Towards a Typology of Learning Workers: Latent Class Analysis of Adult Education Participation in the United States

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Abstract

This study identifies a typology of learning workers by investigating profiles of individuals participating in adult education. Using latent class analysis, we examined four classes and their associations with covariates.
Keywords: learning workers, adult education participation, latent class analysis, PIAAC

In conjunction with the paradigm shift of lifelong learning, many scholarly works offer new theoretical insights – the adult education system must embrace work-related perspectives (Jarvis, 2010). In light of human capital notions, it is obvious that individuals' work and learning are closely tied together (Merriam et al., 2007). For individual workers, adult education in and out of the workplace has been seen as an appropriate venue to fulfill their learning needs. For organizations, *learning workers* are considered an important asset contributing to the acquisition of an organization's intellectual capital, enhancement of resources, and return on its investment in training (Merriam et al., 2007). Based on concrete evidence that adult education and training (AET) and informal learning at the workplace play an imperative role in accomplishing economic initiatives and social responsibilities, many organizations seek to establish relevant strategies directed toward *learning organizations* (Van Noy et al., 2016). Notably, the extent to which workers participate in adult education differs across a diverse group of people for varying reasons. Therefore, investigating who learning workers are and how they diverge depending on the types of adult education has drawn increased attention.

In this context, this study aims to empirically conceptualize learning workers by investigating profiles of individual workers participating in adult education. We applied latent class analysis (LCA) to identify discrete subgroups within populations that share certain outward characteristics (Hagenaars & McCutcheon, 2002). Latent classes and their associations with variables of interest were also examined. Hence, our analytic choice allows us to uncover how various factors shape different profiles of adult education participation across class memberships. The research questions included:

- Research question 1: How can workers be classified according to the extent to which they participate in formal AET, non-formal AET, and informal learning?
- Research question 2: What individual-level and work-related characteristics predict class memberships of adult education participation of workers?

Literature Review

Conceptual Underpinnings of Learning Intention/Decision of Workers

Workers' learning intention to participate in adult education varies depending on social contexts such as demographics, economic and cultural factors, and psychological attributes (Baert et al., 2006; Jung & Cervero, 2002). In the decision-making process of the potential learner, learning intention occurs with the recognition of needs, awareness that something is lacking, and a discrepancy between the worker's current and desired situation (Baert et al.,

2006). For instance, workers tend to feel pressure due to rapidly changing job needs that require a high level of knowledge and skills, leading to an increased learning intention to improve their productivity and skills (Boeren et al., 2010). Related to demographic factors, workers with higher initial levels of education and human capital are more likely to participate in learning (Kyndt et al., 2011). In addition, workers' job-related characteristics influenced their motivation to participate in learning. For instance, employees who enjoy what they do and have more flexibility in their work tend to engage more in learning. Therefore, both individual-level and work-related contexts can be seen as antecedent aspects of learning.

Concept and Typology of Adult Education

The present study considers formal AET, non-formal AET, and informal learning as the three major *pillars* of adult education participation. *Formal AET* refers to formally designed and organized learning that mainly occurs in educational institutions, such as higher education institutions (CEC, 2000). *Non-formal AET*, on the other hand, refers to structured and organized learning that occurs mostly in institutionalized settings such as the workplace. It can be distinguished from formal AET as it does not lead to credentials (Eraut, 2000; Jarvis, 2010). *Informal learning* is predominantly less-structured, experiential, and non-institutionalized learning that takes place in daily life without a specific intention to acquire formalized credentials (CEC, 2000; Merriam et al., 2007).

Theoretical Framework

The Comprehensive Lifelong Learning Participation Model (CLLPM) (Boeren et al., 2010) was employed as a theoretical framework for this study. According to Boeren et al. (2010), the decision to participate in adult education relies on three layers of factors: individual, institution, and socioeconomic contexts. The authors articulate that individuals and institutions are both central elements of adults' learning participation. The intention to participate in adult education is structured by the interconnected relationship between individuals' demands and the institution's supply. More specifically, the CLLPM elaborates that participating in adult education can be seen as the consequence of interactions between individual-level characteristics (e.g., demographic, human capital, and psychological factors) and work-related conditions.

Methods

Data Source and Variables

The data are drawn from the Program for the International Assessment of Adult Competencies (PIAAC) dataset conducted by OECD. PIAAC gathers data concerning education and work history among adult populations, along with extensive background data, including demographic, socioeconomic status, and basic skills. PIAAC provides information about adults' learning and development in and out of the workplace by measuring the degree to which their participation in various types of education and training activities for professional or personal reasons. For this current study, we used the 2017 U.S. PIAAC data. The total sample size includes 1,283 respondents who had recent work experience in the 12 months prior to the survey.

The study variables were selected based on the comprehensive review of key drivers of adult education participation among workers and the theoretical framework (i.e., CLLPM) that holistically demonstrates how the individual-level and work-related contexts are interrelated and how they influence adult education participation. For outcome measures, eight items indicating the types of adult education were entered as indicators: *one* formal AET, *four* non-formal AET, and *three* informal learning. Covariates reflect workers' individual-level and work-related characteristics. The individual-level context indicates respondents' demographic information (gender and age), human capital (education level, monthly income, health, and skills proficiency in literacy and problem-solving in technology-rich environments), and learning-related socio-

psychological states (learning attitudes, cultural engagement, and social trust). The work-related context represents respondents' job-related conditions: employment status, years of work experience, economic sector, organization size, managerial status, working time, job satisfaction, and two sets of skills use at work (literacy and ICT).

Analytic Strategy

LCA is an emerging mixed modeling technique employed primarily to identify sub-groups within populations in which the same groups of individuals share similar attributes and characteristics (Hagenaars & McCutcheon, 2002). The assumption underlying LCA is that latent (or unobserved) heterogeneity in samples determines class membership, and it can explain discrete patterns of responses on the observed variables. For this present study, we applied a two-step LCA approach (Hagenaars & McCutcheon, 2002). The first step is to conduct LCA with indicators only. This is to identify latent classes and to keep the class specification from the influence of covariates. Optimal numbers of classes were determined using fit statistics. LCA was carried out using the "snowLatent" module in jamovi software version 2.3.21 (Seol, 2022). Next, multinomial logistic regression (MLR) analysis was performed to examine which covariates influence the probability of class memberships. This allows for discovering different profiles of adult education participation across latent classes.

Results

Identified Latent Classes

We first assessed the best latent class solutions using model fit indices determining probabilities of class memberships and optimal numbers of latent classes (see Table 1). The values of BIC and CAIC continued to decline as the number of latent classes increased, and they began to increase from the 3-class model. The values of AIC start to decrease at a slower rate after the 4-class model. In addition, BLRT's *p*-value became insignificant after the 5-class model. The value of entropy for the 4-class model was the highest, and thus the 4-class model was selected, identifying four distinctive sub-groups of adult education participation within the population. Figure 1 shows a graphical representation of the selected model, exhibiting different features of latent classes based on responses to eight indicators. We named latent classes of learning workers as follows: *low-participation learners* (class 1), *high-participation learners* (class 2), *informal learners* (class 3), and *structured learners* (class 4).

Informal learners, to which the majority of samples were included (n = 606; 47.2%), indicated probabilities of participating in sub-items of informal learning comparatively higher than low-participation learners and structured learners. Structured learners (n = 225; 17.5%) had relatively higher mean values of formal AET and sub-items of non-formal AET than informal learners and low-participation learners. Low-participation learners (n = 203; 15.8%) had remarkably low probabilities of participation across every type of adult education. In contrast, high-participation learners (n = 249; 19.4%) showed the highest mean values for almost every indicator.

Covariates

Covariates were tested to determine whether they predict class memberships using three separate MLR analyses (see Table 2). When comparing low- and high-participation learners, work-related situational factors were more influential than individual-level factors. Compared to low-participation learners, high-participation learners can be characterized as those who are employed in the public sector, working in large organizations, satisfied with their job, and utilizing literacy skills at work more frequently. Among individual-level context, learning attitudes was the only covariate contributing to the latent class identification. When comparing informal learners and structured learners, individual-level factors tended to be more influential in

this latent class segmentation. Relative to informal learners, more likely structured learners were older, had higher educational attainment, earned less, were healthier, and were proficient in literacy skills. Among work-related context, structured learners were more likely to work in the public sector and less satisfied with their job, compared to informal learners.

The results revealed that work-related situational factors significantly influenced the extent to which workers participate in adult education at large. Meanwhile, individual-level factors tended to classify different profiles of participation according to the types of adult education. For instance, younger and less educated workers were more likely to engage in informal learning experiences. The results also showed that lower income levels and job satisfaction could be a motivator for workers to participate in formal and non-formal AET according to their expected returns on educational investment.

Conclusion and Implications

Several implications are drawn. First, the study findings suggest that there are four latent classes of workers, each with varying probabilities of participating in different types of adult education. Low-participation learners had remarkably low probabilities of participation in adult education, whereas high-participation learners showed the highest mean values for almost every indicator. More specifically, work-related situational factors (e.g., job satisfaction, skills use) were found to be more influential than individual-level factors for adult education participation. These findings imply that workplace organizations should provide appropriate measures to improve workers' satisfaction and opportunities to use learned skills in their job settings.

Secondly, individual-level factors tended to classify different profiles of adult education participation. For instance, younger and less educated workers were more likely to engage favorably in informal learning experiences, while structured learners tended to be older, have higher educational attainment, and be healthier. This finding suggests that decision-makers of adult education should consider the worker's background information in deciding educational delivery formats for higher participation. Furthermore, decision-makers should recognize that decision/intention to learn may vary according to diverse contexts and, therefore, should discern how to deliver tailored learning programs in response to the divergent characteristics of workers.

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Table 1

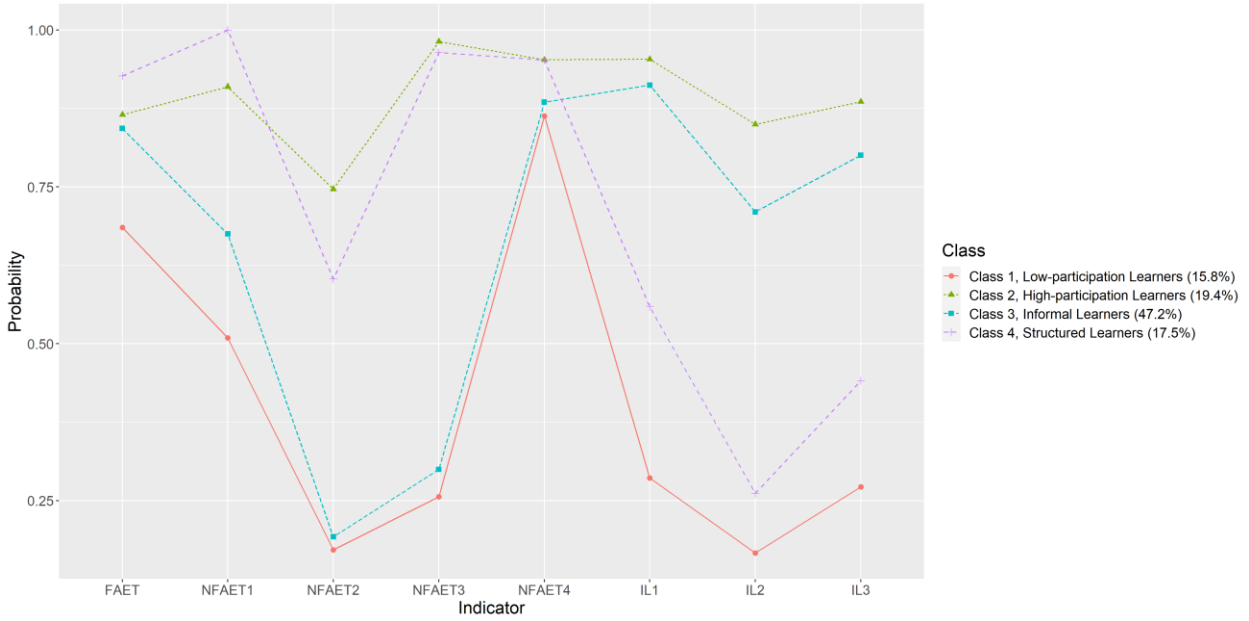
Comparison of Model Fit Indices for Latent Class Solutions

Number of classes	Model fit indices					
	LL	*BIC*	*AIC*	*CAIC*	*BLRT* (*p*)	*Entropy*
2 classes	-5675	11472	11384	11489	**.000**	.552
3 classes	-5570	**11326**	11192	**11352**	**.000**	.613
4 classes	-5539	**11328**	**11148**	11363	**.000**	**.685**
5 classes	-5527	11369	11142	11413	.060	.580
6 classes	-5516	11411	11138	11464	.140	.612
7 classes	-5508	11459	11139	11521	.180	.604

Note. *N* = 1,283; Bold-faced values indicate the best-fit solutions.

Figure 1

Item Probability Plot of the Selected Model



Note. FAET = formal AET, NFAET1 = open or distance education, NFAET2 = on-the-job training, NFAET3 = seminars or workshops, NFAET4 = private lessons, IL1 = learning from co-workers/supervisors, IL2 = learning-by-doing, IL3 = keeping up to date.

Table 2

Multinomial Logistic Regression Analysis Results Across Class Membership by Covariates

Item	Ref. = Class 1[a]						Ref. = Class 2				Ref. = Class 3	
	Class 2[b]		Class 3[c]		Class 4[d]		Class 3		Class 4		Class 4	
	B	*OR*	*B*	*OR*	*B*	*OR*	*B*	*OR*	*B*	*OR*	*B*	*OR*
Individual-level context												
Gender (Ref. = female)	.417	1.518	.067	1.069	.147	1.158	-.350	.705	-.270	.763	.080	1.083
Age	.264	1.303	.154	1.166	-.138	.871	-.111	.895	-.403*	.669	-.292*	.747
Education level (Ref. = less than a bachelor's)	-.459	.632	-.312	.732	-.720**	.487	.147	1.158	-.261	.770	-.408*	.665
Monthly income	-.033	.968	-.061	.941	.103	1.108	-.028	.972	.135	1.145	.164*	1.178
Health	.149	1.160	.201	1.223	-.052	.949	.052	1.054	-.201	.818	-.253**	.776
Skill proficiency (Literacy)	.008	1.008	.012**	1.013	-.001	.999	.005	1.005	-.009*	.991	-.014**	.986
Skill proficiency (PS-TRE)	-.001	.999	-.001	.999	-.002	.998	.000	1.000	-.001	.999	-.002	.998
Learning attitudes	-.741***	.477	-.636***	.530	-.405*	.667	.105	1.111	.336*	1.399	.231	1.260
Cultural engagement	.033	1.034	.133	1.143	.019	1.020	.100	1.105	-.014	.986	-.114	.892
Social trust	.004	1.004	.076	1.079	.024	1.024	.072	1.075	.020	1.020	-.052	.949
Work-related context												
Employment status (Ref. = full-time)	.143	1.154	.007	1.007	.063	1.065	-.137	.872	-.081	.922	.056	1.058
Years of work experience	-.015	.985	-.008	.992	-.004	.996	.006	1.007	.011	1.011	.005	1.005
Economic sector (Ref. = private)	-.756**	.470	-.254	.775	-.911***	.402	.502*	1.651	-.155	.856	-.657**	.519
Organization size	-.303**	.738	-.071	.931	-.144	.866	.232**	1.261	.160*	1.173	-.072	.930
Managerial status (Ref. = non-managerial)	.252	1.286	.226	1.254	.420*	1.522	-.025	.975	.168	1.183	.194	1.214
Working time	-.158	.853	.154	1.167	.056	1.058	.313*	1.367	.215	1.240	-.098	.907
Job satisfaction	-.295*	.744	-.275*	.759	-.092	.913	.020	1.020	.204*	1.226	.184*	1.202
Skill use at work (Literacy)	-1.770***	.170	-1.036***	.355	-1.089***	.337	.734***	2.083	.681***	1.976	-.053	.948
Skill use at work (ICT)	.013	1.013	-.080	.923	-.257	.774	-.093	.911	-.269*	.764	-.176	.838
Intercept	8.617***		4.240**		8.552***		-4.377***		-.065		4.312***	
-2 Log likelihood	2664.439											
χ^2 (*df*)	423.025 (57)***											
Cox & Snell R^2	.281											
Nagelkerke R^2	.309											

Note. *N* = 1,283; OR = odds ratio, PS-TRE = problem-solving in technology-rich environments, ICT = information and communications technology.

[a] Low-participation learners (15.8%), [b] High-participation learners (19.4%), [c] Informal learners (47.2%), [d] Structured learners (17.5%).

***$p < .001$, **$p < .01$, *$p < .05$