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Unlocking financial literacy with machine learning: A critical step to advance personal finance research and practice

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ABSTRACT

Financial literacy is crucial, and measuring it doesn't have to be expensive. In today's world of interactive artificial intelligence, the reduced costs of coding have made machine learning and text mining viable, cost-effective alternatives to traditional assessment methods. This groundbreaking study is the first globally to integrate diverse fields—such as personal finance, socialization, parenting, and family well-being—to train supervised machine learning models for predicting low financial literacy. We labeled a sample of youth in Hong Kong using two definitions of low financial literacy. Our training results revealed that among the four machine learning models trained—decision tree, random forest, light gradient boosting machine, and support vector machine—the light gradient boosting machine was the most effective for predicting low financial literacy based on the first definition (low objective financial knowledge). Conversely, the random forest model performed best according to the second definition, which considers the gap between subjective and objective financial knowledge or a deficiency in both. This research provides educators with a powerful tool to identify and offer targeted financial education to at-risk youth. Additionally, the identification of key features through ablation analyses informs the development of innovative conceptual models for future research. Ultimately, this pioneering study encourages scholars across social science disciplines to collaborate, share data, and advance the research paradigm in their fields.

1. Introduction

Over the past decade, research on financial literacy has surged, highlighting its critical role as a "linkage variable" within the socialization model [1,2]. Financial literacy is typically defined as the understanding of financial principles, instruments, and institutions, along with the ability to apply this knowledge in managing finances [3]. Youth financial literacy is influenced by both inherent factors, such as age and gender, and external factors, including media exposure, socialization through parents and peers, educational experiences, family economic resources, and parenting practices [4,5]. Moreover, financial literacy in youth is linked to changes in financial attitudes, values, confidence in financial behaviors, and decision-making in adulthood, acting as a vital mediator in the socialization model [6]. Therefore, improving financial literacy is viewed as a pathway to fostering positive financial behaviors and enhancing overall financial well-being [7,8].

While standardized financial education in schools is widely recognized for effectively promoting financial literacy [9], the current curriculum often takes a one-size-fits-all approach that fails to account for the varying levels of financial knowledge among students. Some youth may already possess advanced financial understanding from parental guidance, media, and peer interactions, making basic instruction potentially oversimplified or contradictory, which can lead to cognitive dissonance. To optimize educational resources, it is essential to focus financial education on those who need it most. Financial educators advocate for a *filtering system* to prioritize youth with low financial literacy (Organization for Economic Co-operation and Development [10].

The most straightforward way to identify youth with low financial literacy is through standardized testing; however, such assessments can be prohibitively expensive. The Program for International Student Assessment (PISA) and Financial Fitness for Life (FFFL) tests are among the most credible methods for assessing youth financial literacy globally [11,12]. These tests include 48 and 50 items, respectively, covering essential financial literacy domains such as economic reasoning, saving, spending, borrowing, and investing. The extensive number of items requires a lengthy testing duration of approximately 40–60 min and incurs additional costs for translation and local validation. Ensuring participants understand specialized terms further increases time and resource

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costs. Additionally, low response rates for objective financial literacy tests, especially among those with limited financial understanding, often necessitate strategies like personalized testing or financial incentives to boost participation, further inflating overall costs [3].

Supervised machine learning (ML) provides a cost-effective alternative for categorizing financial literacy in large samples, eliminating the need for expensive testing. While previous ML models developed by computer scientists have been able to categorize these groups, their limited focus on personal finance often results in an overreliance on general background variables and a disproportionate emphasis on refining algorithms. As a result, the full potential of ML in assessing financial literacy levels remains underutilized [13]. Recent advancements in personal finance frameworks suggest that financial socialization variables and diverse parenting behaviors are strongly correlated with youth financial literacy [5,14], indicating that these factors could serve as valuable features to enhance model performance. Therefore, this research aims to improve prediction features, train four candidate ML models, compare their performance, and ultimately identify the most effective model for practical application. We expect that the finalized model will show significantly *enhanced predictive performance* compared to existing models in the literature.

The findings of this study could have important practical and theoretical implications. The finalized ML model can be transformed into a low-cost filtering system to identify youth with low financial literacy for targeted financial education in schools. Measuring financial socialization, parenting, and background variables is far more economical than standardized financial literacy tests. In our previous experience, adolescents familiar with basic financial concepts typically require at least 40 min to complete the entire FFFL test, while those lacking foundational understanding may need even more time if they require assistance. In contrast, questionnaires assessing various features of machine learning models, such as parenting, average just 15 min to complete. This efficiency is due to the straightforward nature of the questions, which relate closely to everyday life and do not involve complex reasoning. Furthermore, collecting data for ML features relies solely on participants reporting their experiences, eliminating the need for technical support and further reducing implementation costs. Beyond these practical benefits, training machine learning models produces a valuable byproduct: a ranking of feature importance. This ranking can serve as a crucial reference for developing innovative theoretical models in future research [15].

2. Literature review

2.1. Two definitions of low financial literacy

Before training ML models, it is important to distinguish between two definitions of low financial literacy. Traditionally, low financial literacy is defined as having low objective financial knowledge (the first definition). However, recent studies indicate that young individuals whose subjective financial knowledge does not align with their objective knowledge also demonstrate low financial literacy [16,17]. This includes those who are financially overconfident (having high subjective but low objective knowledge), underconfident (low subjective but high objective knowledge), and financially incompetent (lacking both types of knowledge). This broader definition (the second definition) is significant, as empirical evidence shows that discrepancies between subjective and objective financial knowledge can lead to financial misbehavior [18,19]. For instance, financial overconfidence is linked to riskier financial behaviors and poor financial habits, while underconfidence can lead to overly cautious financial decisions that negatively affect long-term financial well-being [18,20].

The design and cost of financial education programs vary depending on which definition of low financial literacy they target. Programs aimed at the first definition focus solely on enhancing objective financial knowledge, whereas those addressing the second definition seek to improve both objective knowledge and financial confidence, which requires more complex and costly interventions, such as simulated financial practice. Therefore, it is essential to train ML models to identify youth with each type of low financial literacy, as this will inform the delivery of appropriate financial education. In practice, schools will select which ML model to use based on their educational goals and available resources.

2.2. Previous applications of ML models in personal finance

While ML models have been used in the personal finance sector to help banks identify risky customers [21,22], there has been limited research on using these models to detect low financial literacy for educational purposes, particularly among youth. The earliest application of ML in predicting personal finance outcomes involved Neural Networks (NNs) used by Huang et al. [23] and Support Vector Machines (SVM) adopted by the same team in 2008 [24]. Their study, which included a sample of 1010 Australian youth aged 16 to 24, utilized various sociodemographic variables—such as student type, age, gender, marital status, and work status—to predict personal finance outcome variables like credit card and loan statuses. The results showed that SVM outperformed NNs in prediction accuracy, likely due to NNs' tendency to overfit the limited sample size. Notably, both models focused on financial decisions regarding credit cards and loans, rather than assessing objective financial knowledge.

Levantesi and Zacchia [13] claimed to be the first to predict objective financial knowledge using ML models. They empirically tested and compared the performance of tree-based models—such as decision tree, random forest, and gradient boosting machine (GBM)—to identify Italian adults who did not need to improve their financial knowledge. Their outputs categorized individuals into low and high levels of objective financial knowledge, using inputs that included sociodemographic variables (gender, age, education, employment status) and personal finance constructs (financial attitudes, behaviors, and saving outcomes). In contrast to Huang et al. [24], Levantesi and Zacchia used a larger sample size ($N = 2500$) and employed multiple performance indicators (accuracy, precision, sensitivity, and Area Under the Curve) to evaluate the ML models. Specifically, they reported precision ranging from 0.57 to 0.80, sensitivity from 0.61 to 0.72, and accuracy from 0.62 to 0.67. Among the three models, the random forest model (accuracy = 0.67, precision = 0.80) significantly outperformed the decision tree and GBM. Given the actual prevalence of low and high financial literacy levels in their sample (46.5 % vs. 53.5 %), the random forest model demonstrated predictive power but also indicated substantial room for improvement.

Building on the literature that has established the initial efficacy of these tree-based ML models (decision tree, random forest, and GBM; Levantesi & Zacchia, 2021) and SVM (Huang, 2007, 2008), this study aims to extend their application to youth in Hong Kong. Additionally, new features, including financial socialization and parenting variables, will be integrated, with the expectation that these enhancements will improve the performance of the ML models.

2.3. Introduction to four candidate ML models

Decision trees, random forests, GBM, and SVM are prominent machine learning algorithms used for binary classification, each with distinct strengths and applications. Decision trees are simple, interpretable models that emulate human decision-making but can be prone to overfitting [25]. They require minimal data preprocessing, making them suitable for small sample sizes. Random forests enhance accuracy by aggregating multiple decision trees, thereby reducing overfitting and improving generalization on unseen data [26]. GBM builds models sequentially, focusing on correcting errors from previous iterations, which often leads to high predictive performance [27]. Light GBM, an optimized variant of traditional GBM, is particularly effective for complex models due to its efficient handling capabilities. By employing a histogram-based algorithm to determine the best split point for each feature, light GBM significantly outperforms traditional GBM in terms of speed and efficiency [28]. Consequently, light GBM was selected as the preferred algorithm over traditional GBM. Additionally, SVM is well-regarded for its binary classification capabilities, especially for its ability to identify an optimal hyperplane that maximizes the margin between classes [29].

2.4. Financial socialization, parenting, and financial literacy of youth

Financial socialization theory suggests that parents are the primary agents of financial education during youth, exerting greater influence than schools, peers, or media due to their control over essential financial resources and their ability to shape lifestyle and social exposure [5,30]. Parents can impact their children's financial literacy through two distinct channels: a direct channel involving observable parent-child financial activities, and a latent channel where parenting behaviors broadly influence cognitive development, including financial literacy [2,31].

Specifically, parents can directly affect their children's financial confidence, attitudes, and behaviors by teaching money management, budgeting, saving, and investing skills [5,30]. They also serve as role models, demonstrating financial responsibility through their actions and decisions. Consequently, all financial-related interactions between parents and children, such as direct teaching, parental role modeling, financial norms, and the overall financial relationship, can potentially serve as predictive features in training ML models for financial literacy.

Parental influence on youth financial literacy can also emerge from general parenting practices, which may indirectly affect financial literacy. Although the direct connection between these practices and financial literacy isn't always clear, viewing financial literacy as part of cognitive development highlights the importance of general parenting behaviors. Positive parenting, characterized by warmth and responsible supervision, fosters secure attachment, laying a foundation for healthy cognitive development, including financial literacy. Securely attached children are more likely to explore and learn, leading to better cognitive and financial outcomes [32].

In contrast, negative parenting practices, such as harsh discipline or neglect, can hinder cognitive development, resulting in lower IQ scores and academic challenges [33,34]. Such environments can disrupt neural development, impairing a child's ability to engage in complex cognitive tasks, including those related to financial literacy. Recent studies have highlighted the direct correlations between parenting behaviors and children's objective financial knowledge, emphasizing the need to include various parenting behaviors as features in ML model training [35]. This insight has motivated us to incorporate a diverse range of parenting behaviors into our feature set for ML models, anticipating that they will significantly enhance predictive power.

Examining both channels of financial socialization reveals that family economic resources and parental mental health are essential for effective financial socialization and positive parenting. Parents experiencing material hardship often prioritize immediate needs—such as food, shelter, and clothing—over long-term financial planning and education, limiting their ability to impart financial knowledge to their children. Furthermore, financial strain can be a significant source of chronic stress, leading to emotional exhaustion that diminishes a parent's empathy, patience, and emotional availability, ultimately affecting their capacity to provide the necessary support for their children's development. Therefore, family material well-being and parental stress levels should be included as additional features when training ML models to ensure a comprehensive understanding of the factors influencing financial literacy.

3. Method

3.1. Overall design

The reviewed literature establishes a foundation of potential features and candidate ML models for training purposes. Effective features identified in previous research include general socio-demographic and personal finance variables [13]. Building on these, this study adds financial socialization variables and both positive and negative parenting factors to enhance model performance. We began by using two definitions of low financial literacy to label youth, training ML models to accurately classify them into low or high financial literacy groups. Following established practices, we selected decision tree, random forest, light GBM, and SVM as training models, representing a spectrum of algorithms from simple to complex.

3.2. Sample

In Hong Kong, several cross-sectional datasets have examined the financial literacy of youth, with significant contributions from Zhu [36] and the Investor and Financial Education Council [37]. The youth sample from Zhu [36] was selected for its substantial size (N = 989), which supports the training of four ML models. This sample is notable for its comprehensive assessment of objective financial knowledge, utilizing the internationally standardized FFFL test, which includes 50 items evaluating a wide range of financial knowledge and skills. Additionally, the dataset features a measure of subjective financial knowledge on a Likert scale from 1 (least knowledgeable) to 7 (most knowledgeable), with confirmed reliability and validity among Hong Kong youth. It encompasses personal finance variables, family context, parental background, socialization factors, and parenting behaviors, providing all necessary features for training the candidate models.

The sample for ML model training consists of 989 youth from Hong Kong, with a slight female majority (55.8 %). Their ages range from 12 to 18, with an average age of 14.5. Single-parent families account for 9.1 % of the sample, and 9.6 % have at least one parent with an associate degree or higher. Housing data reveals that 49.6 % live in public rental housing, while 35.8 % reside in private permanent housing, indicating a higher representation of economically disadvantaged families. Official surveys report that over 60 % of children live in private permanent housing, a figure significantly higher than that in our sample [38].

The disparity in low and high financial literacy rates, based on two empirical definitions, is noteworthy. The first definition sets a conservative threshold of 40 % correctness on the FFFL test, with 68.1 % of youth classified as having low financial literacy. The second definition categorizes the sample into four subgroups.

- Financially competent: both objective and subjective financial knowledge above the mean;
- Financially overconfident: objective financial knowledge below the mean, subjective financial knowledge above the mean;
- Under-confident: objective financial knowledge above the mean, subjective financial knowledge below the mean;
- Financially naïve: both objective and subjective financial knowledge below the mean.

All youth in the latter three subgroups were considered to have low financial literacy, leading to 79.0 % of the sample being classified as such. Notably, the proportions of youth with high and low financial literacy were highly unbalanced under both definitions, with low-financial-literacy individuals comprising the majority. In imbalanced datasets, common evaluation metrics like accuracy can be misleading, as a model may achieve high accuracy by predominantly predicting the majority class. To address this, we employed random over-sampling to balance evaluation metrics such as precision, recall, and F1-score, ensuring adequate representation of the minority class. This strategy involved randomly duplicating examples from the minority class to balance the class distribution. As a result, the adjusted training sample for the first definition was expanded to 1348 individuals, evenly split with 674 in both the high and low financial literacy groups (50 % each). Similarly, for the second definition, the adjusted training sample grew to 1562 individuals, with 781 in each group (50 % each).

3.3. Measurement of features

The features selected for inclusion in the ML training consisted of personal finance factors, financial socialization elements, parenting behaviors, and measures of material well-being and parental stress. Personal finance variables included financial attitudes, perceived financial behavioral control, and actual financial behaviors. Financial attitudes were assessed by asking youth to rate their agreement with three statements: "Regular saving is important," "Monthly expenses should be tracked," and "Spending should be within a budget," based on frameworks established by Shim et al. [39]. Perceived financial behavioral control was evaluated through four items, including the question, "How easy or difficult is it for you to adhere to your financial plan?" as outlined by Shim et al. [39]. Healthy financial behaviors were measured by the frequency of saving, tracking monthly expenses, and adhering to a budget, aligning with the criteria set by Shim et al. [39].

Financial socialization variables included direct parental teaching, parental financial role modeling, parental financial norms, and the financial relationship with parents. Direct parental teaching was assessed through youth agreement with statements such as, "My parents discuss the importance of saving with me," "My parents guide me on smart shopping," and "My parents and I talk about financing my college education," following Shim et al. [39]. Parental financial role modeling was evaluated with statements like, "I consider my parent(s) as role models for managing money," and "My parent(s) positively influence my financial management," also based on Shim et al. [39]. Parental financial norms were measured through youth agreement with statements like, "My parents believe I should budget my spending," in line with Shim et al. [39]. The financial relationship with parents was assessed through items such as, "Money issues negatively impact my relationship with my parents," and "I frequently argue with my parent(s) about money," using Shim et al. [39] as a reference.

Parenting behaviors were categorized into negative types (over-reactivity, verbosity, laxness, spanking) and positive types (parental warmth and supervision), each measured with various items. Negative parenting was evaluated using 24 items from Arnold et al. [40], covering over-reactivity (7 items, e.g., "Your parent often insults you or says mean things"), verbosity (7 items, e.g., "Your parent tends to give long lectures"), and laxness (9 items, e.g., "Your parent allows you to do whatever you want"). Positive parenting was assessed with 28 items from the Home Observation for Measurement of the Environment [41], focusing on parental warmth (5 items, e.g., "Your parent shows physical affection") and supervision (23 items, e.g., "Your parent sets a curfew on school nights").

Material well-being was measured using 22 questions proposed by Wong et al. [42], such as access to sports and entertainment facilities at home. Parental stress was assessed through 12 items from Haskett et al. [43], reflecting distress or discomfort in parenting, with an example item being, "Your parent feels overwhelmed by parenting responsibilities." Details on the scales, coding, calculations, interpretations of all features, and their descriptive statistics are provided in Table 1.

Table 1
Coding, calculation, interpretation, descriptive statistics of outcome variables and features.

	Range	Mean (SD[1])	Frequency (%)
Outcome variables			
FFFL[2] test	0–39	17.96 (5.52)	
Low financial literacy based on FFFL[2] test, i. e., the first definition			674 (68.1 %)
Subjective financial knowledge	1–7	3.71 (1.59)	
Objective and subjective financial knowledge – four types			
- Financially competent			208 (21.0 %)
- Financially overconfident			323 (32.7 %)
- Financially underconfident			257 (26.0 %)
- Financially incompetent			201 (20.3 %)
Low financial literacy based on the second definition[3]			781 (79.0 %)
Features			
Social and demographic variables			
- Male			437 (44.2 %)
- Age	12–18	14.53 (1.04)	
- Single − parent status			90 (9.1 %)
- Living in public rental housing			491 (49.6 %)
- Living in permanent private housing			354 (35.8 %)
- Parental highest education achievement – associate degree or above			93 (9.6 %)
Personal finance variables			
- Financial attitudes	3–15	10.71 (2.02)	
- Perceived behavioral control	4–20	11.86 (3.13)	
- Parental direct teaching	3–15	9.67 (2.30)	
- The adoption of parental financial role modeling	3–15	9.84 (2.48)	
- Parental financial norms	3–15	10.32 (2.36)	
- Financial behaviors	3–15	9.50 (2.28)	
- Financial relationship with parent	3–15	8.04 (2.53)	
Parenting behaviors			
- Laxness	10–50	28.26 (5.40)	
- Over-reactivity	9–41	22.85 (5.91)	
- Verbosity	5–25	14.40 (3.32)	
- Spanking	0–3	1.15 (0.52)	
- Parental warmth	0–5	3.47 (1.67)	
- Parental supervision	0–23	12.61 (5.71)	
Wellbeing			
- Material wellbeing	0–22	18.39 (4.28)	
- Parental stress	12–60	31.12 (8.50)	

Note. [1] SD = standard deviation. [2] FFFL = Financial Fitness for Life. Under the first definition, the threshold for the FFFL test was established at a 40 % correctness rate, which corresponded to 20 correct responses out of 50 questions. Individuals scoring below this threshold were identified as having low financial literacy. [3] Under the second definition, individuals who were financially overconfident, underconfident, or incompetent were categorized as possessing low financial literacy.

3.4. Data analysis

As previously mentioned, decision tree, random forest, light GBM, and SVM models were employed to predict binary financial literacy outcomes. The performance of each model was evaluated using accuracy, precision, recall, and F1-score. In binary predictions, the confusion matrix consists of four components: true positives, true negatives, false positives, and false negatives. Accuracy measures the proportion of correct predictions (both true low and high financial literacy) relative to the total number of predictions. Precision assesses the proportion of true low financial literacy cases among all predictions made for low financial literacy (both true and false). Recall indicates the proportion of actual low financial literacy cases successfully identified by the model. The F1-score, which is the harmonic mean of precision and recall, offers a single metric that balances both aspects.

During training, hyperparameters such as the maximum depth of the decision tree and the number of estimators in the random forest were fine-tuned to optimize prediction performance. We also implemented cross-validation to obtain a more reliable estimate of model performance compared to a single train-test split. Specifically, we used five-fold cross-validation, dividing the dataset into five equal parts. The model was trained on four folds and tested on the remaining fold, repeating this process five times so that each fold served as the test set once. After each iteration, performance metrics were calculated based on the model's predictions for the test fold, and the metrics from all five iterations were averaged for a more reliable estimate of overall performance.

Once we identified the best-performing model for each definition, we examined the importance of each feature using ablation analysis. This analysis involved systematically removing features to assess their impact on the model's overall performance. Specifically, we employed a leave-one-out ablation approach, removing one feature at a time while retaining the others for training [44]. In this analysis, we focused on accuracy and recall. While accuracy provides a general overview of the model's performance by indicating the proportion of correctly classified instances, recall is more critical for financial educators, as it measures the model's ability to accurately identify individuals with low financial literacy for targeted interventions. We established a 1 % reduction in performance as the criterion for assessing feature importance, based on the belief that even a small change can signify a meaningful improvement or decline in model performance [45].

4. Results

Table 2 presents the performance metrics of four machine learning models—decision tree, random forest, light GBM, and SVM—in predicting financial literacy levels. The models were evaluated using accuracy, precision, recall, and F1 score for both low and high financial literacy groups based on two definitions. Under the first definition, where low financial literacy is defined as low objective financial knowledge, light GBM achieved the highest accuracy at 0.8917, closely followed by random forest at 0.8821. In terms of recall for the low financial literacy group, random forest led with 0.8754, while light GBM followed at 0.8516, illustrating both models' effectiveness in identifying youth with low financial literacy accurately. For the high financial literacy group, light GBM excelled with a recall of 0.9318, showcasing its strong ability to accurately identify youth with high financial literacy. Overall, light GBM was the best-performing model under the first definition.

Table 2
Performance indicators of supervised machine learning models.

Financial literacy group	Performance indicator	Decision tree	Random forest	Light GBM *	SVM
	Accuracy	0.7619	0.8821	**0.8917**	0.7396
Low financial literacy[1]	Precision	0.8132	0.8875	**0.9256**	0.7618
	Recall	0.6900	0.8754	**0.8516**	0.6973
	F1	0.7424	0.8813	**0.8870**	0.7277
High financial literacy[1]	Precision	0.7313	0.8771	**0.8629**	0.7217
	Recall	0.8339	0.8887	**0.9318**	0.7820
	F1	0.7767	0.8828	**0.8960**	0.7503
Financial literacy group	**Performance indicator**	**Decision tree**	**Random forest ***	**Light GBM**	**SVM**
	Accuracy	0.7061	**0.9328**	0.9033	0.6460
Low financial literacy[2]	Precision	0.7770	**0.9556**	0.9646	0.6627
	Recall	0.5851	**0.9078**	0.8374	0.5967
	F1	0.6640	**0.9308**	0.8963	0.6275
High financial literacy[2]	Precision	0.6676	**0.9129**	0.8566	0.6329
	Recall	0.8272	**0.9578**	0.9692	0.6952
	F1	0.7374	**0.9346**	0.9093	0.6623

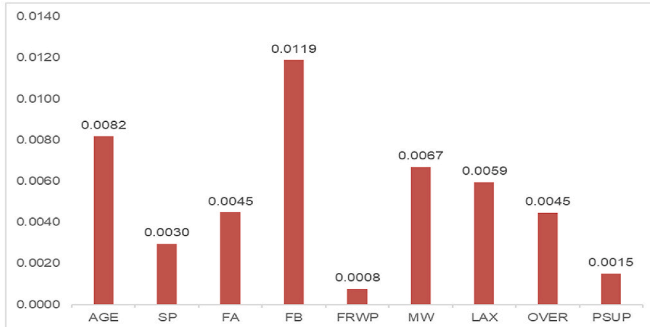
Note. [1] Under the first definition, the threshold for the FFFL test was established at a 40 % correctness rate, which corresponded to 20 correct responses out of 50 questions. Individuals scoring below this threshold were identified as having low financial literacy. Individuals scoring above this threshold were identified as having high financial literacy. [2] Under the second definition, individuals who were financially overconfident, underconfident, or naïve were categorized as possessing low financial literacy. Individuals who were financially competent were categorized as possessing high financial literacy. SVM = Support Vector Machine, GBM = Gradient Boosting Machine. * Algorithms with the best prediction performance; results are presented in bold.

Under the second definition, which defines low financial literacy as a discrepancy between subjective and objective financial knowledge, random forest outperformed all models with an accuracy of 0.9328, significantly surpassing the others. Light GBM followed with an accuracy of 0.9033, while SVM and decision tree performed less effectively. For low financial literacy, light GBM achieved the highest precision at 0.9646, while random forest had the highest recall at 0.9078. Random forest also led in F1 score at 0.9308, demonstrating a strong balance between precision and recall. For high financial literacy, both random forest and light GBM performed well, with random forest achieving the highest precision of 0.9129 and light GBM excelling in recall at 0.9692. Overall, random forest emerged as the best-performing model under the second definition.

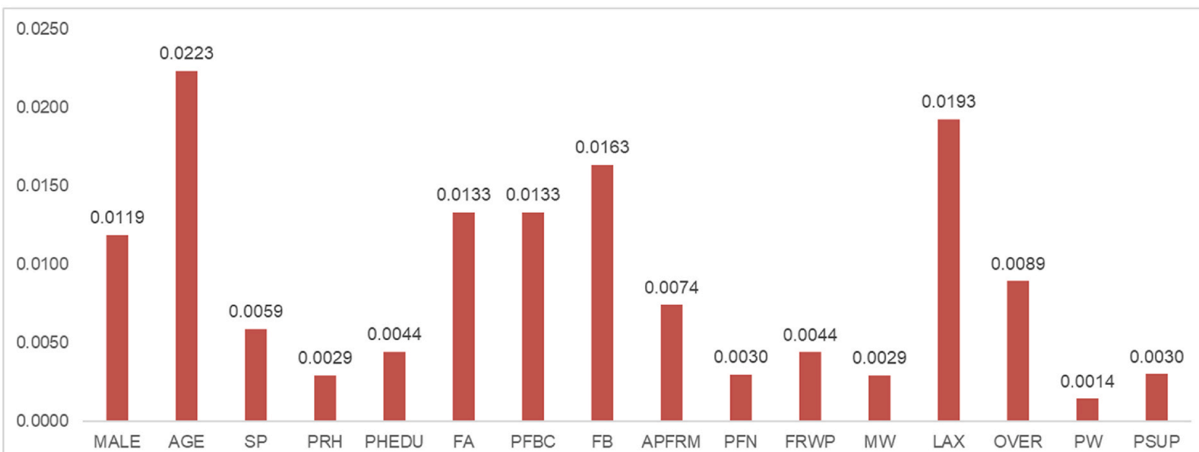
Fig. 1 displays the ablation analysis results for the light GBM model, which was the top performer under the first definition of low financial literacy. Features that significantly contributed to accurate predictions, based on a criterion of at least a 1 % reduction in accuracy or recall, included gender, age, financial attitudes, perceived financial behavioral control, financial behaviors, and laxness. Similarly, Fig. 2 presents the ablation analysis results for the random forest model, the best performer under the second definition. Key features identified included various socio-demographic factors (age, single-parent status, private permanent housing status, parental education level, material hardship), parental financial socialization variables (direct teaching, financial norms, financial relationships with parents), a range of parenting behaviors (laxness, over-reactivity, warmth, spanking, supervision) and financial attitudes and financial behaviors, all of which were important for accurately predicting low financial literacy under this definition.

5. Discussion

This study is the first globally to use interdisciplinary features in training machine learning models to predict financial literacy groups among youth. Our models, which incorporate financial socialization variables and parenting behaviors, significantly outperform the previous model by Levantesi and Zacchia [13], which lacked these interdisciplinary features. Levantesi and Zacchia's model aimed to identify individuals with high financial literacy, defined solely by high objective financial knowledge, with a true prevalence of approximately 50 % (53.5 %) in their sample. Similarly, our sample (after performing the oversampling) had a true 50 % prevalence of high financial literacy, defined in the same way. To enable direct comparison, we extracted the accuracy, recall, and precision of decision tree and random forest models predicting high financial literacy from Table 2, as these two models were also trained by Levantesi and Zacchia [13]. The comparison reveals that our models significantly outperform those of Levantesi and Zacchia [13]. For the decision tree, our model achieved an accuracy of 0.7619 compared to their 0.6337, a precision of 0.7313 versus their 0.7172, and a recall of 0.8339 compared to their 0.6250. Similarly, for the random forest model, our study achieved an accuracy of 0.8821 versus their 0.6737, a precision of 0.8771 compared to their 0.7992, and a recall of 0.8887 versus their 0.6478. Therefore, this paper contributes significantly to the training of machine learning models for predicting financial literacy groups.



(a) The reduction in *accuracy* before and after removing the feature



(b) The reduction in *recall* before and after removing the feature

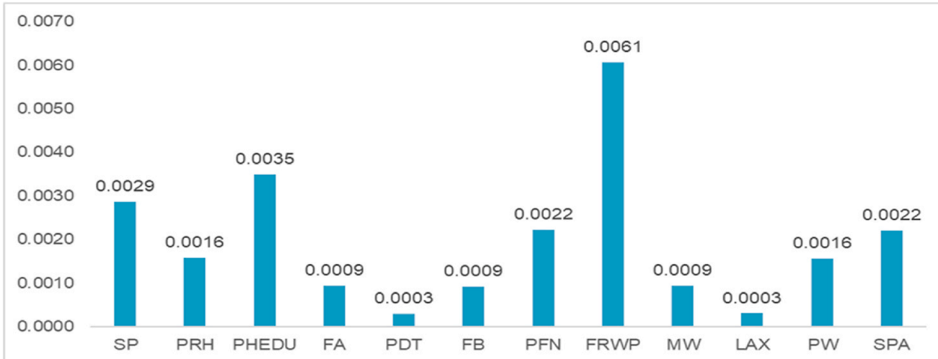
Fig. 1. Ablation analyses of the Light GBM model for the first definition of low financial literacy.
Note.
The threshold for the FFFL test was established at a 40 % correctness rate, which corresponded to 20 correct responses out of 50 questions. Individuals scoring below this threshold were identified as having low financial literacy.
SP = single parent, PRH = private permanent housing, PHEDU = parental highest education achievement, FA = financial attitudes, PFBC = perceived financial behavioral control, FB = financial behaviors, APFRM = adoption of parental financial role modeling, PFN = parental financial norms, FRWP = financial relationship with parent, MW = material wellbeing, LAX = laxness, OVER = over-reactivity, PW = parental warmth, PSUP = parental supervision.

Upon reviewing the full results in Tables 2 and it is noted that light GBM performed best for the first definition of low financial literacy, while random forest excelled in predicting the second definition. Random forest stood out in terms of recall for both definitions, which measures the proportion of disadvantaged youth successfully identified by the ML model. This indicator is crucial for policymakers and financial education providers as it ensures reaching disadvantaged youth, regardless of the waste in resources. At the policy level, low financial literacy is closely linked to financial exclusion, social inequality, and intergenerational poverty, underscoring the need to avoid overlooking any disadvantaged individuals. That is why existing financial education programs often target the general youth population without considering the potential waste of resources on those not in need. Implementors of financial education prioritize reaching those most in need, even if it means providing unnecessary education to others. The random forest models with high recall for both definitions of low financial literacy align with this goal, making them a promising choice for government and financial education providers seeking an effective filtering tool.

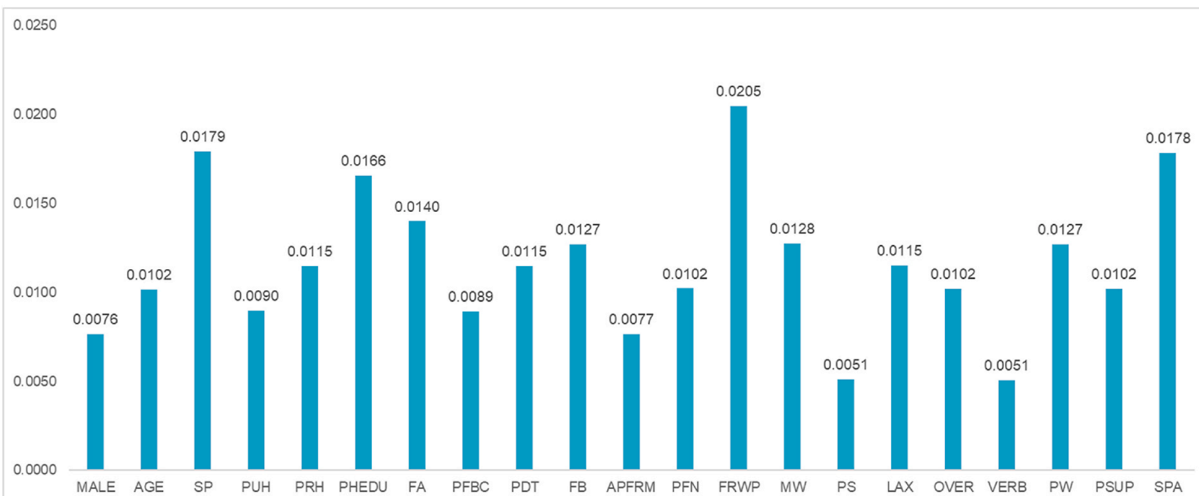
Through ablation analysis, we identified the most influential features for predicting both definitions of low financial literacy (see Figs. 1 and 2). Our analysis is guided by the four-stage conceptual model of financial literacy proposed by Goyal and Kumar [6], which includes antecedents of financial literacy, core financial literacy constructs, attitudinal variables, and financial behaviors. Fig. 3(a) and (b) illustrate that the antecedents of low financial literacy are less complex in the first definition compared to the second. A comparison of the conceptual models reveals that developing objective financial knowledge is more straightforward than achieving sufficient financial knowledge and confidence. Objective knowledge can be cultivated through attentive parenting alone, while establishing both knowledge and confidence requires broader interactions, including financial communication and emotional support from parents, as well as active parental supervision. These conceptual models offer valuable hypotheses for future researchers interested in exploring diverse pathways toward varying definitions of low financial literacy.

5.1. Implications on practice

Previous research has invested considerable resources in assessing financial literacy, such as developing and validating standardized tests,



(a) The reduction in *accuracy* before and after removing the feature



(b) The reduction in *recall* before and after removing the feature

Fig. 2. Ablation analyses of the random forest for the second definition of low financial literacy.
Note.
Individuals who were financially overconfident, underconfident, or incompetent were categorized as possessing low financial literacy.
SP = single parent, PUH = public rental housing, PRH = private permanent housing, PHEDU = parental highest education achievement, FA = financial attitudes, PFBC = perceived financial behavioral control, PDT = parental direct teaching, FB = financial behaviors, APFRM = adoption of parental financial role modeling, PFN = parental financial norms, FRWP = financial relationship with parent, MW = material wellbeing, PS = parental stress, LAX = laxness, OVER = over-reactivity, VERB = verbosity, PW = parental warmth, PSUP = parental supervision, SPA = spanking.

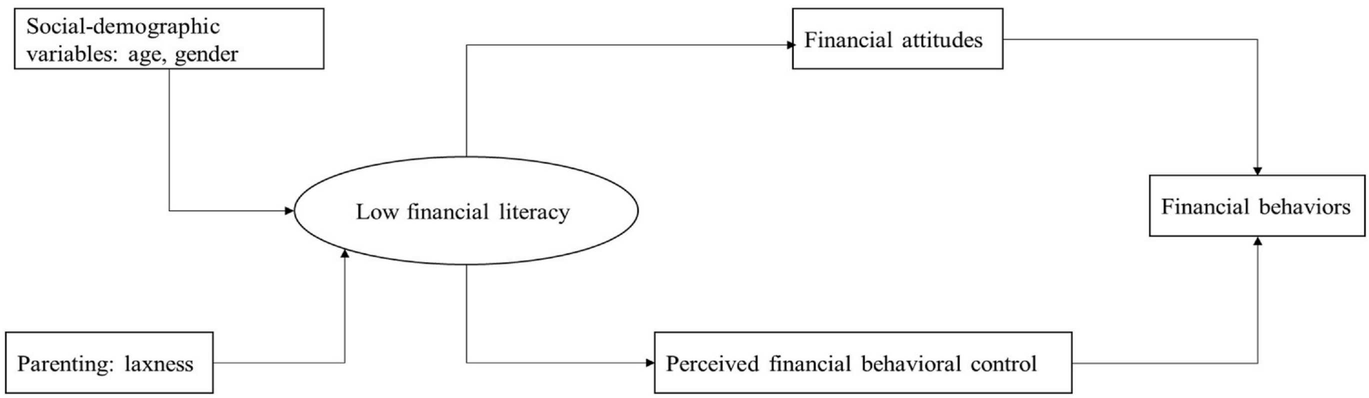
which may not be the most efficient approach. In behavioral science, financial literacy is valued not for its own sake, but for its potential to drive long-term behavioral change. Similarly, financial education often targets financial literacy as an outcome, viewing it as a means to facilitate these changes rather than an inherent goal. Therefore, when financial literacy is treated as a construct in exploratory research, using ML models to reduce measurement costs becomes valuable. For example, ML models can identify individuals with low financial literacy, allowing researchers to create a sample that, when analyzed, can provide deeper insights into the socialization processes affecting financially incompetent individuals and inform more targeted intervention strategies.

Moreover, the ML models we developed can greatly improve the efficiency of social science data utilization and foster genuine interdisciplinary collaboration among research teams. We have pioneered the use of non-financial data to train ML models for predicting financial outcomes like financial literacy. This approach highlights the untapped potential of social science data, which can be discovered through collaboration among researchers from diverse fields. In other words, the extensive panel data collected in Hong Kong across multiple disciplines may currently be underutilized.

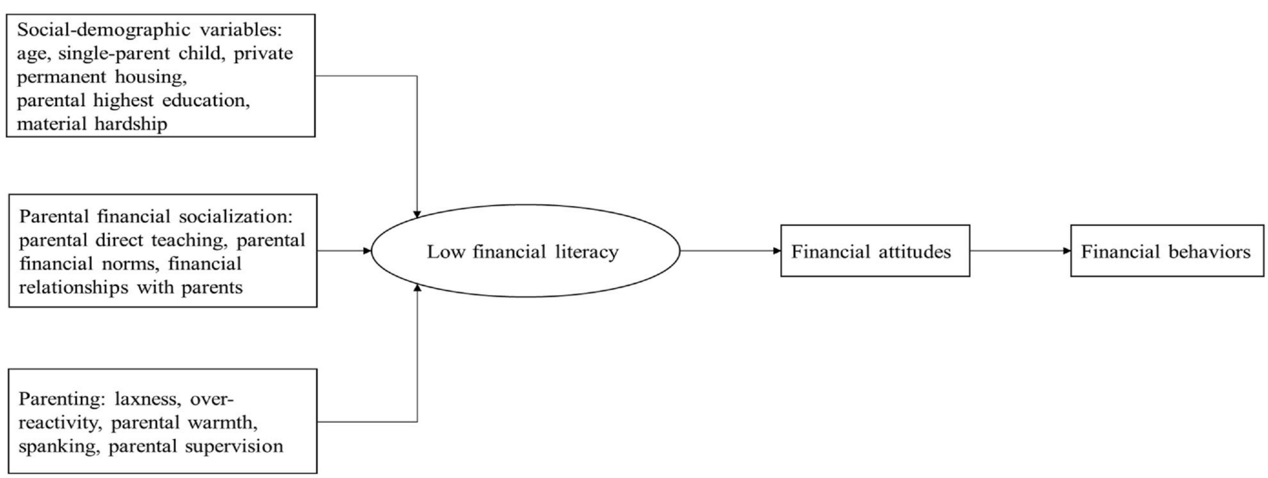
Additionally, this research is particularly timely given the rapid advancements in interactive AI, which have significantly lowered the costs associated with developing and managing ML code [46]. This advancement allows ML to be more accessible to the broader academic community, lowering technical barriers. In this context, scholars are encouraged to think creatively, uncovering hidden data interactions across various social science fields and leveraging ML to lower the costs of discovering new knowledge.

5.2. Limitations

The primary limitation of our study is the small sample size, which constrained our ability to explore a broader range of ML algorithms, such as neural networks. Additionally, the effectiveness of our trained ML models depends heavily on the accuracy of labeling Hong Kong youth using an objective test prior to training. Although the validity and reliability of the FFFL test are established, alternative objective financial



(a) Conceptual model based on the first definition of low financial literacy



(b) Conceptual model based on the second definition of low financial literacy

Fig. 3. Conceptual framework to be tested by future research.

knowledge tests may exhibit higher validity and reliability among Hong Kong youth. The emergence of a superior objective test in the future could potentially enhance the entire ML model training process.

Additionally, the burgeoning field of statistical research on financial socialization may introduce new features to consider, thereby refining the feature pool and optimizing the ML model training process. It is also important to note that the best-performing model may vary when this study is replicated in different societies, as influential features can differ based on social and cultural contexts. We encourage researchers in other social settings to replicate this work, as it presents a valuable opportunity to explore the interplay between algorithms and culture in social science research.

6. Conclusion

Social science scholars have traditionally adopted a theory-driven approach, using data and statistical methods to test hypotheses and uncover new knowledge. In contrast, data-driven technology, often dismissively labeled as "fishing", is typically met with skepticism in social science circles. However, the increasing adoption of interactive AI could unlock the potential of data-driven techniques, such as supervised ML, to enhance research and facilitate knowledge discovery by significantly lowering the costs associated with ML. This shift encourages social science scholars to reassess the value of data-driven technology [47].

This study exemplifies the power of ML by training models to identify youth with low financial literacy, showcasing ML's transformative potential in personal finance research. This approach not only reduces the costs of implementing financial education but also creates opportunities to improve the theoretical model of financial socialization, promotes interdisciplinary collaboration among social science researchers, and uncovers the untapped value of existing social science data.

Informed consent

Informed consent was obtained from all individual participants included in the study.

Ethical statement

Ethical approval for this study was obtained from the Human Research Ethics Committee of The Education University of Hong Kong prior to data collection.

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Conflict of interest

The author declares no potential conflicts of interest concerning the research, authorship, and/or publication of this article.

Data availability

Data will be made available on request.

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