DOI: 10.1111/cdev.13910

CHILD DEVELOPMENT

EMPIRICAL ARTICLE

Cheating among elementary school children: A machine learning approach

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Funding information
Major Project of Philosophy and Social Science Research of the Ministry of Education of China, Grant/Award Number: 22JZD044; National Natural Science Foundation of China, Grant/Award Number: 32171060; Scientific Research Fund of Zhejiang Provincial Education Department of China, Grant/Award Number: Y202250508

Abstract

Academic cheating is common, but little is known about its early emergence. It was examined among Chinese second to sixth graders (N = 2094; 53% boys, collected between 2018 and 2019) using a machine learning approach. Overall, 25.74% reported having cheated, which was predicted by the best machine learning algorithm (Random Forest) at a mean accuracy of 81.43%. Cheating was most strongly predicted by children's beliefs about the acceptability of cheating and the observed prevalence and frequency of peer cheating at school. These findings provide important insights about the early development of academic cheating, and how to promote academic integrity and limit cheating before it becomes entrenched. The present research demonstrates that machine learning can be effectively used to analyze developmental data.

Abbreviations: AUC, area under curve; GEE, Generalized Estimating Equation; GLM, Generalized Linear Modeling; LR, logistic regression; MLP, Multilayer Perceptron; RF, Random Forest; SES, socioeconomic status; XGBoost, Extreme Gradient Boosting.

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How well the predictors are able to predict the dependent variable across the multiple data partitioning and recombination processes can be evaluated statistically, which essentially provides an assessment of the internal validity of the models' predictions (Campbell, 1986; Diener et al., 2022). Furthermore, by using the resultant distributions of model performances, one can estimate effect sizes and the likelihood of false positives (Type 1 errors).

Second, the modern machine learning approaches involve dividing the data into training, testing, and holdout subsets. Then the models from the training–testing process are further validated against the holdout subset, which has never been used in either training or testing. Thus, how well the models perform with this subset provides a statistical assessment of the generalizability of the models and their potential reproducibility with a new group of participants. In other words, this validation against the holdout subsets provides an assessment of the models' external validity (Campbell, 1986; Diener et al., 2022) and can help to address the current replication crisis in psychology and other disciplines (e.g., Blockeel & Vanschoren, 2007; Drubin, 2015).

Third, in the modern machine learning approaches, we can choose a variety of different machine learning algorithms to analyze data. They include multiple linear regression or logistic regression (LR) analyses, which were among the first types of machine learning algorithms to be used in science (Ng, 2017). Regression algorithms can be used to model the linear or curvilinear effects of predictors and their interactions. More modern algorithms include Random Forest (RF), Multilayer Perceptron (MLP), and Extreme Gradient Boosting (XGBoost) decision trees (Chan et al., 2002; Gao et al., 2018; Golino et al., 2014; Yarkoni & Westfall, 2017). These algorithms can model not only linear or curvilinear effects, but also dynamic nonlinear effects (Kurt et al., 2008; Stylianou et al., 2015; Thelen & Smith, 1994). Different algorithms produce different models with different levels of predictive performance, which allows researchers to determine the best technique for analyzing the dataset at hand. Furthermore, using multiple machine learning algorithms can help to reduce the odds of a failure to reveal a true significant association between the predicted variable and the predictors (a false negative or Type 2 error).

Fourth, modern machine learning approaches can use the Shapley values to explain their findings by quantifying the relative importance of different predicting variables (Ghorbani & Zou, 2019; Lundberg & Lee, 2017; Smith & Alvarez, 2021). Shapley values are based on game theory, and were proposed by a Nobel Prize winner Lloyd Shapley (1953). At the beginning, game theory was used only to solve the problem of distributing benefits in complex cooperative relationships. Its distribution principle is that the benefit obtained by individuals should be equal to the value of their contributions. Recently, some scholars have begun to use this approach to measure the relative contributions of all predicting variables in machine learning models, and it has become one of the important metrics for explaining machine learning results (Ghorbani & Zou, 2019; Lundberg & Lee, 2017; Smith & Alvarez, 2021; Sun, Liu, et al., 2022; Sun, Luo, et al., 2022). Because the Shapley values are additive mathematically, one can perform conventional statistical analyses on them to make probabilistic inferences about whether one predictor is significantly superior or inferior to another predictor in its contribution to a computational model's performance. In the present study, the Shapley values allowed us to identify factors that predict cheating, from the most important to the least important.

The present study tested the following hypotheses for both confirmatory and exploratory purposes. First, we hypothesized that the LR, RF, MLP, and XGBoost decision trees each would all be able to produce computational models that predict cheating significantly above the chance level. Second, we hypothesized that among these four different machine learning algorithms, the RF, MLP, and XGBoost would be able to produce computational models that predict cheating significantly better than the traditional LR. These hypotheses were tested for confirmatory purposes because they were based on the fact that existing theoretical models and related empirical evidence suggests that cheating is influenced by a multitude of moderating and mediating factors, and it is likely that some of these effects could be dynamically nonlinear. Thus, because the LR only considers the linear or curvilinear effects of the predictors on the predicted variable, this machine learning algorithm was predicted to perform worse than the other three algorithms, which are capable of considering linear, curvilinear, and nonlinear dynamic relations.

Third, regarding the predictor importance, we tested the *commonalit* hypothesis for confirmatory purposes and hypothesized that, in line with this hypothesis, the important predictors identified by the computational models would align with the model proposed by Whitley et al. (1999). Specifically, in light of evidence of continuity between middle school and older students (Anderman & Midgley, 2004; McCabe et al., 2012), we predicted that the factors affecting cheating in elementary school students would be similar to those affecting cheating in older students. More specifically, we predicted that as with high school and college students, beliefs about the acceptability of peer cheating and observations regarding its frequency would be significantly associated with the likelihood of self-reporting to have cheated on exams (Krou et al., 2021; Lee et al., 2020; see Zhao et al., 2022 for related meta-analyses). Based on previous but relatively weak evidence among older students that males tend to cheat at a slightly higher rate than females (Jensen et al., 2002; Nathanson et al., 2006; Newstead et al., 1996; Whitley, 1998; Yu et al., 2016; see Whitley et al., 1999 for a meta-analysis), for exploratory

the success of studies that use machine learning will provide an impetus for more developmental researchers to use these techniques to address a range of questions and advance our knowledge about child development.

The present study also has several limitations. One is that it only involved children from China. Although our findings are similar to what has been found with older students in the West, they need to be replicated with elementary school children in other countries. Second, in the present study, cheating was assessed using self-report measures only. Even though we took great care to reassure students that their responses would be kept confidential, some children might not have responded truthfully out of a fear that their responses would be accessible to their teachers. Thus, the findings of the present study may have underestimated of the actual prevalence of cheating and the strength of its relations to the predictor variables. Future studies should use self-report and behavioral cheating measures together to address this problem. Since Hartshorne and May (1928), researchers have devised many ingenious and naturalistic methods to assess whether children have cheated on a test. Although most of these methods have been used with older children and adults (Cizek, 1999; Zhao et al., 2021), recent studies have shown that they can be readily used with young children as well (Zhao et al., 2018, 2020, 2021). Another limitation of the present research is that we only examined correlations between variables at one time point. This leaves open questions about how beliefs and behavior influence each other and unfold over developmental time. This limitation could be overcome by using longitudinal designs.

CONCLUSIONS

The present study used a machine learning approach to examine self-reported academic cheating among Chinese second to sixth graders, to bridge a significant gap in the literature regarding the emergence of cheating during the elementary school years. We found that children's cheating was most strongly predicted by their own beliefs about how acceptable it is, by their observations of how prevalent cheating is at their school, and by how frequently they observe peers cheating. These factors are also significantly associated with academic cheating in older students, favoring the commonality hypothesis over the discontinuity hypothesis. The present study also provides important insights into how to promote academic integrity and limit cheating before it becomes entrenched. More broadly, the present research shows that machine learning is a viable and effective approach to analyzing developmental data.

ACKNOWLEDGMENTS

The contribution of L. Zhao was supported by the Major Project of Philosophy and Social Science Research of the Ministry of Education of China (22JZD044) and the National Natural Science Foundation of China (32171060). The contribution of Y. Zheng was supported by the Scientific Research Fund of Zhejiang Provincial Education Department (Y202250508). The funder had no role in the study design, data collection and analysis, decision to publish, or preparation of the manuscript.

DATA AVAILABILITY STATEMENT

The data and the code that support the findings of this study are available from L. Zhao (email: zhaoli@hznu.edu.cn) upon request.

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Q4. How often do you think your classmates have engaged in each the following forms of behavior during an exam?

[The following items used a five point scale: 1 never, 2 somewhat infrequently, 3 neither frequently nor infrequently, 4 somewhat frequently, 5 extremely frequently].

1. Bringing unauthorized materials to an exam.
2. Copying answers from a textbook during an exam.
3. Passing notes during an exam.
4. Copying answers from a neighbor during an exam.
5. Using tools (e.g., dictionaries, cellphones, or smart watches) to search for answers during an exam.
6. Working with one or more classmates to share answers during an exam
7. Deliberately giving a classmate a wrong answer during an exam.
8. Secretly changing a test score.

Q5. To what degree is cheating on exams acceptable to you?

[This item used a five point scale: 1 not acceptable at all, 2 somewhat unacceptable, 3 neither acceptable nor unacceptable, 4 somewhat acceptable, 5 completely acceptable] nothing special.

Q6. To what degree do you think cheating on exams is acceptable among your classmates?

[This item used a five point scale: 1 not acceptable at all, 2 somewhat unacceptable, 3 neither acceptable nor unacceptable, 4 somewhat acceptable, 5 completely acceptable].

Q7. To what degree do you think each of the following items can serve as an effective way to reduce cheating on exams?

[The following items used a five point scale: 1 not effective at all, 2 somewhat ineffective, 3 neither effective nor ineffective, 4 somewhat effective, 5 extremely effective].

1. Increasing the severity of consequences of getting caught cheating (e.g., giving a zero score).
2. Students who sit next to each other getting different versions of the test.
3. Working harder.
4. Teachers emphasizing that academic cheating represents a serious moral transgression
5. Having a teacher who is greatly liked by their students to teach the class.
6. Teachers giving sharp criticism or punishment.
7. Teachers recognize classroom role models by giving praise or prizes to students who behave honestly on exams
8. Parents being informed when their children are caught cheating, and the parents in turn giving sharp criticism or punishment

Q8. To what degree do you think each of the following items is severe?

[The following items used a five point scale: 1 not severe at all, 2 less severe, 3 neither severe nor non-severe, 4 somewhat severe, 5 extremely severe].

1. Being criticized by one's teacher.
2. Being punished by one's teacher.
3. Being criticized by one's parents.
4. Being punished by one's parents.
5. Being criticized or rejected by one's classmates.

Q9. School: _____.

Q10. Date of Birth:_____.

Q11. Gender: _____.

Q12. Grade: _____.

Q13. Do you have any siblings?

[Respondents selected a single item from the above set of options.]

1. No, I am the only child.
2. Yes, I have one or more older siblings.
3. Yes, I have one or more younger siblings.
4. Yes, I have both older and younger siblings

Q14. What level do you think your academic performance is in the class?

[Respondents selected a single item from the above set of options.]

1. Above the average.
2. Average.
3. Below the average.