific community has reached some relevant conclusions, examples of these being: that in parallel to generic indicators, it is important to use indicators that refer to specific life contexts (home, school, and neighbourhood) (Campbell et al., 1976), that the contribution of different indicators to explain SWB is unequal (Hsieh, 2022), and that the importance of each indicator may vary with age, gender and the sociocultural context (Casas & González-Carrasco, 2019; González-Carrasco, 2020). In this respect, each instrument used as an SWB indicator may even display a different degree of sensitivity to each diverse context–leading to different authors recommending that more than one SWB indicator be used with each population. To this we should also add the fact that subjective indicators are now considered to play a much more important role than objective indicators than was the case years ago (Casas, 2011; Margolis et al., 2021).

Lately, the debate has intensified over the extent to which indicators of psychological well-being (PWB) may also contribute to explaining SWB, even though SWB and PWB have traditionally been considered very distinct constructs, since they derive from different philosophical traditions. Specifically, SWB derives from the hedonic tradition revolving around the concept of pleasure (what is pleasurable generates well-being), whereas PWB derives from the eudaimonic tradition, according to which what is important is to feel fulfilled as a human being, regardless of the degree of pleasure this may be associated with. At present, there is an increasing trend to incorporate both hedonic and eudaimonic indicators to measure children's and adolescents' well-being, since a growing number of researchers argue that these are complementary approaches to the same broader construct of well-being (Herd, 2022; Ryan & Deci, 2001; Strelhow et al., 2020; Symonds et al., 2022).

Among the most outstanding findings to date are that of the many indicators identified over time, some are considered as the core of the SWB construct due to their higher contribution—especially those measuring its cognitive and affective dimensions—and others are viewed as more peripheral for just the opposite reason (see the interesting debates on this issue raised by Casas, 2011). Differentiating one from the other is no easy task, however, since models are particularly sensitive to the indicators considered and vary significantly with the introduction of some and exclusion of others, beyond theoretical or conceptual reasons. Another important finding is that the explanatory capacity associated with the models is quite low (Wilckens & Hall, 2015), a limitation that persists irrespective of how many indicators are added.

Although all of the above has allowed for great progress to be made when it comes to knowledge regarding child and adolescent SWB, it has also led to a dead end. In this regard, effect sizes between determinants of SWB are difficult to compare among studies, and some indicators may interact with one another, for example. Testing these interactions exhaustively requires a large enough dataset (Margolis et al., 2021). Besides, while including the exploration of non-linear relationships and interaction effects within linear models clearly improves their explanatory capacity (González et al., 2007, 2008, 2010, González-Carrasco, 2020), it is still insufficient. Therefore, more robust and powerful techniques are needed to better differentiate which indicators make a greater contribution from those that have less "rank ordering", to borrow Margolis et al.'s (2021) term. This would allow prevention and promotion efforts to be concentrated on more specific actions and the design of instruments for data collection with fewer indicators.

The advantages of meeting this challenge are notable, starting with helping to increase the quality of the collected data. It is well-known that respondents, especially children and adolescents, get tired as they go through a questionnaire, and therefore the more things they are asked for, the less attention they pay to them. It would clearly be very helpful to keep the list of indicators short, then; but this is not possible unless there is some certainty that nothing essential will be left out. Shorter instruments would also help broaden monitoring of children's and adolescents' SWB by reducing the huge economic and time-costs associated with multiple data collections. Cross-cultural studies would also strongly benefit from having shorter instruments at their disposal, since it is difficult to reach a consensus on which indicators to use in a given questionnaire when many countries are involved, the numerous participating researchers having their own criteria on what is more important to ask.

An example of this is the Children's Worlds project (https:/isciweb.org), a worldwide research survey of 8, 10 and 12 year-olds' SWB that has been collecting solid and representative data on children's lives and daily activities, time use and, in particular, perceptions and evaluations of their own well-being. Its purpose is to improve children's well-being by raising awareness among children, their parents and their communities, but also among opinion leaders, decision makers, professionals and the general public. In the context of this project, three waves of representative data collections have already been carried out, the third one involving more than 128,000 children from 35 countries on four continents. That makes it one of the biggest data collections on children's well-being worldwide, and certainly the one that considers most multi-item psychometric scales using broader numeric scales to capture more variance of a phenomenon that does not display a normal statistical distribution.

In addition to all of the countries in the study committing to recruiting a minimum sample of the three group ages considered and to collect data through a representative sampling procedure, whether at the regional or national level, a complex and time-consuming agreement process also took place to decide which indicators to include in the questionnaire and how they should be formulated. The questionnaire containing compulsory questions and some optional ones, is translated into several other languages from English and a common database is created so to compare results afterwards. This provides the scientific community with a great amount of data that allows to deepen into how children belonging to different cultures perceive their main life contexts (family, school, and neighbourhood), but at the same time, it raises the question of whether so many indicators are strictly necessary. Even traditional statistics techniques of analysis, such as linear regression seems to indicate that probably a smaller number of indicators will be enough because some of them are finally left out of the equation to the detriment of others but, at the same time, there is also the paradox that the variance explained by these models is low, so reducing many indicators means compromising the explanatory power of the model.

The conclusion seems clear: new avenues need to be explored that will allow us to advance in the objective of better understanding which factors contribute most to the SWB of children and adolescents from their own perspective. It is here that much more computationally powerful techniques considered to be part of artificial intelligence, such as machine learning (ML), make particular sense. This same opinion was also expressed by Oparina et al. (2022) when referring to human well-being in general, and not specifically that of children or adolescents. To this they also added how important SWB data have recently become for international organizations such as the OECD and national governments as a key tool in policy analysis.

ML "involves applying a performance algorithm to a large data set to produce a prediction model and using this model to predict an outcome. Repeating this process iteratively allows for a 'perfected' model and accurate predictions of psychological constructs" (Marinucci et al., 2018, p. 2). For this reason, ML techniques are experiencing an exponential growth in many scientific fields, helping researchers increase their ability to analyse huge amounts of data and giving new perspectives to the results. However, it has seldom been used in the field of children's and adolescents' SWB (Wang et al., 2022). Among its most important advantages is the fact that, in contrast to traditional statistics, it relies on minimal a priori assumptions, such as error distribution and additivity of parameters. ML can also be used "to analyse complex multivariate relationships related to high-dimensional data with known interdependencies" (Dehghan et al., 2022, p. 3). Linear regression is much less capable in this regard, since it assumes a linear relationship between independent and dependent variables. Such an assumption may be unrealistic in large and complex data sets, such as those generated by the Children's Worlds project, as already shown in González-Carrasco et al. (2007, 2008, 2010). ML can be used in either a supervised or unsupervised way. With the former, the dependent variable is defined and used with both the training and the test data, while for the latter it is not. Unsupervised learning is used to interpret complex data structures, whereas supervised learning is generally used for predictions (Wilckens & Hall, 2015), as is the case with the present article.

Taking all of the above into consideration, the *general objective* of this article is to apply ML methodology to data from the 3rd wave of the Children's Worlds project to determine which indicators of SWB and PWB are most relevant to children's and adolescents' well-being. This will be done with the aim of being able to select a limited but statistically sound set of indicators, without ignoring the current important debate around the extent to which ML outperforms more traditional data analysis techniques (see Froud et al., 2021; Margolis et al., 2021). To the best of our knowledge, this is the first attempt to evaluate the use of supervised ML algorithms to study children's and adolescents' SWB on an international scale and based on a very large dataset, as opposed to using a conventional technique such as linear regression. The fact that the questionnaires used in the Children's Worlds project have been developed on the basis of strong empirical evidence on SWB and successfully tested with children and adolescents in different countries on numerous occasions makes the indicators analysed here very robust and particularly suitable for the general objective of this article. To achieve this general objective, three specific objectives have also been formulated. They are described below.

The article also takes as a starting point the work conducted by Zhang et al. (2019), who aimed to "predict" (using their own words) undergraduate Chinese students' SWB by applying ML to 298 indicators. Their analysis showed that 90% of the 1,518 participants could be correctly classified and that the sensitivity and specificity of the model were around 92% and 90%, respectively. The present article also compares a more sophisticated version of the analytical technique used by Zhang et al. (2019) (*Gradient Boosting Classifier*) with another one commonly used within machine learning (*Random Forest*), following the work by Wang et al. (2022) (*Specific objective 1*). This allows us to test which of the two analytical techniques best explains the available data. As in Froud et al. (2021) and Oparina et al. (2022), our results are also compared to those computed through linear regression in order to determine whether using more complex analysis techniques delivers a substantial advantage without overfitting the data (*Specific objective* 2). Finally, once the most appropriate algorithm for the available data has been identified, separate models are compared for each country in terms of suitability and explanatory power (*Specific objective 3*), since important country differences are expected to be found.

2 Method

2.1 Participants

Leaving aside the 2.3% of cases for which gender was not reported, 49.3% of the participants were boys and 50.7% girls. Boys and girls were almost identically distributed within each age group: 1) a late childhood age group – mostly 10-year-olds—and 2) early adolescence age-group – mostly 12-year-olds (Table 1). The 8-year-olds were not considered in this article since the number of indicators included in their questionnaire was very limited with the aim of avoiding fatigue. The mean age for the 10-year-old age group was 10.07 (SD = 0.733, 58.7% of participants being 10-year-olds), while for the 12-year-olds it was 12.02 (SD = 0.766, 54.7% of participants being 12-year-olds). Table 2 displays the number of participants per country and age group. With only some exceptions (England, France,

Table 1 Number of participants by gender and age group

		Age group		TOTAL
		10	12	
Gender	Boys	24,107 (49.2%)	21,890 (49.3%)	45,997 (49.3%)
	Girls	24,853 (50.8%)	22,494 (50.7%)	47,347 (50.7%)
TOTAL		48,960	44,384	93,344

Table 2 Number of participants by country and age group

		Age group		Total
		10	12	
Country	Albania	1,176	1,163	2,339
	Algeria	1,137	1,054	2,191
	Bangladesh	946	1,012	1,958
	Belgium	1,112	1,076	2,188
	Brazil	886	901	1,787
	Chile	913	1,016	1,929
	Croatia	1,240	1,155	2,395
	England (UK)	717	0	717
	Estonia	1,013	1,079	2,092
	Finland	1,067	1,075	2,142
	France	2,184	0	2,184
	Germany	829	1,524	2,353
	Greece	822	0	822
	Hong Kong	709	816	1,525
	Hungary	1,035	994	2,029
	India	946	977	1,923
	Indonesia	7,680	8,038	15,718
	Israel	1,637	1,465	3,102
	Italy	1,074	1,181	2,255
	Malaysia	992	0	992
	Malta	630	752	1,382
	Namibia	1,065	1,099	2,164
	Nepal	1,005	1,041	2,046
	Norway	801	817	1,618
	Poland	1,192	1,156	2,348
	Romania	1,241	1,145	2,386
	Russia	953	951	1,904
	South Africa	3,415	3,699	7,114
	South Korea	3,174	3,395	6,569
	Spain	2,209	2,088	4,297
	Sri Lanka	1,156	1,221	2,377
	Switzerland	1,229	0	1,229
	Taiwan	1,337	1,511	2,848
	Vietnam	946	1,080	2,026
	Wales (UK)	959	1,668	2,627
Total		49,427	46,149	95,576

Greece, Malaysia and Switzerland), all 35 participating countries collected data from both 10 and 12-year-olds.

2.2 Instruments

The Children's Worlds questionnaire is divided into different sections reflecting different domains of children's and adolescents' lives (Rees et al., 2020). All sections were considered in the present analysis, with the exception of the one related to country and children's rights, since the included indicators referred to very specific dynamics taking place in each country. The questionnaire includes several indicators as independent variables, some taken from the following psychometric scales: two measuring the cognitive dimension of SWB—1) The CW-DBSWBS (*Children's Worlds Domain Based Subjective Well-Being Scale*), a multiple-item scale based on the Brief Multidimensional Student Life Satisfaction Scale by Seligson et at. (2003) and 2) The single-item scale on OLS (*Overall Life Satisfaction Scale*) by Campbell et al. (1976); one scale measuring the affective dimension of SWB—the CW-PNAS (*Children's Worlds Positive and Negative Affects Scale*), based on Feldman Barrett and Russell (1998); and finally, one scale measuring PWB, the CW-PSWBS (*Children's Worlds Psychological Subjective Well-Being Scale*), based on Ryff's (1989) theoretical background and only used in the 12-year-old questionnaire. Table s3 (Supplementary Materials) shows all indicators used, whether belonging to specific scales or not, their correspondence to the different life domains assessed and their respective measurement scales.

The mean score for the CW-SWBS5 (*Children's Worlds Subjective Well-Being Scale*), which is the arithmetic sum of the scores obtained for its five items divided by five ($M_{\text{pooled sample}} = 8.19$, $SD_{\text{pooled sample}} = 1.712$; $M_{\text{10-year-olds}} = 8.50$, $SD_{\text{10-year-olds}} = 1.843$; $M_{\text{12-year-olds}} = 8.15$, $SD_{\text{12-year-olds}} = 1.982$), was used as the dependent variable, because this version displays a better cross-cultural comparability than the original six-item one (Casas & González-Carrasco, 2021). This scale is in fact an improved version based on advice from children in different countries, who were asked to suggest new wordings where items did not work properly in an earlier version. It is therefore one of the Children's Worlds most recommended scales for use in international comparisons, as its metric invariance has been clearly supported across the 35 countries included in the 10-year-old sample and the 30 countries included in the 12-year-old sample. This scale is used to appraise the cognitive dimension of SWB and is a context-free scale; that is, it does not focus on specific life domains. The items, measured using an 11-point scale ranging from 0 = Do not agree at all to 10 = Totally agree, are as follows: *I enjoy my life, My life is going well, I have a good life, The things that happen in my life are excellent and I am happy with my life*.

2.3 Procedure

Participants responded to an anonymous questionnaire, which was self-administered in their regular classroom during school hours with the support of the researchers involved. It being a study involving human beings, the ethical norms of the 1964 Declaration of Helsinki and its subsequent modifications were followed, which also implied the voluntary collaboration of the schools and the children themselves. The schools were selected in such a way as to form a representative sample at the country or regional level according to those parameters considered most relevant by each national research team, such as territorial distribution or school characteristics. In each selected school, a second sampling unit was used, which comprised the corresponding class to the target age group, meaning the procedure entailed two-stage probability sampling.

2.4 Data analysis

Following the steps outlined by Froud et al. (2021) and Oparina et al. (2022), in this article we have attempted to elucidate whether ML algorithms perform better than conventional linear regression when explaining SWB, measured via the CW-SWBS5. A further aim was to determine whether the variables identified by each ML algorithm as important for explaining SWB were the same as those yielded by the linear regression model when all models displayed equivalent explanatory capacity and error level. In this study, two ML algorithms were used to estimate scores for the CW-SWBS5: *Extreme Gradient Boosting* (XGBoost) and *Random Forest*, XGBoost being an enhanced and optimized version of Gradient Boosting that improves model generalization capabilities (Bentéjac et al., 2021). According to Shwartz-Ziv and Armon (2022, cited in Oparina et al., 2022), *Random Forest* and *Gradient Boosting* are tree-based algorithms that perform well with tabular data, meaning data that is displayed in columns or tables.

Given the nature and volume of questionnaires conducted in the different countries, null or missing data analysis was required, since missing values cause predictions to be less reliable. These values must be identified and replaced by an estimated value through a data imputation process. In this work, the K-nearest (KNN) technique was used to obtain a numerical value in the missing data. This technique has proven to be effective in several ML applications (Keerin & Boongoen, 2021; Malarvizhi & Thanamani, 2012).

KNN imputation is an algorithm that assigns a value to each missing piece of data based on the k most similar observed data. These closest units are often called neighbours. In this work, the similarity between neighbours was established from the Euclidean distance. A smaller distance value means a higher similarity measure. Since $K=5$ was used to establish the neighbourhood of the missing data, the imputed value was the arithmetic mean from among the five nearest neighbours.

Once the data had been imputed, the ML algorithms were applied. The training process was carried out with both algorithms, 70% of the data was used for training and obtaining the models and the remaining 30% for their evaluation. The R^2 and the Standard Error of Estimate (SEE) were used for the linear regression model, while Root Mean Square Error (RMSE) and the coefficient of determination R^2 were run to evaluate the effectiveness of the ML models. Both SEE and RMSE measure the error between the actual and the predicted values. Specifically, RMSE applies the square root to the difference of the values and the SEE is the absolute value, so they are directly comparable. The linear regression model and ML algorithms were calculated using the SPSS software and Python, respectively.

3 Results

3.1 Linear Regression Model

The adjusted R^2 for the linear regression model was 0.644 with a SEE of 1.143, meaning a low explanatory capacity of the dependent variable and a high error, but a good fit ($F_{77,93343}=2194.423$, $p<0.001$). As Table 3 shows, 11 of the 77 indicators considered here were not statistically significant in explaining the dependent variable

Table 3 Coefficients for indicators included in the linear model (ordered by their standardized beta)

	Unstandardized Coefficients		Standardized Coefficients		
	B	Std. Error	Beta	t	Sig
(Constant)	.389	.061		6.377	<.001
teacherslisten	-.004	.004	-.002	-.807	.420
havemoneyschooltrips	-.023	.013	-.004	-1.744	.081
haveshoes	-.026	.016	-.004	-1.662	.097
frequencylocalareafights	-.010	.004	-.005	-2.420	.016
havegoodclothes	-.043	.021	-.005	-2.089	.037
frequencynothingrest	-.006	.002	-.005	-2.589	.010
friendssupport	-.010	.004	-.006	-2.452	.014
areaplacestoplay	-.009	.003	-.006	-2.455	.014
havemobilephone	-.029	.010	-.007	-2.977	.003
localadultskind	-.012	.005	-.007	-2.645	.008
frequencywatchtv	-.008	.003	-.007	-2.995	.003
frequencysportsexercise	-.009	.003	-.008	-3.520	<.001
learningalot	-.007	.002	-.008	-2.998	.003
areasafewalk	-.014	.004	-.009	-3.627	<.001
frequencyusesocmedia	-.009	.002	-.009	-3.674	<.001
haveequipschool	-.093	.018	-.011	-5.028	<.001
frequencypeersexclude	-.026	.005	-.013	-5.821	<.001
siblingshit	-.027	.004	-.015	-6.528	<.001
frequencypeersunkind	-.027	.004	-.016	-6.777	<.001
frequencyworryfamilymoney	-.033	.004	-.017	-7.935	<.001
feelingstressed	-.009	.001	-.017	-7.261	<.001
frequencyplayelecgames	-.018	.002	-.017	-7.342	<.001
siblingsunkind	-.033	.004	-.018	-7.732	<.001
haveaccessinternet	-.090	.011	-.020	-8.378	<.001
gender	-.082	.008	-.021	-10.485	<.001
agegroup	-.066	.004	-.034	-15.953	<.001
feelingsad	-.024	.001	-.041	-17.222	<.001
teachershelp	-.001	.005	.000	-.152	.879
haveequipsportshobbies	.002	.011	.000	.212	.832
frequencypeershit	.001	.005	.001	.300	.764
feelingbored	.000	.001	.001	.362	.717
familycare	.004	.006	.002	.738	.460
schoolmateshelp	.003	.004	.002	.700	.484
homesafe	.010	.006	.004	1.762	.078
frequencyschoolfights	.007	.004	.004	1.774	.076
friendsenough	.009	.004	.005	2.084	.037
enoughchoicetime	.005	.003	.005	1.968	.049
schooldecisions	.010	.004	.006	2.429	.015
frequencytimewithfamily	.010	.003	.008	3.400	<.001
satisfiedhealth	.008	.003	.008	3.106	.002
friendsnice	.017	.005	.010	3.563	<.001

Table 3 (continued)

	Unstandard-ized Coeffi-cients		Standardized Coefficients		
safetoandfromschool	.025	.005	.010	4.605	< .001
havepocketmoney	.047	.010	.010	4.874	< .001
satisfiedthingslearned	.011	.003	.011	4.236	< .001
teacherscare	.022	.005	.012	4.454	< .001
satisfiedfreetime	.010	.002	.012	5.048	< .001
friendsgeton	.024	.004	.014	5.603	< .001
localpeoplesupport	.020	.004	.014	5.715	< .001
parentsjointdecisions	.027	.004	.016	6.731	< .001
peoplefriendly	.015	.003	.016	5.568	< .001
feelingcalm	.012	.001	.017	7.797	< .001
feelingfullofenergy	.013	.002	.017	7.576	< .001
frequencyplayoutside	.021	.003	.018	7.956	< .001
satisfiedfriends	.018	.002	.020	7.892	< .001
familyhelpproblem	.043	.005	.021	8.187	< .001
parentslisten	.037	.005	.021	8.151	< .001
localareadecisions	.032	.004	.021	8.517	< .001
manageresponsibilities	.021	.003	.022	8.177	< .001
satisfiedhouse	.023	.002	.024	9.500	< .001
satisfiedappearance	.021	.002	.026	9.861	< .001
schoolsafe	.051	.004	.028	11.478	< .001
satisfiedclassmates	.024	.002	.030	12.044	< .001
localadultslisten	.050	.004	.033	12.319	< .001
satisfiedlocalarea	.030	.002	.035	14.211	< .001
satisfiedlistenedto	.029	.002	.035	12.819	< .001
satisfiedtimeuse	.037	.002	.040	15.202	< .001
satisfiedlaterinlife	.036	.002	.043	16.880	< .001
satisfiedthingshave	.044	.003	.043	16.910	< .001
feelpositivefuture	.041	.003	.045	16.282	< .001
satisfiedsafety	.046	.003	.046	16.710	< .001
satisfiedfreedom	.041	.002	.047	17.295	< .001
familygoodtimetogether	.102	.005	.048	19.344	< .001
likewayiam	.054	.003	.057	20.066	< .001
satisfiedpeoplelivewith	.071	.003	.070	27.700	< .001
satisfiedlifeasstudent	.073	.002	.081	29.690	< .001
feelinghappy	.123	.002	.133	50.417	< .001
satisfiedlifeaswhole	.138	.003	.145	50.971	< .001

Note: Dependent Variable: CW-SWBS5

Statistically significant indicators are highlighted in bold

Note: Complete wording of indicators reproduced in Table s3

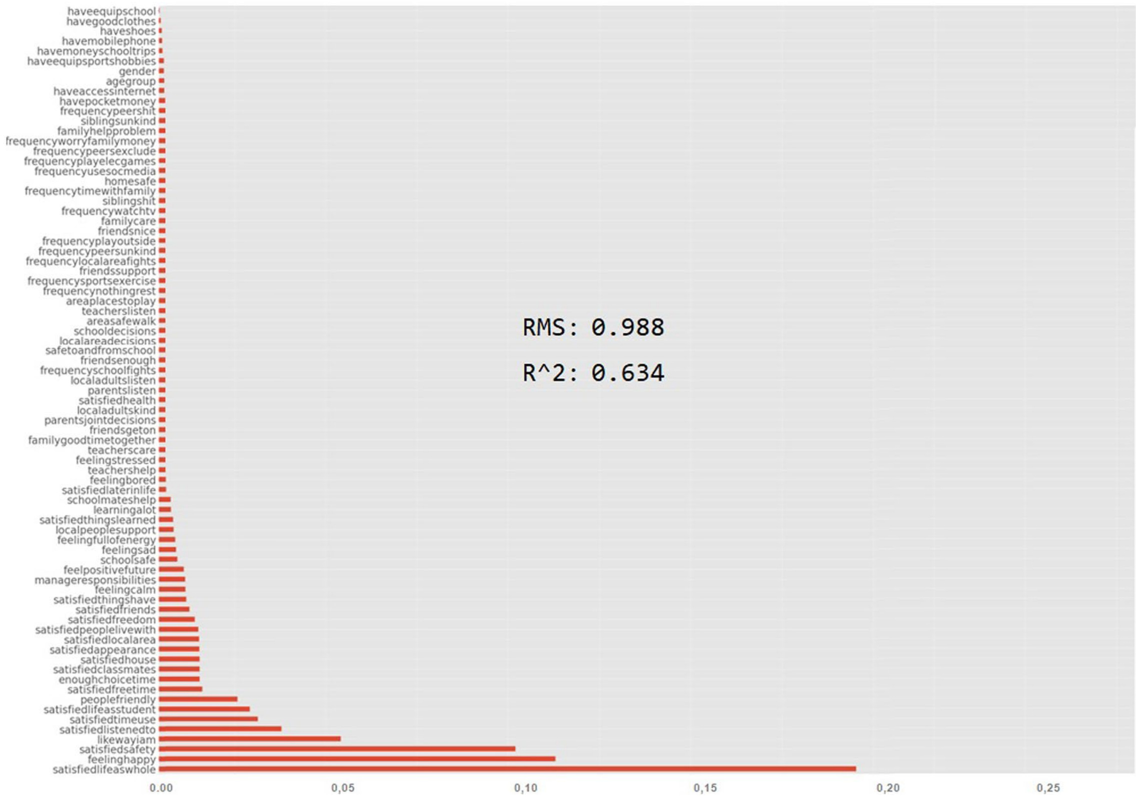

Fig. 1 Visual representation of contributions made by included indicators in explaining scores for the CW-SWBS5 for the Random Forest algorithm (highest contributions at bottom of graph) Note: Complete wording of indicators reproduced in Table s3

Table 4 Coefficients of contributions made by indicators in explaining scores for the CW-SWBS5 in the pooled sample (left column: results of applying the Random Forest algorithm; right column: results of applying the Extreme Gradient Boosting algorithm)

	RandomForest	Extreme-Gradient Boosting
r^2	.634	.765
RMSE	.988	.899
gender	.0022	.0017
agegroup	.0022	.0026
areaplacestoplay	.0054	.0032
frequencynothingrest	.0054	.0034
friendsupport	.0037	.0045
frequencyplayoutside	.0023	.0046
havepocketmoney	.0036	.0046
siblingshit	.0031	.0048
havemobilephone	.0021	.0050
frequencyworryfamilymoney	.0027	.0052
frequencyschoolfights	.0033	.0052
frequencywatchtv	.0076	.0052
frequencypeershit	.0023	.0053
frequencyusesocmedia	.0029	.0053
frequencysportsexercise	.0040	.0054
frequencyplayelecgames	.0028	.0056
localadultskind	.0034	.0056
friendsnice	.0096	.0056
haveaccessinternet	.0022	.0057
schooldecisions	.0062	.0057
friendsenough	.0021	.0058
localadultslisten	.0073	.0058
haveequipschool	.0087	.0058
teachershelp	.0103	.0059
haveshoes	.0021	.0060
areasafewalk	.0057	.0062
havemoneyschooltrips	.0021	.0064
siblingsunkind	.0023	.0066
satisfiedfreetime	.0138	.0069
frequencypeersunkind	.0036	.0070
localpeoplesupport	.0027	.0073
frequencypeersexclude	.0112	.0073
schoolmateshelp	.0105	.0074
frequencytimewithfamily	.0031	.0076
feelingbored	.0022	.0077
haveequipsportshobbies	.0104	.0077
frequencylocalareafights	.0037	.0079
friendsgeton	.0098	.0080
feelingcalm	.0115	.0080
teacherslisten	.0055	.0082
localareadecisions	.0065	.0085
feelingstressed	.0103	.0088

Table 4 (continued)

	RandomForest	**Extreme-Gradient Boosting**
feelingfullofenergy	.0112	.0089
satisfiedhealth	.0096	.0090
safetoandfromschool	.0073	.0091
familycare	.0034	.0093
havegoodclothes	.0021	.0095
satisfiedclassmates	.0134	.0097
manageresponsibilities	.0115	.0102
satisfiedlocalarea	.0129	.0103
satisfiedthingslearned	.0107	.0105
learningalot	.0109	.0105
teacherscare	.0102	.0106
schoolsafe	.0113	.0107
satisfiedhouse	.0134	.0108
peoplefriendly	.0201	.0110
parentslisten	.0089	.0112
satisfiedfriends	.0119	.0115
familygoodtimetogether	.0101	.0120
homesafe	.0031	.0121
satisfiedlaterinlife	.0024	.0123
familyhelpproblem	.0105	.0123
satisfiedlifeasstudent	.0253	.0136
parentsjointdecisions	.0098	.0139
feelingsad	.0112	.0143
satisfiedpeoplelivewith	.0126	.0149
satisfiedthingshave	.0117	.0156
satisfiedtimeuse	.0282	.0159
feelpositivefuture	.0115	.0165
satisfiedfreedom	.0120	.0176
enoughchoicetime	.0135	.0187
satisfiedappearance	.0129	.0189
satisfiedlistenedto	.0324	.0190
satisfiedsafety	.0992	.0250
likewayiam	.0533	.0438
feelinghappy	.1153	.0595
satisfiedlifeaswhole	.1895	.2777

Note: Complete wording of indicators reproduced in Table s3

List of 29 selected indicators marked in bold

(CW-SWBS5). Standardized beta coefficients for those that were significant ranged from -0.002 (*teacherslisten*) to 0.145 (Satisfaction with life as a whole), with only two indicators having a standardized beta coefficient higher than 1 (*satisfiedlifeaswhole* and *feelinghappy*).

3.2 Random Forest Model

The model calculated by means of the *Random Forest* algorithm yielded an R^2 of 0.634 and an RMSE of 0.988. The high error together with a low R^2 are clear signs that this algorithm did not perform well with the available data. The contributions of each of the 77 indicators considered here are shown in Fig. 1 and Table 4, the fact of "having equipment/things you need for school" being the least contributing indicator and "satisfaction with life as a whole" the most in explaining scores for the CW-SWBS5.

3.3 Extreme Gradient Boosting model

The model calculated through the *Extreme Gradient Boosting* (*XGBoost*) *algorithm* yielded an R^2 of 0.765 and an RMSE of 0.899, this meaning a good explanatory power and a reasonable error. More specifically, this model outperformed the linear regression model since its R^2 was higher (0.765 *versus* 0.644), and the *Random Forest* model as well (0.765 *versus* 0.634), not being at the same time suspicious of overfitting the data. It also displayed a lower error compared to the lineal model (0.899 *versus* 1.143) and the Random Forest model (0.899 *versus* 0.988). The contributions of each of the 77 indicators considered here are shown in Fig. 2 and Table 5, "gender" being the least contributing indicator and "satisfaction with life as a whole" the most in explaining scores for the CW-SWBS5.

3.4 Selection of the Short List of Indicators

Having determined that the *Extreme Gradient Boosting* (*XGBoost*) *algorithm* was the most suitable one for our data, the following step was to identify those indicators that best explained the scores for the CW-SWBS5. Since no specific cut-point has been defined within ML applications, we established that a sign of a given indicator making a substantial contribution could be considered a coefficient above 0.01, which resulted in the selection of 29 indicators from the initial list of 77 (see Table 5). These indicators were from the following instruments: the six items of the CW-PSWBS (*Children's Worlds Psychological Subjective Well-Being Scale*), the five items of the CW-DBSWBS (*Children's Worlds Domain Based Subjective Well-Being Scale*), two items (*feelinghappy* and *feelingsad*) from the CW-PNAS (*Children's Worlds Positive and Negative Affects Scale*), eight items on satisfaction with different life domains (*satisfiedthingslearned, satisfiedhouse, satisfiedlaterinlife, satisfiedthingshave, satisfiedtimeuse, satisfiedfreedom, satisfiedlistenedto, satisfiedsafety*), two items on perceptions related to school (*teacherscare, schoolsafe*) and five items measuring family-related perceptions (*parentslisten, familygoodtimetogether, homesafe, familyhelpproblem* and *parentsjointdecisions*). And, finally, the indicator that contributed most was the OLS (*Overall Life Satisfaction Scale*), with a coefficient above 0.2.

3.5 Extreme Gradient Boosting Models by Country

In the next step, we proceeded to calculate one model for each country, again using the *Extreme Gradient Boosting* (*XGBoost*) algorithm, with the aim of exploring whether there were differences between countries in the role played by the 77 indicators in explaining CW-SWBS5 scores. Table s6 (Supplementary Materials) shows the

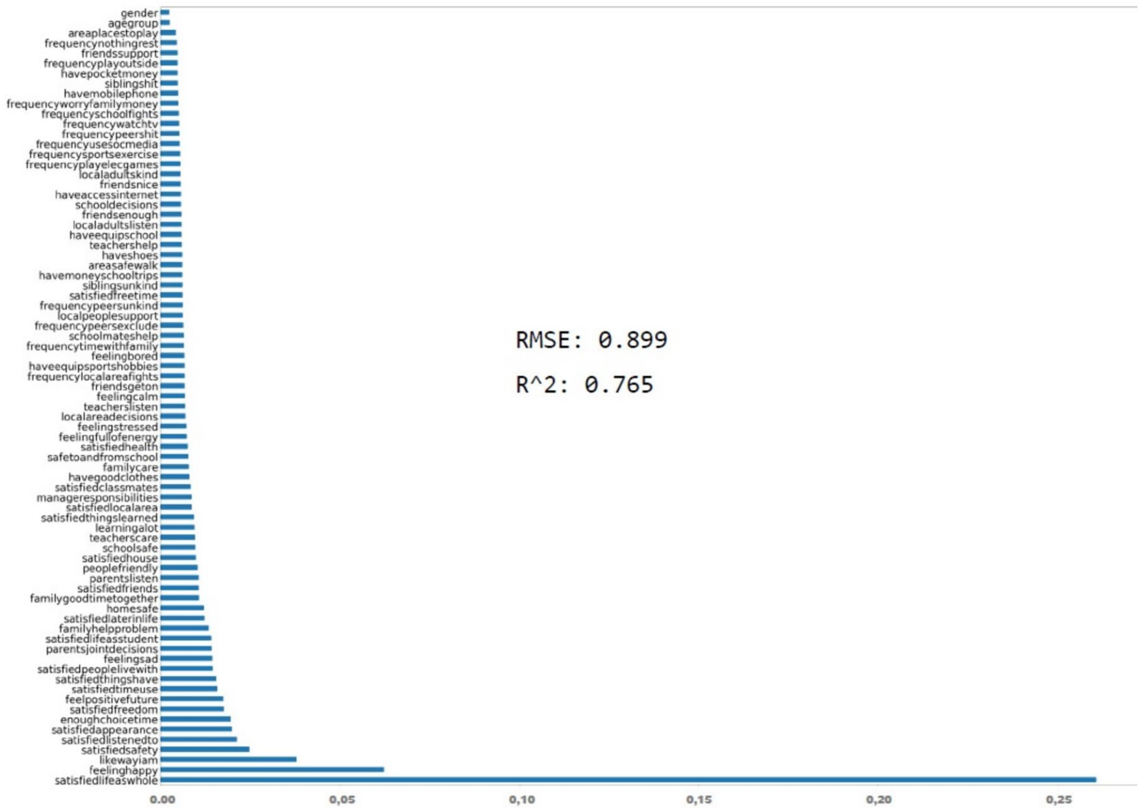

Fig. 2 Visual representation of contributions made by included indicators in explaining scores for the CW-SWBS5 for the Extreme Gradient Boosting algorithm (highest contributions at bottom of graph) Note: Complete wording of indicators reproduced in Table s3

coefficients obtained for each indicator and country, while Table s7 (Supplementary Materials) displays the ordering of these indicators according to their coefficients. This facilitates comparisons between countries regarding how far they are from the ordering in the pooled sample.

Table s6 shows that the R^2 of the different models ranged from a low-medium-range value in England (0.53) to a high range value in Greece (0.93), with twelve countries displaying an R^2 score above that of the pooled sample (0.765) and twenty-three below this value. Regarding the errors contained in the models, twenty-three countries displayed an RSME value below that of the pooled sample (0.899), which represents an acceptable level of error. These oscillated between 0.41 (Croatia) and 0.81 (Bangladesh). However, in thirteen countries this error was above 0.899 (from 0.97 in Switzerland to 1.67 in England), which is undesirably high.

An important variability was observed when the coefficients of the 77 indicators were analysed by country, with seven countries showing coefficients of 0.0000 (Bangladesh, Belgium, England, France, Greece, Malaysia and Switzerland). These corresponded to thirteen indicators, only three of which belonged to the 29 on the list mentioned previously: *parentsjointdecisions*, *schooldecisions* and *peoplefriendy*. In contrast, three countries displayed coefficients of above 0.3, these corresponding to *frequencyschoolfights* (Poland) and *satisfiedlifeaswhole* (South Korea and Germany), with only the latter belonging to the list of 29 selected indicators.

In coherence with the variability in the coefficients commented above, the results displayed in Table s7 also highlight the great variability existing among countries regarding the importance awarded to the 77 indicators considered here. Wales, followed by Brazil, were the countries that displayed the most similar ordering to the pooled sample, while Israel, followed by Bangladesh, displayed the least. In terms of specific indicators, the importance awarded to gender was the indicator with the greatest consensus among countries in terms of ordering (from the 68th position in Bangladesh to the 77th position in 16 countries: Algeria, Chile, Croatia, Hong Kong, Hungary, Indonesia, Israel, Italy, Malta, Poland, South Korea, Spain, Sri Lanka, Taiwan, Vietnam and Wales), while *familyhelpproblem* had the lowest (from the 1st position in India to the 75th position in Indonesia and Israel). Turning our attention to the list of 29 indicators, *familyhelpproblem* continued to be the indicator receiving the lowest consensus, as it was included in this shorter list, while *satisfiedlifeaswhole* was the one receiving the greatest consensus (from the 1st position in England, Finland, France, Germany, Greece, Hong Kong, Hungary, Norway, Russia, South Korea, Spain, Taiwan and Wales, to the 29th in Switzerland, with it being among the top seven positions in most of the countries).

4 Discussion

The premise for this article is the importance of measuring and monitoring children's and adolescents' SWB and the consequent need to have accurate and manageable measures of how children and adolescents perceive their life conditions, considered a prerequisite for having good data and implementing efficient and accountability-based public policies targeted at these age groups (see Ben-Arieh, 2008). Having a good selection of indicators at their disposal is useful for researchers for the following reasons: both time and economic resources are limited; survey questionnaires cannot be too long because respondents get tired and reliability declines; the longer a questionnaire, the higher the complexities to translate it to different languages; and the more difficult is to infer the consequences of the results into practice. Determining which indicators are most salient to children's and adolescents' well-being is a key issue that has only been partially resolved in our view, hence our attempt to fill this gap through the *general objective* of this article.

Although conducted with older participants (university students) than the ones considered here, the 2019 study by Zhang et al. has been used as a departing point for this article. The reason for this is that it shares the same objective of explaining SWB through the use of ML methodology and identifying the most efficient indicators in this explanation. In contrast to the present article, however, Zhang et al. (2019) considered not only a combination of subjective and socioeconomic indicators, but also biological ones, including blood type and weight, to explain SWB measured through the SWLS (Satisfaction with Life Scale) and the PANAS (Positive and Negative Affect Schedule).

Using the *Gradient Boost Classifier* method, they identified the 20 indicators that contribute most to "predicting" participants' SWB. According to the authors, the method can help detect people at risk with a very limited number of indicators, including items taken from the CESD-D (Centre for Epidemiologic Studies Depression Scale), the BFI (Big Five Inventory), sleep quantity, the ASLEC (Adolescent Self-Rating Life Events), the DFS (Dispositional Flow Scale) and the MMCS (Multidimensional-Multifactorial Causality Scale), the latter as a measure of achievement and affiliation locus of control. One important limitation of the study is that all participants belonged to the same college and country. It was therefore necessary to extend this type of analysis to more culturally diversified samples, as we have done here.

The analysis performed in this article, using a more sophisticated version of the *Gradient Boost Classifier,* specifically the *Extreme Gradient Boosting* (*XGBoost*) algorithm (*specific objective 1*), has allowed us to identify 29 of 77 indicators that make a substantial contribution to explaining a general measure of SWB. In terms of their content, these 29 represent a set of indicators that covers both the cognitive (measured through the CW-DBSWBS, the OLS, and different satisfaction with life domains) and the affective dimensions of SWB (although only two of the items from the CW-PNAS are included in this list of 29 indicators). They also contain all of the items that measure PWB through the CW-PSWBS. The other indicators are related to children's and adolescents' opinions, perceptions and evaluations regarding different contexts of their lives: neighbourhood, school and family, with a stronger presence of family-related indicators. Interestingly, some of these indicators have been highlighted in recent years as making more of a contribution to children's and adolescents' well-being than was previously thought, namely: *satisfiedsafety* and *satisfiedlistenedto* (González-Carrasco et al., 2023), and *satisfiedtimeuse* (Casas et al., 2015). It is also worth mentioning that, generally speaking, and unlike classical linear regression, ML methods are not stepwise in nature, meaning more advanced methods are used to select the most relevant explanatory variables for the model. The models used here—*Random Forest* and *XGBoost*—are tree-based models, in which variables are automatically evaluated to determine their ability to divide the data into the branches of the tree, those that variables predominate in these models being the most important (Yilmazer & Kocaman, 2020).

As theoretically anticipated, the OLS is the indicator that contributes by far the most to explaining CW-SWBS5 scores. Although its exclusion from the analysis might be argued as a way of reducing multicollinearity (both are general cognitive measures of SWB), the reason for not doing so is threefold. Firstly, the authors needed to verify whether results obtained through ML algorithms were coherent with the scientific knowledge in the field, given the scarce literature available using both SWB and PWB indicators in childhood and adolescence. Secondly, decision tree-based algorithms like *Random Forest* and *Gradient Boosting* are more flexible than linear models and can better manage non-linear relationships without being as affected by multicollinearity. Since, unlike linear models, ML algorithms do not assume a strict linear relationship between the independent and dependent variables, they can also automatically select the most relevant characteristics and eliminate the redundant ones, thereby decreasing multicollinearity (Chan et al., 2022; Garg & Tai, 2013). This approach therefore yielded sufficiently robust models, as was the case for the *Gradient Boosting* (*XGBoost*) *algorithm.* And, thirdly, despite linear regression being much more sensitive to multicollinearity, when it was performed without including the OLS, the explanatory power of the other indicators was only slightly higher, the number of statistically significant indicators did not display significant changes and the degree of error was very similar.

The process followed here paves the way to consider the use of fewer indicators in this type of study, and the advantages that this would entail, as described in the Introduction section. It also invites further discussion on relevant conceptual issues, such as the differences between the constructs of SWB and PWB in the case of children and adolescents, given that, as our results show, the boundaries between the two are not easy to establish (see the work by Symonds et al., 2022 on this topic), or the importance of the affective dimension of SWB, previously highlighted by Blore et al (2011).

Although the aims of this article did not include investigating the structure of children's and adolescents' well-being, given the important role played by the CW-PSWBS indicators as a measure of PWB in all of the constructed models, the results seem to suggest that a tetrapartite model of well-being would be feasible, as previously suggested by Moreta-Herrera et al. (2023). This would mean taking Savahl et al.'s (2021) quadripartite model as a basis, which includes positive affect, negative affect, cognitive life satisfaction domain-based and cognitive life satisfaction context-free components, and then adding a measure for PWB, as in the model proposed by Strelhow et al. (2020).

Wang et al. (2022) also applied the *Random Forest* technique to data collected from 12,058 Chinese 15-year-olds using the PISA 2018 Chinese dataset. This allowed them to identify nine from a total of 35 indicators with the greatest capacity to separately explain positive affect, negative affect, OLS and PWB; the accuracy in these results ranged from 76 to 78%. Among the background predictors, socioeconomic status was the only key factor, specifically explaining negative affect. The top non-cognitive/metacognitive factors included resilience, self-concept of competence, work mastery, mastery goal orientation, competitiveness, fear of failure and enjoyment, while schooling factors most influencing the students' well-being included a sense of school belonging, parental emotional support, perceived cooperation at school, teacher stimulation, the experience of being bullied, teacher feedback and teacher interests. In the case of our study, the *Random Forest* algorithm did not provide a good model, since it displayed a high error and low explanatory power (*Specific objective 1*). The reason for *Random Forest* performing worse can be attributed to the fact that the trees are built in parallel with random samples from the training set, while in *Gradient Boosting* the trees are built sequentially, this decreasing the error made in the previous tree.

Framed around Axford's (2009) argument that constant critical reflection is required to ensure selection of the best indicators, given that this has direct implications for children's policy, we have compared the results obtained in this article using two widely used ML techniques with those obtained by means of linear regression (*Specific objective 2*), following the steps outlined by Froud et al. (2021). With the aim of explaining the academic performance and quality of life of Norwegian children aged 11–12, these authors concluded that linear regression was less prone to overfitting and that its outperformance was better compared to four machine learning techniques (*K-nearest Neighbours, Neural Networks, Random Forest* and *Support Vector Machine*) for continuous health outcome variables. They therefore recommend ML techniques only in those cases where there are non-linear and heteroscedastic relationships between variables and few missing cases.

Wilckens and Hall (2015) also found that the different ML algorithms they used in their study (*Kernel Smoothing Algorithms, Neural Network Algorithms* and *Feature Selection Algorithms*) aimed at explaining the scores on the Human Flourishing Index using a combination of demographic and personality indicators among adults from four data collections over four weeks did not provide higher prediction accuracies than the general linear model when appropriately tested with sufficient cross-validation. The authors considered three possible explanations for these results: 1) the algorithms used were not able to sufficiently fit the existing structure within the data; 2) the dataset was too small, so cross-validation does not allow existing structures to be found; and 3) the links between personality, demographics and well-being were linear, and therefore well-described by the generalized linear model.

In contrast with the above works by Froud et al. (2021) and Wilckens and Hall (2015), in the present article the conventional linear model only outperforms one, rather than two, of the ML techniques used. Specifically, the *Extreme Gradient Boosting* (*XGBoost*) *algorithm* performed better than the *Random Forest algorithm* and the linear regression model (*Specific objective 1* and *Specific objective 2*). This might be explained by the fact that *Random Forest* first combines the prediction of multiple parallel trees before then combining the results of these trees into one mean or mode value. If one of the trees has a high error value because it selected the least significant variables, then that tree contributes to a high error value. With the *Extreme Gradient Boosting* (*XGBoost*) *algorithm*, by sequentially improving the prediction of each tree, the error of one tree is decreased in the next, and so on, until a value with the lowest prediction error is obtained.

Compared to the study by Oparina et al. (2022), the R^2 obtained through the *Extreme Gradient Boosting* (*XGBoost*) *algorithm* was around 0.7, far above the around 0.3 achieved with data from three other surveys (the German Socio-Economic Panel – or SOEP, the UK Longitudinal Household Survey – or UKHLS, and the US Gallup Daily Poll). One explanation for this result is that the Gradient Boosting Classifier does not have a native implementation of regularization, which can make the model prone to overfitting in certain cases. In contrast, *Extreme Gradient Boosting* (*XGBoost*) incorporates L1 (Lasso) and L2 (Ridge) regularization into its algorithm, which helps prevent overfitting, while improving the generalizability of the model (Bentéjac et al., 2021).

None of the works mentioned above included such an array of countries as the one considered here, this being an unprecedented contribution of the current study. Specifically, this has made it possible to test the fit and explanatory capacity of the models for each of the 35 countries involved after establishing the best algorithm to do so according to *Specific objective 3*. For most of the countries, the R^2 and RMSEA were found to be adequate, although for twelve of them (Brazil, England, France, Hong Kong, Namibia, Nepal, South Africa, Sri Lanka, Switzerland, Taiwan, Vietnam and Wales) the combination of a low R^2 and a high RSME suggests their corresponding models should be treated with special caution. Limitations of this kind when trying to compare different countries in terms of children's and adolescents' well-being—which are related to different ways of understanding the indicators and constructs under study—have already been reported using different means of analysis but the same dataset (see Casas & González-Carrasco, 2021).

As expected, another important finding from the process followed was the huge variability observed among countries, both when the coefficients corresponding to each indicator were compared in terms of their higher or lower contribution to explaining scores on the CW-SWBS5, and when they are ordered according to weight. This variability did not seem to be reduced when the focus was placed on selection of the 29 highest contributing indicators, which suggests that caution should be exercised in interpreting the results from the pooled sample, since they do not represent all participating countries equally.

4.1 Limitations and future research

As with the study by Oparina et al. (2022), we focused our analysis on identifying the variables key to explaining children's and adolescents' SWB, rather than on clusters of individuals selected according to specific variables, such as the country participants belong to, this being a second step to be explored in the future. Neither were gender differences analysed here, since this would have exceeded the scope of this article, although this could be an interesting future avenue to explore.

Furthermore, the approach adopted here was supervised ML. It is therefore necessary to verify the feasibility of an unsupervised ML approach using the data available from the Children's Worlds project. One limitation of ML methods is that they are not thought to analyse the theoretical mechanisms connecting the different explanatory factors in any depth. In the future, more classical statistical analyses such as mediational models and structural equation modelling would be of great help in this regard (Wang et al., 2022).

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Declarations

Conflict of interest On behalf of all authors, the corresponding author states that there are no conflicts of interest.

Ethical Statement The researchers declare that they have complied with all the ethical requirements for this type of study, having received authorization from each school's education authority.

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