Associations between Volunteering, STEM Backgrounds, and Information-Processing Skills in Adult Populations of the United States

By Takashi Yamashita,[1*] Donnette Narine, [2] Wonmai Punksungka, [3] Jenna W. Kramer, [4] Rita Karam., [4] & Phyllis A. Cummins [5]

Publication date: August 29, 2023 (online first) in Social Indicators Research.

https://doi.org/10.1007/s11205-023-03201-x

*Corresponding author

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

Email: yamataka@umbc.edu

ORCID: 0000-0003-2325-126X

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

3. Department of Sociology and Anthropology, George Mason University, Fairfax, VA, U.S.A.

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

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

Keywords: civic engagement; STEM; literacy; numeracy; PIAAC

Statements and Declarations

In this research, Takashi Yamashita, Donnette Narine, Wonmai Punksungka, Jenna W. Kramer, Rita Karam, & Phyllis A. Cummins were partially supported by the Institute of Education Sciences, U.S. Department of Education, through Grant R305A200261 to the 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. This study was reviewed and approved by the Institute of Education Sciences Data Security team for the Program for the International Assessment of Adult Competencies U.S. restricted use file data.

Conflict of Interest

The authors report no conflict of interest.

Associations between Volunteering, STEM Backgrounds, and Information-Processing Skills in Adult Populations of the United States

Abstract

Volunteering, STEM education and occupation, and information-processing skills such as literacy, numeracy, and digital problem-solving skills are important indicators of a nation's well-being as they represent civic engagement, economic development, and the human capital of the population. Although these critical social indicators have been previously examined in silos, the interrelationships are yet to be examined in the adult populations in the United States. The current study analyzed the 2012/2014/2017 U.S. Program for the International Assessment of Adult Competencies (PIAAC) data of adults aged between 25 and 65 years old (n = 8,330). Results from the structural equation model showed that STEM education and occupation as well as information-processing skills, independently promote volunteer participation. Also, STEM education and occupation are positively associated with information-processing skills. Yet, when simultaneously examining the mediation relationship, STEM education, and occupation are no longer promoters of volunteering. Findings from the current studyprovide preliminary education, labor, and social policy implications for promoting the nation's economy and well-being and inform future research to disentangle complex interrelationships across the important social indicators.

Keywords: civic engagement; STEM; literacy; numeracy; PIAAC

Introduction

What is volunteering, and why is it important?

Formal volunteering is a type of civic engagement and is considered an unpaid service through community, organization, or charity (Wilson & Musick, 1997). For example, fundraising

for an organization, food preparation for a local cultural event, and provision of mentoring/instruction at educational institutions without compensation, are common formal volunteering. Informal volunteering is also an unpaid service but is less structured and organized (Wilson, 2000). Helping neighbors with yard work and caregiving to relatives are examples of informal volunteering. Volunteering is an important topic both at the individual and societal levels. With respect to the individual level, engagement in volunteer activities is linked with higher income and career advancement (Wilson et al., 2020), as well as with physical and mental well-being (Jiang et al., 2021; McDougle et al., 2014; Tse, 2018; Yeung et al., 2017). In addition, adults often learn new knowledge through their volunteer activities (Rüber et al., 2018; Vera-Toscano et al., 2017). With respect to the societal level, the estimated total formal volunteer hours can be translated into an economic value of $147 billion in the United States (AmeriCorps, 2021). Finally, volunteering is known to strengthen social trust and other forms of civic engagement, such as voting and participation in civic groups (Atwell et al., 2017). However, less than one in three adults formally volunteer and one-quarter of volunteers serve less than 10 hours a year (AmeriCorps, 2021).

Theoretical framework

This study is framed by the three capitals model developed by Schuller et al. (2004). Schuller et al.'s model is originally developed to depict a wide range of benefits from education and learning. This study adopted the framework and operationalized it with respect to volunteering as a joint outcome of human, social, and identity capitals. Human capital is a collection of acquired abilities and qualifications (e.g., skills and educational attainment), which promote one's economic advantage, such as employment prospects and career advancement (Becker, 2009). Social capital consists of support systems and resources (e.g., timely

information, social trust) from one's social network, such as family, friends, and community (Putnam, 2015). Identity capital represents a set of social-psychological features such as personal aspiration and self-efficacy (e.g., political efficacy or the feeling of individuals being able to make an impact on the political process) (Campbell et al., 1954; Schuller et al., 2004). Volunteering can be considered a product of multiple determinants, including the three capitals. For example, adults with higher educational attainment are more likely to possess job-related skills in demand, develop a larger professional network, and boost one's confidence in their abilities to make changes in communities (Spera et al., 2013). Through these improved capitals, one may be motivated and be able to afford to volunteer more. Another strength of the Schuller et al.'s model is to reflect interrelationships across volunteering, capitals, and relevant factors (i.e., covariates, such as demographic, socioeconomic and social-psychological characteristics).

The importance of STEM education and occupations in the U.S.

Science, Technology, Engineering, and Mathematics (STEM) education as well as occupation (STEM backgrounds, hereafter) have received increasing attention throughout modern U.S. history. While the definition of STEM is still unestablished, this study adopted a relatively broader definition of STEM, which includes health care (Shapiro et al., 2015). In 2019, about 10-16% of the 162 million occupations were classified as STEM (U.S. Bureau of Labor Statistics, 2020, 2021). The growth rates (10.5%) and average wages ($95,420) of the STEM occupations tend to be greater than those of non-STEM counterparts (7.5% and $40,120, respectively) (U.S. Bureau of Labor Statistics, 2020). Indeed, STEM backgrounds are linked to higher socioeconomic status (SES) (e.g., income) and upward social mobility in the U.S. (Rothwell, 2013; U.S. Bureau of Labor Statistics, 2021; Xie et al., 2015). STEM-related occupations not only show greater growth rates but also face lower risks of job replacement due

to the automation compared to non-STEM occupations (e.g., service, sales) (Yamashita & Cummins, 2021). At the same time, certain STEM industries tend to have the sub-groups of the population --- for example, women (e.g., 15 to 25% in computer and engineering) and racial/ethnic minorities such as Black and Hispanic adults (17% of the STEM jobs, while 28% of all jobs) --- underrepresented or overrepresented (women make up 74% of health-related jobs) (Pew Research Center, 2021). Finally, STEM has been the driving force of technological and scientific innovation, which contribute to economic development in general and in the U.S. in particular (Xie & Killewald, 2012). Indeed, publicly funded STEM research and development have historically generated 20 to 67% return on investment (National Academy of Sciences et al., 2007).

Yet, most research exclusively focuses on the economic benefits of STEM backgrounds. Both STEM and non-STEM education provide non-economic benefits such as better health, life satisfaction, civic engagement, and social well-being (e.g., social trust) (Schuller & Desjardins, 2010). STEM backgrounds are known for valuable skills and knowledge (i.e., human capital), and thus, one may argue that both economic and non-economic benefits may be more strongly linked to STEM backgrounds than their non-STEM counterparts. It should also be noted that the STEM-originated innovations in public infrastructure (e.g., public health systems, transportation) certainly resulted in non-economic benefits such as improved health, longevity, quality of life, and civic engagement (Rüber et al., 2018; Vera-Toscano et al., 2017). However, to date, the associations between STEM backgrounds and non-economic outcomes like civic engagement have not been extensively studied (Vera-Toscano et al., 2017).

What are information-processing skills, and why are they important?

According to the Organization for Economic Cooperation and Development (OECD, 2021b), information processing skills, which generally consist of literacy and numeracy skills, are essential human capitals necessary to fully participate in education, the labor market, and social and civic life in the modern societies (see the Methods section for the definitions of skill domains). These information-processing skills represent individual as well as collective competencies to access, understand, analyze and make decisions based on text and numeric information, and in turn, higher-level cognitive and learning skills, such as logical thinking and reasoning (OECD, 2013b). In addition, starting in the 1990s, the population-level assessment of information processing skills has been one of the critical indicators of a country's economic competitiveness and well-being. In more recent years, digital skills, which are necessary to use information and communication technology (e.g., internet, email), and computer and software (e.g., spreadsheet applications) both at work and at home, have been recognized as an additional components of information processing skills (OECD, 2016a).

Information processing skills have been consistently linked with economic (e.g., greater employment security, higher income) and non-economic benefits (e.g., more active civic engagement, such as volunteering, and better health) (Belzer & Kim, 2018; OECD, 2019; Rose et al., 2019). Additionally, literacy, numeracy and digital skills are positively associated with political efficacy (i.e., perception of a chance to make a difference in the community and society through political participation) (Saal et al., 2020). Moreover, information processing skills are the foundational skills to learn higher-level contents, and one may be unable to enhance knowledge and skills without them. In other words, lower information processing skills may prevent participation in necessary adult education and training for economic stability and civic participation (Boeren, 2016; Yamashita et al., 2019). The lack of lifelong learning or skill

upgrading may result in economic disadvantages (e.g., lower employment security, lower chance of career advancement) throughout adult life stages (Cummins & Kunkel, 2015). On a related note, information processing skills are more feasible to improve, compared to educational attainment and occupations in adult life stages (Reder, 2014).

State of the Art

Volunteering and STEM backgrounds

Whereas the population-level study on the STEM its relationship to volunteering is limited, a state-level case study reported that internships and externships through nonprofit organizations tend to increase the chance of working in STEM industries (VCU College of Engineering, n.d.). While internships and externship at the for-profit organization may not fit the narrow definition of civic engagement or unpaid service, work-related learning opportunities can be seen as unpaid labor or a form of volunteering. Given that previous volunteer experience can lead to subsequent volunteering, one of the possible pathways may be through prior experience with internships and volunteering among individuals with STEM backgrounds (Niebuur et al., 2018). At the same time, volunteer participation may be partially determined by individual qualifications (Wilson, 2012). That is, adults with lower educational attainment, and lower skills are more likely to face poorer access to formal volunteer opportunities (Grotlüschen, 2018). As STEM workers tend to have higher educational attainment and more economically valued skills, STEM backgrounds may provide better access to volunteer opportunities. However, more direct empirical inquiries at the population level are certainly needed to document the STEM-volunteer relationship.

Volunteering and information processing skills

Belzer (2018) points out that the growing number of population-level studies support the associations between volunteering and information-processing skills, although the empirical evidence is still somewhat limited in the U.S. context. It should be noted that educational attainment, which is known to promote information-processing skills, has been consistently linked with economic and a variety of non-economic outcomes, such as civic engagement (Desjardins, 2008; Schuller, 2017). Vera-Toscano et al. (2017) found that educational attainment, as well as literacy and numeracy skills, are significant predictors of volunteering across European nations. Grotlüschen (2018) explains that the reason for low participation rates of adults with lower literacy skills is lower political efficacy, in addition to a selective exclusion of low-skilled adults on the volunteer market. Rose et al. (2019) found that only numeracy skills are associated with volunteering in the German and the U.S. adult populations (ages 16-65 years old), whereas literacy and digital problem-solving skills are not. Despite somewhat mixed findings, these previous studies are generally consistent with the identified major barriers, including a lack of resources (e.g., financial, time), qualifications (e.g., educational attainment), skills, and opportunities to volunteer (Southby et al., 2019).

STEM backgrounds and information-processing skills

Despite the common perception that STEM students and workers having greater information processing skills, the empirical evidence of differences with non-STEM counterparts is still limited (Yao, 2019). The emphasis on mathematics education in STEM programs through the formal education systems is well-documented, and as such, one may argue that individuals with STEM backgrounds have greater numeracy skills (National Council of Teachers of Mathematics, 2000; OECD, 2021a). Also, the STEM workforce is more likely to have a bachelor’s degree or higher, which is an indication of greater information-processing

skills, compared to those with less than a bachelor's degree (National Science Foundation, 2022; OECD, 2013a). Furthermore, since STEM students as well as workers are more likely to use STEM-related skills, such as mathematics and digital skills, at school and at work, the adults with STEM backgrounds should have, on average, greater information processing skill than non-STEM counterparts (National Science Foundation, 2021).

Why study volunteering, STEM and information-processing skills?

Under Schuller et al.'s model (2004), STEM background, information-processing skills and volunteering can be theoretically linked. The importance of civic engagement, such as volunteering, is well-documented (Grotlüschen, 2017). The associations between human and social capitals (e.g., educational attainment and information-processing skills such as literacy and digital skills) and civic engagement – one of which is volunteer participation - are documented in economically developed nations (Rose et al., 2019). Additionally, although still limited, skill advantages of people with STEM backgrounds are reported in the U.S. (Yao, 2019). Moreover, STEM skills are in high demand due to the importance of technological and scientific advancement (National Academies of Sciences, 2016). Although our study focuses specifically on the associations between STEM background, information processing skills and volunteering as a form of civic engagement, Schuler et al.'s three capital model suggests a wider application in societies. Thus, we argue that an empirical examination of the relationships between STEM background, information-processing skills, and civic engagement can provide helpful information to promote social cohesion and then, societies' well-being (Grotlüschen, 2018).

Taken together, both STEM backgrounds and information-processing skills make positive impacts on volunteer participation. The majority of adults complete their formal education and start working by their late twenties (National Center for Education Statistics,

2020). As such, it is from that time the effect of STEM backgrounds and information-processing skills will be evident on volunteer participation. STEM backgrounds, which promote the relevant skill use, likely results in greater information-processing skills. In this respect, information-processing skills may mediate or indirectly impact the relationship between STEM backgrounds and volunteering.

There are several reasons to study the mediation relationships across STEM backgrounds, information-processing skills, and volunteering. First, from the volunteer market standpoint, adults with STEM backgrounds and greater skills can be, on average, considered more capable volunteers. A better understanding of how STEM backgrounds and information processing skills are interrelated with volunteering may inform future recruitment of capable volunteers as well as training for potential volunteers. Relatedly, information-processing skills are more malleable than STEM backgrounds at the adult population-level (Belzer & Kim, 2018). Additional empirical evidence may contribute to the promotion of STEM education as well as information-processing skill training among adults. Second, although previous studies found a relationship between information-processing skills and volunteering (Rose et al., 2019), the findings with regard to specific types of skills (e.g., literacy or numeracy) are not yet clear. Third, the mediation analysis may shed light on possible barriers to volunteer opportunities and contribute to a reduction of social inequality by education and skills (Grotlüschen, 2018). Finally, STEM backgrounds, information-processing skills and volunteering can be considered joint products of human, social, and identify capitals (Schuller et al., 2004). An examination of the interrelationship and mediation relationship will contribute to a gap in the literature and inform future policies for growing volunteer participation through STEM education in earlier life stages and in information-processing skills promotion.

Relevant factors to volunteering, STEM backgrounds, and information processing skills

Relevant factors to the focus of this study should be acknowledged. Previous studies included age, gender, race, ethnicity, nativity (i.e., U.S. born vs. non-U.S. born/immigrant), educational attainment, employment, income, information-processing skills, social networks (e.g., relationship status, household composition), attitudes toward community/society, health status, and self-efficacy as well as living environment into their analyses (Grotlüschen et al., 2016; Rose et al., 2019; Southby et al., 2019). These demographic and socioeconomic characteristics, as well as human, social and identity capitals, collaboratively impact one's volunteer behaviors and opportunity structure in the community. Additionally, some of the individual characteristics (e.g., age, gender, educational attainment, race, ethnicity, nativity, income and health) are also known to be associated with information-processing skills (OECD, 2013a; Rose et al., 2019). Furthermore, from a life course perspective, some of the volunteer predictors may be linked. For example, lower educational attainment in the earlier life stages may lead to lower information-processing skills as well as types of occupations with lower pay, which may limit one's capacity (e.g., time and financial resources) to engage in formal volunteering (OECD, 2021b).

Research questions and hypotheses

(1) Are there differences in the information-processing skill proficiencies between adults with STEM backgrounds and those with non-STEM backgrounds in the U.S.? It is hypothesized that those with STEM backgrounds have greater information-processing skills than their counterparts.

(2) Are volunteering, STEM backgrounds, and information-processing skills interrelated in the U.S. adult population? It is hypothesized that volunteering, STEM backgrounds and

information-processing skills are all positively associated with each other even after adjusting for the covariates.

(3) Do the information-processing skills mediate the relationship between volunteering and STEM backgrounds? It is hypothesized that information-processing skills mediate the relationship between STEM backgrounds and volunteering, even after adjusting for the covariates. In other words, information-processing skills partially explain the path between STEM background and volunteering, and therefore, the effect of STEM background on volunteering is expected to be smaller once introducing an indirect path through information-processing skills.

Methodology

Data

Data were obtained from the 2012/2014/2017 Program for the International Assessment of Adult Competencies (PIAAC) Restricted Use File (RUF), the U.S. Department of Education, National Center for Education Statistics (NCES; license #17080026). PIAAC is a continuing study to gather large-scale skill assessment data from 16 years and older adult populations in 33 OECD countries. PIAAC employs a computer-based adaptive assessment design and provides data on information-processing skills, including literacy, numeracy and digital-problem-solving skills, in addition to a series of individual and skill use characteristics (OECD, 2016b). The 2012/2014/2017 PIAAC RUF includes the adjusted sampling weights, which allow the estimation of nationally representative figures during the period of 2012 to 2017 (National Center for Education Statistics, n.d.-a).

In the current study, adults aged between 25 and 65 years old were included in the analysis. Given most adults complete formal education by their mid-twenties, the cut-off point of

age 25 is an approximation of the working age in the U.S. (National Center for Education Statistics, 2020). In addition, age 65 is a common retirement age in the U.S. Schooling and retirement life stages likely have different opportunity structures for volunteering, and therefore, should be considered separately from the typical working-age populations. PIAAC RUF data included 8,690 eligible participants. After excluding the missing values (4.1%) in all variables of interest, the final sample size was 8,330. Additional participants had the missing values of the digital problem-solving skills due to the screening process (e.g., basic computer use). Thus, the analytic sample size for the digital problem-solving skills was 6,840 (about 17% missing rate given all eligible participants). Based on the bivariate comparisons of the variables of interest between the samples with complete information and those with missing values, systematic patterns of missing values were not identified. Thus, we assumed conditionally missing at random (Enders, 2022). The final models that are reported in this study excluded the missing values. However, the results were assessed using the models with the full information maximum likelihood estimation to include the cases with missing values in the analyses (Arbuckle, 1996). The main findings were found to be consistent.

Measures

Outcome variable. Volunteer participation was recorded based on the PIAAC participants' responses to the survey item -- "In the last 12 months, how often, if at all, did you do voluntary work, including unpaid work for a charity, political party, trade union or other nonprofit organization? In this study, considering the conceptual distinction and frequency distributions, volunteer participation was dichotomized into (1) every day; at least once a week but not every day; less than once a week but at least once a month; and less than once a month,

and (0) never. The dichotomization was intended to cover an inclusive definition of volunteering, as no specific cut-point or frequency is commonly accepted.

Predictor variable. STEM backgrounds was a dichotomous measure indicating a respondent had a postsecondary STEM education and/or worked in the STEM occupations. Specifically, the International Standard Classification of Occupation (ISCO) codes 21 (science and engineering professional), 22 (health professionals), 25 (information and communication technology professional), 31 (science and engineering associate professional), 32 (health associate professional) and 35 (information and communication technician) were considered STEM occupations (International Labour Organization, 2016). Postsecondary education in science, mathematics, computing, engineering, manufacturing, and construction were considered STEM education in this study. For STEM education, health care was not included due to the lack of detailed information to separate from relevant areas of study (e.g., welfare, social work).

Mediator variables. *Literacy, numeracy* and *digital problem-solving skills* proficiency measures were provided as a set of 10 statistically derived plausible values (0 – 500 points) in the PIAAC data. In PIAAC, literacy, numeracy and digital problem-solving skills are defined as "…understanding, evaluating, using and engaging with written text to participate in the society, to achieve one's goals and to develop one's knowledge and potential," "the ability to access, use, interpret, and communicate mathematical information and ideas, to engage in and manage mathematical demands of a range of situations in adult life," and "using digital technology, communication tools, and networks to acquire and evaluate information, communicate with others, and perform practical tasks," respectively (National Center for Education Statistics, n.d.-b). The plausible values are derived from the skill proficiency distributions estimated based on

the respondents’ performance on the skill assessments. More details have been published elsewhere (OECD, 2016b).

Covariates: *Age* was recorded in years. *Gender* was a dichotomous measure indicating female (vs. male = reference group). Each of *Black, Hispanic, Others, and White* (reference group) was a dichotomous measure. *Education* was dichotomized into (1) college (e.g., community college) or higher and (0) less than college. The total years of formal education was not selected due to a large proportion of missing values. *The number of household members* was top-coded to 6 (6 or greater was coded 6 due to the infrequent observations) in PIAAC. *U.S. born* was a dichotomous measure (vs. immigrants). *Living with spouse* was a dichotomous measure (vs. not living with a spouse). On a related note, more conventional measures of marital status were unavailable in PIAAC. *Income level* (0-5) is the six levels of income from no income (0) to income quintile (1-5). *The number of children* was a count measure. *Self-rated health* was a dichotomous measure of good (excellent, very good and good) and fair/poor. *Social trust* is based on the survey item “There are only a few people you can trust completely.” *Social trust* was dichotomized into positive (strongly disagree and disagree) and neutral/negative (neither agree or disagree, agree, and strongly agree). *Political efficacy* is based on the response to the survey item “People like me don’t have any say about what the government does.” *Political efficacy* was dichotomized into positive (strongly disagree and disagree) and neutral/negative (neither agree or disagree, agree, and strongly agree).

Analytic approach

The final sampling weights (SPFWT0) and 80 replicate weights (SPFWT1 – SPFWT80) were applied to all analyses in Mplus version 8 (Muthén & Muthén, 1998-2017). Weighted descriptive statistics were computed for all, and by volunteering and STEM backgrounds. Given

the primary outcome is a dichotomous measure, structural equation models with the mean and variance adjusted weighted least square (WLSMV) estimator and the probit link function were used to address the research questions (Kline, 2016; Wang & Wang, 2020). The analysis was conducted sequentially. First, volunteering was regressed on STEM backgrounds and each of three information-processing skills, separately and then together. Subsequently, a mediation model (Figure 1) was constructed. Volunteering was regressed on all variables, and the information-processing skills were regressed on the selected variables based on the previous studies (OECD, 2013a) and preliminary analyses. The mediation (a.k.a., indirect) effect was estimated by computing the product of the estimated coefficient for the STEM backgrounds on information processing skills, and for the information processing skills on volunteering (Muthén et al., 2016). This study used the replicate weights and plausible values to generate an empirical distribution of the mediation effect to estimate the standard errors, although a bootstrapping technique is generally more common in a mediation analysis (Wang & Wang, 2020).

The model fit was evaluated using the recommended indices, including the chi-square statistic ($p > 0.05$); comparative fit index (CFI > 0.90 ~ 0.95); root mean squared error of approximation (RMSEA < 0.08); and weighted root mean square residual (WRMR < 1.0) (DiStefano et al., 2018; Kline, 2016). The final model was considered empirically identified, based on the difference between the off-diagonal elements of the variance-covariance matrix [(n*n+1)/2 = 153] and the number of estimated coefficients (k = 30) (Wang & Wang, 2020). The power analysis was conducted using the Monte Carlo simulation function in Mplus (Muthén & Muthén, 2002). Based on the estimated coefficients from the final models, the simulation was conducted with 1,000 replications. For all key variables of interest [1 – beta (type II error rate) 0.90 and higher], except for the STEM background and volunteer relationship, showed the

generally accepted levels of statistical power (> 0.80). On a related note, considering the secondary data analysis and relatively complex model specifications in our study, the power of each estimated coefficient instead of the overall minimum required sample size was reported.

A few sensitivity analyses with different model specifications (e.g., with and without additional and alternative measures [e.g., parents'/guardians' education, years of education]) showed consistent main findings. Also, in a preliminary analysis, all three information processing skills were included in the full model. However, the estimation was not feasible without making major changes in the model specification. Presumably, high correlations across three information-processing skills (i.e., multicollinearity) was the issue, although the confirmation of exact methodological issues was beyond the scope of this study. As such, each of the information processing skills was analyzed separately.

Result Analysis

The weighted descriptive summary are presented in Table 1 (by volunteer participation) and Table 2 (by STEM backgrounds). Approximately 54% of the respondents reported volunteer activity at least once in the last 12 months. Most of the measures, except for age and number of children, showed statistically significant differences between volunteers and non-volunteers. Overall, volunteers tended to have STEM backgrounds, greater information-processing skills, higher socioeconomic status, and higher social trust as well as political efficacy. Approximately 21% of the respondents were classified as those with STEM backgrounds. Those with STEM backgrounds had significantly higher volunteer engagement, information-processing skills, socioeconomic status, and social trust as well as political efficacy, than those with non-STEM backgrounds.

Regarding the first research question, the hypothesis was supported as the adults with STEM backgrounds (see Table 2; literacy, numeracy and digital problem-solving skill proficiency scores = 292, 284 and 287 points), had significantly higher information processing skills than those without (266, 251, and 268 points, $p < 0.05$). The structural equation model results, including the 95% confidence intervals of estimated coefficients, are reported in Tables 3 (literacy), 4 (numeracy) and 5 (digital problem-solving skills). Regarding the second research question, the statistically significant positive relationships between STEM backgrounds and information-processing skills [e.g., 95% confidence-interval (STEM backgrounds coefficient) = 1, 8]; as well as between information-processing skills and volunteering [e.g., 95% confidence-interval (literacy coefficient) = 0.003, 0.005] were identified. However, the relationship between STEM backgrounds and volunteering was not explicitly identified, after accounting for the covariates. Indeed, the estimated coefficients suggest that STEM backgrounds are negatively associated with volunteering [e.g., 95% confidence-interval (STEM backgrounds coefficients) = -0.213, -0.020 (Table 3); -0.219, -0.026 (Table 4) and -0.216, -0.025 (Table 5)], which is an unexpected finding. Therefore, only a part of the hypothesis for the second research question was supported.

Regarding the third research question, the results showed that all information processing skills [e.g., 95% confidence-interval (Indirect effect) = 0.005, 0.035 (Literacy in Table 3); 0.009, 0.041 (Numeracy in Table 4) and 0.007, 0.039 (digital problem-solving skills in Table 5)] mediated the associations between STEM backgrounds and volunteering. Although the estimated coefficients of STEM backgrounds on volunteering, after adjusting for the covariates and indirect effect, were unexpected, the results suggested that the information-processing skills

partially explained the pathways between STEM backgrounds and volunteering in view of the conceptual model of this study.

In respect to the covariates and relevance to the STEM backgrounds, two key findings should be highlighted. First, even after accounting for the known determinants of volunteering, women were more likely to volunteer than men (see Tables 3, 4 and 5). In addition, when accounting for the numeracy skills and other determinants, Black adults were more likely to volunteer than their White counterparts (see Table 4).

Discussion

The present study examined civic engagement (volunteering), STEM education and occupation, and information-processing skills in typical working-age U.S. adults, in view of the three capitals conceptual model by Schuller et al. (2004). Results showed adults with STEM backgrounds had approximately 9, 12 and 7 percentage points higher literacy, numeracy, and digital problem-solving skill proficiencies, respectively, than the non-STEM counterparts. STEM education programs are known to underscore math and science education due to their relevance to the fields and are likely to promote students' and workers' information-processing skills (National Council of Teachers of Mathematics, 2000; OECD, 2021a). Also, it is possible that adults with STEM backgrounds currently had higher educational attainment, which is linked with information processing skills (National Science Foundation, 2022). In other words, a selection effect or possible systematic difference in the baseline information-processing skills and choice of one's major in formal education, cannot be ruled out. Moreover, adults with STEM occupations tend to have more opportunities to practice information-processing skills at work than their counterparts (Bol & Heisig, 2021; Gal et al., 2020; Reder et al., 2020). After accounting for educational attainment and other relevant factors, the difference in the

information-processing skill proficiency between adults with STEM backgrounds and those without was statistically significant based on the nationally representative PIAAC samples in the present study. However, future research needs to clarify specific explanations on the information-processing skill advantages among adults with STEM backgrounds.

In view of the operationalized conceptual model (Figure 1), the interrelationships between volunteering, STEM backgrounds, and information-processing skills were somewhat unexpected as the negative effect of STEM background on volunteering was observed in the final model. STEM backgrounds were positively associated with all three types of information-processing skills, which were positively associated with volunteering, after accounting for the covariates. These findings are consistent with the previous studies (Desjardins, 2008; Schuller, 2017; Vera-Toscano et al., 2017). As Grotlüschen (2018) explained, lower skills are linked to lower socioeconomic status, and in turn, fewer volunteer opportunities. However, limited theoretical explanations are available for the role of higher information-processing skills for higher formal volunteer participation. Per the three-capital framework by Schuller et al. (2004), the greater educational attainment and information-processing skills as a learning outcome might have enhanced three capitals as well as time and financial resources (e.g., higher paying jobs), and led to volunteer participation. Whereas the STEM backgrounds-volunteering relationship was present in bivariate comparisons, the relationship was no longer clear after adjusting for the relevant covariates. A part of the explanations may be found in the mediation relationship, which is discussed next.

Information-processing skills partially mediated the relationship between STEM backgrounds and volunteering. Given the focus of the present study was adult populations aged between 25 and 65 years old, it is possible that the effect of STEM education on volunteering

diminished over time after the completion of formal education, typically in the late twenties. As the law of diminishing return (Bennett & Vedder, 2015) suggests, the effect of education on an outcome, such as income and skills, may diminish over time. Thus, information-processing skills, which might have been updated after completion of formal education, may explain the pathways between STEM backgrounds and volunteering. Considering the interrelationships discussed above, the partial mediation effect of information-processing skills, which can be seen as more updated human capital indicators (e.g., skill credentials) than the educational attainment among adult populations, is reasonable (Belzer & Kim, 2018). Since the effect of STEM education on volunteer participation changed to negative after introducing the relevant covariates and indirect effects (i.e., mediation path), the pathways between STEM backgrounds and volunteering might have been accounted for by the information-processing skills and other covariates. Our follow-up analysis with each covariate at a time showed that only educational attainment turned the coefficient of STEM background on volunteering to negative. Moreover, given the negative coefficients, adults with STEM backgrounds might have had lower volunteer participation than those with non-STEM backgrounds, holding all other characteristics constant. That is, STEM workers who are the minority (10-16%) of the U.S. labor force, are likely in higher demand in the labor market due to their importance to the U.S. economy and technological advancement, than non-STEM workers (U.S. Bureau of Labor Statistics, 2020; Xie et al., 2015), and thus STEM workers might have hypothetically limited time available for volunteering. Yet, more data and research, as well as sub-population analysis (e.g., within STEM occupations) is needed to confirm the role of STEM backgrounds in the context of volunteering.

Conclusions, Implications and Limitations

Main Findings

The findings from the present study mostly supported the theoretical proporitons of STEM background, information-processing skills and civic engagement (see Figure 1), except for the direction of the relationships between STEM background and civic engagement. While STEM education should continue receiving attention, education and labor policy and practice must consider outcome-specific approaches --- economic outcomes and non-economic outcomes such as civic engagement (Vera-Toscano et al., 2017). For example, given the empirical evidence from this study, promotion of the formal volunteering as a form of civic engagement may benefit more from the information-processing skills training than STEM education per se in the adult populations. Also, the lack of longitudinal data and unexpected negative effect of STEM background on civic engagement are to be addressed in future research. Nonetheless, the nationally representative findings from this present study have implications, although several methodological challenges and remaining questions are yet to be addressed.

Thepretical and Practical Implications

There are two preliminary implications from the present study. First, the documented information-processing skill advantages among adults with STEM backgrounds, compared to those with non-STEM backgrounds are convincing empirical data points to enhance basic skill training in the non-STEM education programs as well as occupations. The nationally representative findings regarding the quantified differences in skills between adults with STEM backgrounds and those with non-STEM backgrounds inform the literature on the systematic inequality to participation in and opportunities of civic engagement (Grotlüschen, 2018; Grotlüschen et al., 2019). The findings from this study provided additional nationally representative empirical evidence to the education and volunteering literature. Indeed, the

promotion of information-processing skills can be expected to positively impact not only on civic engagement but also on economic outcomes, well-being, as well as additional lifelong learning participation (Belzer & Kim, 2018; Boeren, 2016; Cummins et al., 2015).

Second, based on the mediation analysis results, the reasonable point of interventions for civic engagement promotion seems to be the information-processing skills rather than education and training, while STEM education, which are clearly crucial for the advancement of the science and economy in the U.S., should also be promoted (National Academy of Sciences et al., 2007; Xie et al., 2015). The findings from this study provided insights that are specific to STEM education and occupations in relation to civic engagement. In particular, given the scant literature that examined multiple types of information-processing skills and civic engagement (Rose et al., 2019), the specific roles of literacy, numeracy, and digital problem-solving skills in the U.S. context of STEM backgrounds and volunteering have not been explicitly examined before. As stated earlier, because the sub-population distributions across STEM industries are disproportionate (Pew Research Center, 2021), simply increasing STEM education and training in general may not be an equitable policy strategy if the purpose is to enhance civic engagement. In this respect, the individual characteristics that were treated as the covariates in the present study, warrant more detailed analysis in future research. Thus, given the positive impacts of STEM backgrounds on information-processing skills, education policies may adopt the specific curriculum of STEM education and training in non-STEM programs to improve information-processing skills, which provides a wide range of social, economic, educational, health, and labor-related benefits.

Limitations and Future Directions

Several study limitations should be noted. First, possible omitted variable bias due to the unavailability of relevant information cannot be ruled out. Specifically, information on marital status, religion, baseline cognitive skills in the earlier life stages, and environmental factors (e.g., rural and urban; local volunteer organization) was not available in the data. Also, only one type of volunteering – formal volunteering – was examined in the present study. Informal volunteering (e.g., caregiving responsibility) should be incorporated into future data collection. While the current study adopted an inclusive measure of volunteering, future research may explore a reasonable cut-point or meaningful frequency of volunteering from multiple perspectives (e.g., economic standpoint, individual well-being). Relatedly, other classifications of volunteering such as expressive volunteering, which serves an organization's purpose such as leisure promotion, and instrumental volunteering, which serves others and the community, such as advocacy for underserved sub-populations, should be considered in future study (Valentova & Alieva, 2018; Voicu & Şerban, 2012). In addition, the interpretation of the results relied on the existing literature and operationalized conceptual framework. Further empirical evidence with longitudinal data is necessary to verify the findings as well as to refine the interpretation of the results. Also, the conceptual model should be further refined and adjusted based on future research findings and research questions. Finally, the present study focused on typical working-age adults who were able to complete the information-processing skills assessment at the time of the 2012/2014/2017 U.S. PIAAC data collection. The findings should not be extended to populations with a different age range, sub-populations with limited reading skills and computer experience, or at different timeframes due to potential age, period, and cohort effects.

References

AmeriCorps. (2021). *Key Findings from the 2019 Current Population Survey: Civic Engagement and Volunteering Supplement*. https://americorps.gov/sites/default/files/document/2019%20CPS%20CEV%20findings%20report%20CLEAN_10Dec2021_508.pdf

Arbuckle, J. L. (1996). Full information estimation in the presence of incomplete data. In G. A. Marcoulides & R. E. Schumacker (Eds.), *Advanced structural equation modeling* (Vol. 243-277, pp. 277). Lawrence Erlbaum.

Atwell, M. N., Bridgeland, J., & Levine, P. (2017). *Civic Deserts: America's Civic Health Challenge*. https://www.ncoc.org/wp-content/uploads/2017/10/2017CHIUpdate-FINAL-small.pdf

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

Belzer, A., & Kim, J. (2018). We Are What We Do: Adult Basic Education Should Be About More Than Employability. *Journal of Adolescent & Adult Literacy*, *61*(6), 603-608. https://doi.org/https://doi.org/10.1002/jaal.693

Bennett, D. L., & Vedder, R. K. (2015). PUBLIC POLICY, HIGHER EDUCATION, AND INCOME INEQUALITY IN THE UNITED STATES: HAVE WE REACHED DIMINISHING RETURNS? *Social Philosophy and Policy*, *31*(2), 252-280. https://doi.org/10.1017/S026505251400034X

Boeren, E. (2016). *Lifelong learning participation in a changing policy context: An interdisciplinary theory*. Springer.

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

Campbell, A., Gurin, G., & Miller, W. E. (1954). *The voter decides*. Row, Peterson, and Co.

Cummins, P., & Kunkel, S. (2015). A Global Examination of Policies and Practices for Lifelong Learning. *New Horizons in Adult Education and Human Resource Development*, *27*(3), 3-17. https://doi.org/https://doi.org/10.1002/nha3.20107

Cummins, P., Taylor, P., & Kunkel, S. (2015). Working longer, learning longer. *Public Policy & Aging Report*, *25*(4), 120-124. https://doi.org/10.1093/ppar/prv025

Desjardins, R. (2008). Researching the Links between Education and Well-Being. *European Journal of Education*, *43*(1), 23-35. https://doi.org/https://doi.org/10.1111/j.1465-3435.2007.00333.x

DiStefano, C., Liu, J., Jiang, N., & Shi, D. (2018). Examination of the Weighted Root Mean Square Residual: Evidence for Trustworthiness? *Structural Equation Modeling: A Multidisciplinary Journal*, *25*(3), 453-466. https://doi.org/10.1080/10705511.2017.1390394

Enders, C. K. (2022). *Applied missing data analysis* (2 ed.). The Guilford Press.

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

Grotlüschen, A. (2017). The narrative of ‘equality of chances’ as an approach to interpreting PIAAC results on perceived political efficacy, social trust and volunteering and the quest

for political literacy. *European Journal for Research on the Education and Learning of Adults*, *9*(1), 109-125. https://doi.org/https://doi.org/10.3384/rela.2000-7426.rela0211

Grotlüschen, A. (2018). The narrative of 'equality of chances' as an approach to interpreting PIAAC results on perceived political efficacy, social trust and volunteering and the quest for political literacy. *European Journal for Research on the Education and Learning of Adults*,, *9*(1), 109-125. https://doi.org/https://doi.org/10.25656/01:15535

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 Eduacation Working Papers, Issue. O. Publishing. https://www.oecd-ilibrary.org/content/paper/5jm0v44bnmnx-en

International Labour Organization. (2016). *ISCO: International Standard Classification of Occuopations*. https://www.ilo.org/public/english/bureau/stat/isco/isco08/

Jiang, D., Warner, L. M., Chong, A. M.-L., Li, T., Wolff, J. K., & Chou, K.-L. (2021). Benefits of volunteering on psychological well-being in older adulthood: evidence from a randomized controlled trial. *Aging & Mental Health*, *25*(4), 641-649. https://doi.org/10.1080/13607863.2020.1711862

Kline, R. B. (2016). *Principles and practice of structural equation modeling* (4 ed.). The Guilford Press.

McDougle, L., Handy, F., Konrath, S., & Walk, M. (2014). Health outcomes and volunteering: The moderating role of religiosity. *Social Indicators Research*, *117*(2), 337-351.

Muthén, B. O., Muthén, L. K., & Asparouhov, T. (2016). *Regression and mediation analysis using Mplus*. Muthén & Muthén.

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

Muthén, L. K., & Muthén, B. O. (2002). How to Use a Monte Carlo Study to Decide on Sample Size and Determine Power. *Structural Equation Modeling: A Multidisciplinary Journal*, *9*(4), 599-620. https://doi.org/10.1207/S15328007SEM0904_8

National Academies of Sciences, E., and Medicine,. (2016). Developing a National STEM Workforce Strategy: A Workshop Summary. https://doi.org/https://doi.org/10.17226/21900

National Academy of Sciences, National Academy of Engineering, & Institute of Medicine. (2007). *Rising Above the Gathering Storm: Energizing and Employing America for a Brighter Economic Future*. The National Academies Press. https://doi.org/doi:10.17226/11463

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

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

National Center for Education Statistics. (n.d.-b). *What PIAAC measures*. https://nces.ed.gov/surveys/piaac/measure.asp

National Council of Teachers of Mathematics. (2000). *Principals and standard for school mathematics*. https://www.nctm.org/standards/

National Science Foundation. (2021). *The STEM Labor Force of Today: Scientists, Engineers, and Skilled Technical Workers*. https://ncses.nsf.gov/pubs/nsb20212

National Science Foundation. (2022). *U.S. and Global STEM Education and Labor Force*. https://ncses.nsf.gov/pubs/nsb20221/u-s-and-global-stem-education-and-labor-force

Niebuur, J., van Lente, L., Liefbroer, A. C., Steverink, N., & Smidt, N. (2018). Determinants of participation in voluntary work: a systematic review and meta-analysis of longitudinal cohort studies. *BMC Public Health*, *18*(1), 1213. https://doi.org/10.1186/s12889-018-6077-2

OECD. (2013a). *OECD skills outlook 2013: First Results from the Survey of Adult Skills*. https://www.oecd-ilibrary.org/education/oecd-skills-outlook-2013/the-supply-of-key-information-processing-skills_9789264204256-6-en

OECD. (2013b). *Relationship of the survey of adult skills (PIAAC) to other international skills surveys*. OCED Publishing https://www.oecd-ilibrary.org//sites/f9a05f72-en/index.html?itemId=/content/component/f9a05f72-en#

OECD. (2016a). *Skills for a digital world*. https://www.oecd.org/employment/emp/Skills-for-a-Digital-World.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. (2019). *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. (2021a). *The assessment framework for cycle 2 of the Programme for the International Assessment of Adult Competencies*. OECD Publishing https://www.oecd.org/skills/piaac/publications/PIAAC-Frameworks-Cycle2-en.pdf

OECD. (2021b). *OECD Skills Outlook 2021*. https://doi.org/doi:https://doi.org/10.1787/0ae365b4-en

Pew Research Center. (2021). *Stem jobs see uneven progress in increasing gender, racial and ethnic diversity*. https://www.pewresearch.org/science/wp-content/uploads/sites/16/2021/03/PS_2021.04.01_diversity-in-STEM_REPORT.pdf

Putnam, R. D. (2015). Bowling alone: America’s declining social capital. In *The city reader* (pp. 188-196). Routledge.

Reder, S. (2014). *The impact of ABS program participation on long-term economic outcomes*. U.S. Department of Education, Office of Career, Technical, and Adult Education.

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.

Rose, A. D., Smith, T. J., Ross-Gordon, J. M., Zarestky, J., Lopes, T., Cecil, S. M., Grotlüschen, A., & Fleige, M. (2019). *Adults’ Civic Engagement in the U.S. and Germany: Evidence from the PIAAC Survey* (PIAAC Gateway, Issue. http://piaacgateway.com/s/2019_Rose_Adults_Civic_Engagement_US_Germany.pdf

Rothwell, J. (2013). *The hidden STEM economy*. https://www.brookings.edu/research/the-hidden-stem-economy/

Rüber, I. E., Rees, S.-L., & Schmidt-Hertha, B. (2018). Lifelong learning – lifelong returns? A new theoretical framework for the analysis of civic returns on adult learning.

International Review of Education, *64*(5), 543-562. https://doi.org/10.1007/s11159-018-9738-6

Saal, L. K., Yamashita, T., Shaw, D. M., & Perry, K. H. (2020). An exploration of U.S. adults' information processing skills and political efficacy. *Journal of Adult and Continuing Education*, *26*(2), 178-202. https://doi.org/10.1177/1477971419852750

Schuller, T. (2017). *What are the wider benefits of learning across the life course?* https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/635837/Skills_and_lifelong_learning_-_the_benefits_of_adult_learning_-_schuller_-_final.pdf

Schuller, T., & Desjardins, R. (2010). Wider Benefits of Adult Education. In P. Peterson, E. Baker, & B. McGaw (Eds.), *International Encyclopedia of Education (Third Edition)* (pp. 229-233). Elsevier. https://doi.org/https://doi.org/10.1016/B978-0-08-044894-7.00045-2

Schuller, T., Preston, J., Hammond, C., Brassett-Grundy, A., & Bynner, J. (2004). *The benefits of learning: The impact of education on health, family life and social capital*. Routledge.

Shapiro, H., Østergård, S., & Hougard, K. (2015). *Does the EU need more STEM graduates?* Publications Office of the European Union. https://op.europa.eu/s/pbOC

Southby, K., South, J., & Bagnall, A.-M. (2019). A Rapid Review of Barriers to Volunteering for Potentially Disadvantaged Groups and Implications for Health Inequalities. *VOLUNTAS: International Journal of Voluntary and Nonprofit Organizations*, *30*(5), 907-920. https://doi.org/10.1007/s11266-019-00119-2

Spera, C., Gherthner, R., Nerino, A., & DiTommaso, A. (2013). *Volunteering as a Pathway to Employment: Does Volunteering Increase Odds of Finding a Job for the Out of Work?*

https://www.americorps.gov/sites/default/files/evidenceexchange/FR_2013_VolunteeringasaPathwaytoEmployment_1.pdf

Tse, D. C. K. (2018). Volunteers' Felt Respect and Its Associations With Volunteering Retention, Daily Affect, Well-being, and Mortality. *The Journals of Gerontology: Series B*, *75*(8), 1625-1636. https://doi.org/10.1093/geronb/gby117

U.S. Bureau of Labor Statistics. (2020). *Employment projections: Employment by major industry sector*. U.S. Bureau of Labor Statistics,. Retrieved June 2 from https://www.bls.gov/emp/tables/employment-by-major-industry-sector.htm

U.S. Bureau of Labor Statistics. (2021). *Employment in STEM occupations*. Retrieved May 18 from https://www.bls.gov/emp/tables/stem-employment.htm

Valentova, M., & Alieva, A. (2018). Do non-EU immigrants exhibit different patterns of participation in voluntary associations from those of natives and EU immigrants? *Ethnic and Racial Studies*, *41*(5), 804-823. https://doi.org/10.1080/01419870.2017.1297844

VCU College of Engineering. (n.d.). *Tech-talent pathways final report*. https://egr.vcu.edu/media/engineering/documents/egr/Tech-TalentPathwaysFinalReport.pdf

Vera-Toscano, E., Rodrigues, M., & Costa, P. (2017). Beyond educational attainment: The importance of skills and lifelong learning for social outcomes. Evidence for Europe from PIAAC. *European Journal of Education*, *52*(2), 217-231. https://doi.org/https://doi.org/10.1111/ejed.12211

Voicu, B., & Şerban, M. (2012). Immigrant Involvement in Voluntary Associations in Europe. *Journal of Ethnic and Migration Studies*, *38*(10), 1569-1587. https://doi.org/10.1080/1369183X.2012.711046

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

Wilson, J. (2000). Volunteering. *Annual Review of Sociology*, *26*(1), 215-240. https://doi.org/10.1146/annurev.soc.26.1.215

Wilson, J. (2012). Volunteerism Research: A Review Essay. *Nonprofit and Voluntary Sector Quarterly*, *41*(2), 176-212. https://doi.org/10.1177/0899764011434558

Wilson, J., Mantovan, N., & Sauer, R. M. (2020). The economic benefits of volunteering and social class. *Social Science Research*, *85*, 102368. https://doi.org/https://doi.org/10.1016/j.ssresearch.2019.102368

Wilson, J., & Musick, M. (1997). Who Cares? Toward an Integrated Theory of Volunteer Work. *American Sociological Review*, *62*(5), 694-713. https://doi.org/10.2307/2657355

Xie, Y., Fang, M., & Shauman, K. (2015). STEM Education. *Annual Review of Sociology*, *41*(1), 331-357. https://doi.org/10.1146/annurev-soc-071312-145659

Xie, Y., & Killewald, A. A. (2012). *Is American science in decline?* Harvard University Press.

Yamashita, T., & Cummins, P. A. (2021). Jobs at Risk of Automation in the USA: Implications for Community Colleges. *Community College Journal of Research and Practice*, 1-4. https://doi.org/10.1080/10668926.2021.1876782

Yamashita, T., Cummins, P. A., Millar, R. J., Sahoo, S., & Smith, T. J. (2019). Associations between motivation to learn, basic skills, and adult education and training participation among older adults in the USA. *International Journal of Lifelong Education*, *38*(5), 538-552. https://doi.org/10.1080/02601370.2019.1666927

Yao, K. (2019). Heterogeneous skill distribution and college major: evidence from PIAAC. *Journal of Applied Economics*, *22*(1), 504-526. https://doi.org/10.1080/15140326.2019.1665310

Yeung, J. W. K., Zhang, Z., & Kim, T. Y. (2017). Volunteering and health benefits in general adults: cumulative effects and forms. *BMC Public Health*, *18*(1), 8. https://doi.org/10.1186/s12889-017-4561-8

Table 1: Weighted Descriptive Summary by Volunteer Participation

	All (n = 8,330) [a] Mean or percentages (SE)	Volunteers (n = 4,530) [a] Mean or percentages (SE)	Non-volunteers (n = 3,800) [a] Mean or percentages (SE)
Volunteer participation in the last 12 months (Yes)	54.50% (0.01)	-	-
STEM backgrounds	21.54% (0.54)	23.80% (0.75)*	18.80% (0.76)
Literacy (0- 500) [b]	271.10 (0.77)	283.12 (1.01)*	256.80 (1.07)
Numeracy (0- 500) [b]	257.75 (1.02)	271.04 (1.09)*	241.89 (1.38)
Digital problem-solving skills (0- 500) [b]	272.45 (0.93)	279.76 (0.99)*	262.10 (1.39)
Age	44.69 (0.15)	44.85 (0.14)	44.54 (0.19)
Gender (Women)	51.69% (0.65)	53.04% (0.88)*	50.08% (0.97)
Race		*	
White	66.00% (0.63)	70.40% (0.81)	60.78% (0.96)
Black	12.41% (0.41)	11.57% (0.54)	13.41% (0.62)
Hispanic	13.72% (0.49)	10.86% (0.60)	17.15% (0.80)
Others	7.87% (0.35)	7.21% (0.45)	8.66% (0.56)
Education (college degree of higher)	43.17% (0.64)	53.60% (0.88)*	30.71% (0.88)
Number of household members	3.10 (0.03)	3.06 (0.03)*	2.38 (0.07)
U.S. born (Yes)	84.33% (0.50)	87.17% (0.63)*	80.93% (0.81)
Parents'/guardians' education (College degree or higher)	32.90% (0.80)	44.70% (1.00)*	22.10% (0.20)
Living with spouse (Yes)	67.35% (0.58)	70.40% (0.75)*	63.72% (0.89)
Income level (0-5)		*	
0	30.30% (0.29)	25.71% (0.75)	35.79% (0.91)
1	9.05% (0.37)	8.90% (0.49)	9.23% (0.56)
2	12.85% (0.44)	11.22% (0.55)	14.80% (0.69)
3	15.20% (0.47)	15.53% (0.63)	14.80% (0.71)
4	15.95% (0.47)	17.33% (0.66)	14.30% (0.67)
5	16.65% (0.50)	21.31% (0.74)	11.09% (0.64)
Number of children	1.81 (0.02)	1.81 (0.02)	1.81 (0.03)
Self-rated health (Excellent, very good and good)	82.49% (0.50)	87.01 (0.59)*	77.01% (0.83)
Social trust (positive)	22.70% (0.54)	28.14 (0.79)*	16.19% (0.70)
Political efficacy (positive)	11.42% (0.65)	49.91% (0.88)*	37.87% (0.94)

*$p < 0.05$ (vs. Non-volunteers)

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

Data Source: 2012/2014/2017 PIAAC Restricted Use File Data (National Center for Education Statistics, 2017)

Table 2: Weighted Descriptive Summary by STEM backgrounds

	All (n = 8,330) Mean or percentages (SE)	STEM backgrounds (n =1,790) Mean or percentages (SE)	Non-STEM backgrounds (n = 6,540) Mean or percentages (SE)
Volunteer participation in the last 12 months (Yes)	54.50% (0.65)	60.23% (1.38)*	52.90% (0.73)
STEM backgrounds	21.54% (0.54)	-	-
Literacy (0- 500)	271.10 (0.77)	291.81 (1.37)*	265.50 (0.90)
Numeracy (0- 500)	257.75 (1.02)	284.02 (1.44)*	250.63 (1.19)
Digital problem-solving skills (0- 500) [c]	272.45 (0.93)	287.37 (1.48)*	267.80 (1.00)
Age	44.69 (0.15)	43.84 (0.32)*	44.93 (0.17)
Gender (Women)	51.69% (0.65)	41.78% (1.37)*	54.41% (0.73)
Race		*	
White	66.00% (0.63)	70.93% (1.32)	64.64% (0.71)
Black	12.41% (0.41)	8.25% (0.74)	13.55% (0.48)
Hispanic	13.72% (0.49)	8.74% (0.90)	15.09% (0.58)
Others	7.87% (0.35)	12.07% (0.95)	6.72% (0.36)
Education (college degree of higher)	43.17% (0.64)	75.17% (1.27)*	34.39% (0.68)
Number of household members	3.09 (0.034)	3.00 (0.04)	3.09 (0.02)
U.S. born (Yes)	84.33% (0.50)	81.66% (1.12)*	85.06% (0.56)
Parents'/guardians' education (College degree or higher)	32.90% (0.80)	51.10% (1.20)*	36.10% (0.80)
Living with spouse (Yes)	67.35% (0.58)	72.44% (1.17)*	65.96% (0.66)
Income level (0-5)		*	
0	30.30% (0.29)	20.09% (1.12)	33.11% (0.68)
1	9.05% (0.37)	3.68% (0.52)	10.52% (0.45)
2	12.85% (0.44)	6.34% (0.64)	14.64% (0.52)
3	15.20% (0.47)	12.67% (0.90)	15.89% (0.55)
4	15.95% (0.47)	22.26% (1.14)	14.22% (0.51)
5	16.65% (0.50)	34.96% (1.37)	11.63% (0.48)
Number of children	1.81 (0.02)	1.63 (0.04)*	1.86 (0.02)
Self-rated health (Excellent, very good and good)	82.49% (0.50)	90.47% (0.84)*	80.30% (0.58)
Social trust (positive)	22.70% (0.54)	24.72% (1.20)*	22.14% (0.60)
Political efficacy (positive)	11.42% (0.65)	47.75% (1.41)*	43.51% (0.73)

*p < 0.05 (vs. Non-STEM backgrounds)

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

[c] The final sample size was 6,840 due to the screening process of the digital problem-solving skills assessment in PIAAC.

Data Source: 2012/2014/2017 PIAAC Restricted Use File Data (National Center for Education Statistics, 2017)

Table 3: 95% Confidence Intervals of Estimated Coefficients for Volunteering and the Literacy Skills

	Model 1	Model 2	Model 3	Model 4
Outcome: Volunteering (Yes)				
Literacy skills (0- 500) [a]		0.06, 0.07*	0.005, 0.007*	0.003, 0.005*
STEM backgrounds	0.099, 0.269*		-0.063, 0.105	-0.213, -0.020*
Age				-0.001, 0.006
Gender (Women)				0.018, 0.157*
Race				
White				Reference
Black				-0.119, 0.110
Hispanic				-0.213, -0.010
Others				-0.236, -0.003*
Education (college degree of higher)				0.372, 0.523*
Number of household members				-0.036, 0.031
U.S. born (Yes)				0.103, 0.331*
Parents'/guardians' education (College degree or higher)				0.070, 0.197*
Living with spouse (Yes)				0.017, 0.196*
Income level (0-5)				0.033, 0.077*
Number of children				0.004, 0.068*
Self-rated health (Excellent, very good and good)				0.125, 0.302*
Social trust (positive)				0.163, 0.347*
Political efficacy (positive)				0.088, 0.220*
Outcome:				
Literacy skills (0-500)				
STEM backgrounds (Yes)			23.634, 29.512*	1.168, 8.129*
Indirect effect			0.140, 0.188*	0.005, 0.035*
(Literacy skills)				
Model fit indices				
Chi-square (Degrees of freedom)				140.815 (4)*
Comparative fit index (CFI)				0.933
Root mean standardized error of approximation (RMSEA)				0.064
Weighted root mean square residual (WRMR)				2.088

*$p < 0.05$

Notes: The sampling and replicate weights were applied.

[a] 10 plausible values

Data Source: 2012/2014/2017 PIAAC Restricted Use File Data (National Center for Education Statistics, 2017)

Table 4: 95% Confidence Intervals of Estimated Coefficients for Volunteering and the Numeracy Skills

	Model 1	Model 2	Model 3	Model 4
Outcome: Volunteering (Yes)				
Numeracy skills (0- 500) [a]		0.005, 0.006*	0.004, 0.007*	0.003, 0.005*
STEM backgrounds	0.099, 0.269*		-0.080, 0.086	-0.219, -0.026*
Age				-0.001, 0.006
Gender (Women)				0.018, 0.157*
Race				
White				Reference
Black				-0.119, 0.110
Hispanic				-0.213, 0.110
Others				-0.236, 0.003
Education (college degree of higher)				0.372, 0.523*
Number of household members				-0.036, 0.031
U.S. born (Yes)				0.103, 0.331*
Parents'/guardians' education (College degree or higher)				0.070, 0.197*
Living with spouse (Yes)				0.016, 0.196*
Income level (0-5)				0.033, 0.077*
Number of children				0.004, 0.068*
Self-rated health (Excellent, very good and good)				0.125, 0.302*
Social trust (positive)				0.163, 0.347*
Political efficacy (positive)				0.089, 0.219*
Outcome:				
Numeracy skills (0-500)				
STEM backgrounds (Yes)			29.719, 37.019*	2.531, 10.351*
Indirect effect			0.141, 0.222*	0.009, 0.041*
(Numeracy skills)				
Model fit indices				
Chi-square (Degrees of freedom)				101.229 (4)*
Comparative fit index (CFI)				0.957
Root mean standardized error of approximation (RMSEA)				0.054
Weighted root mean square residual (WRMR)				1.769

*$p < 0.05$

Notes: The sampling and replicate weights were applied.

[a] 10 plausible values

Data Source: 2012/2014/2017 PIAAC Restricted Use File Data (National Center for Education Statistics, 2017)

Table 5: 95% Confidence Intervals of Estimated Coefficients for Volunteering and the Digital Problem-Solving Skills

	Model 1	Model 2	Model 3	Model 4
Outcome: Volunteering (Yes)				
Digital problem-solving skills (0- 500) [a]		0.005, 0.006*	0.004, 0.006*	0.003, 0.005*
STEM backgrounds	0.099, 0.269*		-0.002, 0.159	-0.216, -0.025*
Age				-0.001, 0.006
Gender (Women)				0.018, 0.157*
Race				
White				Reference
Black				-0.119, 0.110
Hispanic				-0.214, 0.011
Others				-0.237, 0.004
Education (college degree of higher)				0.372, 0.523*
Number of household members				-0.036, 0.031
U.S. born (Yes)				0.013, 0.253*
Parents'/guardians' education (College degree or higher)				0.070, 0.197*
Living with spouse (Yes)				0.017, 0.196*
Income level (0-5)				0.025, 0.068*
Number of children				0.004, 0.068*
Self-rated health (Excellent, very good and good)				0.125, 0.302*
Social trust (positive)				0.163, 0.347*
Political efficacy (positive)				0.089, 0.220*
Outcome:				
Digital problem-solving skills (0-500)				
STEM backgrounds (Yes)			16.645, 22.704*	1.725, 9.685*
Indirect effect			0.082, 0.129*	0.007, 0.039*
(Digital-problem-solving skills)				
Model fit indices				
Chi-square (Degrees of freedom)				90.587 (4)*
Comparative fit index (CFI)				0.946
Root mean standardized error of approximation (RMSEA)				0.053
Weighted root mean square residual (WRMR)				1.752

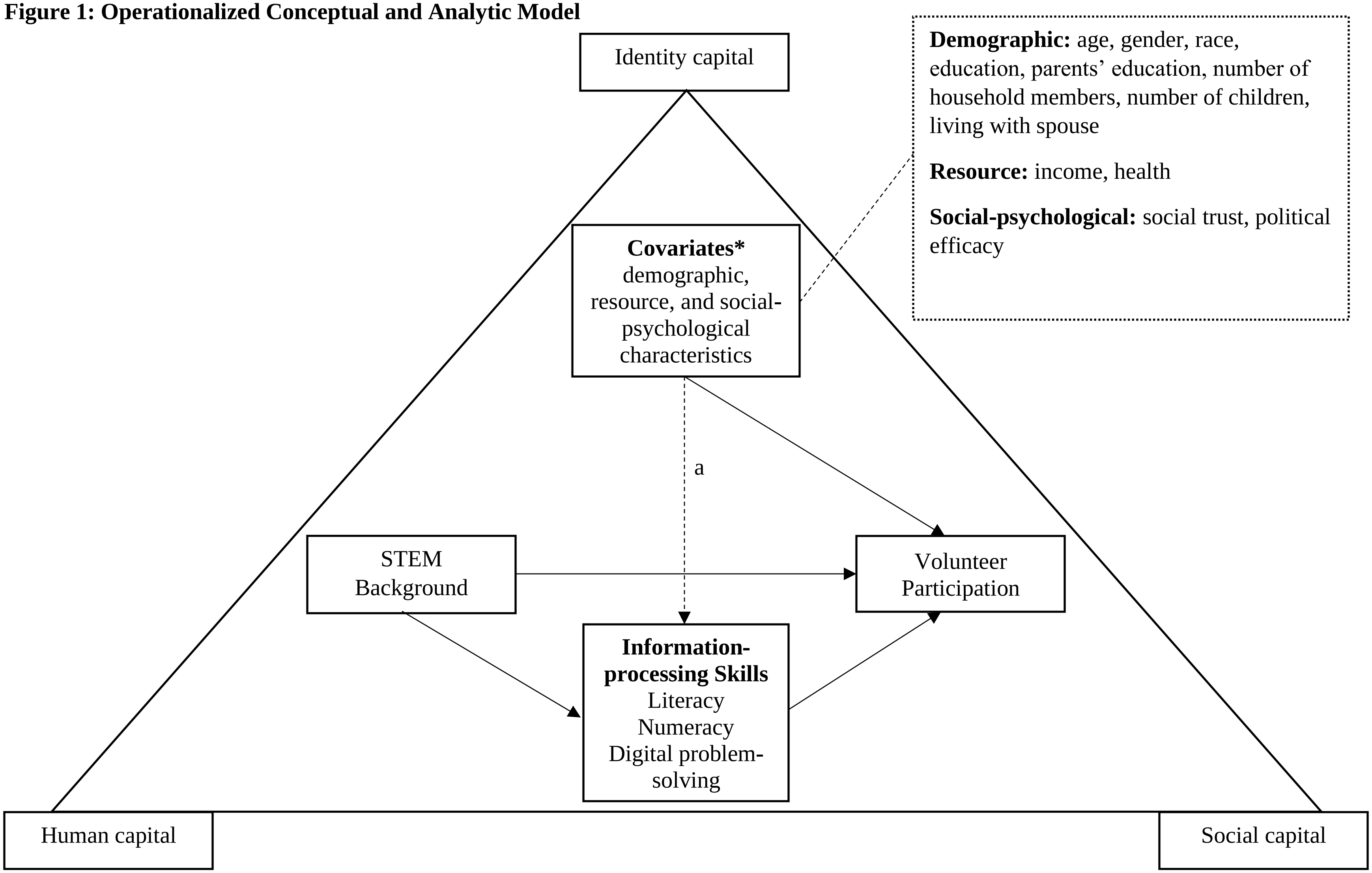
*$p < 0.05$

Notes: The sampling and replicate weights were applied. The final sample size was 6,840 due to the screening process of the digital problem-solving skills assessment in PIAAC.

[a] 10 plausible values

Data Source: 2012/2014/2017 PIAAC Restricted Use File Data (National Center for Education Statistics, 2017)

Figure 1: Operationalized Conceptual and Analytic Model



a. Selected covariates: age, gender, race, education, parents' education, income, health