Adult Numeracy Skill Practice by STEM and Non-STEM Workers in the USA: An Exploration of Data using Latent Class Analysis

Published Online on November 14, 2022 in the International Journal of Lifelong Education

By Takashi Yamashita,[1] Wonmai Punksungka, [1] Donnette Narine, [2] Abigail Helsinger, [3] Jenna W. Kramer, [4] Phyllis A. Cummins[3] & Rita Karam[4]

*Corresponding author

1. Department of Sociology, Anthropology, and Health Administration and Policy, University of Maryland, Baltimore County, Baltimore, MD, U.S.A

University of Maryland, Baltimore County

Public Policy Building, PUP252, 1000 Hilltop Circle, Baltimore, MD 21250

Phone: 410-455-5938

Fax: 410-455-1154

yamataka@umbc.edu

2. Gerontology Doctoral Program, University of Maryland, Baltimore, Baltimore, MD, U.S.A

3. The Scripps Gerontology Center, Miami University, Oxford, OH, U.S.A

4. RAND Corporation, Santa Monica, CA, U.S.A

Acknowledgement

In this research, Takashi Yamashita, Wonmai Punksungka, Donnette Narine, Abigail Helsinger, Jenna W. Kramer, Phyllis A. Cummins & Rita Karam, were partially supported by the Institute of Education Sciences, U.S. Department of Education, through Grant R305A200261 to University of Maryland, Baltimore County. The opinions expressed are those of the authors and do not represent the views of the institute or the U.S. Department of Education.

Adult Numeracy Skill Practice by STEM and Non-STEM Workers in the USA: An Exploration of Data using Latent Class Analysis

Abstract

Adult numeracy is one of the essential skill sets to navigate through numeric information-rich labor markets in general, and STEM industries in particular. Yet, relatively little is known about how numeracy skills are used in different settings in the USA. This study examined numeracy skill use patterns of STEM and non-STEM workers at work and home. Data were obtained from the 2012/2014/2017 Program for International Assessment of Adult Competencies, USA restricted-use file. Adults who were employed and aged between 25 and 65 years old (n = 5,220) were included in this study. Latent class analysis revealed four numeracy skill use patterns: non-users, non-occupational (i.e., at home) simple numeracy users, ubiquitous numeracy users, and occupational numeracy users. Additional multinomial logistic regression analysis showed that the STEM occupation was associated with a greater likelihood of being ubiquitous users than being non-occupational simple users. Results also showed that numeracy proficiency, socioeconomic statuses (i.e., educational attainment and income), as well as demographic characteristics (i.e., gender and race/ethnicity), were predictive of the numeracy skill use patterns in terms of the level of engagement and settings. Findings from this study inform policies and interventions which promote skill engagement and improvement among workers in the USA.

Key Words: Numeracy; practice engagement; STEM

Introduction

The aim of this study is to document numeracy skill use patterns among employed adults in the United States of America (USA), both at work and at home, using nationally representative data.

In the study, identified skill use patterns were linked to numeracy proficiency as well as sociodemographic identity and socioeconomic status. In general, greater use of numeracy skills is associated with higher proficiency. However, little is known about the specific numeracy skills used in multiple contexts (i.e., at work and at home) among USA workers. Given the importance of adult numeracy in information-rich societies, the findings from this study will inform future numeracy interventions and discussions on education and labor policies.

What is numeracy, and why is numeracy important?

Adult numeracy is “the ability to access, use, interpret, and communicate mathematical information and ideas, in order to engage in and manage the mathematical demands of a range of situations in adult life” (OECD, 2019b, p. 24). Common numeracy skills include quantitative measurement, calculation, and interpreting diagrams with numeric information (Marr & Hagston, 2007). The opportunities and demands and necessity of numeracy skills have been steadily increasing in the modern world (e.g., numerate environment) where information explosion, globalization, and technological advancement are rapidly taking place (Evans et al., 2021; Parsons & Bynner, 2006; Saal et al., 2018). Adult numeracy is particularly important in the STEM (Science, Technology, Engineering, and Mathematics) labor market in terms of employability, job security, and productivity (Redmer & Dannath, 2020).

An assessment of adult numeracy may indicate current skill levels more strongly than other well-known skill indicators such as educational attainment (Gal et al., 2020). Educational attainment is generally measured by an academic degree or years of education, which often occur in early adult life, so it may not reflect the most current or specific skill indicators. Additionally, numeracy skills tend to decline with aging, but the rate of decline accelerates if skills are not regularly utilized (i.e., use-it-or-lose-it hypothesis; Støren et al., 2018). In short, adult numeracy is a dynamic and essential skill set required to navigate through and participate in information-rich, complex, global communities.

Previous studies linked adult numeracy skills with a series of economic outcomes. Numeracy is a critical component of human capital, which enhances one's economic advantage, productivity, and career advancement (Becker, 2009; Shomos, 2010). Specifically, studies show that numeracy is positively associated with greater employability (Saal et al., 2018; Windisch, 2015) and higher wages (Bol & Heisig, 2021; Green & Riddell, 2001; Holzer & Lerman, 2015). Individual human capital and numeracy skills collectively impact the economic well-being of communities and societies (Jonas, 2018; Schwerdt et al., 2020).

Adult numeracy skills have also been linked to non-economic outcomes. Low numeracy may differentiate capacity and opportunity to engage in society, and, in turn, result in social inequality (Grotlüschen et al., 2016). Indeed, greater numeracy is correlated with greater social, cultural, and civic participation, such as voting, volunteering, and engaging in recreation activities (Gal et al., 2020; Goos et al., 2014). Moreover, adults with lower numeracy skills are less likely to maintain social trust (OECD, 2016a). Also, the higher levels of numeracy proficiency correlate more strongly with non-economic outcomes, among certain subgroups, such as women, older adults, and racial and ethnic minorities, more than their counterparts (Saal et al., 2018). Therefore, promoting adult numeracy skills is arguably one way to address social inequality due to gender, race and ethnicity, and socioeconomic status(Redmer & Dannath, 2020).

The average numeracy skills of USA adults was the third-lowest among 33 of the OECD (Organization for Economic Co-operation and Development) nations (Goodman et al., 2013; OECD, 2019a). Nearly one in three (30%) USA adults have difficulty performing simple mathematical tasks in their everyday lives (National Center for Education Statistics, 2020a). In addition, older age, gender (women), racial and ethnic minority status, being foreign-born, lower educational attainment (both own and parent's/guardian's), lower-income, and poorer health are consistently associated with lower numeracy skills in the USA (Goodman et al., 2013). Given the positive correlation between numeracy proficiency and individual and societal well-being, and related implications for existing social inequality, promoting adult numeracy should be on the national education policy agenda.

Why focus on STEM?

STEM industries drive the USA economy through technological innovations in the global community (Xie & Killewald, 2012). Whether or not certain occupations, such as health care and education, should be considered STEM is debated (Noonan, 2017). In this study, given the lack of previous studies that focus on specific occupations/industries, we adopted a broad STEM definition that includes professionals and technicians, as well as health care (European Commission, 2016; Siekmann & Korbel, 2016).

Anywhere from 6% to 23% of USA jobs are considered STEM, depending on whether a narrow or broad definition of STEM is used. In the USA, STEM workers tend to have greater earnings than non-STEM workers (e.g., median $55,000 vs. $33,000 in non-STEM workers) (National Science Foundation, 2021). Additionally, STEM industries are growing faster than non-STEM counterparts. Even with a narrower definition (e.g., without health care occupations), job growth in STEM fields over the next decade is projected to be about 40% greater than that of non-STEM occupations (U.S. Breau of Labor Statistics, 2021).

STEM occupations and numeracy are associated in several ways. First, STEM workers are often required to update their job-related knowledge and skills over the course of their careers (Deming & Noray, 2018). Basic cognitive skills, such as numeracy, are critical to upgrading individuals' human capital, as individuals use their foundational skills to develop new skills (Bol & Heisig, 2021). Job automation technology is replacing jobs, especially in low-skilled occupations (Redmer & Dannath, 2020); this underscores the importance of updating job-related knowledge and skills among low-skilled workers. Second, STEM occupations often require greater numeracy skills for obtaining and performing a job than non-STEM professions (Lindeman, 2015). Third, given that there is greater numeracy skills use in STEM occupations than non-STEM occupations, as well as the general underrepresentation of women in STEM industries, women tend to use numeracy skills less frequently than men, affecting their overall numeracy proficiency (Borgonovi et al., 2018). However, little is known about how STEM and non-STEM workers use their numeracy skills at work and at home. We need further evidence on how STEM occupations are linked to greater numeracy skills through differential skill use in the USA. Since numeracy, as well as numeracy skill use, is linked to social inequality, systematic numeracy gaps between STEM and non-STEM workers has societal implications above and beyond the workforce and education issues (Nienkemper & Grotlüschen, 2019).

Theoretical framework

Our theoretical framework for this study is practice engagement theory, which states that skill proficiency is enhanced by skill use activities, or the engagement and opportunity structure. One's skill proficiency and availability of skill use opportunity cyclically determines subsequent frequency with which an individual can practice their skillset across the adult life course (Reder, 1994; Reder et al., 2020). That is, the more adults use numeracy skills at work and at home, the greater their numeracy proficiency is over time (Reder et al., 2020). Conversely, the low skill trap theory states that lower skill proficiency may result in fewer opportunities to use specific skillsets, and, therefore, a lower chance of skill development (Parsons & Bynner, 2006). Other theoretical framework such as andragogy (Knowles et al., 1998); activity theory (Devane & Squire, 2012) as well as expectancy-value theory (Eccles, 2005) were also considered. However, the practice engagement theory was the most suitable to the current study in view of the explicit relationship between skill use patterns and skill proficiency across adult life stages, whereas other theories focused more on specific underlying mechanisms (e.g., motivation, perceived values), earlier life stages (e.g., students) and participation in general learning activities rather than specific skill use.

Despite the growing opportunity and demands in the numerate environment across nations (Evans et al., 2021), numeracy skill use in the USA has likely decreased in the recent decades (Desjardins, 2017). Given that numeracy skills are essential to navigate through and fully participate in the complex modern information-rich society, better understanding of numeracy skill use and proficiency is informative to future labor and education policy discussions (e.g., skill-mismatch and skill development) as well as potential numeracy intervention programs among workers. The close relationship between STEM occupations and numeracy proficiency suggests that a study contextualizing numeracy skill engagement (e.g., in occupations or in everyday life) by STEM and non-STEM occupations is urgently needed (Gal et al., 2020; Grotlüschen et al., 2016; Redmer & Dannath, 2020; Windisch, 2015).

Literature review of the relationships between numeracy skill use, occupations and skill proficiency

To date, only a handful of studies have focused specifically on numeracy skill use and examined skill use by occupation. STEM workers generally have greater numeracy skills and use numeracy skills at work more often than their non-STEM counterparts (Dennis, 2014).

Lindemann (2015) found that, in the USA, male workers tend to use more numeracy skills at work than female workers, both in STEM and non-STEM occupations. Billington and Foldnes (2021) identified that greater occupational complexity (e.g., job demands and use of data skills) is linked to greater numeracy proficiency across economically developed nations. Bol and Heisig (2021) reported that STEM workers are more likely to have greater numeracy proficiency, which increases the opportunities for numeracy skill use, and specific numeracy skill use (e.g., preparing charts and tables) is positively associated with higher wages across STEM industries. For example, certain types of employment (e.g., white collar occupations, such as accountants and computer programmers) that require greater numeracy skill use are more likely to develop workers' numeracy skills over time (Desjardins, 2003). Interestingly, a study of Swedish workers found the length of time they were out of work was negatively correlated with numeracy skill proficiency, presumably due to the lack of numeracy practice at work (Edin & Gustavsson, 2008). Finally, Nienkemper and Grotlüschen (2019) distinguished three skill use patterns, including mostly at work, mostly at home, and ubiquitous skill use (both at work and at home), and noted that workers in Germany who used their numeracy skills more often at work were likely to do the same outside of work (e.g., at home), compared to the counterparts that used their skills less often at work.

The existing evidence suggests one overarching insight for numeracy skill use and STEM occupations. That is, consistent with the practice engagement theory (Reder, 1994; Reder et al., 2020), numeracy skill use is positively associated with numeracy proficiency, which may lead to more skill use opportunities (e.g., STEM occupations) and skill proficiencies (Billington & Foldnes, 2021; Desjardins, 2003). The virtuous cycle or reciprocal relationships between numeracy skill use, skill use opportunity, and skill proficiency hints at two underlying processes.

First, any of these three factors might have operated through a selection process. That is, individuals with greater numeracy skill use and proficiency experiences might have had more opportunities (i.e., employability) in certain occupations with greater demands for numeracy, such as STEM (Wilms & Murray, 2007). Second, greater demands and opportunities for numeracy skill use at work are likely to contribute to numeracy skill maintenance and development over time (Reder & Bynner, 2009; Reder et al., 2020). On a related note, given the ubiquitous skill use hypothesis, both at work and outside of work contexts should be considered (Barton & Hamilton, 2000; Lindeman, 2015; Nienkemper & Grotlüschen, 2019). In short, numeracy skill use, type of occupation, and skill proficiency are reciprocally associated through the occupation selection and skill development across multiple contexts, including at work and in everyday life.

Relevant factors

Prior research has, thus, identified a number of relevant factors to examination of numeracy skill use: Older age, gender (women), racial and ethnic minority (vs. Whites), immigrants (vs. USA born), lower educational attainment, parent's/guardian's socioeconomic status (i.e., lower educational attainment), lower income and poorer health seem to be jointly inter-related with numeracy skill practice opportunities, proficiency and occupations (Bol & Heisig, 2021; Ford & Umbricht, 2016; Green & Riddell, 2001; Jonas, 2018; Parsons & Bynner, 2006; Patterson, 2020; Plasman et al., 2021; Reder, 2020; Schwerdt et al., 2020). Specifically, socioeconomic and health disadvantages are persistently associated with fewer opportunities for numeracy skill practice at work and lower numeracy proficiency. However, when expanding the context to outside of work, adults with lower numeracy skills may use specific numeracy skills (e.g., calculating a budget) at home as often as their counterparts (Gal et al., 2020; Grotlüschen et al., 2016).

There are a number of opportunities to expand the existing. First, most of the relevant studies used a summary measure of numeracy use or one selected numeracy skill (e.g., calculating price) (Bol & Heisig, 2021; Jonas, 2018; Nienkemper & Grotlüschen, 2019), and, as such, which types as well as combinations of numeracy skill use that may be linked to numeracy proficiency or occupations are yet to be identified (Holzer & Lerman, 2015; St Clair et al., 2010). Second, numeracy skill use has been primarily studied in relation to wage differences by sub-groups (e.g., gender) and not in multiple contexts (e.g., at work and at home) (Bol & Heisig, 2021; Lindeman, 2015). Third, whereas STEM workers are generally known to have higher numeracy skill use and proficiency, less is known about specific numeracy skill use difference within-group (STEM occupations) and between-group (vs. non-STEM occupations) (Bol & Heisig, 2021; Redmer & Dannath, 2020). Fourth, the relevant studies are conducted mainly in European nations and in cross-national comparisons, and therefore, specific country characteristics may not have been incorporated into the research design (Desjardins, 2003; Nienkemper & Grotlüschen, 2019). Specifically, the important country characteristics, such as immigrant populations and race/ethnicity should be considered in numeracy skill use among the diverse USA workforce.

Finally, virtually all relevant studies, except for one (Nienkemper & Grotlüschen, 2019), used a variable-centered approach (Jonas, 2018). A variable-centered approach examines the relationships between two individual measures at a time (e.g., use of math skills and age) and is only applicable for investigating a relationship between two measures while holding everything else constant or assuming that an identified relationship between two variables is applicable for all persons. However, each person’s experience is informed by multiple, varied characteristics. By contrast, a person-centered approach uniquely identifies sub-groups of persons based on the combination of multiple characteristics and/or patterns of behaviors (Collins & Lanza, 2010). Nienkemper and Grotlüschen (2019) adopted a person-centered approach (i.e., latent class analysis) and found that there were three sub-groups of German workers --- ubiquitous skill use (e.g., literacy), learning from co-workers, and skill use at home. The strengths of person-centerted approach, althouth not specifically intended to study numeracy skill use, include the abilities to simuntaneously take multiple characteristics into account and to identify target subpopulations of future interventions (Wang & Wang, 2020). Taken together, our person-centered analysis of numeracy skill use and proficiency by STEM and non-STEM workers in the the USA context will contribute to the literature, and in turn, future discussions on numeracy-based social vunerability and inequality.

Research Questions and Hypotheses

Based on the theoretical framework and literature review, the aim for this study is two-fold: (1) to identify numeracy skill use subgroups based on the numeracy skill use patterns, and numeracy skill proficiency among U.S workers by STEM versus non-STEM workers; and (2) to examine relevant characteristics of numeracy skill use subgroups.

This study addresses the following three research questions (RQ):

- RQ 1: What are underlying sub-groups based on numeracy skill use patterns both at work and at home among the USA workforce?
- RQ 2: How is numeracy proficiency different across the identified numeracy skill use sub-groups among the USA workforce?

- RQ3: What are the demographic and occupational characteristics (i.e., STEM vs. non-STEM) of the identified numeracy skill use sub-groups of the USA workforce?

In view of the practice engagement theory, it is hypothesized that there are underlying numeracy skill use patterns, and higher numeracy proficiency and STEM occupation are linked to more frequent numeracy skill use. Overall, this current study contributes to the literature by analyzing a series of specific numeracy skill use measures both at work and at home, using the person-centered approach (i.e., latent class analysis – see the methods section), and linking the identified sub-groups to numeracy proficiency and individual sociodemographic characteristics as well as STEM occupations.

Methods

Data

The 2012/2014/2017 Program for the International Assessment of Adult Competencies (PIAAC) Restricted Use File (RUF) data were obtained from the U.S. Department of Education, National Center for Education Statistics (NCES; license# *masked for blind review*). Per the PIAAC RUF data use guidelines, the figures were rounded to the nearest 10. PIAAC is an ongoing study to gather large-scale basic skill assessment data from adult populations age 16 years and older in 33 of OECD countries. The USA study adopted the multi-stage stratified probability sampling with the supplemental samples of unemployed and older adults (age 66 to 74) (Hogan et al., 2016). PIAAC employs a sophisticated skill assessment - computer-adaptive testing and item response theory - and provides data on basic skills, including literacy, numeracy and digital-problem solving skills, in addition to sociodemographic characteristics (OECD, 2016b). The 2012/2014/2017 PIAAC RUF combined three waves of cross-sectional data and incorporated adjusted sampling weights to generate nationally representative figures during the period of 2012 to 2017 (National Center for Education Statistics, n.d.).

In the current study, only employed adults aged 25 to 65 years were included to focus on the USA adult workforce population. As the majority of adults complete initial formal education and enter the workforce full-time by their late twenties, the cut-off point of age 25 is reasonable (National Center for Education Statistics, 2020b). Also, age 65 is a common retirement age, and those who work after age 65 instead of retiring may not be comparable with the general adult workforce. PIAAC RUF data included 5,410 eligible participants. After excluding the missing values (3.6%) in all variables of interest, the final sample size was 5,220. No appreciable systematic patterns in the missing values were observed. Given the small percentage and no systematic pattern, the participants with missing values were excluded from the analysis.

Measures

Predictors of the numeracy skill use subgroups

Twelve items of numeracy skill use at work and at home in PIAAC were examined. The items addressed, “In your job, how often do/did you usually…” and “In everyday life, how often do/did you usually…” for the following numeracy practice: (1) calculate costs or budget; (2) use or calculate fractions or percentages; (3) use a calculator; (4) prepare charts or graphs; (5) use simple algebra or formulas; (6) use advanced math or statistics. The original 5-point response categories include never, less than once a month, less than once a week but at least once a month, at least once a week but not every day, and every day. The responses were dichotomized to *regular use* (every day, at least once a week but not every day) and infrequent/no use, with respect to the distributions and conceptual differences. One nominal variable of four numeracy skill use subgroups was based on the identified latent classes (see below for more details and Supplemental Table 2).

STEM occupations are based on the International Standard of Occupation Classification (ISOC) codes. As this study adopted a broad STEM definition, the corresponding ISOC codes are 21 (science and engineering professionals), 22 (health professionals), 25 (information and communications technology professionals), 31 (science and engineering associate professionals), 32 (health associate professionals) and 35 (information and communications technology associate professionals) (European Commission, 2016; ILO, 2016).

The PIAAC measures numeracy proficiency on a scale from 0 to 500 points (less to more proficient). As an example, one assessment item asks the respondents to find a certain pattern (i.e., decline) in a time trend data graph. PIAAC employed the systematic assessment and item response theory to generate a set of 10 plausible values for numeracy (National Center for Education Statistics, n.d). In statistical analysis, all 10 plausible values need to be incorporated for a correct variance estimation. The PIAAC numeracy assessment was validated with earlier assessment and field data, and detailed descriptions have been published elsewhere (OECD, 2016b).

Covariates

Age at the time the survey is recorded in years. Gender (women vs. men), USA born (vs. immigrants), race/ethnicity (Black and Hispanic, vs. Whites), educational attainment (high school diploma and less than high school, vs. college [associate, bachelor, graduate, and professional degree] or higher), parent's/guardian's educational attainment (less than college vs. college or higher), and self-rated health (good [excellent, very good & good] vs. fair/poor) are recorded in or converted to dichotomous variables. The "Other" racial and ethnic group was excluded due to the relatively small sample size and issues with the interpretation (i.e., multiple sub-groups were classified in one group). Income quintile plus no income is an ordinal measure ranging from 0 (no income) to 5 (fifth quintile or about top 20%).

Statistical analysis

This study employed a classical three-step approach, and analysis was conducted sequentially --- (1) latent class analysis (LCA), (2) latent class extraction, and (3) multinomial logistic regression (Asparouhov & Muthén, 2014). Compared to the one-step approach, which simultaneously conducts all steps (1-3), the three-step approach allows an examination both from the theoretical and empirical standpoint for the measurement, latent class determination, and relationships between the identified latent class and covariates. The analytic approach is summarized in Figure 1.

In the first step, LCA, which identifies unobserved/underlying subgroups based on a series of observed categorical measures of characteristics, is a measurement model (i.e., finite mixture model) of the structural equation model with underlying subgroups (Porcu & Giambona, 2017). The LCA model is estimated as follows:

$$P(C = k|u_1 \dots u_{12}) = \frac{P(C=k)P(u_1|C = k)\dots(u_{12}|C = k)}{P(u_1 \dots u_{12})} \text{ [Equation 1]}$$

Let *C*, *k*, and *u* be latent class, number of latent class and indicator variable. Unconditional probability [$P(C = k)$] and conditional probability [$P(u_n|C = k)$] are estimated, and the conditional probability for each observed numeracy skill use indicator is the measurement parameter, which is equivalent to a factor loading in factor analysis models (Wang & Wang, 2020). Using Mplus version 8 (Muthén & Muthén, 1998-2017), the LCA model with the robust maximum likelihood estimation was constructed with TYPE = MIXTURE command.

After different numbers of latent class (k) were tested in LCA, the final model was selected based on the series of criteria, including Akaike Information Criterion (AIC; the smaller the better model fit); Bayesian Information Criterion (BIC; the smaller the better model fit); entropy (0-1: the lowest-the highest-class classification quality); average latent class membership probability (> 0.70 is acceptable); Vuong-Lo-Mendell-Rubin likelihood ratio (VLMR-LR) test (LCA with k class vs. k-1 class, $p < 0.05$ indicates a significant improvement); number of class members; and interpretability of results (Collins & Lanza, 2010; Wang & Wang, 2020).

Based on the previous simulation studies and applied examples, Nylund-Gibson and Choi (2018) suggested that a sample size of 300 to 1,000 seems to be sufficient for the evaluation of the commonly used model fit indices. In the current study, the sample size is over 5,000, and thus, the statistical power was assumed to be adequate for LCA. On a related note, unconditional LCA without covariate can be a logical approach for certain research objectives and class classification quality (e.g., high entropy) (Clark, 2010). The PIAAC sampling weight (SPFWT0) was applied in all LCA models.

In the second step, based on the final LCA model, the samples were assigned to the most likely latent class membership. At this point, the class membership was treated as the observed measure.

In the third step, given the nominal variable of the class membership (k), multinomial logistic regression model with the maximum likelihood estimation was used to examine the associations between the class membership and a series of characteristics.

$$log\frac{\pi_{M-1}}{\pi_M} = \beta_0^{M-1} + \beta_1^{M-1}x_1 + \cdots + \beta_k^{M-1}x_k \text{ [Equation 2]}$$

Let π , M, β, and x be the class membership probability, number of class, estimated coefficient, and covariates. The probability (π) of being in the class M was modeled as the log-odds (i.e., logit link function) and as a function of *k* covariates (x) (DeMaris, 2005). The model was constructed based on the conceptual framework and evaluated based on the likelihood ratio test against the null model. Finally, the independence of irrelevant alternatives (IIA) assumption was checked using the Hausman test, and results showed no indication of the IIA assumption violation (Cheng & Long, 2007). In order to estimate the multinomial logistic regression with the numeracy proficiency plausible value as one of the covariates, the repest macro program in STATA version 17 was used (Avvisati & Keslair, 2019; StataCorp, 2021). The repest macro incorporates the PIAAC sampling weight, 80 replicate weights, and 10 plausible values to estimate the regression coefficient and correct standard errors.

Results

The weighted descriptive summary is presented in Table 1. About 17% of the workers were in STEM occupations. The average numeracy proficiency was 266 out of 500 points. The mean age was 43 years, and most of the individuals in the sample were born in the USA (84%) and were healthy (89%). In the first step, two to seven latent classes were tested in LCA. Based on the comparisons across multiple fit indices (see Supplemental Table 1), the latent class of four was adopted (RQ 1). Although other numbers of latent classes might have been adopted, the latent class model with four groups showed the adequate overall model fit relative to others, and the results were more in alignment with a similar study (Nienkemper & Grotlüschen, 2019). Also, the skill use patterns were more clearly distinguished in the four groups than other number of groups.

In the second step, the four latent classes were extracted (see Table 2 and Supplemental Table 2), and numeracy skill use patterns were visualized in Figure 2. Class 1 (numeracy non-users) used the least amount of numeracy skills compared to other subgroups both at work and at home. Class 2 (non-occupational simple numeracy users) did not use numeracy skills at work but used relatively simple numeracy skills, including calculating cost or budget and using a calculator, at home. Class 3 (ubiquitous numeracy users) used numeracy skills more often than other groups both at work and at home. Finally, Class 4 (occupational numeracy users) use numeracy skills at higher levels at work but did not use them at home. The use of advanced math or statistics was uncommon, even in the heavy and ubiquitous numeracy users of Class 3 (about 21%). Sociodemographic characteristics of each group are presented in Table 1. The hypothesis for RQ1 was supported.

In the third step, results from multinomial logistic regressions (Table 2). Overall, numeracy proficiency was associated with more frequent numeracy skill use (RQ2). Specifically, workers with higher numeracy proficiency were more likely to be non-occupational simple numeracy users (Class 2), ubiquitous numeracy users (Class 3) or occupational numeracy users (Class 4) than numeracy non-users (Class 1). Also, those with higher numeracy proficiency were more likely to be ubiquitous numeracy users than non-occupational simple numeracy users or occupational numeracy users. However, the numeracy skill proficiency was not predictive of the class memberships for non-occupational simple numeracy users versus occupational numeracy users. The hypothesis for RQ2 was mostly supported.

STEM occupation was only associated with distinctions between two sets of numeracy skill use patterns. STEM workers were more likely to be ubiquitous numeracy users than non-occupational simple numeracy users, compared to their non-STEM counterparts. Also, STEM workers were more likely to be ubiquitous numeracy users than occupational numeracy users, compared to the non-STEM counterpart. The hypothesis for RQ3 was only partially supported.

Discussion

Given the importance of numeracy and numeracy skill use, as well as recent and predicted continued growth in STEM occupations, this study explored the numeracy skill use patterns using a person-centered approach, LCA, and found four numeracy skill use sub-groups and associations with numeracy proficiency and STEM occupations among the USA workforce. Generally, numeracy proficiency was associated with more frequent and ubiquitous numeracy skill use, while STEM occupation was associated with ubiquitous numeracy skill use only in relation to specific subgroups including non-occupational simple numeracy users and occupational numeracy users.

Specifically, LCA identified the four numeracy skill use subgroups, including numeracy non-users, non-occupational simple numeracy users, ubiquitous numeracy users and occupational numeracy users. One of the advantages of the person-centered approach is that knowing one numeracy skill use behavior may provide clues for other behaviors. For example, when workers use advanced math or statistics at work, these workers most likely belong to the ubiquitous numeracy users subgroup or the occupational numeracy users subgroup. In addition, some of the sociodemographic characteristics seem to be relevant. For example, the percentage (56%) of women in the non-occupational simple numeracy users subgroup appears to be higher than in other subgroups (42-49%); Black workers tend to be in the subgroups with lower numeracy skill use (14-16% of the total), numeracy non-users and non-occupational simple numeracy users, than those with higher numeracy skill use (9-10% of the total); and lower income levels seem to be more common among the lower numeracy skill users (Grotlüschen et al., 2019; Lindeman, 2015). Also, the percentage (23%) of STEM workers in the ubiquitous numeracy users tended to be higher than other subgroups (14-17%). Although these observations need more rigorous analyses and confirmation in future research, the descriptive statistics of each numeracy skill use subgroup are useful to inform future research as well as to advance the discussions on skill use patterns by individual characteristics and occupational field.

Regarding the relationship between numeracy skill use subgroups and numeracy proficiency, the findings from the current study supported practice engagement theory (Reder, 1994; Reder et al., 2020). Although there are differences in the ubiquitous and at-work contexts, numeracy proficiency was predictive of higher numeracy skill users. This finding is consistent with a previous study with the mixed skill use (e.g., literacy and numeracy) (Nienkemper & Grotlüschen, 2019). One of the interesting findings is that numeracy proficiency was not only linked to the difference between higher and lower numeracy user subgroups, but it is also predictive of the difference between the lower numeracy users: non-occupational simple numeracy users and non-users. Such between- and within-group differences could be partially due to the numeracy skill demands at work. Yet, socioeconomic status and contexts seem to be highly relevant (Billington & Foldnes, 2021; Edin & Gustavsson, 2008). Grotlüschen et al. (2019) found that those with socioeconomic disadvantages need to use simple numeracy skills (e.g., calculating the cost of budget at home) outside of work, regardless of their numeracy proficiency, occupation, and numeracy skill needs at work. Gender (women), racial/ethnic minority (Black) and lower socioeconomic status (i.e., educational attainment and income) were linked with a greater likelihood of being non-occupational simple numeracy users than non-users (Windisch, 2015). While numeracy proficiency and skill use are associated both with the frequency and specific skill use, demographic characteristics and socioeconomic status are also relevant contributing characteristics.

The findings from this study only partially supported the practice engagement theory (Reder, 1994) and showed that STEM occupations was predictive of differences between ubiquitous numeracy users and non-occupational simple numeracy users, as well as occupational numeracy users. As shown in a previous study (Bol & Heisig, 2021), STEM occupations tend to have greater numeracy demands and skill use opportunities than non-STEM occupations, and therefore, STEM occupations may be linked to higher numeracy skill use. Whereas the previous study reported numeracy skill use spillover effects from work to outside of work (Nienkemper & Grotlüschen, 2019), the findings from this study showed the spillover effects may depend on the contexts as well as specific numeracy skill uses (e.g., calculating cost and budget). STEM occupations may be connected to one's financial well-being, and those in non-STEM occupations may face a greater chance of economic vulnerability, which requires frequent calculation of costs and budgets outside of work (Grotlüschen et al., 2019; Hampf et al., 2017). Another possible explanation is gender differences in numeracy use. STEM employment as the predictor of numeracy use could be due to the underrepresentation of women in STEM occupations (Lindeman, 2015).

The findings also suggested that non-STEM workers who use numeracy skills at work are less likely to use numeracy skills outside of work than STEM workers. Not all workers are required to use numeracy skills at work (Marr & Hagston, 2007). While one worker might use numeracy skills in a team project at work, others may not have opportunities to use numeracy skills on the same project and see little need for numeracy improvement. Indeed, one study found that a higher level of collaboration at work is negatively associated with workers' numeracy proficiency (Lopes et al., 2020). The same thing can be said for the context of numeracy skill use at home. For example, when one household member can take care of tracking costs and budgeting, other household members may not need to practice such skills at home. Similarly, collective proficiency as a team (e.g., one member has high numeracy proficiency) may be more relevant to the specific work contexts than individual proficiency. Future research needs to clarify social and professional networks in relation to numeracy skill use and proficiency. In addition, while this study focused on numeracy, the scope of future research may include other skills such as literacy, digital skills, and soft skills (e.g., interpersonal communication) (Liu et al., 2019).

Limitations

There were several limitations in the current study. First, the present study adopted a broad STEM definition, which is slightly different from the one used by the USA Department of Labor but close to the one used by researchers at leading think tanks, such as the Brookings Institute (Siekmann & Korbel, 2016). Thus, the findings may not be comparable with some existing reports. At the same time, a broad definition of STEM is a logical starting point in the context of skill use research and informative for a future study. Arguably, a next step is to examine numeracy skill use patterns with the different STEM definitions as well as specific occupation types to contextualize the nationally representative findings from the current study. Second, although the LCA may be considered a somewhat data-driven approach, the use of a person-centered approach that was framed and interpreted with the practice engagement theory (Reder, 1994) makes a contribution to the literature (Collins & Lanza, 2010). Future research needs to explore different criteria for the latent class identification (e.g., different number of latent class; alternative skill use indicators when available). Third, the findings from the present study cannot describe the background and nuance of skill use both at work and at home. For example, numeracy skill use at work may be moderated by the career stage (e.g., technical vs management positions) and motivation (Westerman, 2021). Also, some of the implicit numeracy skills (e.g., informal mathematics activities with family members; selection of health insurance plans based on the estimated/guessed risk) use that are embedded in the work responsibilities and every life might have been overlooked (Mutaf-Yıldız et al., 2020). Relatedly, the present study does not provide information on whether the participants routinely used the same numeracy skills or learned new skills. Finally, other sets of skills such as literacy, digital problem-solving, soft skills (e.g., interpersonal) and job-specific skills as well as how these skill needs are distributed at work and at home should be taken into account in future research (Barton & Hamilton, 2000; Liu & Fernandez, 2018).

Implications

Given that engagement in numeracy skill use most likely enhances skill proficiencies, the findings from the present study provide a few preliminary implications. As numeracy proficiency is linked to a series of social as well as socioeconomic inequalities, the opportunity structure, which promote skill proficiency and observed distributions of numeracy use can be considered the points for intervention (Grotlüschen et al., 2019). Any intervention and policy discussion should consider specific numeracy skill use and contexts (i.e., at work and home). Also, it is critical to raise awareness of the use-it-or-lose-it hypothesis and long-term consequences (e.g., skill gaps) to the numeracy non-users and non-occupational simple numeracy users. For example, workers without regular numeracy practice may face numeracy skill obsolescence over time, and in turn, socioeconomic disadvantages, compared to those who regularly use numeracy. In addition, specific numeracy skill use, such as advanced math and statistics, seems to be one of the useful skill use spillover effect indicators. Specifically, if a worker never uses advanced math or statistics, neither at work nor home, it is likely that other advanced numeracy skills (e.g., using algebra or formulas) are also not regularly practiced. Such indicator(s) may be incorporated into a numeracy skill use screening, along with the sociodemographic characteristics that were linked to each identified subgroup in the present study. Finally, the empirical evidence on numeracy skill use patterns in both at-work and at-home contexts of the USA workforce contributed to the gaps in the literature. Future research can further expand the scope of analysis to different countries or focus more on specific numeracy skills and potential consequences (e.g., proficiency, socioeconomic outcomes).

A few insights from the previous studies in relation to the numeracy skill improvement are worth noting. For adult learners, one-on-one or small group with consideration to cultural sensitivity (e.g., education background) may promote numeracy learning (Vorhaus et al., 2011). The identified associations between the numeracy skill use subgroups and sociodemographic characteristics can be used to classify potential participants in the numeracy interventions. Also, a long-term approach most likely benefits participants because the dose-response relationships between numeracy training and outcome are still unclear (Reder, 2012). In particular, the workers who do not use numeracy at work or at home may need extra time and motivation (e.g., positive experience, qualified teachers) to see benefits from the numeracy education programs (Vorhaus et al., 2011; Windisch, 2015). Relevant policy examples, such as Australia's mandatory literacy and numeracy training program among jobseekers who applied for unemployment benefits, can be modeled for prevention of long-term unemployment in case the USA workers had poor numeracy proficiency as well as little to no practice (Saal et al., 2018; Windisch, 2015). The findings from the present study not only provides the skill use patterns but also helps identify target subgroups in possible interventions.

Conclusion

The person-centered approach with LCA identified four numeracy skill use subgroups, including numeracy non-users; non-occupational simple numeracy users; ubiquitous numeracy users; and occupational numeracy users, in USA workers. These subgroups had distinctive patterns of specific numeracy skill use both at work and at home. Generally, higher numeracy proficiency was associated with greater use of numeracy skills in broader contexts (i.e., both at work and at home). Also, among the USA workforce, STEM occupations were partially associated with how much and where (i.e., at work and/or at home) the numeracy skills were used. Older age, female gender, racial minority (i.e., Black), lower educational attainment, and lower income were mostly predictive of the lower numeracy skill use patterns. Findings from the present study can be used for interventions and policies to increase numeracy skill use opportunities at work and in everyday life, and in turn, enhance numeracy proficiency, to establish a beneficial numeracy engagement in the USA labor force.

References

Asparouhov, T., & Muthén, B. (2014). Auxiliary Variables in Mixture Modeling: Three-Step Approaches Using Mplus. *Structural Equation Modeling: A Multidisciplinary Journal*, *21*(3), 329-341. https://doi.org/10.1080/10705511.2014.915181

Avvisati, F., & Keslair, F. (2019). *REPEST: Stata module to run estimations with weighted replicate samples and plausible values*. In https://EconPapers.repec.org/RePEc:boc:bocode:s457918

Barton, D., & Hamilton, M. (2000). Lieracy practices. In D. Barton & M. Hamilton (Eds.), *Situated literacies. Reading and writing in contet* (pp. 7-15). Routledge.

Becker, G. S. (2009). *Human capital: A theoretical and empirical analysis, with special reference to education*. University of Chicago press.

Billington, M. G., & Foldnes, N. (2021). Exploring the association between occupational complexity and numeracy. *Large-scale Assessments in Education*, *9*(1), 19. https://doi.org/10.1186/s40536-021-00112-6

Bol, T., & Heisig, J. P. (2021). Explaining wage differentials by field of study among higher education graduates: Evidence from a large-scale survey of adult skills. *Social Science Research*, *99*, 102594. https://doi.org/https://doi.org/10.1016/j.ssresearch.2021.102594

Borgonovi, F., Choi, Á., & Paccagnella, M. (2018). (OECD Education Working Paper, Issue 20). https://www.oecd.org/officialdocuments/publicdisplaydocumentpdf/?cote=EDU/WKP(2018)20&docLanguage=En

Cheng, S., & Long, J. S. (2007). Testing for IIA in the multinomial logit model. *Sociological Methods & Research*, *35*(4), 583-600.

Clark, S. L. (2010). *Mixture modeling with behavioral data* [Doctoral dissertation, University of California, Los Angeles]. Los Angeles, CA.

Collins, L. M., & Lanza, S. T. (2010). *Latent class and latent transition analysis: with application in the social, behavioral, and health sciences*. John Wiley & Sons.

DeMaris, A. (2005). *Regression with social data: modeling continuous and limited response variables*. John Wiley & Sons, Inc.

Deming, D. J., & Noray, K. L. (2018). *STEM Careers and the Changing Skill Requirements of Work* (National Bureau of Economic Research Working Paper Series, Issue. https://www.nber.org/system/files/working_papers/w25065/w25065.pdf

Dennis, V. (2014). *STEM 101: Intro to tomorrow's jobs*. https://dspace.ceid.org.tr/xmlui/handle/1/1575

Desjardins, R. (2003). Determinants of literacy proficiency: a lifelong-lifewide learning perspective. *International Journal of Educational Research*, *39*(3), 205-245. https://doi.org/https://doi.org/10.1016/j.ijer.2004.04.004

Desjardins, R. (2017). Is literacy and the practice of literacy on the decline? In A. T. de Matos, G. d. O. Martins, & P. Hanenberg (Eds.), *The Future Within Reach* (pp. 761-766). Catholic University of Portugal.

Devane, B., & Squire, K. D. (2012). Activity theory in the learning technologies. In D. H. Jonassen & S. M. Land (Eds.), *Theoretical foundations of learning environments* (pp. 242-267). Routledge.

Eccles, J. S. (2005). Subjective task value and the Eccles et al. model of achievement-related choices. In A. J. Elliot & C. S. Dweck (Eds.), *Handbook of competence and motivation* (pp. 105-121). Guilford.

Edin, P.-A., & Gustavsson, M. (2008). Time out of work and skill depreciation. *ILR Review*, *61*(2), 163-180.

European Commission. (2016). *Does the EU need more STEM graduates? : final report*. Publications Office. https://doi.org/doi/10.2766/000444

Evans, J., Yasukawa, K., Mallows, D., & Kubascikova, J. (2021). Shifting the gaze: From the numerate individual to their numerate environment. *Adult Literacy Education: The International Journal of Literacy, Language, and Numeracy*, *3*(3), 4-18.

Ford, K. S., & Umbricht, M. (2016). Persisting gaps: Labor market outcomes and numeracy skill levels of first-generation and muli-generation college graduates. http://piaacgateway.com/s/Ford_Umbricht_PIAAC-8w7d.pdf

Gal, I., Grotlüschen, A., Tout, D., & Kaiser, G. (2020). Numeracy, adult education, and vulnerable adults: a critical view of a neglected field. *ZDM*, *52*(3), 377-394. https://doi.org/10.1007/s11858-020-01155-9

Goodman, M., Finnegan, R., Mohadjer, L., Krenzke, T., & Hogan, J. (2013). *Literacy, numeracy, and problem solving in technology-rich environments among U.S. adults: Results from the Program for the International Assessment of Adult Competencies 2012: First look*. https://nces.ed.gov/pubs2014/2014008.pdf

Goos, M., Geiger, V., & Dole, S. (2014). Transforming professional practice in numeracy teaching. In Y. Li, E. A. Silver, & S. Li (Eds.), *Transforming Mathematics Instruction-Multiple approaches adn practices* (pp. 81-102). Springer.

Green, D. A., & Riddell, W. C. (2001). *Literacy, numeracy and labour market outcomes in Canada*. http://en.copian.ca/library/research/nls/ials/numeracy/english/numeracy.pdf

Grotlüschen, A., Buddeberg, K., Redmer, A., Ansen, H., & Dannath, J. (2019). Vulnerable Subgroups and Numeracy Practices: How Poverty, Debt, and Unemployment Relate to Everyday Numeracy Practices. *Adult Education Quarterly*, *69*(4), 251-270. https://doi.org/10.1177/0741713619841132

Grotlüschen, A., Mallows, D., Reder, S., & Sabatini, J. (2016). *Adults with low proficiency in literacy or numeracy* (OECD Education Working Papers, Issue. O. Publishing. http://www.oecd.org/officialdocuments/publicdisplaydocumentpdf/?cote=EDU/WKP(2016)5&docLanguage=En

Hampf, F., Wiederhold, S., & Woessmann, L. (2017). Skills, earnings, and employment: exploring causality in the estimation of returns to skills. *Large-scale Assessments in Education*, *5*(1), 12. https://doi.org/10.1186/s40536-017-0045-7

Hogan, J., Thornton, N., Diaz-Hoffmann, L., Mohadjer, L., Krenzke, T., Li, J., VanDeKerckhove, W., Yamamoto, K., & Khorramdel, L. (2016). *U.S. Program for the International Assessment of Adult Competencies (PIAAC) 2012/2014: Main Study and National Supplement Technical Report*. N. C. f. E. Statistics. https://nces.ed.gov/pubs2016/2016036_rev.pdf

Holzer, H. J., & Lerman, R. I. (2015). *Cognitive skills in the U.S. labor market: For whom do they matter?* http://piaacgateway.com/s/Holzer_Lerman_PIAAC.pdf

ILO. (2016). *International standard classification of occupations*. https://www.ilo.org/public/english/bureau/stat/isco/isco08/

Jonas, N. (2018). *Numeracy practices and numeracy skills among adults* (OECD Education Working Paper, Issue. https://www.oecd.org/officialdocuments/publicdisplaydocumentpdf/?cote=EDU/WKP(2018)13&docLanguage=En

Knowles, M., Holton, E. F., & Swanson, R. A. (1998). *The adult learner: The definitive classic in adult education and human resource development* (5, Ed.). Gulf Publishing Company.

Lindeman, D. J. (2015). *Gender and numeracy skill use: Cross-national revelations from PIAAC* (AIR Commissioned Paper, Issue. http://piaacgateway.com/s/Lindemann_PIAAC.pdf

Liu, H., & Fernandez, F. (2018). *Examining the Ways that Numeracy Skills and Soft Skills are Related to Occupational Status: The Case of U.S. Workers*. http://piaacgateway.com/s/Liu_Fndz_Soft_Skills_Report_2018_Final-wcr2.pdf

Liu, H., Fernandez, F., & Grotlüschen, A. (2019). Examining self-directedness and its relationships with lifelong learning and earnings in Yunnan, Vietnam, Germany, and the

United States. *International Journal of Educational Development*, *70*, 102088. https://doi.org/https://doi.org/10.1016/j.ijedudev.2019.102088

Lopes, T., Scully-Russ, E., Zarestky, J., & Collins, J. C. (2020). The effects of social characteristics of jobs on the cognitive skills of adults in the United States: A PIAAC analysis. *Adult Education Quarterly*, *70*(2), 140-174.

Marr, B., & Hagston, J. (2007). *Thinking Beyond Numbers: Learning Numeracy for the Future Workplace*. https://www.ncver.edu.au/__data/assets/file/0017/5426/nl05002.pdf

Mutaf-Yıldız, B., Sasanguie, D., De Smedt, B., & Reynvoet, B. (2020). Probing the Relationship Between Home Numeracy and Children's Mathematical Skills: A Systematic Review. *Front Psychol*, *11*, 2074. https://doi.org/10.3389/fpsyg.2020.02074

Muthén, L. K., & Muthén, B. O. (1998-2017). *Mplus statistical analysis with latent variables user's guide*. Muthén & Muthén.

National Center for Education Statistics. (2020a). *Adult numeracy in the United States*. https://nces.ed.gov/pubs2020/2020025/index.asp

National Center for Education Statistics. (2020b). *Characteristics of postsecondary students*. https://nces.ed.gov/programs/coe/indicator_csb.asp#info

National Center for Education Statistics. (n.d). *What does the cognitive assessment of PIAAC measure?* Retrieved June 17 from https://nces.ed.gov/surveys/piaac/measure.asp

National Center for Education Statistics. (n.d.). *History of international adult literacy assessments*. https://nces.ed.gov/surveys/piaac/history.asp

National Science Foundation. (2021). *The STEM labor force today: Scientists, Engineers and Skilled Technical Workers* (Science and Engineering Indicators 2022, Issue. https://ncses.nsf.gov/pubs/nsb20212

Nienkemper, B., & Grotlüschen, A. (2019). Using PIAAC data to learn more about the literacy practices of adults. *International Journal of Lifelong Education*, *38*(4), 393-405. https://doi.org/10.1080/02601370.2019.1596171

Noonan, R. (2017). *STEM Jobs: 2017 Update* (ESA Issue Brief, Issue. http://www.esa.gov/reports/stem-jobs-2017-update

[Record #491 is using a reference type undefined in this output style.]

OECD. (2016a). *Skills matter: Further results from the survey of adult skills* (OECD Skills Studies, Issue. O. Publishing. https://www.oecd.org/skills/piaac/Skills_Matter_Further_Results_from_the_Survey_of_Adult_Skills.pdf

OECD. (2016b). *Technical report of the Survey of Adult Skills (PIAAC)*. OECD Publishing. http://www.oecd.org/skills/piaac/PIAAC_Technical_Report_2nd_Edition_Full_Report.pdf

OECD. (2019a). *Skills matter: Additional results from the Survey of Adult Skills* (OECD Skills Studies, Issue. https://read.oecd.org/10.1787/9789264258051-en?format=pdf&_ga=2.149483391.838450505.1621437518-453853953.1589205204

OECD. (2019b). *The survey of adult skills : Reader's companion* (3 ed.). https://doi.org/https://doi.org/10.1787/f70238c7-en.

Parsons, S., & Bynner, J. (2006). *Does numeracy matter more?* http://www.nrdc.org.uk/wp-content/uploads/2005/01/Does-numeracy-matter-more.pdf

Patterson, M. B. (2020). PIAAC Numeracy Skills and Home Use among Adult English Learners. *Adult Literacy Education*, *2*(1), 22-40.

Plasman, J., Gottfried, M., Williams, D., Ippolito, M., & Owens, A. (2021). Parents' Occupations and Students' Success in STEM Fields: A Systematic Review and Narrative Synthesis. *Adolescent Research Review*, *6*, 33-44.

Porcu, M., & Giambona, F. (2017). Introduction to Latent Class Analysis With Applications. *The Journal of Early Adolescence*, *37*(1), 129-158. https://doi.org/10.1177/0272431616648452

Reder, S. (1994). Practice-engagement theory: A sociocultural approach to literacy across languages and cultures. *Literacy across languages and cultures*, 33-74.

Reder, S. (2012). *The longitudinal study of adult learning: Challenging assumptions*. http://www.centreforliteracy.qc.ca/sites/default/files/CFLRsrchBrief_Chllngng_Assmptns.pdf

Reder, S. (2020). A lifelong and life-wide framework for adult literacy education. *Adult Literacy Education*, *2*(1), 48-53.

Reder, S., & Bynner, J. (2009). *Tracking adult literacy and numeracy skills: Findings from longitudinal research* (1 ed.). Routledge.

Reder, S., Gauly, B., & Lechner, C. (2020). Practice makes perfect: Practice engagement theory and the development of adult literacy and numeracy proficiency. *International Review of Education*, *66*, 1-22.

Redmer, A., & Dannath, J. (2020). Changes in employment since the 1990s: numeracy practices at work in IALS and PIAAC. *ZDM*, *52*(3), 447-459. https://doi.org/10.1007/s11858-019-01112-1

Saal, L. K., Gholson, M., Machtmes, K., & Machtmes, R. (2018). *Associations Between Adults' Numeracy Skills and Employment Status: An Analysis of PIAAC's U.S. Dataset*.

http://piaacgateway.com/s/2018_Saal_Gholson_Machtmes_Machtmes_Numeracy_EmploymentStatus.pdf

Schwerdt, G., Wiederhold, S., & Murray, T. S. (2020). *Literacy and growth: New evidence from PIAAC*. http://piaacgateway.com/s/2020_Schwerdt_Wiederhold_Murray_Literacy-and-Growth.pdf

Shomos, A. (2010). *Links between literacy and numeracy skills and labour market outcomes*. https://www.pc.gov.au/research/supporting/literacy-numeracy-labour-outcomes/literacy-numeracy-labour-outcomes.pdf

Siekmann, G., & Korbel, P. (2016). *Defining 'STEM' skills: review and synthesis of the literature*. https://www.ncver.edu.au/__data/assets/pdf_file/0022/61339/Support-doc-1-Defining-STEM-skills-review-and-synthesis-of-the-literature.pdf

St Clair, R., Tett, L., & Maclachlan, K. (2010). *Scottish Survey of Adult Literacies 2009: Report of Findings*. http://eprints.hud.ac.uk/id/eprint/13416/1/TettScottish0102005.pdf

StataCorp. (2021). *Stata Statistical Software: Release 17*. StataCorp LLC.

Støren, L. A., Lundetræ, K., & Børing, P. (2018). Country differences in numeracy skills: how do they vary by job characteristics and education levels? *International Journal of Lifelong Education*, *37*(5), 578-597. https://doi.org/10.1080/02601370.2018.1554718

U.S. Breau of Labor Statistics. (2021). *Employment in STEM occupations*. https://www.bls.gov/emp/tables/stem-employment.htm

Vorhaus, J., Lister, J., Frearson, M., & Johnson, S. (2011). *Review of research and evaluation on improving adult literacy and numeracy skills*. Department for Business Innovation & Skills.

https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/32356/11-1418-review-research-on-improving-adult-skills.pdf

Wang, J., & Wang, X. (2020). *Structural equation modeling: Applications using Mplus* (2 ed.). John Wiley & Sons.

Westerman, J. (2021). Post-educational motivation to learn cognitive skills in three European labour markets. A comparative analysis of the PIAAC. *Journal of Education and Work, 34*(4), 459-471. https://doi.org/10.1080/13639080.2021.1953693

Wilms, J. D., & Murray, T. S. (2007). *Gaining and losing literacy skills over the lifecourse*. https://www150.statcan.gc.ca/n1/en/catalogue/89-552-M2007016

Windisch, H. C. (2015). *Adults with low literacy and numeracy skills: A literature review on policy intervention* (OECD Education Working Papers, Issue. https://dx.doi.org/10.1787/5jrxnjdd3r5k-en

Xie, Y., & Killewald, A. A. (2012). *Is American Science in Decline?* Harvard University Press. https://doi.org/doi:10.4159/harvard.9780674065048

Table 1: Weighted Descriptive Summary by the Identified Latent Classes of Numeracy Skills Use at Work and at Home

Variables	All (n = 5,310) [a] Mean or percentage (SE)	Class 1 (n = 1,440) [a] Mean or percentage (SE)	Class 2 (n = 1,090) [a] Mean or percentage (SE)	Class 3 (n = 1,250) [a] Mean or percentage (SE)	Class 4 (n = 1,530) [a] Mean or percentage (SE)
STEM occupation	17.31% (0.55)	14.27% (1.27)	14.24% (0.95)	23.44% (1.44)	17.42% (0.98)
Numeracy proficiency (0-500 points) [b]	265.78 (1.20)	247.88 (2.31)	262.87 (1.85)	285.40 (2.00)	269.07 (1.83)
Age (years)	43.42 (0.12)	44.79 (0.30)	42.21 (0.44)	42.16 (0.34)	43.97 (3.09)
Gender (Women)	47.83% (0.61)	48.83% (1.42)	56.25% (1.29)	41.76% (1.17)	45.96% (1.42)
Race/Ethnicity					
White	72.86% (0.56)	65.80% (1.44)	69.68% (1.64)	77.52% (1.10)	78.01% (1.29)
Black	11.86% (0.28)	14.18% (0.86)	16.14% (1.22)	9.63% (0.90)	8.53% (0.78)
Hispanic	15.13% (0.54)	19.92% (1.37)	13.88% (1.48)	12.79% (0.89)	13.32% (0.95)
USA Born (Yes)	87.66% (0.54)	82.65% (1.21)	88.34% (1.17)	90.99% (1.21)	89.30% (0.76)
Education					
Less than high school	6.94% (0.39)	12.58% (1.00)	6.34% (0.81)	3.11% (0.49)	5.08% (0.57)
Highschool	46.41% (0.68)	50.15% (1.51)	47.53% (1.47)	40.21% (1.52)	47.04% (1.36)
College or higher	46.65% (0.73)	37.27% (1.46)	46.13% (1.66)	56.68% (1.42)	47.87% (1.48)
Parent's education College or higher (vs. less than college)	41.85% (0.70)	35.05% (1.20)	44.16% (1.90)	47.96% (1.56)	41.82% (1.31)
Income					
No self-reported income	9.53% (0.67)	13.37% (1.04)	9.99% (0.90)	12.01% (1.10)	14.08% (0.99)
1st quintile	12.21% (0.44)	16.84% (1.12)	17.50% (1.16)	6.52% (0.51)	8.10% (0.75)
2	16.74% (0.52)	20.97% (1.00)	22.75% (1.43)	12.85% (0.89)	12.06% (0.72)
3	19.36% (0.72)	17.81% (0.99)	19.79% (1.61)	18.74% (1.43)	18.52% (1.18)
4	20.76% (0.69)	17.19% (1.21)	16.73% (1.23)	21.94% (1.24)	22.54% (1.05)
5th quintile	21.39% (0.64)	13.83% (1.06)	13.24% (1.16)	27.94% (1.24)	24.69% (1.07)
Self-rated health (Excellent, very good, good)	88.98% (0.43)	86.69% (1.02)	86.30% (1.26)	91.45% (0.91)	91.01% (0.82)

Notes: The sampling and replicate weights were applied.
[a] Unweighted Sample size rounded to the nearest 10 per the PIAAC restricted-use file data use guideline.
[b] 10 plausible values
Each class was named as Class 1 (numeracy non-users); Class 2 (non-occupational simple numeracy users); Class 3 (ubiquitous numeracy users); Class 4 (occupational numeracy users)
Data Source: 2012/2014/2017 PIAAC Restricted Use File Data (National Center for Education Statistics, 2017)

Table 2: 95% Confidence Intervals of Estimated Odds Ratios from Multinomial Logistic Regressions

Variables	Model 1a Class 1 vs. Class 2 LL, UL	Model 1b Class 1 vs. Class 3 LL, UL	Model 1c Class 1 vs. Class 4 LL, UL	Model 2a Class 2 vs. Class 3 LL, UL	Model 2b Class 2 vs. Class 4 LL, UL	Model 3a Class 3 vs. Class 4 LL, UL
STEM occupation	0.690, 1.183	0.985, 1.741	0.744, 1.127	**1.153, 1.822***	0.868, 1.333	**0.611, 0.901***
Numeracy proficiency (0-500 points) [b]	**1.002, 1.007***	**1.007, 1.013***	**1.001, 1.006***	**1.003, 1.009***	0.997, 1.002	**0.991, 0.996***
Age (years)	**0.974, 0.990***	**0.973, 0.989***	**0.984, 0.999***	0.990, 1.008	**1.002, 1.018***	**1.004, 1.017***
Gender (Women)	**1.148, 1.593***	0.733, 1.040	0.836, 1.172	**0.557, 0.749***	**0.633, 0.847***	0.970, 1.325
Race/Ethnicity						
Black	**1.002, 1.629***	0.725, 1.445	**0.494, 0.887***	0.589, 1.090	**0.378, 0.710***	**0.476, 0.879***
Hispanic	0.623, 1.268	0.786, 1.498	0.626, 1.160	0.875, 1.703	0.647, 1.422	0.581, 1.062
White	*Ref*	*Ref*	*Ref*	*Ref*	*Ref*	*Ref*
USA Born (Yes)	0.825, 1.601	0.903, 1.996	0.917, 1.520	0.794, 1.719	0.720, 1.464	0.612, 1.262
Education						
Less than high school	**0.419, 0.908***	**0.291, 0.706***	**0.395, 0.907***	0.471, 1.148	0.629, 1.499	0.860, 2.027
Highschool	0.737, 1.143	0.705, 1.090	0.811, 1.218	0.791, 1.153	0.888, 1.322	0.937, 1.374
College or higher	*Ref*	*Ref*	*Ref*	*Ref*	*Ref*	*Ref*
Parent's education						
College or higher (vs. less than college)	0.905, 1.430	0.836, 1.227	0.828, 1.186	0.733, 1.081	0.724, 1.048	0.815, 1.173
Income (6 levels: no income, 1st – 5th quintile)	**0.939, 1.040***	**1.061, 1.194***	**1.113, 1.244***	**1.077, 1.204***	**1.125, 1.260***	0.986, 1.109
Self-rated health (Excellent, very good, good)	0.526, 1.080	0.736, 1.287	0.854, 1.472	0.941, 1.771	**1.087, 2.037***	0.853, 1.557

* $p < 0.05$; LL = lower limit; UL = upper limit; *Ref* = reference group
Reference groups were Class 1 in Model 1, Class 2 in Model 2, and Class 3 in Model 3
Notes: The sampling and replicate weights were applied
[a] Unweighted Sample size rounded to the nearest 10 per the PIAAC restricted-use file data use guideline.
[b] 10 plausible values
Each class was named as Class 1 (numeracy non-users); Class 2 (non-occupational simple numeracy users); Class 3 (ubiquitous numeracy users); Class 4 (occupational numeracy users)
The percentages may not add up to 100% due to rounding
Data Source: 2012/2014/2017 PIAAC Restricted Use File Data (National Center for Education Statistics, 2017)

Supplemental Table 1: Model Fit Indices by the Number of Estimated Latent Class Models

Class (k)	AIC	BIC	LCMP 95% CL LL	LC 95% CL UL	Entropy	VLMR LRT test	Minimum class size	ΔAIC (k-1)	ΔBIC (k-1)	ΔLCMP LL (k-1)	ΔLCMP UL (k-1)	ΔEntropy (k-1)
2	59,750.567	59,915.481	0.945	0.95	0.812	$p < 0.05$	2699	5,9751	5,9915	0.945	0.95	0.812
3	57,590.879	57,841.549	0.866	0.95	0.806	$p < 0.05$	1527	-2,159.7	-2,073.9	-0.079	0	-0.006
4	**56,555.904**	**56,892.329**	**0.822**	**0.903**	**0.766**	**$p < 0.05$**	**1070**	**-1,035**	**-949.22**	**-0.044**	**-0.047**	**-0.04**
5	55,813.655	56,235.835	0.793	0.902	0.765	$p < 0.05$	837	-742.25	-656.49	-0.029	-0.001	-0.001
6	55,570.723	59,078.658	0.797	0.904	0.794	$p < 0.05$	197	-242.93	2842.8	0.004	0.002	0.029
7	55,447.494	56,041.184	0.783	0.883	0.796	$p > 0.05$	79	-123.23	-3037.5	-0.014	-0.021	0.002

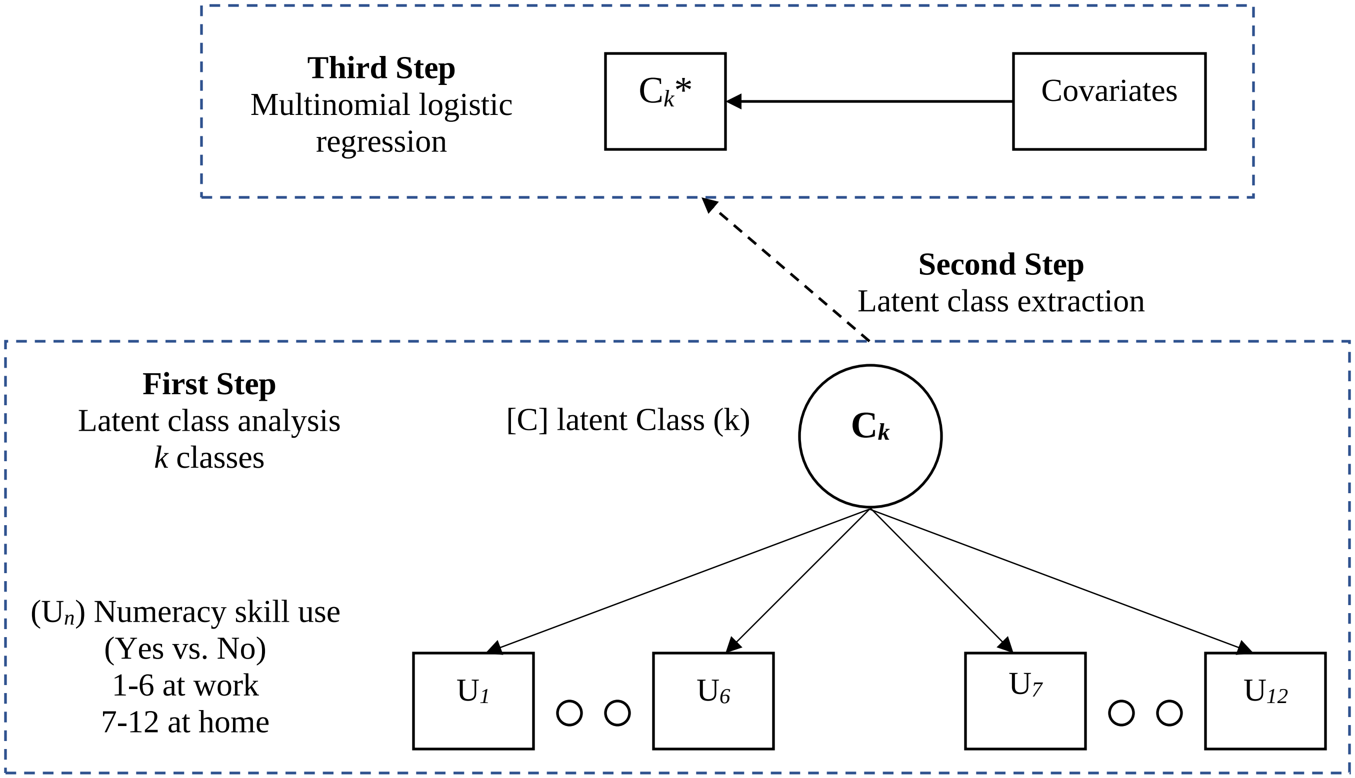
AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion; LCMP = Latent Class Membership Probability; CL = Confidence Interval; LL = Lower Limit; UL = Upper Limit; VLMR LRT = Vuong-Lo-Mendell-Rubin Likelihood Ratio Test; Δ = Difference in

Supplemental Table 2: Four Identified Laten Classes and Names

Latent class	**Names**
Class 1	Numeracy non-users
Class 2	Non-occupational simple numeracy users
Class 3	Ubiquitous numeracy users
Class 4	Occupational numeracy users

Note: See the Methods section for more details.

Figure 1: Analytic Approach

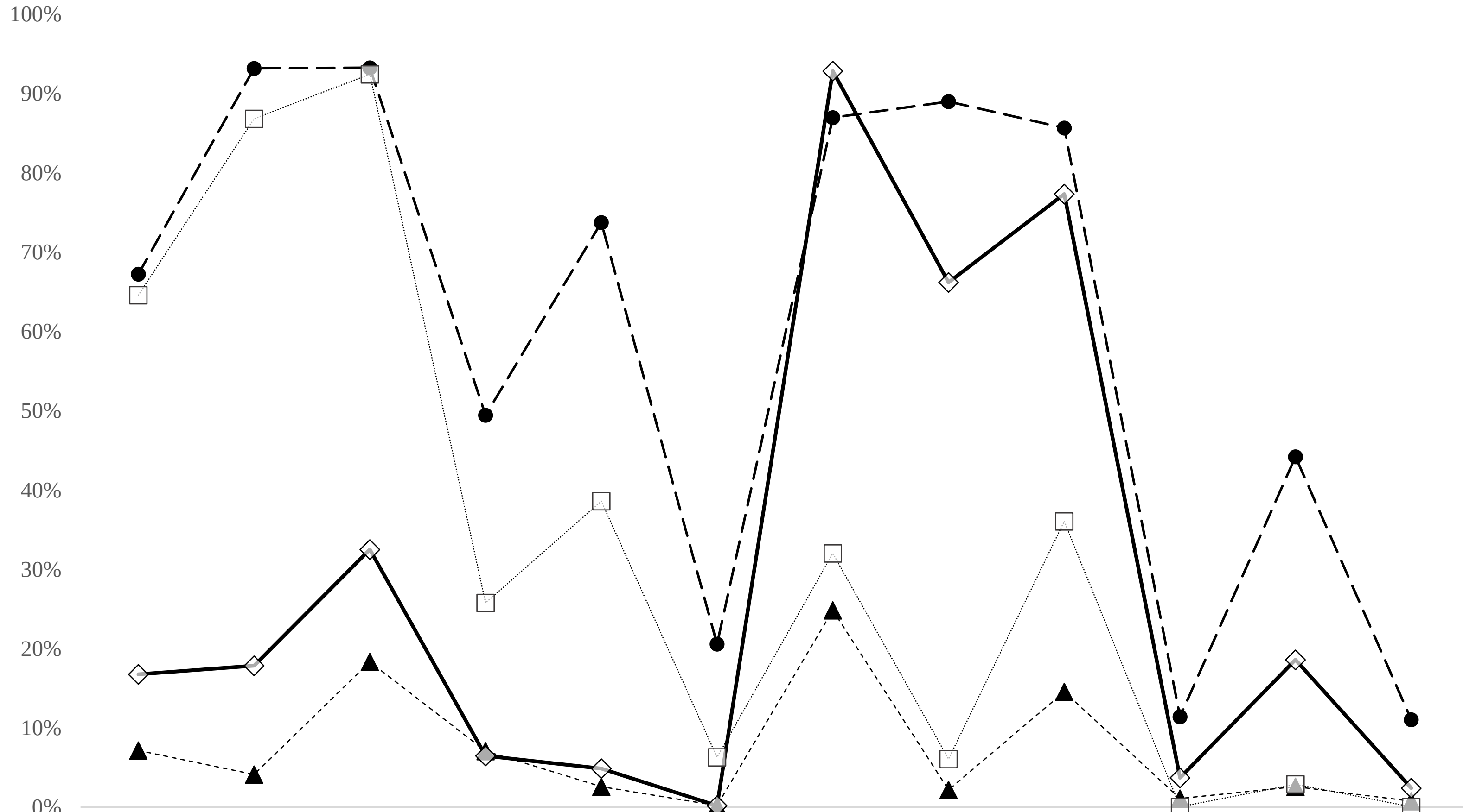


Note: C = latent class; k = number of latent class; u = observed indicator of numeracy skill use; n = number of observed indicator

*Latent class was treated as an observed measure in the third step.

See the Methods section and Table 1 for the covariates.

Figure 2: Identified Latent Classes and Percent Numeracy Skill Use at Work and at Home



	Calculating costs or budgets at work	Use of calculate fractions or percentages at work	Use a calculator at work	Prepare charts graphs or tables at work	Use simple algebra or formulas at work	Use advanced math or statistics at work	Calculating costs or budgets at home	Use of calculate fractions or percentages at home	Use a calculator at home	Prepare charts graphs or tables at home	Use simple algebra or formulas at home	Use advanced math or statistics at home
Class1	7%	4%	18%	7%	3%	0%	25%	2%	15%	1%	3%	1%
Class2	17%	18%	33%	7%	5%	0%	93%	66%	77%	4%	19%	2%
Class3	67%	93%	93%	49%	74%	21%	87%	89%	86%	11%	44%	11%
Class4	65%	87%	92%	26%	39%	6%	32%	6%	36%	0%	3%	0%