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Moving well-being well: Using machine learning to explore the relationship between physical literacy and well-being in children

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Abstract

Physical literacy provides a foundation for lifelong engagement in physical activity, resulting in positive health outcomes. Direct pathways between physical literacy and health have not yet been investigated thoroughly. Associations between physical literacy and well-being in children ($n = 1073$, mean age 10.86 ± 1.20 years) were analysed using machine learning. Motor competence (TGMD-3 and BOT-2) and health-related fitness (PACER and plank) were assessed in the physical competence domain. Motivation (adapted-Behavioural Regulation in Exercise Questionnaire) and confidence (modified-Physical Activity Self-Efficacy Scale) were assessed in the affective domain. Well-being was measured using the KIDSCREEN-27. Accuracy of predicting well-being from physical literacy was investigated using five machine learning classifiers (decision tree, random forest, XGBoost, AdaBoost, *k*-nearest neighbour) in the full sample and across subgroups (sex, socioeco-

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nomic status [SES], age). XGBoost predicted well-being from physical literacy with an accuracy of 87% in the full sample. Predictive accuracy was lowest in low SES participants. Contribution of physical literacy features differed substantially across subgroups. Physical literacy predicts well-being in children but the relative contribution of physical literacy features to well-being differs substantially between subgroups.

KEYWORDS
children, health, machine learning, physical literacy, prediction, well-being

INTRODUCTION

Physical health problems associated with an unhealthy lifestyle during childhood often manifest in early-late adulthood. However, mental health problems can become evident at a much younger age. Ireland ranks within the top four European countries for the number of citizens over the age of 15 years reporting mental health disorders, and in 2015, it was estimated that the total cost to the Irish exchequer from mental ill health was €8.3million, or 3.2% of GDP (OECD/European Union, 2018). While a relatively small percentage of children suffer from mental health problems (approx. 8–10% in five European countries studied; OECD/European Union, 2018), it has been found that about half of all mental health disorders in adulthood manifest by the mid-teens (Kessler et al., 2007). Protecting and promoting health, both physical and mental, in childhood, is paramount for future health and well-being.

Engaging in physical activity (PA) has been shown to be beneficial to overall health, both physical and mental. Children who meet the international PA guidelines of an average of 60 min moderate-vigorous PA (MVPA) daily (World Health Organisation [WHO], 2020) have been found to have improved quality of life (Shoup et al., 2008) and more favourable well-being (Breslin et al., 2017) compared with those who do not meet the guidelines. Engaging in PA is also associated with improved cardiometabolic health, with evidence suggesting that, although there is as yet no established dose–response, greater amounts and higher intensities of PA produce more favourable health outcomes (Chaput et al., 2020). Engaging in PA or sport has been found to have a beneficial impact on children's well-being and mental health with Murphy et al. (2020) reporting a positive effect on well-being from participating in team sports, whereas higher levels of physical self-efficacy have been associated with better general mental health (Tahmassian & Moghadam, 2011). Despite clear evidence of the benefits of sufficient PA to health, the majority of children worldwide are not achieving the PA guidelines (Guthold et al., 2020). In Ireland, the most recent national PA surveillance data showed that only 17% of primary school children surveyed (age range: 10–12 years) met the PA guidelines (Woods et al., 2018). In essence, this means that 83% of primary school children are not experiencing the positive health benefits associated with being physically active.

One potential reason for low levels of PA, despite the known health benefits, is that individuals may lack the skills, knowledge, motivation, and confidence—together defined as ‘physical literacy’ (PL) (Whitehead, 2001)—to enable them to actually engage in PA. Physical literacy, a multidimensional construct comprising physical, social, cognitive, and affective domains (Hyndman & Pill, 2018), is posited as an essential foundation for engagement in lifelong PA (Edwards et al., 2017; Hyndman & Pill, 2018; Whitehead, 2001). Earlier research that examined not explicitly PL, but included indicators now understood to be part of the PL construct, has led to the informed theory that PL provides a foundation for PA and that interventions aimed at developing an individual's PL will likely lead to increased PA throughout the lifespan (Stodden et al., 2008). Despite this well-accepted hypothesis, it must be acknowledged that studies measuring PA change directly associated with PL are actually quite scarce. A large proportion of the existing research regarding investigations into the relationship between PL and PA is limited to studies that measure just one or two indicators, or domains, of PL and their associations with PA (De Meester et al., 2016), rather than measuring the full PL construct (Cairney, Clark, et al., 2019). In addition, many PL intervention studies do not actually objectively measure PA as an outcome (Bremer et al., 2020; Lane et al., 2022). In spite of these caveats, recently the emergence of some empirical studies has lent support to the theory that PL as a holistic construct is an essential foundation for PA engagement (Belanger et al., 2018; Brown et al., 2020). Belanger et al. (2018) found that Canadian children who had higher PL scores in the physical and affective domains were significantly more likely to meet the PA and sedentary behaviour guidelines. Brown et al. (2020) also found that children who displayed moderate and high scores across combined PL domains had higher PA levels than children who scored low across PL domains. Thus, evidence is emerging to support the theory that PL will lead to higher levels of engagement in PA.

Considering the known positive associations between PA and health (Bailey et al., 2012; Breslin et al., 2017; Shoup et al., 2008), it can be interpreted that PL may have a positive impact on mental and physical health. However, pathways directly from PL to health need to be further explored (Dudley et al., 2017), with only a limited amount of research that looks at associations directly from PL to health outcomes, be they physical or mental. Cairney, Dudley, et al. (2019) and De Meester et al. (2016) examined associations between PL and physical health outcomes. A positive association was found between PL and cardiovascular endurance by Cairney, Dudley, et al. (2019), whereas De Meester et al. (2016) found that children who demonstrated combined high perceived competence and high actual competence had lower body mass index (BMI) than children who demonstrated a combined low perceived and low actual competence. Less well understood is the association directly between PL and mental health. From the studies that have explored this association, Melby et al. (2022) reported positive correlations between overall PL and well-being, and between the physical and affective domains and well-being. Jefferies et al. (2019) similarly found a clear positive correlation between PL and resilience in children while another recent study examining associations between PL and both physical health and well-being found that PL was positively associated with both physical and mental health (Caldwell et al., 2020).

From a public health policy perspective, national (Department of Transport Tourism and Sport, 2018; Healthy Ireland; Department of Health, 2016, 2021) and international (WHO, 2018) policies are increasingly including PL in their PA promotion strategies. One of the main goals identified in the UN Sustainable Development Goals is a reduction in premature mortality from NCDs “through prevention and treatment, to promote mental health and wellbeing” (UN DESA, 2016). Establishing a clear pathway from PL not just to PA, but directly to health outcomes, will lend further support to PL development strategies, not just for immediate PA engagement, but for good health and well-being throughout the lifespan. Expanding the promotion of PL to outside of the PA promotion field towards a health promotion field could increase the impact that PL interventions can have in improving health outcomes for children and adults.

Caldwell et al. (2020) and Melby et al. (2022) have emphasised the need for further studies, using robust analyses, to explore the direct links between PL and health outcomes in order to expand the PL field into health promotion and disease prevention. The focus of the current study was to address this need by examining direct links between PL and well-being, as a marker of health, in a large sample of children. Well-being is defined as "a multidimensional construct covering physical, emotional, mental, social, and behavioural components of well-being and function as perceived by patients and/or other individuals" (The KIDSCREEN Group Europe, 2006). A number of machine learning (ML) functions were used to investigate the relationship between PL and well-being in an attempt to improve our understanding of the accuracy to which PL indicators can predict levels of well-being in children. ML is a data-driven approach to the construction of analytical models (Hastie et al., 2009). In effect, it automates the process of learning from PL indicators, identifying patterns and making decisions. ML is arguably utilised extensively in PA related research, primarily with the use of accelerometer data (Narayanan et al., 2020), though it has largely been ignored in PA and PL research methodologies. Fuller et al. (2022) state that ML has failed PA related research, citing a lack of ML training as a reason. While most research in PL has a strong statistical grounding, few researchers in this field have more than a basic knowledge of ML methods. The aim of this study is to investigate how PL indictors can predict well-being in children. By adopting a ML approach to analysis, the aim is to learn two things: (1) Categorical subsets of children for which we have good predictive ability and those categories for which we do not; (2) PL features that provide the strongest markers for predictive accuracy.

METHODS

Participants

Participants were primary school children involved in the Moving Well-Being Well national PL study in Ireland (Behan et al., 2019; Peers et al., 2020) ($n = 1073$, mean age 10.86 ± 1.20 years; age range: 9–14 years; 47% female).

Measures

Physical literacy

Physical literacy was measured using protocols outlined in Britton et al. (2022). Measurement of PL as a three-domain construct (physical competence, confidence, and motivation) was in keeping with findings from our construct validation study (Britton et al., 2022). Physical competence measurement included assessment of balance (Bruininks, 2005), object-control, and locomotor skills (Ulrich, 2016) as components of motor competence along with VO_2max and plank as components of health-related fitness. The confidence domain was assessed using the modified Physical Activity Self-Efficacy Scale (PASES) (Bartholomew et al., 2006) to measure self-efficacy in PA. According to Bandura (1977, 1997), self-efficacy is an individual's belief in their ability to engage in a particular behaviour. While the term "confidence" is generally the term referred to when listing the domains of PL (International Physical Literacy Association [IPLA], 2017; Whitehead, 2001), Bandura (1977) has highlighted that confidence refers simply to a "strong belief" in one's ability to complete a task, whereas self-efficacy refers to a strong and positive belief in the ability to successfully complete a task. Therefore, measurement of the confidence domain was conducted by assessing self-efficacy in PA (Bartholomew et al., 2006). The motivation domain was assessed across three subscales (intrinsic, identified, and introjected) from the adapted Behavioural Regulation In Exercise Questionnaire (BREQ-adapted) (Sebire et al., 2013). Detailed protocols for each of these measures are reported elsewhere (Britton et al., 2022).

Well-being

Well-being was measured using the Kidscreen-27 (The KIDSCREEN Group Europe, 2006). Health-related quality of life across five dimensions—(1) physical, (2) psychological, (3) parents and autonomy, (4) peer acceptance, and (5) school and learning—was assessed using 27 questions from the Kidscreen27 questionnaire. Participants responded on a 5-point Likert scale (*never* to *always*) to each question to indicate the frequency with which they felt or experienced specific things relating to each dimension. The five KIDSCREEN-27 dimensions were shown to have satisfactory internal reliability in this study, with Cronbach α ranging from 0.7 to 0.79.

Data processing

Locomotor and object-control skill scores were created by summing the scores obtained for individual skills in each category. Scores from the two balance tests were summed, creating an overall balance score. VO_2max was predicted from the number of laps completed in the 20MST (Léger et al., 1988; Plowman & Mahar, 2013). Total scores for measured subscales of the BREQ-adapted were created by obtaining the average of the items scored for each subscale (Sebire et al., 2013). A total score for well-being (0–135) was produced by summing individual scores on each item.

Data analysis

After removing NULL values, nine data subsets were extracted from the main database to enable an understanding of the differences among participants in predicting well-being based on sex, socioeconomic status (SES), and age group. All categories were binary. Sex was grouped by male or female, with 47% of the sample female and 53% male. SES was determined by the status of the school. In Ireland, schools that have a high percentage of students at risk of educational disadvantage qualify for the Delivering Equality of Opportunity in Schools (DEIS) programme (Department of Education and Skills, 2017a). SES categories in this study were labelled as “DEIS” for schools designated as having a high proportion of students at risk of educationally disadvantaged, and “non-DEIS” for schools designated as having a majority of students not at risk of educational disadvantage. Reflecting the population statistics, 25% of the sample were DEIS and 75% were non-DEIS. For age group, children were categorised into age 9–10 years (57%), and age 11–12 years (43%), based on school class, that is, children in third and fourth class (age range 9–10 years), and children in fifth and sixth class (age range 11–12 years).

For each dataset category, well-being is regarded as the *dependent* variable, which we are attempting to classify. The independent variables used to predict well-being are motivation (intrinsic, identified, introjected; scale 1–5), confidence (scale 0–2), and physical competence (locomotor skill; scale 0–48), object-control skill (scale 0–54), balance (scale 0–16), VO_2max (ml kg min), and plank (s).

The dependent variable was subcategorised into two classes: A low class with well-being values ≤90 (13% of the sample) and a high class with well-being values >90 (87% of the sample). In ML, all of the data are used in experiments rather than a statistical sample. However, disjoint subsets of the data are used for *training* (building the predictive model) and *testing* where the class that is being predicted (well-being score) is removed and the algorithm attempts to predict the missing score. Each dataset was then split into 70% training set and a 30% test set for this purpose.

The five ML classifiers used in this study were the decision tree, random forest, XGBoost, AdaBoost, and *k*-nearest neighbour (KNN) algorithms. These classifiers are nonparametric supervised learning algorithms, of which the first four employ tree structures to this classification problem. They were deliberately chosen, as tree-based algorithms have been shown to model nonlinear relationships with high predictive accuracy in different domains. A decision tree (Han & Kamber, 2012) is one of the simplest ML algorithms whose goal is to create a model that predicts the value of a target variable by learning simple decision rules inferred from the data. A random forest classifier (Han & Kamber, 2012) contains multiple decision trees generated from the same dataset and takes the *average* to improve the predictive accuracy of that dataset. Gradient boosting is a technique to construct a prediction model in the form of an ensemble of (typically) decision tree models where each subsequent model is used to improve the accuracy of the previous model. XGBoost (Friedman, 2001) and AdaBoost (Friedman et al., 1998) are two different forms of Ensemble classifiers which attempt to improve the overall accuracy of the selected models. The KNN algorithm (Han & Kamber, 2012) is another simple classification algorithm. An NN classifier learns by comparing a test data point with training data that are *similar* to it. Training data are described by *n* variables, in this case: motivation, confidence, physical competence, object-control skill, balance, VO_2max, and plank. Thus, all training data are stored in an *n*-dimensional pattern space. When presented with a new data point, the KNN classifier searches the pattern space for the *k* training tuples that are closest. These *k* training tuples are its *k* "nearest neighbours," and their class is used to predict the class of the test data point.

Our methodology was to begin with a simple ML classifier and then gradually introduce the more complex models. It is expected that the more complex models will have greater performance (predictive accuracy). However, there is a trade off in terms of speed as the more complex models may take far longer to build. Thus, the aim is to determine the point at which there is no added benefit in using a more complex model.

The validation of the predictive classifier is of utmost importance. *Accuracy*, *recall*, *precision*, and F_1 metrics were used to validate the classifier (Hastie et al., 2009). Each metric use the same four counts: True positives (TP), a count of the correctly predicted positive values; true negatives (TN), a count of the correctly predicted negative values; false positives (FP), which count the occurrences where the actual class is false but is predicted as true; and false negatives (FN), which count the occurrences of where the actual class is true but is predicted as false. The sum of all four counts is the total number of observations.

$$accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

In Equation (1), *accuracy* (sometime referred to as recognition rate) is the ratio of correctly predicted observations (TP + TN) divided by the total observations. This is the *primary metric* used to validate the classifier.

$$precision = \frac{TP}{TP + FP} \quad (2)$$

In Equation (2), *precision* is seen as a measure of *exactness*: The percentage of observations labelled as positive that are actually positive. This is important where we require the true classification to be *as correct as possible*, for example, in cases of serious illness.

$$recall = \frac{TP}{TP + FN} \tag{3}$$

In Equation (3), *recall* (sometimes referred to as sensitivity) is a measure of completeness: The percentage of positive observations that are classified as positive. Recall is used when, in predicting true classifications, we require our model to detect *as many as possible*.

$$f_1 = \frac{2TP}{2TP + FP + FN} \tag{4}$$

In ML experiments, datasets should have an even distribution of class instances, in our case, low and high well-being values. However, this is not possible for our dataset, and in circumstances such like these, we require a further metric to validate our results. In Equation (4), the F_1 value is a *weighted average* of Precision and Recall and is useful for imbalanced class distributions. This metric is used when there is a serious downside to predicting false negatives and here, it is used as a *supporting metric* for imbalanced experiments.

RESULTS

Mean scores for each feature in the full sample are provided in Table 1.

When discussing results, *Accuracy* is used as the main reference, but given the heavily imbalanced datasets, the F_1 score will also be referred to, which if poor, will negate a good *Accuracy*

TABLE 1 Mean scores for each feature

Feature	*N*	Possible range	Mean (SD)
Confidence	948	0–2	1.66 (.29)
Intrinsic motivation	828	1–5	4.59 (.64)
Identified motivation	828	1–5	4.31 (.76)
Introjected motivation	828	1–5	2.93 (1.01)
Balance	1055	0–16	6.90 (1.78)
Locomotor skill	1007	0–48	37.66 (7.02)
Object control skill	1050	0–54	39.83 (8.11)
VO_2max	1028	Continuous	48.95 (6.10)
Plank	919	Continuous	1.34 (.99)
Well-being total	948	0–135	103.77 (11.66)

TABLE 2 Classifier results using full dataset (all: low well-being = 41, high well-being = 244)

Model	Accuracy	Precision	Recall	F_1 score
Decision tree	0.76	0.78	0.76	0.77
Random forest	0.84	0.79	0.84	0.81
XGBoost	**0.87**	**0.83**	**0.87**	**0.83**
AdaBoost	0.85	0.82	0.85	0.83
k-nearest neighbours	0.85	0.78	0.85	0.81

Note: Best-performing predictive models are in bold.

TABLE 3 Classifier results analysed by sex (males: low = 19, high = 131; females: low = 15, high = 121)

	Accuracy		Precision		Recall		F_1 score	
Model	Male	Female	Male	Female	Male	Female	Male	Female
Decision tree	0.76	0.81	0.82	0.87	0.76	0.81	0.79	0.85
Random forest	0.89	0.90	0.84	0.87	0.89	0.90	0.86	0.89
XGBoost	0.91	0.91	0.82	0.84	0.91	0.91	0.86	0.88
AdaBoost	0.90	0.87	0.86	0.88	0.90	0.87	0.87	0.87
k-nearest neighbours	**0.91**	**0.91**	**0.88**	**0.88**	**0.91**	**0.91**	**0.88**	**0.89**

Note: Best-performing predictive models are in bold.

TABLE 4 Classifier results analysed by SES (DEIS = low SES schools, non-DEIS = high SES schools) (DEIS: low = 11, high = 58; non-DEIS: low = 22, high = 194)

	Accuracy		Precision		Recall		F_1 score	
Model	DEIS	Non-DEIS	DEIS	Non-DEIS	DEIS	Non-DEIS	DEIS	Non-DEIS
Decision tree	0.71	0.83	0.61	0.82	0.71	0.83	0.70	0.82
Random forest	0.68	**0.88**	0.58	**0.84**	0.68	**0.88**	0.62	**0.84**
XGBoost	0.72	0.87	0.54	0.81	0.72	0.87	0.62	0.84
AdaBoost	0.68	0.86	0.61	0.81	0.68	0.86	0.63	0.83
k-nearest neighbours	**0.74**	0.84	**0.68**	0.78	**0.74**	0.84	**0.65**	0.81

Note: Best-performing predictive models are in bold.

score. Each table highlights the level of imbalance for that particular dataset, for example, Table 2 shows that of the 285 instances used for testing, more than 85% (244) are classified as *High*.

Table 2 demonstrates the overall performance of the four classifiers. One of the more complex ML models, XGBoost performed best getting 87% of predictions correct and importantly the F_1 score, while less accurate, is ranked joint best at 83%. With the exception of the decision tree, the models performed well overall, across all metrics, so it was necessary to drill down into categorical subsets to get a better understanding of the predictive power of these models.

The results in Table 3 show a breakdown by sex, investigating if the predictive models work best for males or females. Results show there is very little difference when predicting well-being from PL for either sex. The decision tree model again did not perform as well as other models, but F_1 scores support all *Accuracy* rankings, giving similar scores.

Validation metrics in Table 4 highlight a clear difference for predicting between participants in DEIS and non-DEIS schools, with the model performing better in the non-DEIS cohort. The stark difference may be a result of a double imbalance; that is, the full sample was recruited based on a representative 20:80 split between DEIS and non-DEIS schools (Behan et al., 2020), and within both these groupings, the data are imbalanced towards the majority reporting higher well-being than lower.

Table 5, which separates the cohort by age, shows little difference in validation metrics between groups. Predictive accuracy for well-being from PL is similarly accurate for both the 9–10 year old cohort and the 11–12 year old cohort.

TABLE 5 Classifier results analysed by age-group (age 9–10 years: low = 21, high = 137; age 11–12 years: low = 16, high = 111)

-Model	Accuracy		Precision	
	9–10 years	11–12 years	9–10 years	11–12 years
Decision tree	0.75	0.73	0.81	0.83
Random forest	0.85	**0.87**	0.84	**0.84**
XGBoost	**0.89**	0.86	**0.84**	0.82
AdaBoost	0.82	0.87	0.82	0.78
k-nearest neighbours	0.87	0.86	0.83	0.82

Note: Best-performing predictive models are in bold.

TABLE 5 (continued)

Model	Recall		F_1 score	
	9–10 years	11–12 years	9–10 years	11–12 years
Decision tree	0.75	0.73	0.78	0.75
Random forest	0.85	**0.87**	0.84	**0.85**
XGBoost	**0.89**	0.86	**0.85**	0.82
AdaBoost	0.82	0.87	0.82	0.85
k-nearest neighbours	0.87	0.86	0.85	0.82

Note: Best-performing predictive models are in bold.

Feature importance

The PL features that contributed most to the accuracy of the well-being prediction models for the total sample (Figure 1) and for each subgroup (Figures 2–4) are displayed.

Feature importance by sex

Object-control skills, identified motivation, and confidence are the three features that contribute most to the accuracy of predicting well-being in females, but balance and locomotor skills also contribute (Figure 2). For males, there are just three primary contributing features—confidence, balance, and object-control skills, with object-control skills contributing substantially less to the predictive accuracy than the confidence and balance skills (Figure 2).

Feature importance by SES group

For participants from DEIS schools, there are three features having high importance in predicting well-being from PL—intrinsic motivation, confidence, and locomotor skills (Figure 3). For participants from non-DEIS schools, there are five primary contributing features, with object-control skills, locomotor skills, and intrinsic motivation contributing equally, followed by VO_2max and identified motivation (Figure 3).

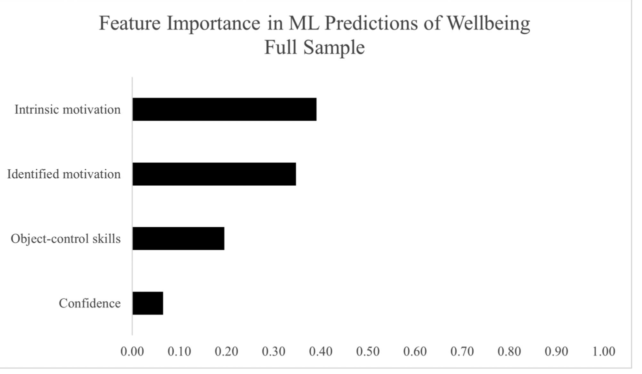

FIGURE 1 Feature importance for predicting well-being, full sample. Note: Data are normalised to a range of 0–1.

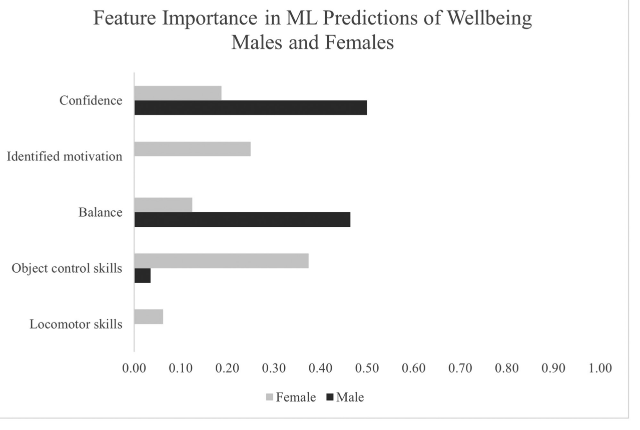

FIGURE 2 Feature importance for PL predicting wellbeing, males and females. Note: Data are normalised to a range of 0–1.

Feature importance by age

For younger participants (aged 9–10 years) all nine of the PL features contributed to the accuracy of the model in predicting well-being (Figure 4). The three features that contributed most were object-control skills, balance, and intrinsic motivation. For older participants (aged 11–12 years), only four features contributed to the accuracy of the model in predicting well-being, with VO_2max the most substantial contributor, followed by confidence, locomotor skills, and then introjected motivation (Figure 4).

DISCUSSION

Accuracy in predicting well-being

When taking the full sample together, the model has reasonably good levels of accuracy for predicting well-being from PL indicators, that is, the model predicted the correct result approximately

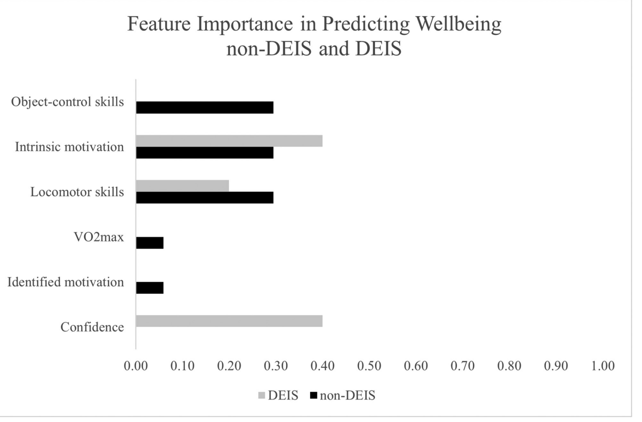

FIGURE 3 Feature importance for PL predicting well-being, non-DEIS and DEIS schools. Note: Data are normalised to a range of 0–1.

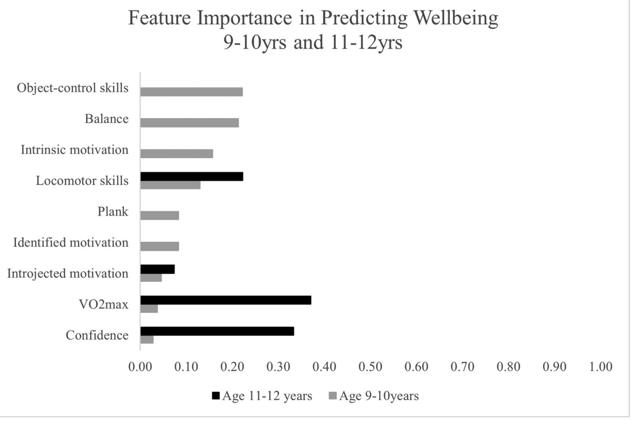

FIGURE 4 Feature importance for PL predicting well-being, 9-10 years and 11-12 years. Note: Data are normalised to a range of 0–1.

eight out of 10 times. Differences in well-being based on sex (Shannon et al., 2017), SES (Gall et al., 2020; Ravens-Sieberer et al., 2007), and age (Berman et al., 2016; Gall et al., 2020) have previously been reported. In addition, sex and age differences within PL domains are frequently found (Behan et al., 2019; Blanchard et al., 2020). To better understand how PL might contribute to well-being across these different cohorts, comparisons in predictive accuracy of the model across three subgroups (sex, SES, and age-group) were carried out.

For males and females, the model performs better than average (i.e., better than when using the full sample) in predicting well-being from PL indicators. For the high SES group (non-DEIS), the model performs better than average in predicting well-being, yet for the low SES group (DEIS) the model performs worse than average. This indicates that PL features can be quite accurately used to predict well-being in non-DEIS students, but predicting well-being from PL in DEIS students is not as accurate. The same can be said for predicting well-being in different age groups. In the younger cohort, the model performs slightly better than average in predicting well-being, but in the older cohort, it performs slightly worse than average when predicting well-being. Considering the generally good results obtained, it was important to delve further into the data to really understand which PL components are associated with predicting well-being in the different subgroups, by examining the feature importance for each group.

Sex differences

The accuracy of the ML models for predicting well-being are similar for males and females. Figure 2 shows the differences in feature importance for males and females. For females, there is a wider spread of PL features, which contribute to the model's predictive accuracy when compared with males. However, some similarities between the sexes are evident, with object-control skills and confidence contributing to the accuracy of well-being predictions for both males and females. Object-control skills are required for many of the most popular team sports among primary school children in Ireland (Woods et al., 2018). Participating in sport, and team sports in particular, has been found to be positively associated with well-being in adolescents (Murphy et al., 2020), which may explain why object-control skills are a key feature in well-being predictions for both males and females. Gender distinction in the contribution of object-control skills to well-being predictions are apparent however, with object-control skills contributing to a much larger degree to predicting well-being for females when compared with males. Females tend to perform worse than males in object-control skills (Behan et al., 2019; Emm-Collison et al., 2016). A possible explanation for the greater contribution of object-control skills to well-being predictions in females could be that, for males, there is almost an expectation that they will be proficient in object-control skills. Therefore, high or low levels of object-control skills may not impact on their sense of well-being. For females, it could be that where girls have higher proficiency in object-control skills, this is a significant and identifiable factor that marks them as being "proficient" in something, over and above expectations, and would thus lead to higher well-being, or lower should they not be proficient. The same could be said for balance in males, which appeared as a much stronger feature in contributing to accuracy of well-being predictions for males than for females. In an Irish setting, males have been found to perform worse on balance skills than females (Behan et al., 2019). Therefore, being good at balance skills for males might be an "extra string to your bow," which may lead to greater choice in sport participation and thus improved well-being (Murphy et al., 2020).

For both males and females in the current sample, confidence (or more specifically physical self-efficacy) is one of the top three PL features contributing to the accuracy of well-being predictions, albeit to a much stronger degree in males than females. Previously, significant and negative associations between physical self-efficacy and mental health have been identified in adolescents (Tahmassian & Moghadam, 2011). Therefore, it is perhaps unsurprising that self-efficacy, or confidence in the physical domain, should be a prominent feature in the predictive accuracy of the current well-being models.

For females, identified motivation is one of the top three PL features contributing to the accuracy of well-being predictions, whereas for males, this feature does not contribute at all to predicting well-being. Identified motivation is a form of extrinsic motivation but is considered a positive or autonomous form of motivation (Sebire et al., 2013). In a PA setting, individuals who are high in identified motivation for PA are motivated to engage in PA due to the personal value they place on being physically active (Sebire et al., 2013). By improving identified motivation in females through, for example, a PL intervention, overall improvements in well-being may be elicited. That being said, motivation appears to be one of the most difficult components of PL to change during PL interventions (Bremer et al., 2020; Coyne et al., 2019). Our findings suggest that efforts to target improvements in identified motivation, specifically in females, are warranted, as they will likely result in the positive health outcome of improved well-being, in addition to any improvement in PL.

The contribution of a combination of features from the physical competence domain (object-control skills, balance) and the affective domain (confidence, motivation) is interesting because it suggests that it is not just the affective domains of PL (confidence and motivation) correlating with well-being (a psychosocial outcome) (Caldwell et al., 2020) but a mixture of physical and affective features that are contributing to accuracy of well-being predictions for both males and females. This lends further support to the importance of focusing on PL as a multidimensional construct when looking to improve health outcomes in children, rather than conflating PL with physical competence, or fundamental movement skills, as has been noted to occur (Edwards et al., 2017). For males, motor competence (balance and object-control skills) and confidence are the only features of PL that contribute to the accuracy of predicting well-being, whereas for females, there is a much broader range of PL features that play a role in predicting well-being. This suggests that PL as a whole may be more important for well-being for females compared with males, but future research should investigate this specifically.

SES differences

In the current study, the machine is better at predicting well-being for participants in non-DEIS (higher SES) compared with DEIS (lower SES) schools. Children from higher SES backgrounds frequently report better well-being than those from lower SES backgrounds (Gall et al., 2020; Ravens-Sieberer et al., 2007). In the current sample however no statistically significant difference for total well-being score was found between participants who attended non-DEIS or DEIS schools.

Differences in the accuracy of well-being predictions from PL features between non-DEIS and DEIS school participants may have occurred for a number of reasons. In a study of general correlates of well-being in children, Patalay and Fitzsimons (2016) found that perceiving your neighbourhood as safe was one of the strongest correlates of better well-being. Individuals from lower SES backgrounds frequently report low perceived safety in their neighbourhoods (McGrath & Chananie-Hill, 2011). Therefore, while PL might contribute somewhat to overall well-being, for children in socioeconomically disadvantaged areas, the significance of neighbourhood safety perceptions may be more influential to well-being compared with a construct like PL. In Ireland, schools are designated DEIS or non-DEIS based on the concentration of students in a school who are at risk of educational disadvantage (Department of Education and Skills, 2017b). As such, where a school is designated as a DEIS school, not all students in that school will come from a low SES family; that is, SES category in this study is at the school level, not the individual level. Thus, one reason for the poor precision and accuracy of the machine for predicting well-being in students in DEIS schools from PL features could be that other important correlates of well-being, such as perceived neighbourhood safety (Patalay & Fitzsimons, 2016), may vary widely between individuals and may have a significantly greater impact on well-being than PL.

Figure 3 shows the differences in feature importance for non-DEIS and DEIS school participants. For DEIS school participants, there is a wider array of features contributing to the accuracy of well-being predictions, compared with for non-DEIS school participants. The most important features for accuracy of well-being predictions in DEIS participants are confidence and intrinsic motivation, whereas for non-DEIS participants the most important features are object-control skills, locomotor skills, and intrinsic motivation. Intrinsic motivation is the most autonomous form of motivation (Sebire et al., 2013). Individuals who are intrinsically motivated to engage in a behaviour do so purely for the satisfaction that doing that behaviour brings, rather than any external reward or pressure (Sebire et al., 2013). Children who are intrinsically motivated are usually happier and have lower levels of anxiety (Froiland et al., 2012). Therefore, it is perhaps unsurprising that intrinsic motivation for PA contributes highly to the accuracy of well-being predictions in this cohort, for both non-DEIS and DEIS school students. It must be noted however, that when grouped by sex, it was not intrinsic motivation but identified motivation that contributed to well-being, and for females only. Motivation for PA, in any form, was not an important feature for accurate well-being predictions for males.

For DEIS school participants, confidence was an equally important feature to intrinsic motivation in contributing to the accuracy of the model in predicting well-being, while confidence did not contribute in the non-DEIS subsample. Participating in sport is associated with better well-being (Murphy et al., 2020). There is however an SES gradient in sport participation in Ireland, with 83% of non-DEIS students and only 63% of DEIS students participating in organised sport (Woods et al., 2018). With the majority of non-DEIS students engaging in sport, it may be that their physical self-efficacy, or confidence to engage in PA, is more uniform across the board, leading to confidence not being a significant factor in predicting well-being. Children from lower SES families may have fewer opportunities to engage in PA and sport than their more socioeconomically advantaged peers (Tandon et al., 2012; Woods et al., 2018). Thus, those who do have the opportunity to engage in sport, or have higher confidence to engage, may benefit from this with more positive well-being.

For non-DEIS school participants, motor competence in the form of locomotor and object-control skills, as well as intrinsic motivation, were the three most prominent PL features in contributing to the accuracy of well-being predictions. It is interesting to note that findings from this study indicate physical competence features to be more important in predicting well-being for non-DEIS school participants, whereas affective features (confidence and motivation) are more important features for DEIS students. In fact, object-control skills did not contribute to predictive accuracy at all for DEIS students. This points to the need for targeted interventions, where subgroups, be it sex or SES, are taken into account insofar as is possible when designing PL interventions.

Age differences

The ML models perform similarly for accuracy in well-being predictions for younger (9–10 years) and older (11–12 years) children. However, there are stark differences in the feature contributions to the accuracy of the models between age groups.

For younger children, all nine of the PL features contribute to the accuracy of well-being predictions, whereas for older children, only four features (VO_2max, confidence, locomotor skills, and introjected motivation) are contributing to the predictive accuracy of the model. In the younger cohort, the most prominent contributing features are FMS (object-control skills, balance and locomotor skills are three of the top four features). In comparison, VO_2max is the strongest feature in the older cohort, followed by confidence and locomotor skills. FMS are often referred to as the building blocks for movement (Clark & Metcalfe, 2002). Development of FMS at a young age increases the likelihood of and opportunity to engage in varied PA throughout the lifespan (Clark & Metcalfe, 2002; Gallahue & Ozmun, 2012). In the younger cohort, being proficient, or not, in these basic skills may have an impact on overall well-being, as these skills are the first steps required for engaging in sport, which positively impacts well-being (Murphy et al., 2020). In comparison, for the older cohort, the most prominent feature of PL contributing to the predictive accuracy of the model is VO_2max, rather than FMS. As children get older, elements of health-related fitness such as VO_2max have been found to be important predictors of PA (Britton et al., 2020). Fitness levels, irrespective of skill level, have also been found to be associated with engagement in recreational team sport (Ré et al., 2016). It may be that physical competence features such as fitness become more important for participation in sport and PA in older children, and as a result, for older children there may be a greater association between health-related fitness and well-being through the sport participation-well-being link (Murphy et al., 2020), compared with for younger children where FMS may be the more important element of physical competence.

Intrinsic motivation is one of the top contributors to the predictive accuracy of the model for younger children but does not feature for older children. The only type of motivation which is contributing to model accuracy for older children is introjected motivation, and even at that, it is the least important of the contributing features. As children progress into adolescence, they are often subject to external pressures from significant adults such as parents, teachers, or coaches, to engage in behaviours for the purpose of achieving some external goal, rather than for the inherent pleasure of engaging in the behaviour (Froiland et al., 2012). This might explain why intrinsic motivation is a key contributor to the accuracy of the model in the younger cohort, but does not play a role for the older cohort. The form of motivation that contributes to predicting well-being in older children is introjected motivation, which is often seen as a controlling or "bad" form of motivation (Owen et al., 2014). When an individual's motivation for engaging in a specific behaviour is introjected, it means they are motivated to engage in that behaviour for external reasons, often to avoid feelings of guilt, or to protect their ego (Sebire et al., 2013). Introjected motivation is likely a factor in the older cohort in this study rather than the younger, as peer comparison and external pressures to act and behave in certain socially acceptable ways often only begin to manifest as children transition into adolescence. Introjected motivation is not always interpreted as having a negative effect on behaviour though. In adolescents, being introjectedly motivated to engage in PA has been found to be positively associated with adaptive PA behaviours, with no negative effects (Gillison et al., 2009). According to Deci and Ryan (2002) individuals can move along the motivation continuum from external to internal sources of motivation in a process called "internalisation." It may be that introjected motivation in older children is the first step in this process and in the long term may lead children to more self-determined forms of motivation (Gillison et al., 2009).

LIMITATIONS

PL in this study comprised three domains; physical competence, confidence, and motivation. Due to recognised issues surrounding the fit of the knowledge and understanding domain within the PL construct (Britton et al., 2022; Gunnell et al., 2018), as well as difficulties in adequately measuring this domain, a PL construct that excluded the knowledge and understanding domain (but has been previously validated; Britton et al., 2022) was used in the well-being prediction models. Thus, the findings from this study must be interpreted in that context, where knowledge and understanding was not included in the analysis. As recommended previously (Britton et al., 2022), research should be carried out to investigate methods for measuring the knowledge and understanding domain, focusing on a broad understanding of how to be active, where to find information on getting active, and how to apply existing skills in order to be physical active. This type of representation of knowledge and understanding may be more in line with Whiteheads (Whitehead, 2001) interpretation and may fit the PL construct better than current methods of measurement that focus narrowly on knowing specific guidelines and definitions.

It should also be noted that the cross-sectional nature of the data in the current study impacts on the ability to truly make predictions of behaviour. Future studies should look to carry out this type of ML analysis on longitudinal datasets.

Finally, as noted earlier the dataset was imbalanced in relation to the outcome variable, with 87% of the sample scoring high for well-being. As identified earlier, this was accounted for in the analysis by using the F_1 score as an additional metric to examine predictive accuracy in imbalanced datasets. However, in the case of the DEIS cohort, the dataset had a double imbalance, which may have resulted in the poorer predictive accuracy findings for this cohort. It may be that in circumstances such as these, ML does not perform at its optimum.

CONCLUSION

This study is an exploratory study into using ML to predict well-being from PL indicators and to determine how this type of analysis can assist in understanding and identifying the associations between PL and health in children. As such, a broad overview of findings has been presented, which points to the need for more detailed investigations into the interrelationships between PL and well-being, particularly in different subgroups. Of key interest are the differences in feature importance seen between subgroups and indeed between the full sample and the various subgroups. The primary contributing features for the overall sample were intrinsic and identified motivation, object-control skill, and confidence (Figure 1), with no substantial contribution made by introjected motivation, locomotor skill, balance, VO_2max, or plank when looking at the full sample. When analyses were conducted within the various subgroups however (sex, SES, and age), each of the features included in PL were shown to contribute substantially to well-being predictions for at least one of the subgroups. Analysing by subgroup (sex, SES, and age) provides much more detail regarding the associations between PL and well-being and could prove useful in intervention design, adding to the groundswell that the "one size fits all" model is not a realistic option in societal change (Abraham et al., 2009). By focusing on the features most important for each subgroup, targeted interventions can be developed. Future studies should investigate the associations found in this sample with different cohorts, to see if these patterns are replicated. Available analyses, such as the ML models used in this study, should be considered more often in PA and PL research as an analytical tool. For example, carrying on from this study, it would be interesting to investigate the accuracy and feature importance of ML models in predicting other markers of health (e.g., weight status, cardiovascular health, and body image) from PL.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

ETHICS STATEMENT

Ethical approval was granted by the institution's research ethics committee, and parental consent and child assent were obtained prior to data collection.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available on request from the corresponding author (Dr. Úna Britton; una.britton@insight-centre.org).

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