

Kansas State University Libraries

New Prairie Press

Adult Education Research Conference

2022 Conference Proceedings (Norman, OK)

The Determinants of Adult Education and Training Participation in the US: A Machine Learning Approach

Chang Sung Jang

University of Oklahoma Norman Campus, csjang1227@ou.edu

Junghwa Choi

University of North Carolina at Pembroke, junghwa.choi@uncp.edu

Romit Maulik

Argonne National Laboratory, rmaulik@anl.gov

Doo Hun Lim

University of Oklahoma Norman Campus, dhlum@ou.edu

See next page for additional authors

Follow this and additional works at: <https://newprairiepress.org/aerc>



Part of the [Adult and Continuing Education Commons](#)



This work is licensed under a [Creative Commons Attribution-Noncommercial 4.0 License](#)

Recommended Citation

Jang, C., Choi, J., Maulik, R., & Lim, D. (2022). *The Determinants of Adult Education and Training Participation in the US: A Machine Learning Approach*. Adult Education Research Conference. <https://newprairiepress.org/aerc/2022/papers/23>

This Event is brought to you for free and open access by the Conferences at New Prairie Press. It has been accepted for inclusion in Adult Education Research Conference by an authorized administrator of New Prairie Press. For more information, please contact cads@k-state.edu.

Author Information

Chang Sung Jang, Junghwa Choi, Romit Maulik, and Doo Hun Lim

The Determinants of Adult Education and Training Participation in the US: A Machine Learning Approach

Chang Sung Jang¹, Junghwa Choi², Romit Maulik³ and Doo Hun Lim¹

¹The University of Oklahoma, Norman, OK

²The University of North Carolina at Pembroke, Pembroke, NC

³Argonne National Laboratory, Lemont, IL

Abstract

This study aims to explore the determinants of adult education and training (AET) participation of working adults. Through random forest analysis, we discovered important factors contributing to AET participation.

Keywords: adult education and training participation, working adults, machine learning, PIAAC

Learning takes place everywhere, at all times as an individual participates in educational activities throughout their lifetime (Billett, 2010). In fact, much learning occurs through formal and non-formal settings of organization, community, and society at large, accordingly, the underlying principle of lifelong learning (LLL) becomes a primary source of strengthening human capital (Boeren et al., 2010). Given the increasing and complicated demand of the modern workplace, knowledge and skills acquired in public school systems are not sufficient to meet the job requirements of adults. Hence, more and more adults seek further education to continue their professional growth and to sustain increased employability in today's competitive labor market (Dibra et al., 2014). Especially for adults who are in the labor force, job-related adult education and training (AET) is one avenue in which knowledge is attained and skills are upgraded for the ever-changing needs of the world of work.

In many countries, a dominant form of adult education is employment-related (Desjardins, 2020). In response, there has been growing interest in research concerning job-related AET and its benefits to employees and organizations. AET refers to a form of learning contributing to the accumulation of knowledge and skills throughout an adult's life course (Desjardins, 2020). According to Punksungka and coauthors (2021), job-related AET brings a wide range of benefits to individuals, firms, and society. By participating in job-related AET, employees can hold greater employment opportunities and enhanced human capital such as work-related skills and competencies (Schuller & Desjardins, 2010). Individuals who received positive returns through job-related AET participation, in turn, serve as an important asset to maintain the competitive edge of the organization (Gherardi, 2006). Not surprisingly, a great volume of literature offers abundant evidence that job-related AET is often seen as an overarching goal of human resource development itself (Watkins & Marsick, 2014).

Nevertheless, the empirical findings pertaining to what contextual factors were most influential for working adults' participation in job-related AET are still obscure. Typically, prior studies rely on only a few predictors to investigate. From a methodological standpoint, the detailed demonstration of how micro- and macro-level characteristics influence dependent variables is limited when relying solely on traditional regression models which are deficient in coping with multivariate structure of the data (Breiman, 2001). In order to address this concern, we leverage random forest classifier (RFC) technique as an analytic method, which is one of the machine learning algorithms. The advantage of using RFC over traditional regression models is

that it allows a comprehensive examination of multiple factors at once, regardless of collinearity. More importantly, our analytic choice enables us to compare the relative importance of the given factors. In this context, this study aims to explore the determinants of job-related AET participation of working adults by applying the machine learning approach.

Literature Review

Concept and Typology of AET

In the past decades, the concept of adult learning has been widely reviewed for its social and policy implications (Jarvis, 2011). A broad range of LLL policies and initiatives across countries have apparently been implemented in an effort to offer work-related learning in line with labor market demands. As work-related learning is regarded as a primary focus of the LLL agenda, the timely provision of occupational AET has received increased policy attention (Yamashita et al., 2018). In general, the definition of AET refers to “a form of learning that takes place in addition or as a complement to formal education and is distinct from informal learning, that is intentional but less structured” (Widany et al., 2019, p. 8). An underpinning premise of AET is that it typically occurs through both formal and non-formal means of participation (OECD, 2013). Formal AET is formally designed and organized learning that occurs in educational institutions such as colleges or universities (Commission of the European Communities, 2000). The goal of formal AET is often geared toward gaining certified educational outputs such as college diplomas or course completion certificates in order to compensate for the lack of education of the workforce (Yamashita et al., 2018). Non-formal AET is also structured and organized learning that takes place alongside educational institutions, however, it can be distinguished from formal training by its tacit nature of knowledge accumulation and does not lead to credentials (Punksungka et al., 2021). By accommodating organized forms of the learning process, it occurs mostly in institutionalized settings such as the workplace offering short-term courses, workshops or seminars (Eurostat, 2016).

Key Drivers of AET Participation

Many studies have sought to examine how personal predispositions and experiences and work-related contextual factors predict job-related AET participation among employees (e.g., Punksungka et al., 2021). Based on previous studies addressing the topics of what determines adult workers' participation in AET, two categories of contexts (i.e., individual, work-related) and their relevant factors are identified. It is widely acknowledged that individuals who have higher human capital tend to pursue additional knowledge and skills (Boeren et al., 2010). This statement has been supported by the research that shows a direct association between individuals' socioeconomic status and the degree of AET participation. Components of the individual context originated from the literature are *gender*, *age*, *education level*, and *income*. Furthermore, the organization plays a vital role in fulfilling employees' learning potential. In order to stimulate working adults to seek further educational opportunities, organizations provide relevant environments and multiple options for learning to take place. It reiterates that the institutional work-based factors can be regarded as a condition of AET participation among working adults. Identified work-related predictors are *employment status*, *managerial status*, *economic sector*, *organization size*, *work flexibility*, *job satisfaction*, and *skills use at work*.

Methodology

Data Source and Sample

The data is drawn from the Program for the International Assessment of Adult Competencies (PIAAC) conducted and developed by the Organization for Economic Cooperation and Development (OECD). PIAAC data provides nationally representative estimates of adults' learning in and out of the workplace by measuring the degree to which their participation in various types of AET activities. For this current study, we used the latest U.S. PIAAC data collected in 2017. The respondents aged 25 to 65 years old who had recent work experience in the last 12 months preceding the survey were selected. Consequently, our total sample size includes 1,334 respondents.

Variables

Herein we focus on working adults' participation in job-related *formal AET* and *non-formal AET* as dependent variables. In the PIAAC data, formal AET is recorded as a dichotomous measure indicating whether the respondent has participated in job-related formal education and training (0 = no, 1 = yes). Non-formal AET is a binary variable that refers to whether the respondent has participated in non-formal education for job-related reasons (0 = no, 1 = yes). Independent variables include the respondent's individual and work-related contexts. The individual context reflects the respondent's demographic information such as *gender*, *age*, *education level*, and *monthly income*. The work-related context of the respondent contains factors representing their job-related conditions: *employment status*, *managerial status*, *economic sector*, *organization size*, *work flexibility*, *job satisfaction*, and three types of *skills use at work* (i.e., literacy, numeracy, and ICT).

Analytic Strategy

As the main analysis technique, RFC is a popular ensemble machine learning method that social scientists have recently applied to calculate the relative importance of explanatory variables (Choi et al., 2020). RFC utilizes multiple decision trees and these trees are collected to construct forests that provide information on what factors most efficiently predict and explain the dependent variables without strong parametric assumptions. Decision trees use simple rules to split the dataset via a tree-based algorithm. These rules may vary primarily depending on the level of measurement of the explanatory variables in a model. In our study, each forest includes 100 decision trees and calculates the mode rankings of each independent variable. Due to the socioeconomic nature of our dataset, we also implement a 5-fold cross-validation strategy before concluding on the importance of factors on the dependent variables. This means that we create 5 forests that include a total of 500 decision trees using random sampling with replacement. This strategy helps us improve our model accuracy. It should be noted that RFC is not a parameterized model, therefore, do not provide correlation coefficients or their statistical significance. Therefore, the utilization of RFC provides information on the relative importance of each independent variable but not on the directionality of these variables.

Findings

We provide several figures to present the results of RFC analysis. Figures 1 and 3 show the overall rankings of each independent variable. While the x-axis of these figures presents the percentage of the relative importance of each independent variable, RFCs do not intend to provide quantitative interpretation with these percentages. Instead, it helps us identify the

clusters of important factors among all independent variables. If a factor is associated with a higher percentage (longer blue bar), this variable is more important than others. Furthermore, it should be noted that the rankings of each variable in Figures 1 and 3 are mode rankings of independent variable importance in shaping individual participation in formal and non-formal AET, respectively. As we created multiple trees and forests, the rankings of each variable may slightly vary throughout the models. Therefore, we provide box plots indicating the variance of mode rankings (see Figures 2 and 4). In Figures 2 and 4, a higher mode ranking of a variable implies that this factor is less important than others with regard to each AET participation.

Important Factors for Job-Related Formal AET Participation

Based on our analysis, we assigned variables into five categories: (1) most important, (2) important, (3) somewhat important, (4) less important, and (5) least important factors in shaping individual participation in job-related formal AET. It should be noted that this categorization is rather subjective. The RFC fit process for this experiment led to a model with an average testing classification accuracy of 88%. Our results indicate that *age* and *literacy skills* are the most important factors to shape formal AET participation. Followed by this first group, *numeracy skills*, *ICT skills* seem to be more important than other factors. The third category includes *work flexibility* and *monthly income*. The result shows that *education level*, *managerial status*, *economic sector*, *organization size*, and *employment status* are only important at the low level. As we can see from Figure 2, the variance of the mode rankings of these variables is wider, which suggests that the impact of these variables is rather undetermined. Finally, at the lowest level, our result suggests that *job satisfaction* and *gender* may be associated with formal AET participation but they are not very important factors in explaining our dependent variable.

Important Factors for Job-Related Non-Formal AET Participation

The average testing classification accuracy of the second model is 71%. Similar to the previous analysis, our results show that *literacy skills* is the most important factor in shaping individual participation in job-related non-formal AET. Additionally, two other skills that individuals utilize at work, *ICT skills* and *numeracy skills*, and *organization size* seem to be more important than other factors. The importance of organization size seems to be greater in shaping individual participation in non-formal AET in comparison to formal AET participation. The third set includes the *economic sector*, *monthly income*, and *work flexibility*. The fourth category includes *education level* and *age*. Unlike the previous analysis, age does not seem to be more important in shaping non-formal AET participation. Finally, at the lowest level, our result suggests that *job satisfaction*, *managerial status*, *gender*, and *employment status* are the least important factors in explaining non-formal AET participation.

Conclusion and Implications

When we compare working adults' participation in job-related formal AET and non-formal AET, several interesting findings are revealed. The results show that three skills (i.e., literacy, numeracy, and ICT) are found to be important influencing factors both for formal and non-formal AET participation. This implies that basic skills become critical and foundational factors to start a new learning experience for adult learners. For age, our findings indicate a contradicting result from a UK study in 2017 (Egglestone et al., 2018). In the UK study, the younger the age, higher participation rates are found for formal adult education participation. Also, age was not an important factor for non-formal AET participation. Education level is also compared with the previous study. For the UK study, education level was a significant factor for

adult learning participation whereas this study found it to be a less important factor. Regarding work-related context, work flexibility would be considered a highly important factor for AET participation in general, but not for this study. It is similar to other work-related factors such as job satisfaction and organization size. Based on these findings, individual-level factors (e.g., age, skills proficiency) look to influence AET participation more compared to organizational factors.

One limitation of the study is the analytical approach. While the use of RFC is beneficial to social science studies as indicated above to calculate the relative importance of explanatory variables, it is still unclear about the degree of importance in categorizing the independent variables. For example, we cannot tell the difference between important and somewhat important levels and this makes it difficult to interpret the findings in terms of its significance. Due to this limitation, it will be beneficial to use other statistical approaches (e.g., regression analysis) to clearly specify the directionality of the study findings along with RFC method.

References

- Billett, S. (2010). The perils of confusing lifelong learning with lifelong education. *International Journal of Lifelong Education*, 29, 401–413. <https://doi.org/10.1080/02601370.2010.488803>
- Boeren, E., Nicaise, I., & Baert, H. (2010). Theoretical models of participation in adult education: The need for an integrated model. *International Journal of Lifelong Learning*, 29(1), 45–61. <https://doi.org/10.1080/02601370903471270>
- Breiman, L. (2001). Random forests. *Machine Learning*, 45(1), 5–32. <http://dx.doi.org/10.1023/A:1010933404324>
- Choi, J., Robinson, S., Maulik, R., & Wehde, W. (2020). What matters the most? Understanding individual tornado preparedness using machine learning. *Natural Hazards*, 103, 1183–1200. <https://doi.org/10.1007/s11069-020-04029-1>
- Commission of the European Communities. (2000). *A memorandum on lifelong learning* (Commission Staff Working Paper). European Commission.
- Desjardins, R. (2020). *PIAAC thematic review on adult learning* (OECD Education Working Papers No. 223). OECD Publishing. <https://doi.org/10.1787/19939019>
- Dibra, G., Kashahu, L., Bushati, J., & Priku, M. (2014). Learning among adults. *European Scientific Journal*, 10(13), 498–506. <https://doi.org/10.19044/esj.2014.v10n13p%25p>
- Egglestone, C., Stevens, C., Jones, E., & Aldridge, F. (2018). *Adult participation in learning survey 2017* (Learning and Work Institute Report). UK Department of Education.
- Eurostat (2016). *Classification of learning activities (CLA): Manual*. Publications Office of the European Union.
- Gherardi, S. (2006). *Organizational knowledge: The texture of workplace learning*. Blackwell Publishing.
- Jarvis, P. (2011). Adult education and the changing international scene: Theoretical perspectives. *PAACE Journal of Lifelong Learning*, 20, 37–50.
- OECD (2013). *OECD skills outlook 2013: First results from the survey of adult skills*. OECD Publishing. <http://dx.doi.org/10.1787/9789264204256-en>
- Punksungka, W., Yamashita, T., Helsing, A., Karam, R., Cummins, P., & Kramer, J. (2021). Re-examining adult education and training participation by education, literacy, gender, and race/ethnicity in the U.S. *Journal of Adult and Continuing Education*. <https://doi.org/10.1177/14779714211049261>

Schuller, T., & Desjardins, R. (2010). Wider benefits of adult learning. In Rubenson, K. (Ed.), *International Encyclopedia of Adult Learning and Education* (pp. 294–298). Elsevier.

Watkins, K. E., & Marsick, V. J. (2014). Adult education and human resource development: Overlapping and disparate fields. *New Horizons in Adult Education and Human Resource Development*, 26(1), 42–54. <https://doi.org/10.1002/nha3.20052>

Widany, S., Christ, J., Gauly, B., Massing, N., & Hoffmann, M. (2019). The quality of data on participation in adult education and training: An analysis of varying participation rates and patterns under consideration of survey design and measurement effects. *Frontiers in Sociology*, 4(71), 1–18. <https://doi.org/10.3389/fsoc.2019.00071>

Yamashita, T., Cummins, P. A., Arbogast, A., & Millar, R. J. (2018). Adult competencies and employment outcomes among older workers in the United States: An analysis of the program for the International Assessment of Adult Competencies. *Adult Education Quarterly*, 68(3), 235–250. <https://doi.org/10.1177/0741713618773496>

Figure 1
Relative importance of factors for job-related formal AET participation

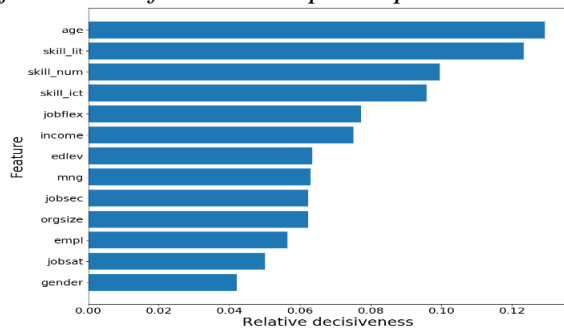


Figure 2
Mode rankings of factors for job-related formal AET participation

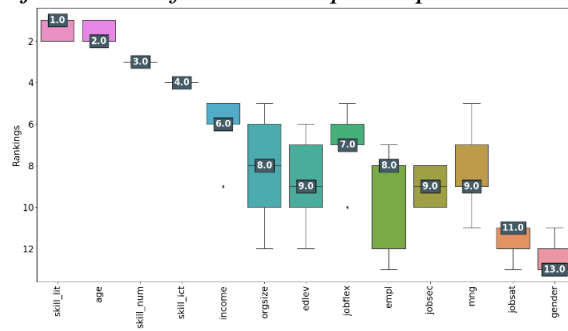


Figure 3
Relative importance of factors for job-related non-formal AET participation

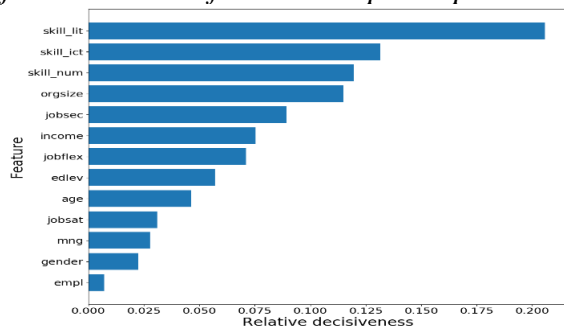


Figure 4
Mode rankings of factors for job-related non-formal AET participation

