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Baby Boomers in Technology-Rich Environments: Using PIAAC to Study the Association of Workplace Learning with Technology Competency

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Using PIAAC to Study the Association of Workplace Learning with Technology Competency

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by

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Abstract

A skill gap in Problem Solving in Technology-Rich Environments (PS-TRE) between U.S. Baby Boomers and younger generations has been documented in previous studies using the Programme for the International Assessment of Adult Competencies (PIAAC) Survey of Adult Skills (Rampey et al., 2016). Bringing this generation of workers up to speed in this competency area is important because older workers are a growing segment of the U.S. workforce with 13 million employees expected to be age 65 or older by 2024 (Toossi & Torpey, 2017). Workplace learning may be a solution, but few studies in adult learning document outcomes of training interventions specifically for this generation, and few if any studies explore the efficacy of informal learning to improve technology competency among Baby Boomers. By using PIAAC to study the association of nonformal and informal workplace learning with PS-TRE competency among U.S. Baby Boomers, this study directly responds to these gaps in the literature. Multiple linear regression was used to conduct this analysis. Results indicate that Baby Boomers may make significant gains in PS-TRE if they participate in an optimal amount of nonformal workplace learning (on-the-job training or seminar/workshop participation). Some caution may be warranted, however, in use of on-the-job training among workers age 60-70. Learning informally from coworkers or supervisors was not associated with significant gains in PS-TRE. An optimal amount of learning-by-doing may be beneficial in large organizations, but findings also indicate too much learning-by-doing may be detrimental. No significant differences were found between men and women, between supervisors and non-supervisors, or between workers in different economic sectors. Since this is a cross-sectional study, findings are not causal; however, future research seems most promising in exploring the impact of seminar or workshop participation on PS-TRE competency for Baby Boomers.

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Dedication

For Leah:

Find what you love to do and go after it tenaciously.

Stay curious and you will find that the world is full of wonder.

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Chapter 1: Introduction

Today in the United States and internationally, older workers comprise a growing segment of the overall workforce, and they are struggling within increasingly technological workplaces. Several trends converge to form the background of this problem. First, Baby Boomers (individuals born between 1946-1964) are redefining expectations about retirement in ways that benefit both themselves and society (Boveda & Metz, 2016; Collinson et al., 2019). The longer working lives of Baby Boomers result in growth in the labor force participation of older employees (Lee, 2014; Dong et al., 2017). At the same time, our workplaces are becoming increasingly reliant on information and communication technology (Colbert et al., 2016). Previous studies indicate that older employees have less comfort with technology (Czaja et al., 2006; Lee et al., 2019), different perceptions about the usefulness of technology (Hauk et al., 2018), and have lower competency scores in problem solving requiring the use of technology (Rampey et al., 2016) than their younger peers. Workplace training has been suggested as a solution to bring older employees up to speed (Elias et al., 2012; Hämäläinen et al., 2017), yet access to training for older workers can be limited by economic conditions (Olsen & Tikkanen, 2018; Warhurst & Black, 2015) and by negative stereotypes about older workers (Posthuma & Campion, 2009). Each of these trends is described in greater detail in the background section of this chapter.

Since Baby Boomers' access to training may be limited, it is important to utilize that time efficiently. Identifying which workplace learning approaches are associated with significant gains in technology competency for Baby Boomers could help those who oversee workplace learning opportunities for this generation. This study responds to that need by utilizing the Programme for the International Assessment of Adult Competencies (PIAAC) Survey of Adult

Skills. The PIAAC Survey asks participants about their engagement in different learning approaches while also assessing the technology competency of participants. The technology competency measure in the PIAAC Survey is called problem solving in technology-rich environments (PS-TRE). PS-TRE entails using computers to access and share information needed to solve problems that arise in modern workplaces (PIAAC, 2009). Additional justification for using PIAAC to conduct this study is included in the discussion of the study's purpose and significance. After that, key terms and concepts are explained, all research questions are specified, and I conclude the chapter with a discussion of the scope and limitations of this study.

Background of the Study

Toossi (2015) estimates that adults ages 55-64 will make up more than 17% of the total labor force by 2024—an increase of 8% in thirty years. In 2019, according to the U.S. Bureau of Labor Statistics, 19.6% of people in the 65 and over age group were still employed. Whether workers extend their working lives beyond age 65 could have significant economic repercussions.

In a 2014 report, Lee discusses increasing U.S. life expectancy and indicates that the consequences of population aging will depend on how long people choose to work in the future. Increasing life expectancy has changed the total percentage of life that people spend in retirement. Whereas in 1950 people spent about 15% of their total lives in retirement, by 2050 that number is projected to have reached 24%. Our current social service systems, Social Security and Medicare, cannot handle the additional burden of supporting people through unemployed lives that are nine percent longer. According to Dong et al. (2017), "concern over the ability to support an increasing proportion of retirees in the U.S. population has sparked

widespread interest among individuals, policy makers, and society in promoting delayed retirement and longer working lives" (p. 315). Baby Boomers are leading the process of changing retirement expectations and promoting longer working lives in America.

Retirement of U.S. Baby Boomers

Baby Boomers are working longer and transitioning into retirement differently than previous generations. Boveda and Metz (2016) credit Baby Boomers with changing the paradigm of traditional retirement by introducing retirement trajectories that are different from a point-in-time cessation of paid work. The authors describe four different retirement scenarios among Baby Boomers and use data from the University of Michigan Health and Retirement Study to determine percentages of Baby Boomers within those categories. The first scenario described is "nonretirement" (p. 155), which represents the decision of some Baby Boomers to simply continue working in their current jobs longer than has historically been expected. In their nationally representative sample of 3,737 Baby Boomers, 63.6% were not retired. Retirement, the second scenario, indicated that a person was no longer in the labor force—15.5% of participants were retired. A third group of participants—16.4%—sought "bridge employment" (p. 156), described as part-time work in or outside of one's field that allows people to continue saving and perhaps earning benefits. Finally, the authors distinguished between bridge employment and the "encore career" (p. 156), indicating that some Baby Boomers retire and then seek new, full-time employment in roles that are more personally fulfilling. Of the participants in their sample, 4.5% were potentially engaged in an encore career (as evidenced by full retirement followed by another full-time job).

Whether through delayed retirement, bridge employment, or encore careers, clearly Baby Boomers are working beyond the traditional retirement age. One might wonder, what kinds of

work are they doing? Toossi and Torpey (2017) used U.S. Bureau of Labor Statistics data from 2016 to examine the employment of workers ages 55 and older. Most of these workers—almost 15,000 people—were in management and related occupations. This aligns with findings from Moen et al. (2017) who conducted a qualitative study of 23 organizations in Minnesota. The authors found that 83% of the organizations interviewed were rehiring their retirees, often for help with special projects. Pryor (2017) used U.S. Bureau of Labor Statistics data from 2014 to look specifically at careers of workers over age 65. Pryor reported that workers over age 65 make up 9.4% of the total workforce in management, 9.8 % in sales and related occupations, 9.9% in office and administrative support, and 5.2% in education, training, and library occupations. Notably, all of these are fields in which it may be necessary for workers to have skills in information and communication technology.

The youngest Baby Boomers still have about a decade before they will make firm retirement decisions, so their retirement intentions are also a point of interest. Dong et al. (2017) used data from the University of Michigan Health and Retirement Study to examine the self-reported intent of older workers (not exclusively Baby Boomers) to work full-time past ages 62 and 65. The youngest group studied, those born between 1954-1959 (the middle of the Baby Boomer generation), showed the highest desire to maintain full-time employment. At age 62, 53.9% intended to still work full-time; at age 65, 40.7% intended to still work full-time. The authors found individual differences in these overall trends, though, with males being more likely to work longer, and with Black workers and low-educated workers being less likely to work at older ages. Although it is often discussed as a motivator of delayed retirement (Collinson et al., 2019; Toosey & Torpey, 2017), the authors interestingly did not find evidence that

changes to Social Security benefits significantly impacted the intent of workers to remain employed.

In a recent report from the Transamerica Center for Retirement Studies, Collinson et al. (2019) investigated the retirement intentions of a national sample of 1,477 U.S. Baby Boomers. Their findings indicate that 54% of Baby Boomers expect to retire after age 65, and an additional 15% do not plan to retire *at all*. When asked about how they would like to spend their time in retirement, 26% of Baby Boomers planned to continue paid work in some capacity, and 31% intended to engage in volunteer work. This intent to volunteer aligns with the current level of Baby Boomer volunteerism as reported on the Corporation for National and Community Service's website (https://www.nationalservice.gov/serve/via). The website indicates volunteer time donated by Baby Boomers was worth an estimated value of $54.3 billion per year in 2017.

This generation's commitment to volunteerism is important to consider along with paid employment when examining Baby Boomers' overall workforce contributions. In 2013, Moen and Flood used data from the American Time Use Survey to determine the extent of employment and/or volunteerism among men and women aged 50 to 75. Among men and women between ages 60-64, 4.8% of men and 8.9% of women were volunteering within organizations (formal volunteering, as opposed to helping out a friend or family member). Those numbers increase with age. Between ages 70-74, 10.28% of men were working as volunteers, as were 9.48% of women. For people aged 50-75, the authors reported a daily average of 1.5-2.5 hours of volunteer work. When considering the impact of individual characteristics on the odds of a person volunteering, the authors found that possession of a college degree doubled the odds of volunteering for both men and women. Good health increased the odds for women, while being married increased the odds for men.

Einolf and Yung (2018) recently completed a qualitative study wherein they chose to specifically interview volunteers who contributed ten or more hours of service per week at nonprofit organizations in the Chicago area. Their findings highlight the extensive contributions volunteer Baby Boomers can make in organizations under the right circumstances. The authors interviewed both volunteers and people who manage volunteers. Most of these high contributing volunteers, whom the authors called "super-volunteers" (p. 789), were White, all but two were over the age of 50 (with an average age of 69), and most had earned master's degrees. Most super volunteers had retired from highly skilled professions, and these skills are reflected in the kinds of work the participants were doing as volunteers. The authors report the comments of one manager who, "noted that his volunteer had a prior career in management consulting where his 'billable hours were like $950 an hour,' adding that 'he's given us nearly 20 a week now for four years. That's a lot of capacity'" (p. 800). As we saw with trends in paid employment (Pryor, 2017; Toossi &Torpey, 2017), this example demonstrates that Baby Boomers are doing managerial work as volunteers.

This trend is not unique to Einolf and Yung's (2018) small sample. In 2009, Hong and colleagues collected information from 51 programs in order to learn about the capacity of volunteer programs to engage older volunteers. Volunteers in 60% of the programs were doing work in the areas of education, health, and the environment. More specifically, the authors indicate the volunteers were likely to spend their time educating others within or about these areas. As we can see from these examples, even as volunteers it is important for Baby Boomers to have or develop skills in workplace information and communication technology.

Baby Boomers and Technology

Whether through paid employment or volunteering, Baby Boomers clearly contribute to the U.S. workforce. While the U.S. workforce is aging, U.S. workplaces are changing at unprecedented rates due to the implementation of new information and communication technologies. Colbert et al. (2016) indicate that technology is changing both the ways that people approach work and the ways work is accomplished. Change has already come in the form of email, the introduction of virtual meetings, and virtual collaboration. With the introduction of stay at home orders in most U.S. states beginning in March 2020 as a response to the spread of the novel coronavirus (SARS-CoV-2, commonly known as Covid-19), virtual meetings have become—at least temporarily—the new norm. Colbert et al. emphasize, however, that the potential impact of technology on virtual meetings is yet to be realized. Some organizations, for example, use virtual reality headsets during virtual meetings to eliminate distractions and truly bring people together in a shared, virtual space.

Schwarzmüller et al. (2018) recently surveyed "49 German-speaking digitalization experts" (p.121), largely from business and research backgrounds, regarding how digital transformation alters work design and leadership. As leaders, these respondents note both positive and negative impacts of technology. Positive impacts include increased communication with team members and better decision-making due to better visualization of data and easier access to important data points. However, the respondents point out that work itself has become more complex due to increased information density, and the potential for distraction is heightened due to increased use of social media and email in the workplace. At the same time, the pressure is heightened to produce deliverables at a rapid pace in order to remain competitive. These factors contribute to an increased workload and increased stress for workers. The authors

emphasize the need for lifelong learning and technology competency for workers and supervisors, alike.

How are the increasing number of older employees faring in increasingly technological workplaces? Elias et al. (2012) surveyed U.S. Baby Boomers to examine the impact of age on attitude toward technology, motivation, and job satisfaction. The authors found that overall attitude towards technology worsened with increased age. Those with negative attitudes toward technology were more likely to have less motivation and less overall job satisfaction. In a large sample of adults ranging in age from age 18-91, Czaja et al. (2006) found that older adults (those age 60 or above) reported less use of technology and indicated more computer anxiety and lower self-efficacy than middle-aged and younger adults. Although they may report less computer use, Lee et al. (2019) add an important nuance. Like Czaja et al., they found that younger people reported significantly higher computer efficacy and comfort with computers. Interest in computers, however, was not significantly different between age groups, and their sample included people ranging in age from 18-98.

Important within-group differences are noted in the literature regarding older employees' use and adoption of technology. For example, in their study of European countries in PIAAC, Hämäläinen et al. (2017) found those with strong skills in PS-TRE were somewhat younger, more often male, more often in skilled occupations, had more cultural capital (defined as parents' education and number of books at home), used skills in literacy, numeracy, and ICT both at work and at home, and had participated in training. The older people became, the less likely they were to have strong skills in PS-TRE. Lee et al. (2019) also found differences by gender. Males in their study showed significantly more interest in computers, computer efficacy, and computer

comfort than females. Interestingly, however, the difference between genders disappeared in older age.

Finally, Rampey et al. (2016) provide a review of PS-TRE skills by age group in PIAAC. The authors used 2012 and 2014 PIAAC data, so Baby Boomers would have been between ages 47-68 at the time of survey completion. PS-TRE scores are reported in three levels with an additional category for people who score below Level One. The authors examined PS-TRE proficiency in ten-year age intervals. Among those between ages 16-24 and 25-34, only 16% of each age group scored below Level One. Among those aged 45-54, that number increased to 29%, and it increased to 31% among those aged 55-65. Similar generational trends are seen on the other end of the scale. Among those aged 16-24, 35% of respondents achieved Level Two scores, and that number increased to 37% among those aged 25-34. For Baby Boomers, though, only 26% of those aged 45-54 achieved Level Two scores, and that percentage dropped to 23% among those aged 55-65. These trends are captured graphically in Figure 1. Compared to younger workers, Baby Boomers distribute more equally into score categories, which reiterates the opportunity to assist the large low-scoring group through workplace learning.

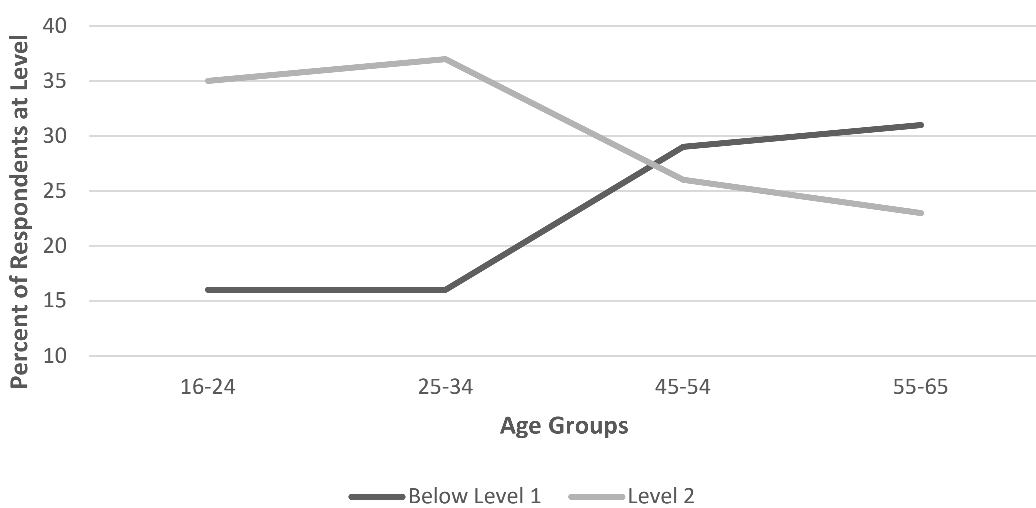


Figure 1: PIAAC PS-TRE Level by Age Group

Baby Boomers and Workplace Training

Workplace training is a recommendation of choice in the literature to address older employees' skill gaps related to technology comfort and adoption (Elias et al., 2012; Hämäläinen et al., 2017). Since 40% of Baby Boomers have self-reported their efforts to keep job skills up to date (Collinson et al., 2019), it seems reasonable that workplace training opportunities may be valued by the intended recipients. Whether Baby Boomers are realistically given access to training, though, is another matter.

Several factors have been shown to impact older workers' access to workplace training. Different economic sectors, for example, provide different incentives and access to training for their employees, and the size of the organization in which an employee works has been shown to impact access as well (Olsen & Tikkanen, 2018). Within organizations in Finland, men and supervisors have been shown to generally receive more training opportunities than women and staff (Silvennoinen & Nori, 2017). The same has been shown regarding informal learning in Spain (Pineda-Herrero et al., 2017).

Negative workplace stereotypes about older workers have also been shown to impact older workers' training access and training outcomes. Posthuma and Campion (2009) identify several stereotypes through an extensive literature review. For example, there is a stereotype that older workers resist change and therefore provide a lower return on investments in training. Similarly, there is a stereotype that older workers have less potential for development due to lower ability to learn. Training outcomes for older workers are impacted by negative workplace stereotypes as well. McCausland et al. (2015) conducted an experiment which demonstrated that a trainer's perception of an employee as being older in a technology training setting influenced the overall score the trainer awarded for the training task.

Ng and Feldman (2012) searched for empirical evidence that would support any of six common stereotypes about older workers. They found evidence supporting a stereotype that older workers are less willing to participate in training and career development. If older workers are, in fact, less willing to participate in training and are perceived as not being worth the effort to train, then organized workplace training may need to be reconsidered as a recommended solution for updating technology skills.

To summarize, then, we learned from Collinson et al. (2019) that Baby Boomers and their younger colleagues all have the same level of desire to keep job skills up to date, yet stereotypes impact access to training for older workers (Posthuma & Campion, 2009) and, potentially, outcomes of training for older workers (McCausland et al., 2015). Instead of utilizing work-based training, one might wonder if Baby Boomers are, instead, looking to informal paths of workplace learning to update their skills. In order to keep our workplaces competitive in a globalized, knowledge-based economy, we need to know how to best support Baby Boomers in developing technology skills. Are the skills best learned through seminars or workshops offered by their employers? Or are the skills best learned informally—on demand while on the job, or through interactions with coworkers?

Purpose and Significance

The purpose of this study is to describe the relationship of workplace learning with Baby Boomers' skills in problem solving in technology-rich environments. In order to access a national sample of U.S. Baby Boomers and measure their technology skills, this study utilizes data from PIAAC. In 2018, Olsen and Tikkanen published a literature review of peer-reviewed publications that used PIAAC to study workplace learning. The authors found only seven peer-reviewed publications internationally. The authors note that these existing publications, "provide

only a limited contribution to our general understanding of learning at work" (p. 553), and none contribute to specifically understanding workplace learning for older workers. Of those seven publications, no corresponding authors were in the United States, and only two of the studies used or discussed U.S. PIAAC data.

This information alone provides two important justifications for this study. First, U.S. PIAAC data has been underutilized to study workplace learning. To use PIAAC to study the workplace learning of Baby Boomers as this study does responds directly to a call from Cummins et al. (2015) for research studying the relationship between participation in adult education and training and problem solving skills among older adults. Second, the trend toward an aging workforce is causing labor shortage concerns worldwide (Berg et al., 2017; Ng & Feldman, 2010; Silvennoinen & Nori, 2017). Retirement trajectories of Baby Boomers are being studied in multiple member countries of the Organisation for Economic Co-operation and Development (OECD) as evidenced in the work of Sewdas et al. (2017) in the Netherlands, Simpson et al. (2012) in New Zealand, and in the work of Taylor et al. (2014) in Australia. In line with the objective of the OECD, this study provides an important research framework that can be repeated using the PIAAC data of other OECD member countries.

Justification for this study extends beyond requests for more of this type of work to be conducted using PIAAC. This study responds to recent calls for more quantitative studies in the field of adult and continuing education (Boeren, 2018; Daley et al., 2018). Indeed, Fejes and Nylander (2015) go so far as to call quantitative methods "endangered" (p. 115) in the field of adult education. This study also fulfills requests cited within the literature for additional research on the role of age in relation to technology at work (Elias et al., 2012), on interventions to support older workers (Truxillo et al., 2015), and to establish technology training plans that

account for generational differences (Fernández-de-Álava et al., 2017). Knowledge gained from this study could benefit individual employees, employers, and U.S. policymakers. For employees who might wish to extend their working lives and for employers that want to increase the skills of their workers, this study may shed light on the most effective way to learn technology skills in a given employment context. Given that age-related stereotypes exist among employers (Posthuma & Campion, 2009), the ability for an older worker to demonstrate strong skills in technology-rich environments may lead to more job offers. On a national level, those working on social policies to involve larger numbers of older citizens in ongoing, active employment may have interest.

Key Terms and Concepts

The Organisation for Economic Co-operation and Development (OECD) is an international organization the mission of which is to, "promote policies that will improve the economic and social wellbeing of people around the world" (OECD, 2011a, p. 8). The OECD began in 1961 with the objective, "to help member and partner country's governments to formulate and implement better policies for better lives" (OECD, 2011a, p. 5). The United States has been an OECD member since its founding, working alongside other member countries, "to share experiences and seek solutions to common problems" (OECD, 2011a, p. 8).

The Programme for the International Assessment of Adult Competencies (PIAAC) is one example of the open exchange of information that takes place between countries through OECD initiatives. The OECD (2019b) describes the PIAAC *Survey of Adult Skills* as a two-part survey consisting of a background questionnaire and measures of three sets of cognitive skills—literacy, numeracy, and problem solving in technology-rich environments. These competencies are "essential for full participation in the knowledge-based economies and societies of the 21st

century" (p. 18). Stein (2017) describes *competency* as the ability to draw on skills in a novel context. The PIAAC Survey, therefore, is designed to measure the performance of adults in specific situations.

Kirsch and Thorn (2013) indicate that the PIAAC *Survey of Adult Skills* was developed in response to "a critical need for information about the distribution of knowledge, skills and characteristics that are needed for full participation in modern societies" (p. 1). The authors outline the Survey objectives, indicating that policymakers in each participating country would receive valuable information about the performance of adults in skills "thought to underlie both personal and societal success" (p. 1). Having this information could then lead to examination of whether educational systems were working to build these skills and consideration of policy development for skill-building in crucial areas.

The PIAAC *problem solving in technology-rich environments (PS-TRE)* competency is the dependent variable in this study. According to the PIAAC PS-TRE Expert Group (2009), problem solving in technology-rich environments is defined as, "using digital technology, communication tools and networks to acquire and evaluate information, communicate with others and perform practical tasks" (p. 9). In other words, the assessment encompasses much more than just the ability to use a computer; it is about using the computer (and various applications installed on it) to solve problems that are prevalent in today's technologically infused workplaces.

Baby Boomer is a generational term for those people who were born between 1946-1964 (Collinson et al., 2019; Dimock, 2019; Moen et al., 2017), although there is some disagreement on these birth years. Cox et al. (2018), for example, identify people born between 1945-1965 as Baby Boomers. This analysis makes use of 2017 U.S. PIAAC data. Baby Boomers born between

1946-1964 would have ranged from age 53-71 at the time of survey completion. PIAAC, however, only reports age in five-year intervals (not as a continuous variable). Therefore, in this analysis, employed people ranging in age from 50-70 at the time of PIAAC survey completion are referred to as Baby Boomers.

Recently, Cox et al. (2018) demonstrated that the use of the term Baby Boomer in the workplace has more negative consequences for employees than the use of the term older employee. In comparison to those labeled as older employees, people labeled as Baby Boomers were less likely to be hired for two different roles, less likely to be provided training, and significantly less likely to be defended by a manager when a joke was made about the person's age. I want to be clear that Baby Boomer is used here because Baby Boomers as a generational cohort are being studied. While there is some disagreement in the literature over the age range for Baby Boomers, there is far more variation in the literature over what it means to be an older employee or older worker. While I would not advocate for the use of the term Baby Boomer in the workplace, using it in academic literature adds clarity for the reader.

Older worker is a term associated with Baby Boomers, but which is not always exclusive to this generation. A lot of workplace literature uses older workers as a key term but, problematically, the term does not always refer to exactly the same age group. Ng and Feldman (2008), for example, used this term to refer to workers at or above age 40. Findsen (2015), meanwhile, argues that since people can draw pensions after age 64, older workers, "might be perceived as 65+ in age" (p. 583). Using these examples alone, then, we can see a 25-year difference in the age at which a person might first be labeled as an older worker. Many relevant empirical studies are not restricted to Baby Boomers yet include members of this generation with

their older workers. If a pertinent study included Baby Boomers in the group of older workers studied, it was included in the literature review.

Adult learning occurs in three types of settings: formal, nonformal, and informal (Merriam & Bierema, 2014; OECD, 2014). *Formal education* is, “education provided in the system of schools, colleges, universities and other formal educational institutions” (OECD, 2011b, p. 25). *Nonformal education* is, “any organised and sustained educational activities that do not correspond exactly to the above definition of formal education” (OECD, 2011b. p. 31). Merriam and Bierema clarify that nonformal learning is provided by various organizations and includes all workplace training. The PIAAC background questionnaire (OECD, 2011b), designates a specific set of indicators as components of nonformal learning. This study uses two of those measures as independent variables: “organised sessions for on-the-job training or training by supervisors or co-workers” (p. 31), and “seminars or workshops” (p. 31).

The third category of adult learning, *informal learning,* is defined by Marsick and Watkins (1990) as, “predominantly experiential and non-institutional” (p. 7). This is the learning that happens in everyday situations such as learning-by-doing or learning through interactions with coworkers. The OECD specifies that informal learning is, “not covered in the Survey of Adult Skills” (2014, p. 1). Pineda-Herrero et al. (2017), however, identified several indicators of informal learning based on the work Marsick and Watkins and others (e.g. Eraut, 2004; Tynjälä, 2008). The authors drew some of their informal learning indicators from the “learning environment” (OECD 2011b, p. 42) section of the PIAAC Background Questionnaire. This study utilizes two of those indicators as independent variables: learning work-related things from co-workers or supervisors; and learning-by-doing.

Research Questions

Two primary research questions guide this study:

1. Is participation in nonformal workplace learning associated with significantly higher PS-TRE performance among U.S. Baby Boomers?
2. Is participation in informal workplace learning associated with significantly higher PS-TRE performance among U.S. Baby Boomers?

Four specific categories of nonformal workplace learning are measured in PIAAC (OECD, 2011b), two of which are used in this study. Question one is, therefore, broken down into two sub-questions:

1a: Is participation in organized sessions for on-the-job training or training by supervisors or co-workers associated with significantly higher PS-TRE performance among U.S. Baby Boomers?

1b: Is participation in seminars or workshops associated with significantly higher PS-TRE performance among U.S. Baby Boomers?

Similarly, only certain indicators of informal workplace learning have been studied in PIAAC (Pineda-Herrero et al., 2017). Question two is, therefore, broken down into two sub-questions:

2a: Is learning-by-doing associated with significantly higher PS-TRE performance among U.S. Baby Boomers?

2b: Is learning new work-related things from co-workers or supervisors associated with significantly higher PS-TRE performance among U.S. Baby Boomers?

Finally, many other variables have been shown to influence learning for older workers, technology use among older workers, or both. To address these moderating relationships, additional sub-questions include:

3. Does supervisory status influence the relationship between workplace learning and PS-TRE competency among U.S. Baby Boomers?
4. Does economic sector influence the relationship between workplace learning and PS-TRE competency among U.S. Baby Boomers?
5. Does size of the organization influence the relationship between workplace learning and PS-TRE competency among U.S. Baby Boomers?
6. Does the relationship between gender, workplace learning, and PS-TRE vary as a function of age among U.S. Baby Boomers?

For each sub-question, all four workplace learning measures were used in analysis. Therefore, the phrase "workplace learning" in each sub-question is broken down into a) on-the-job training, b) seminar or workshop participation, c) learning-by-doing, and d) learning from coworkers or supervisors. So, for example, results are reported in Chapter Four for research question 3a, 3b, 3c, and 3d.

Scope and Limitations

The PIAAC Survey utilizes a sampling technique that draws thousands of participants from residences in all regions of the country. In round three of the first cycle of the PIAAC Survey, U.S. participants resided in eighty different counties from states across the country (Krenzke et al., 2019). Since this study uses PIAAC, the data is nationally representative. Findings are representative of Baby Boomers across the United States and may be highly relevant to labor policy discussions. While the data is nationally representative, they may not hold true for all occupations or geographic locations. Findings may reduce in importance over time as Baby Boomers age out of the workplace.

Given the rapid pace of technological change, the argument could be made that the PIAAC measure of PS-TRE does not capture enough of today's information and communication technology. The PS-TRE competency measure did not, for example, require participants to use social media or mobile technology. Similar limitations could apply regarding the measures of workplace learning in PIAAC. For example, PIAAC asks specifically about nonformal learning participation within the last year (OECD, 2011b), so one limitation of this study is that the accumulated benefits of nonformal learning over the lifetime are not accounted for. Furthermore, information about the content of workplace learning is limited in PIAAC. We do not know the topics of workshops that a worker attended—we only know he or she participated in nonformal workplace learning through workshops.

Finally, findings in PIAAC are not causal. This correlational study can identify important relationships between variables. It could show, for example, that higher participation in workplace learning is associated with a significant increase in PS-TRE score. It cannot definitively claim, however, that participation in workplace learning *causes* a significant increase in PS-TRE score. This is because, in correlational research, there is always the possibility that an unidentified third variable is influencing the other variables. This limitation of correlational research is known as the tertium quid (Field, 2018).

Summary

Toossi and Torpey (2017) indicate that the labor force participation rate of older employees (those above age 55) is expected to increase through 2024. The most notable gains are expected to be among people age 65 or older, with 13 million employees in this age group projected by 2024. This increase comes at a time when the participation rates of other age groups in the labor force are not expected to change.

What is unknown, however, is how the Covid-19 pandemic will impact these trends. Coibion et al. (2020) published preliminary findings on how Covid-19 is impacting the labor market. The authors used the Nielsen Homescan survey to get a sneak peek at labor market outcomes before official indicators by the Bureau of Labor Statistics are released. The authors found that participation in the labor force has declined by about seven percentage points, which they call a, "historic decline" (p. 4). The authors attribute the drop to early retirements.

Indisputably, Covid-19 has put the health of our older workers in jeopardy. Marc Larochelle (2020), a primary care physician, recounts the loss of one of his patients, Mrs. M. Reviewing data from China (where the pandemic originated), Larochelle indicates, "the case fatality rate may approach 10% for people, like Mrs. M., who are in their 60s and have diabetes—more than 20 times that among people under 50 without a high-risk chronic condition" (p. 1). Larochelle proposes a framework "to help clinicians counsel patients about continuing to work in the midst of the pandemic" (p. 2). According to the framework, if a person is older with a high-risk condition and is also likely to encounter people at work who have contracted the disease, Larochelle advises that the person stop work.

It seems reasonable to believe, then, that part of the drop in labor force participation noted by Coibion et al. (2020) could be health related. Some research indicates, however, that younger workers have significantly more computer efficacy than older workers (Lee et al., 2019). In these unprecedented times, is it possible that some older workers are simply unwilling or unable to transition into new, fully virtual work environments?

All may not be hopeless on that front. In our current study of retirees who volunteer as architecture tour docents (Galliart et al., 2020), we recently learned that docents who had previously only interacted with guests face-to-face have begun offering lectures via Zoom to

audiences of generally more than 100 attendees. They saw a need for their organization to do something different to generate income during the pandemic, and they responded to it. As one participant remarked, "when you're a volunteer, you volunteer." It seems, therefore, that the question of whether early retirements are due in part to issues with technology acceptance is one that warrants further investigation.

Before the Covid-19 pandemic, the growth in labor force participation among older workers was clearly an upward trend. Charted measures of PS-TRE performance by generation in PIAAC, however, shows a downward trend with Baby Boomers scoring significantly lower than their younger peers. Use of technology is crucial to remain competitive in the global economy, and the only segment of our workforce that is growing is struggling with this competency. The urgency inherent in that opposite trajectory of labor force participation and technology competency is what first drew me to this problem.

As I have spent more time learning about these topics, though, I have come to view older workers' limited access to workplace learning as an issue of social justice. I agree with Warhurst and Black's (2015) assertion: "ageing populations need to be seen as a key, growing, natural asset rather than, as typically construed today, a liability" (p. 468). Identifying what learning format may be most effective for improving the technology competency of older workers in various contexts could be an important step in helping organizations adopt an asset mindset regarding older workers.

This chapter has focused on how the working lives of U.S. Baby Boomers are extending both through paid and volunteer work. The changing nature of workplace technology was noted, and a few key findings regarding the performance of older workers in technological environments were introduced. Workplace training is offered in the literature as a solution to

increase the technology competency of older workers, but older workers are often marginalized in training contexts. In an effort to provide organizations with better direction regarding what learning format may be most effective for helping Baby Boomers update their technology skills, this study examined whether participation in nonformal or informal workplace learning is associated with significantly improved PS-TRE scores as measured in PIAAC. This study responds to several opportunities noted in previous literature, but perhaps most notably provides a model that can be replicated using other OECD countries data in PIAAC.

Chapter 2: The Literature Review

Baby Boomers are those individuals who were born between 1946-1964 (common years used, for example, by Collinson et al., 2019; Dimock, 2019; Moen et al., 2017). A generation, according to Howe and Strauss, “is shaped by events or circumstances according to which phase of life its members occupy at the time” (2007, p. 42). As a generation, Baby Boomers shared the experience of having the personal computer introduced to the workplace. In line with Howe and Strauss’s definition, one might ask, what phase of life were Baby Boomers in when workplace technologies were introduced?

This timeline is important to consider in a study using the Programme for the International Assessment of Adult Competencies (PIAAC) Survey of Adult Skills. The expert group members who created the competency measure of problem solving in technology-rich environments (PS-TRE) in PIAAC relied heavily on participant’s use of Internet browsers during the assessment (PIAAC, 2009). When the World Wide Web became publicly available in 1991 (Lagasse, 2018), Baby Boomers—then age 27-45—were a decade outside of their years of mandatory K-12 schooling. Unlike other crucial PIAAC competencies (literacy and numeracy), Baby Boomers were not taught the technology skills used in PIAAC during their formative years of public education. Those Baby Boomers who went straight into college after high school might not have formally learned PS-TRE skills during college as undergraduates, either.

Baby Boomers who did not go straight into college, or who perhaps returned to college for advanced degrees later in life, could have been provided formal instruction in PS-TRE through college education undertaken after the mid-90s. Due to the advent of Web browsers, this is the general time when the World Wide Web became widely utilized (Lagasse, 2018). Nevertheless, a group of Baby Boomers remains for whom technology skills were not taught in a

formal educational environment. For that group of Baby Boomers, it is imperative for individuals who oversee workplace learning to have solid information about what nonformal and informal workplace learning formats are associated with greater technology competency gains for this generation.

This study uses 2017 U.S. PIAAC data. Baby Boomers would have been age 53-71 when they completed the PS-TRE competency measure, placing them among the oldest group of employees surveyed. Today (in 2020), Baby Boomers are between 56-74 years of age. The generation is divided in terms of retirement. People born in 1955, for example, (in the middle of the Baby Boomer generation) can retire with full Social Security benefits next year, at age 66 and two months according to the Social Security Administration (n.d.). To review the current literature on Baby Boomers' experiences with technology, then, presents a few challenges.

Current research on Baby Boomers and technology addresses both those still in the workplace and those who have retired. For those who have retired, the literature is often about the use of technology to promote health outcomes (see, for example, Schulz et al., 2015). My specific goal at the conclusion of this study is to be able to suggest which workplace learning formats are associated with significantly higher technology competency among Baby Boomers in different employment contexts. The body of literature that addresses Baby Boomers and technology but does not relate to the workplace is, therefore, omitted from this review.

Another significant challenge is the sheer volume of literature written internationally about Baby Boomers. To make the review manageable, I conducted four waves of research. First, I completed a search for subject terms using five databases: ERIC, Academic Search Complete, JSTOR, Business Source Complete, and ABI/INFORM. These databases were selected due to the multidisciplinary nature of their collections. The database search was

restricted to include only peer-reviewed articles published since 2015. Search terms included: *Baby Boomer, older workers, workplace learning, training, informal learning, computer, information and communication technology*, and *technology*. This produced 80 articles. Articles were reviewed to ensure they were of an empirical nature and addressed the relationship between older workers and workplace learning, older workers and technology, or both. Articles that did not meet these criteria (65 in total) were excluded. Of the 15 that remained, most were studies conducted outside of the U.S.

I wanted to increase the number of articles reporting research in the U.S. and ensure the field of adult learning was well represented. I visited the websites of the following journals to locate additional sources published since 2015: *Human Resource Development Review; Adult Education Quarterly; New Horizons in Adult Education & Human Resource Development*; *Human Resource Development Quarterly;* and *Performance Improvement Quarterly*.

Third, I examined the reference lists of articles and retrieved additional sources based on these reviews. This led to the inclusion of several frequently cited resources published before 2015. Finally, there are numerous reports from the Organisation for Economic Co-operation and Development (OECD) as well as papers commissioned by the American Institutes for Research that relay previous findings from PIAAC. The PIAAC Bibliography – 2008-2019 by Maehler et al. (2020) was reviewed to identify papers relevant to this topic.

All of this information has been synthesized and organized into the following sections: (a) introduction to nonformal and informal learning in the workplace; (b) workplace learning and the older worker; (c) older workers in technology-rich environments; and (d) intersections of workplace learning and technology for the older worker. The Dreyfus Model of Skill Acquisition

is introduced as this study's theoretical framework (e). Research questions are restated with their attendant hypotheses (f), and the review concludes with a summary (g).

Introduction to Nonformal and Informal Learning in the Workplace

Like many concepts about learning, the idea that learning can take place in different settings was initially extended in response to the needs of children. In their study of children in rural areas of developing nations, Coombs et al. (1973) designated learning settings as being formal, nonformal, or informal. Setting the precedent for the field of adult learning, Merriam and Bierema (2014) base their discussion of learning settings on the terms used by Coombs et al. Literature from other fields, however, blurs these terms. I will point out some of the discrepancies while providing a brief review of workplace learning.

You might recall from Chapter One that formal learning is that which takes place in traditional educational settings—elementary schools, high schools, colleges, and universities. Of the three learning settings first designated by Coombs et al. in 1973, formal learning is not a category considered in studies of workplace learning. A workplace might offer incentives for employees to continue their formal education, but the workplace itself cannot award these qualifications. Some scholars (Kraiger, 2017; Marsick & Watkins, 1990) refer to structured training within a workplace as formal learning to distinguish it from learning that happens outside of training events offered by the organization. In adult education, we would call structured workplace training nonformal education.

Coombs (1976) defined nonformal education as, "organized educational activities outside the formal system that are intended to serve identifiable learning needs of particular subgroups in any given population" (p. 282). The OECD (2011b) adds that two such learning needs fulfilled by nonformal education are life skills and work skills. According to Merriam and Bierema

(2014), nonformal learning is planned and organized: “there is usually a curriculum and often a facilitator” (p. 17). Nonformal workplace learning, then, might be referred to variously as training, professional development, seminars, or workshops.

The OECD (2011b) specifies that four types of nonformal education are measured in PIAAC. Two of those measures—participation in seminars or workshops, and participation in on-the-job training—are included in this study. On-the-job training warrants a moment of consideration because it can either be nonformal (planned—sometimes referred to as structured on-the-job training) or informal (unplanned). Ahadi and Jacobs (2017) explain that structured on-the-job training is an approach that brings organized instruction (a trainer with training materials) to individual workers at their worksites. The OECD indicates that the measure of on-the-job training in PIAAC aligns with this approach, describing organized on-the-job training as being, “characterized by planned periods of training, instruction or practical experience, using normal tools of work” (p. 31). Twyford et al. (2016) suggest that small businesses in particular (where on-the-job training is often the primary or only training method utilized) could benefit from a structured approach.

Initially popular for quality improvement initiatives in manufacturing settings, structured on-the-job training has now been utilized (although not as extensively) for a broad array of audiences including bankers, managers, and surgeons, among others (Ahadi & Jacobs, 2017). In their integrative literature review of structured on-the-job training, Ahadi and Jacobs (2017) note the need for more empirical evidence about the financial benefits to organizations when utilizing this method and for more evidence about the relationship between this type of training and performance outcomes. This study responds to the need noted by Ahadi and Jacobs by

considering the relationship between participation in organized sessions for on-the-job training and the outcome of technology competency among U.S. Baby Boomers.

We know, however, that even when people are not participating in organized training, they learn informally through their daily work and workplace interactions. Marsick and Watkins (1990) are key researchers in this area and authored the theory of informal and incidental learning in the workplace. They define informal learning as, “predominantly experiential and non-institutional” (p. 7). The authors later clarified that informal learning is, “usually intentional but not highly structured” (2001, p. 25). Examples of informal learning include coaching, mentoring, self-directed learning, and networking. As we saw with on-the-job training, coaching and mentoring could also be classified as nonformal learning depending on the structure of the activities. The authors indicate that incidental learning, defined as unplanned, “unintentional, a byproduct of another activity” (1990, p. 7), is a subcategory of informal learning. Learning from mistakes and learning-by-doing are examples of incidental learning that can happen in a workplace. Sometimes people learn incidentally without being consciously aware that learning has occurred.

Marsick and Watkins (1990) advocate that, in workplaces, the focus needs to shift from training to learning. Some of the differences they point out between these mindsets are captured in Table 1. Training is an important part of the learning a person does at work, but the authors indicate the opportunity exists for human resource development professionals to more fully capitalize on, “the natural opportunities for learning that occur every day in a person’s working life” (p. 4). These opportunities tend to arise when workers encounter situations wherein their normal responses are inadequate, and they need to determine a different way to solve the problem. The authors suggest that an individual worker’s propensity to take initiative, to be

reflective, and to engage in creative thinking will influence the quality of the informal learning experience.

Table 1
Workplace Training Versus Workplace Learning

Training	*Learning*
A short-term activity	A daily activity
Scheduled by the organization	Initiated by the employee as the need arises
Topics selected by the organization	Topics determined by the employee's needs
Learning occurs outside of context, and it may be difficult to transfer skills back to normal work environment	Learning occurs in the employee's normal working environment

Note. Based on discussion in V.J. Marsick and K.E. Watkins, 1990, *Informal and incidental learning in the workplace*. Copyright 1990 by V.J. Marsick and K.E. Watkins.

Another frequently cited researcher in the informal learning literature is Michael Eraut. Eraut (2004) diverges slightly from the theory of Marsick and Watkins (1990) by calling informal learning a "partner to learning from experience" (p. 247), whereas Marsick and Watkins assert learning from experience is a hallmark characteristic of informal learning. Eraut discusses informal learning in terms of the level of intention demonstrated by the worker. Some informal learning at work is *implicit*, indicating no conscious attempt by the worker to learn. Informal learning can also be *reactive*. A problem arises and the worker intentionally scrambles to find the information needed to respond. In other circumstances, the worker has the time to be more *deliberative*—a gap in knowledge is identified, and the worker sets out with a clear goal and intent to learn. Interestingly, the learner in that position might choose a mix of both nonformal and informal strategies to achieve the learning goal. In that case, the learner's process might be called informal, but the learning strategies could represent a mix of nonformal and informal learning.

Eraut (2004) emphasizes the interpersonal nature of informal learning, reporting that learning often results from participation in group activities, working with others or with clients,

and from undertaking challenging tasks. There is, however, significant variability in the amount of informal learning observed between different individuals and between different employment contexts. Managers can positively or negatively influence the amount and quality of informal learning their employees are likely to experience, so even within the same organization there can be variability in informal learning among subgroups of employees.

This variability of informal learning as experienced by different work groups is accounted for in a recent classification of informal learning proposed by Jeong et al. (2018). Through an integrative literature review, the authors identified individual, group, and organizational factors affecting informal learning in the workplace. Individual factors included sociodemographic characteristics such as age, gender, and level of education. They also included personal characteristics (self-efficacy, cognitive ability, and motivation to learn among others) and job characteristics (role, seniority, and employment status among others). At the group level, factors impacting informal learning included leadership support (managers who model and encourage learning), receiving feedback from peers and leaders, and interpersonal relationships with colleagues. Finally, at the organizational level, offering formal training and performance rewards promoted informal learning, as did a supportive learning culture within the organization. Aligning with Eraut's (2004) observation, organizational characteristics (size of business, economic sector, type of organization) were also noted by Jeong et al. to impact informal learning opportunities within a given organization.

Recognizing that informal learning varies by size of business, Coetzer et al. (2017) recently looked specifically at factors that influence informal learning in small businesses employing 10-49 people. The authors completed an integrative literature review on this topic but found only 15 empirical articles published between 2000—2016. This low number reinforces a

need noted by the editors of *Human Resource Development Quarterly* for more research specifically on learning within small and medium-sized enterprises (Short & Gray, 2018). Coetzer et al. organize their findings from the literature into four themes. First, a great deal of literature indicates that a small business cannot be treated like a big business—these are unique enterprises where resources are often scarce and nonformal learning through training might not be offered. Yet small businesses also promote informal learning because workers tend to be responsible for a larger number of tasks. Second, informal learning in small businesses is influenced by the business environment to which a particular small business is exposed. Learning strategies employed by commercial partners or by suppliers are apt to be picked up by the small business. Third, as noted previously by Eraut (2004) and Jeong et al. (2018), the role of the manager is critical. A difference for small businesses, though, is that an entrepreneurial mindset in an owner/manager creates a stronger learning environment. The final theme noted in the literature is a call for small businesses to develop learning strategies that capitalize on their unique characteristics. The authors conclude by proposing five areas of future research on learning in small businesses.

As we conclude this broad discussion of informal workplace learning, one final article warrants close examination. Pineda-Herrero et al. (2017) used PIAAC to explore informal learning in Spain. As indicated in Chapter One, the measures of informal learning used in the current study were identified by these authors. Based on a review of literature by Marsick and Watkins (1990) and Eraut (2004) among others, the authors constructed a list of six manifestations of informal learning in the workplace that are measured in PIAAC:

- Collaborating and sharing information with colleagues
- Teaching others and giving advice

- Carrying out oral presentations
- Planning activities (own and of others), organizing own time
- Negotiating, convincing and selling
- Solving complex problems (p. 153)

The authors aligned these manifestations to two sets of items from the PIAAC background questionnaire, the *learning environment* and *job requirements approach*. The current study uses two of the measures from the *learning environment* module: learning work related things from coworkers or supervisors and learning-by-doing. In their study of 3,386 employed Spaniards, the authors found 52.8% of respondents reported learning-by-doing as an everyday occurrence, and 36.1% reported informal training as an everyday occurrence. While these were the highest levels reported, it is also noteworthy that 17.2% reported never learning from coworkers, and 9.9% reported never learning-by-doing.

Pineda-Herrero et al. (2017) also investigated factors that impacted those overall participation rates. Men and respondents who were supervisors were more likely to learn from colleagues and learn by doing. Participation also varied by economic sector with the public sector showing the highest levels of learning from colleagues and learning-by-doing, followed by the private sector and nonprofit organizations.

From this review of nonformal and informal workplace learning, we can identify a few key messages. First, as Marsick and Watkins (1990) pointed out regarding coaching, sometimes learning activities are difficult to categorize. Formal, nonformal, and informal designations help us recognize the array of learning strategies in existence. Realistically, however, these are not dichotomies, but rather parts of a learning continuum (Eraut, 2004). Second, as a continuum, both nonformal and informal learning are important in the workplace (Clardy, 2018; Marsick &

Watkins, 1990). Although informal learning is more pervasive, nonformal learning can be more effective depending on the need and circumstances. As Clardy (2018) asserts, "what is needed is a catalog of the full variety of potential learning contexts and processes in the workplace and integrating them into designed and managed—or structured—development experiences" (p. 169). In other words, development professionals need to find out what works when it comes to mastering certain workplace competencies and then put their efforts into strengthening those experiences. This research helps with that by determining which types of learning experiences are associated with greater gains in technology competency among Baby Boomers.

Third, the setting in which a person works and the role a person has within an organization significantly impact the type and extent of learning opportunities they are likely to encounter in the workplace (Coetzer et al., 2017; Eraut, 2004; Jeong et al., 2018; Pineda-Herrero et al., 2017). Due to this expected variability, economic sector, size of business, and supervisory status are engaged as moderators in this study.

Having reviewed enough literature to facilitate a better understanding of key authors and current trends in nonformal and informal workplace learning, let us turn now to a consideration of the older worker in these contexts. As we have seen, individual factors including cognitive ability and motivation to learn impact the amount of learning a person experiences (Jeong et al., 2018; Marsick & Watkins, 1990). What can we learn about these important individual factors for older workers, and what other trends are apparent in the literature on the topic of workplace learning and the older worker?

Workplace Learning and the Older Worker

Upon review, the last five years of literature on workplace learning for the older worker falls into five categories. Some articles attend to the issue of access to workplace learning

opportunities for older workers, answering the question, do older workers have the same opportunities to participate as their younger colleagues? Then, the next three groups of articles address things that influence the success of older workers in workplace learning. Specifically, the motivation to learn and cognitive abilities of older workers are discussed, and strategies to enhance the training experience and outcomes of older workers are reviewed. Finally, a few articles look at big picture outcomes of participation in learning activities, answering the question, what outcomes beyond skill gain are evident when older workers participate in workplace learning? Each of these topics is explored in the sections that follow.

Older Workers' Access to Workplace Learning

Access to training for older workers is impacted by variables including workplace stereotypes and resource availability. Several articles reviewed (Fleming et al., 2017; Jeske et al., 2017; Lössbroek & Radl, 2019; McCausland et al., 2015) discuss the impact of negative stereotypes on older workers' access to training opportunities. Works commonly cited include those by Posthuma and Campion (2009) and Ng and Feldman (2012).

Posthuma and Campion (2009) studied common age stereotypes in the workplace. Their review included 117 articles. The authors identify stereotypes and literature that supports or refutes them. One stereotype of particular relevance here is that older workers are, "more difficult to train. For this reason, the return on training investments will be lower for older workers than for younger workers who can be more easily trained" (p. 167). Interestingly, the authors found, "virtually no research that examines the validity of this stereotype" (p. 168), and they call for future research on the subject. A second, highly relevant stereotype reviewed is, "that older workers are viewed as having lower ability to learn than younger workers" (p. 168). The authors note mixed findings on this, with some studies supporting the claim while others

refute it. The authors note a growing body of research indicating that certain training methods may be more effective for older workers and call for more research in this area. Some of the current ideas about training older workers are reviewed later in this section.

Ng and Feldman (2012) used 418 empirical studies to complete a meta-analysis of six stereotypes about older workers. Two stereotypes the authors studied are especially relevant here. The authors asked, "are older workers less willing to participate in training and career development," and, "are older workers less willing and able to change?" (p. 830). Of importance here, the authors note the prevalence of a belief that older workers are unable to adapt to technological change. The authors found that older workers are, in fact, less willing to participate in training. Interestingly, the level of training participation itself was not significant, but workers' motivation to learn and motivation to participate in career development were weakly related to age. The stereotype that older adults were less willing to change was not, however, supported. The authors note that the computer self-efficacy measure was close to being significant, but ultimately age was not related to change orientation.

What can happen in a workplace if someone in a position of power knowingly or unconsciously believes stereotypes about older workers? McCausland et al. (2015) recently explored this question by studying the impact of perceived age on technology training scores. Their study employed an innovative method to isolate the issue of agism. Utilizing a sample entirely composed of undergraduate students under the age of 30, the authors divided students into 85 trainer/trainee pairs. The trainer was given the job of teaching the trainee about personalizing Excel macros (automating tasks). Training took place through Skype with video disabled. Stock photographs of older workers and voice distortion software were used to manipulate the perception of age from both perspectives—some participants experienced an

older looking/sounding trainer while others experienced an older looking/sounding trainee. The authors' interest was in determining whether these perceptions impacted participants' expectations about training, the instructional quality of training, and/or performance in training. From the trainee perspective, the perceived age of the trainer did not influence the trainee's expectation of the trainer to be able to provide adequate training. Trainers who had older-looking trainees, though, had lower expectations for success of the trainee, and that expectation ultimately influenced how the trainer evaluated the trainee. Interestingly, the quality of the trainers' instruction was not impacted by their perceptions. The authors conclude, "although participant evaluations point to noteworthy disadvantages [for older trainees], objective evaluations suggest participants were able to overcome these stereotype induced barriers" (p. 704). Nevertheless, the authors point out that training intended to eliminate a competency gap has, in this case, added to the gap since trainees perceived as older received lower scores.

Importantly, older workers who internalize stereotypes about age have also been shown to limit their own opportunities. To understand how being labeled as an older worker impacted participation in training, Meyers (2016) conducted a phenomenological study of eight older workers (age 55 or greater) in Australia. Participants in the study were low-skilled and under-employed or unemployed. The author concludes, "the participants internalized the perceptions of their age and capabilities, and turned them into a form of self-discrimination" (p. 140) which limited their engagement in training and in job-seeking behavior.

Stereotypes, then, may influence both older workers' participation in training (Meyers, 2016; Ng & Feldman, 2012) and potentially their evaluations as recipients of training (McCausland et al., 2015). A similar issue is that of perceived availability of resources. Through a series of four studies, North and Fiske (2013) developed and validated a prescriptive ageism

scale, helpful for identifying specific resource tensions between generations. The authors note that this approach diverges from prior scales that have relied on *descriptive* stereotypes about older people and shifts to *prescriptive* beliefs held by younger generations about how older people should use resources. Prescriptions fall into three categories: (s) succession (older workers should make way for younger workers), (i) identity (older people should act their age and not try to fit in with younger people), and (c) consumption (older people should not take more than their share of societal resources). The authors refer to this categorization as the SIC Scale.

In a subsequent series of experiments, North and Fiske (2016) set out to determine how the perceived abundance or scarcity of resources impacted older workers' access to networking and training opportunities. The experiments are based on their SIC Scale (North & Fiske, 2013). The first three experiments used a similar 2 x 2 design in that participants were asked to read a mock newspaper article about the growing, older U.S. workforce. The article either presented a message of abundance (there are plenty of job opportunities for everyone) or of scarcity (there will not be as many job opportunities). Then the participants (age 18-31) were given a profile of a 71-year-old man, Max, and asked about their likelihood to network with him. In the first experiment, Max was either thinking about retiring or stated he had no plans to retire (violating an assumption about employment succession). In the second experiment, Max has a serious illness and decides to either pursue resource intensive treatment (violating an assumption about consumption of resources) or not. In the third, Max either says he likes pop music (violating an identity assumption) or oldies music. In all three experiments, a significant interaction was found between scarcity and violating behavior; young respondents were less likely to network with Max under these conditions.

In North and Fiske's (2016) fourth experiment, participants read a mock news article as above but then were asked to determine which of three employees (aged 24, 43, or 64) similar in education and tenure with the company should receive training when there was not enough in the budget to fund training for all three. The factorial ANOVA determined a significant main effect wherein the 64 year-old worker received significantly lower training investment. Rater age was found to be a significant covariate; rater age predicted the amount of training dollars awarded to the older worker, with younger raters allotting less funding. This significance disappeared, however, in a subsequent mediation analysis controlling for age. The authors found that succession attitudes mediate the relationship between rater age and training investment in older employees. This leads the authors to suggest workplace interventions that encourage changing prescriptive attitudes regarding succession.

Unsurprisingly, actual resource scarcity can also impact older workers' access to training. In their qualitative study of ten middle-managers over the age of 50, Warhurst and Black (2015) found that most respondents had assumed personal responsibility for their learning due to a lack of support for formal training. Participants, especially from the public sector, noted decreased training availability due to the economic climate in the U.K. Participants also, however, emphasized the need for ongoing learning in their roles. The authors note, "the data show the considerable extent of informal learning achieved by the participants" (p. 463). Additional information from Warhurst and Black's study is reviewed in the section on learning outcomes for older workers.

We saw in the introduction to nonformal and informal learning in the workplace that access to workplace learning differs between types of workplaces, worker roles, and individual worker characteristics. It seems that older workers' access to workplace training may be

complicated by additional factors. Negative stereotypes can influence opportunities extended to older workers (Ng & Feldman, 2010; Posthuma & Campion, 2009), or even what opportunities they are likely to seek themselves (Meyers, 2016). Perceived (North & Fiske, 2016) or actual (Warhurst & Black, 2015) resource scarcity can also impact learning opportunities for older workers. Since this study is interested in what learning formats are associated with higher technology competency among older workers, the findings of McCausland et al. (2015) that stereotypes can influence the score a younger trainer awards an older worker during technology training are especially concerning.

The solution may appear to be to encourage informal learning strategies, as the managers in Warhurst and Black's study demonstrated. Indeed, Marsick and Watkins (2001) discuss the unlimited nature of informal learning, indicating that it can take place any time provided that an individual has the motivation to pursue it. An important problem arises when considering North and Fiske's networking studies, though. Networking is widely recognized as an informal learning activity (Marsick & Watkins, 1990; Warhurst & Black, 2015), and North and Fiske's experiments demonstrate that networking opportunities can be withheld under conditions where younger workers feel that their opportunities or resources are threatened by older workers. Therefore, we cannot assume *all* informal strategies are truly unlimited, but approaches like self-directed learning could be if the employee has the motivation needed to engage in that process.

Older Workers' Motivation to Learn and Training Participation

As we have seen, however, there is a reduction in motivation to learn associated with increased age (Ng & Feldman, 2012). Previous work in PIAAC has helped to illuminate the extent of this. In 2016, Gorges et al. made an important discovery about a PIAAC background questionnaire construct called *readiness to learn*. The authors took this set of six background

questionnaire questions and divided it into two new constructs which they called *motivation to learn* and *elaboration*. The four *motivation to learn* questions essentially ask if the respondent enjoys various aspects of learning, whereas the two *elaboration* questions ask how often learners consciously relate new concepts to real situations or to their own prior knowledge. The authors used regression to validate their new scale using data from 21 countries in PIAAC. This is important because Roessger et al. (2020) would later use *motivation to learn* and *elaboration* to study preferences for andragogical learning in PIAAC.

Roessger et al. (2020) explain that, according to the concept of andragogy proposed by Knowles (1980), both *motivation to learn* and *elaboration* should increase with age. Their actual findings, however, indicate that across 32 countries in PIAAC, *motivation to learn* and *elaboration* decreased overall with age. The authors did, however, note significant variation by country, with Western countries such as the U.S. achieving higher overall scores than Eastern countries. Their study included PIAAC data from 2011-15, so Baby Boomers across all countries were approximately between age 47-69 as participants. Those learners who were 45-54 and those who were 55 and older were respectively 6.4% and 6.8% less motivated to learn than those who were age 16-24. Older people were also less likely to undertake the deep learning of *elaboration*, relating new skills to prior experience. On *elaboration* items, Baby Boomers scored 6.9-8.0% lower than those aged 16-24. The authors also found that, across all countries, men, those who had earned at least a high school diploma, and those who were in skilled occupations had significantly higher scores on both constructs.

Research has shown, then, that older adults have lower motivation to learn, but does motivation to learn predict their participation in training? Here, too, previous PIAAC studies are an excellent source of information. Yamashita et al. (2019) looked specifically at the relationship

between Gorges et al.'s (2016) *motivation to learn* construct and adult education participation among 2,580 older adults (defined as those over age 50). The study used 2012/2014 U.S. PIAAC data, so Baby Boomers would have been age 47-68 at the time of data collection. The authors found that 44% of respondents had participated in adult education (formal or nonformal learning) in the year before completion of the PIAAC Survey. When compared to the 66% participation rate of adults aged 26-35 reported by Desjardins (2015), we can appreciate how big of a gap there is between generations in training participation. Importantly, Yamashita et al. note, "Overall, AET participants were more likely to be younger, White (vs. non-White), more educated, and healthier than the non-participants" (p. 544). Motivation to learn was significantly associated with participation in both formal and nonformal learning. The authors call for more research on this relationship, indicating the need for interventions to systematically increase motivation to learn among this population.

Research in this area is already underway. Marsick and Watkins (1990) suggested that a proactive personality, defined as a "readiness to take initiative" (p. 28) enhances the effectiveness of informal learning. Setti et al. (2015) recently tested whether a proactive personality predicted training motivation among 2,215 older workers in an Italian bank. They found a significant direct relationship between these two variables, indicating that a proactive personality is an important determinant of nonformal learning as well. Setti et al. also, however, tested the idea that goal orientation mediates the relationship between proactive personality and training motivation. Goal orientation explained 70% of the relationship between proactive personality and training motivation. The authors examined both learning and performance goal orientation and found that learning goal orientation (a tendency to seek out challenging tasks in order to increase overall competence in spite of potential for failure) was the stronger mediator.

The authors conclude that older workers' training motivation could be increased by organizations that encourage a learning goal orientation among employees. Importantly, Marsick and Watkins also note, "empowerment is a precondition for proactivity" (p. 29). For workers to be proactive about embracing learning opportunities, the workplace must empower them to make decisions about their learning.

Becker Patterson (2018) undertook a study to learn more about PIAAC participants aged 20-74 in the U.S. who *did not* undertake formal or nonformal education in the year leading up to PIAAC. As above, the study used 2012/2014 U.S. PIAAC data, so Baby Boomers would have been age 47-68 at the time of data collection. The largest groups of nonparticipants noted were those aged 50-59 and 60-74 (Baby Boomers), with respectively 23% and 30% of respondents being nonparticipants.

Becker Patterson's (2018) findings add a new level of complexity because of the presence of regional differences in overall participation in educational activities—44% of nonparticipants were from the South. Additionally, "half of nonparticipants in the Midwest and 40% of nonparticipants in the South live in rural areas" (p. 47). Other noteworthy overall findings are that 30% of nonparticipants reported fair or poor health compared to 15% among participants. Most respondents from both the participant and nonparticipant groups worked in the private sector, but there were differences noted in specific jobs with nonparticipants being more likely to have the occupations of, "personal service workers, building and related trades, metal and machinery trades, and drivers and mobile plant operators" (p. 51). Nonparticipants were also more likely to be self-employed.

To summarize, then, we have learned from previous research that people who are age 45 or older have about 6.5% less motivation to learn than those between age 16-24 (Roessger et al.,

2020). For older workers, motivation to learn directly impacts participation in nonformal learning (Yamashita et al., 2019). Through encouraging a learning goal orientation, organizations could potentially increase motivation to learn among older workers (Setti et al., 2015), but this is not the only factor that influences participation in nonformal learning. Since attainment of formal education, self-rated health, and race also impact participation in nonformal learning (Becker Patterson, 2018; Yamashita et al., 2019), these factors are controlled in this study.

Fluid and Crystallized Intelligence Among Older Workers

In the earlier discussion of stereotypes about older workers, we learned that stereotypes pertained to both the motivation and learning ability of older workers, with mixed findings regarding learning ability (Posthuma & Campion, 2009). Part of this lack of clarity has to do with the concept of fluid versus crystallized intelligence first posited by Cattell in 1941 (per Cattell, 1963) and then refined by Horn and Cattell in 1966. This review, however, focuses on Salthouse's (2012) discussion of age and cognition due to the influence this scholar has had on others who study the relationship between age and technology aptitude, technology use, technology acceptance, etc. (such as Czaja et al., 2006; Czaja & Sharit, 1998; Hauk et al., 2019; and Meyer, 2011).

Salthouse (2012) explains that there are two types of cognition. Fluid abilities are those that involve the use of "reasoning, memory, and speed" (p. 203), whereas crystallized abilities are those that utilize knowledge gained over time. These types of intelligence cross paths as people age. Fluid intelligence has an early peak with declines starting in a person's 20s and continuing throughout the remainder of the lifespan. Crystallized intelligence takes the opposite path with increases over time until about age 60. In controlled experiments, this gain and loss do not even out—the gain of crystallized intelligence is not enough to offset the loss of fluid

intelligence on achievement scores. In real life, however, “there is little evidence of a negative relation of age (at least within the range of 20 to 75 years of age) and indices of overall level of functioning” (p. 215). Presently we can only theorize about this perplexing mismatch between the laboratory and real life. Salthouse offers four possible explanations:

- Cognitive tests are harder than the typical proficiency a person generally needs in real life
- As we age, we encounter fewer novel situations and have more opportunities to utilize relevant knowledge from experience
- Success is influenced by more factors than cognition. Consider, for example, the role of emotional intelligence in the workplace
- As people age, they adapt by shifting into roles or tasks that utilize crystallized abilities

Let us consider the implications of this discussion for the present study. Technology competency is the dependent variable in this study. New technologies introduce novel situations, so older workers may be required to use more fluid abilities in those situations. In an oft-cited article on the impact of aging on work motivation, Kanfer and Ackerman (2004) indicate older workers are more likely to perform poorly compared to younger workers in situations where new job skills—such as learning to use a new operating system—are taught. If older workers naturally tend to adapt by pivoting away from situations requiring the use of fluid abilities, then the result could be avoidance of new technologies. We shall see what the current literature indicates about these possibilities in the section of this review focused on older workers in technology-rich environments. Learning strategies, the independent variables in this study, are also impacted by changes in the primary type of intelligence over the life course. As we will see in the next section, the idea that people lose cognitive processing speed as they age heavily influences the recommended strategies for training older workers.

Strategies and Sources of Learning for Older Workers

Truxillo et al. (2015) provide a review of literature related to the aging workforce and propose recommendations for future intervention research to address challenges. The authors indicate there are five types of changes that take place within individuals as they age, and these changes in turn impact the workplace. Changes in cognition have already been covered in this review. Physical changes relate to the aging body and include reduced ability to see and hear, increased likelihood of illness, and longer recovery times from things that stress the body. Affective changes are positive for older workers, with increased positive emotions and less perceived stress. Personality changes are also positive, with increased conscientiousness and agreeableness. Finally, changes in motivation are noted. This discussion includes, but is not limited to, motivation to participate in training. The authors note that older workers are more inclined to intrinsic motivation and show more interest in helping others. Therefore, they suggest taking individual motivational changes into account in designing training by emphasizing the intrinsic benefits of training.

Truxillo et al. (2015) recommend training that incorporates a life-span development theory called Selection, Optimization, and Compensation (SOC) Theory. SOC was proposed by Baltes and Baltes in a 1990 book about successful aging. Selection suggests that a person should be selective about goals, redirecting all resources to achievement of whatever is most important. Optimization is the process through which the individual focuses attention and resources on the manageable number of goals. Compensation is a process through which someone attempts to replace losses with identifiable gains. Truxillo et al. (2015) suggest that workplace training should help the older worker prioritize goals in order to enact this theory. Fisher et al. (2017) provide examples of changes to workplace training aligning to SOC. According to the authors,

allowing more time for training is an optimization strategy, and recording training so that people can go back and take notes at their pace is a compensation strategy.

Given the longer working lives of Baby Boomers described in Chapter One, designing training for older workers has become a popular topic in recent literature. Indeed, according to Taylor and Bisson (2020), “firms that understand the value of training older workers and are able to properly train and retrain this older workforce will hold a competitive edge” (p. 2). Taylor and Bisson (2020) and Kraiger (2017) provide similar discussions of how cognition changes with age and suggest ways to improve training for older trainees. Both resources note the impacts of reduced fluid abilities for older workers. Older workers have slower cognitive processing speed, reduced working memory capacity (increased difficulty with complex tasks); and problems with attention (older workers are more easily distracted and less able to divide their attention between tasks). Since businesses tend to invest in training when new skills are needed, the older worker’s ability to draw on previous experience (crystallized abilities) may be reduced, and the potential for them to struggle in training increases. Common suggestions from these authors and others to improve the training experience of older workers are synthesized in Table 2.

Kraiger (2017) notes a disagreement between scholars about whether training should be tailored specifically to older workers. Some argue the emphasis should be on creating stronger training for all participants. Kraiger lands in the middle, suggesting that training should be designed with all in mind, but that small changes specifically addressing the needs of the older worker could be included in delivery if many older participants are expected. The author suggests that some of the strategies in Table 2 could be effective as pre-training interventions for older workers. Topics to cover before training might include why the workers were selected for training, why the training is important, how it will benefit the worker and others in the

organization, and what to expect during training. When appropriate, the older worker should be provided with pre-work to recap foundational knowledge that will not be covered in the training or to practice with software that will be utilized in training.

Table 2

Common Strategies to Improve Training Outcomes for Older Workers

Strategy	*Suggested in*
Allow additional time for training	Kraiger, 2017; Taylor & Bisson, 2020; Truxillo et al., 2015
Allow self-paced training (through e-learning or on-the-job-learning, for example)	Czaja & Sharit, 2013; Jeske et al., 2015; Kraiger, 2017; Taylor & Bisson, 2020; Truxillo et al., 2015
Emphasize learning goals (over performance goals)	Setti et al., 2015; Truxillo et al., 2015
Provide memory aids (summaries of important points, for example)	Czaja & Sharit, 2013; Taylor & Bisson, 2020
Allow time for repetition and practice (learning-by-doing)	Czaja & Sharit, 2013; Kraiger, 2017; Taylor & Bisson, 2020
Use multiple, shorter training sessions instead of training days	Kraiger, 2017; Taylor & Bisson, 2020
Provide an overview of the purpose and goals of training	Czaja & Sharit, 2013; Kraiger, 2017; Taylor & Bisson, 2020
Provide summaries throughout training, continuing to emphasize purpose and goals of training	Kraiger, 2017; Taylor & Bisson, 2020
Highlight critical information and reduce overall content	Czaja & Sharit, 2013; Taylor & Bisson, 2020
Emphasize the intrinsic value of training	Kraiger, 2017; Truxillo et al., 2015
Use real examples from the job to increase transferability; relate training to prior experience	Jeske et al., 2015; Kraiger, 2017
Utilize recordings of tasks being modeled and/or record sessions so that people can review the content again, later	Fisher et al., 2017; Kraiger, 2017

Jeske et al. (2017) share the view that pre-training interventions may be useful. They specifically suggest pre-training assessment to determine workers' readiness to participate in training. This way those workers who need to build skills in order to participate effectively in training can be identified and given the help they need. The authors emphasize that both individual and organizational factors impact the training performance of older workers. As

individuals, older workers' success in training can be impacted by whether they have any prior experience with the training topic, whether they believe they can learn and change, and whether they engage in help-seeking behaviors. Organizations can enhance the performance of older workers. The authors emphasize the importance of a supportive learning culture in the organization and note the potential for increasing attendance through engaging older workers in planning the training (participative design) and by empowering them to choose whether to attend training.

Similarly, in an earlier work, Jeske and Stamov Roβnagel (2015) suggest that organizations allow older workers to self-regulate their learning, setting their own learning goals and assuming responsibility for monitoring their learning progress. They also suggest that an even stronger strategy might be to have workers design their own learning models, not only setting goals, but reflecting about what facilitates their learning and identifying resources for learning that align with what works best for them as individuals.

As we have seen, many authors have suggested specific learning strategies for older workers intended to increase their attendance and/or success in training. Ultimately, the question is, do these suggestions work? Lopina et al. (2019) tested the appeal of some of these strategies to older workers. They conducted an experiment to determine whether age and the way training opportunities were presented to potential participants (129 faculty members at a public university in the U.S.) impacted motivation to participate. Their study uses a policy-capturing design which presents participants with multiple scenarios and then captures their decision-making patterns as they respond.

Consistent with the recommendations of Setti et al. (2015) regarding goal orientation, Jeske et al. (2017) regarding time control, and Truxillo et al. (2015) regarding emphasizing

generativity and the use of SOC Theory, Lopina et al. (2019) hypothesized that older workers would respond more positively to training that was self-paced and focused on generativity, preventing loss of skill (as opposed to gaining new skills), and mastery (over performance) goals. They found that age was related to the training topic, but in an unexpected turn, the relationship was opposite of what had been hypothesized. Older faculty preferred to learn about instructional technology over service learning (the generativity topic). However, upon further investigation, neither topic had been rated by participants as relevant to their work. When the authors controlled for relevance in the model, the relationship between age and topic became insignificant, and none of the other hypotheses were supported. Interest in training topics did not vary by age. For example, most participants (not just older participants) indicated a higher likelihood to attend mastery-oriented training. The authors postulate that the sample could have impacted the outcomes of this study. Faculty might be less susceptible to losses in fluid intelligence due to the nature of their working environment. As we saw in the overview of nonformal and informal learning, this highlights the need to be mindful of the work environment as we consider specific training strategies for older workers. Older workers may have certain commonalities, but they are not a homogenous group. What motivates them to attend training could vary by the setting in which that training is offered.

What about the perceptions of workers who actually attend trainings using these older-worker-friendly formats? A recent article by Zwick (2015) reports how age impacted perceived training effectiveness as reported by 6,349 employees from approximately 150 organizations in Germany. Measures of effectiveness included, “professional productivity, adaptation to new professional challenges, promotion chances, earnings, job security, professional new orientation (employer change, new profession/occupation, self-employment)” (p. 141). Based on a review

of changes in motivation and type of intelligence as previously discussed, the author hypothesized older workers would rate training as more effective if it was, “time flexible” (p. 139), immediately applicable to real problems, and if the training was on a topic where crystallized abilities could be utilized.

Interestingly, Zwick (2015) found no significant differences between age groups regarding total trainings attended or total training time in the last year before data collection. Similarly, satisfaction with training was rated the same between groups regardless of training topic or format. There were, however, significant differences between age groups on all ratings of training effectiveness. Older workers rated seminars as less effective but found on-the-job training and “self-managed learning” (p. 143) to be as effective as younger workers. Problematically, older workers were significantly less likely to receive on-the-job training. Information technology and technical training were rated as less effective by older workers, but communication and management training ratings were similar between groups. The author notes that gender and health moderate these relationships, with greater significance for healthy people and men.

Older workers in Zwick’s (2015) study were defined as those born in 1951 or before, which includes only the oldest third of the Baby Boom generation. Some care is, therefore, warranted in considering implications of these findings to the current study. Nevertheless, it is noteworthy that an informal learning format (self-managed learning) rose to prominence in effectiveness for this group.

It is also worth pointing out that this entire discussion about training formats for older workers has generally omitted informal strategies. In fact, I only located one study specifically addressing the impacts of informal learning among older workers. Warhurst and Black (2015)

studied ten middle managers over age 50 in the United Kingdom to determine their, “extent and nature of learning” (p. 458). Managers in the study came from both the private and the public sector. Findings cover older managers’ motivation to learn as well as their sources for learning. The managers reported a sense of needing to assume responsibility for their own learning and noted that contemporary managers need to adopt a continuous learning mindset. As previously noted, the managers largely did not participate in training and blamed the lack of training opportunity on economic conditions. Instead, managers turned to informal and social learning strategies. The authors note the managers relied heavily on experiential learning and reflection. Interestingly, the authors attribute the “reflective disposition” of the managers to the fact that they were later in their careers. This suggests that greater capacity for reflection may be an additional positive quality of older workers.

Warhurst and Black (2015) report, “virtually, all participants were experiencing substantial learning as a result of workplace changes” (p. 464). Changes in a manager’s responsibilities, for example, prompted learning from challenging tasks and problem solving—two of the most frequent sources of learning reported in the study. For managers in this study, learning was also a social process. The most frequent sources of social learning reported by the managers were informal mentoring and role modeling from senior managers, networking with colleagues, and learning from other team members.

To summarize, then, training strategies for older workers are a topic of much discussion in recent literature. Engagement in training is expected to increase if older workers are given the opportunity to help design training (Jeske et al., 2017) and set and monitor their own learning goals (Jeske & Stamov Roβnagel, 2013). Before participating in training, older workers could benefit from readiness assessment (Jeske et al., 2017) and from receiving content in advance

providing the purpose and goals of training and a review of background concepts (Kraiger, 2017). During training, timing is thought to be especially important, with recommendations in the literature to either allow total self-pacing or at least additional time for older workers (Jeske et al., 2015; Kraiger, 2017; Taylor & Bisson, 2020; Truxillo et al., 2015). In recent literature, these ideas fell short in motivating older workers to voluntarily attend training (Lopina et al.,2019), but did impact perceived effectiveness of training for workers who attended (Zwick, 2015). Training, however, is neither the only source of learning for these workers, nor should we assume it is the most effective learning format. As seen in Warhurst and Black's (2015) study, sometimes training is not even available as a learning strategy for workers. Although Warhurst and Black had a very small sample, the extent of informal learning through networking and other social encounters is noteworthy. The present study could help fill a significant gap in the literature by providing evidence about whether informal strategies like these are associated with gains in technology competency for older workers. Precisely as Marsick and Watkins (1990) have advocated, it could be that this conversation needs to shift away from training minutiae to a focus on creating opportunities for learning about technology to emerge more naturally in our workplaces.

Big Picture Outcomes of Older Workers' Participation in Learning

The final theme apparent in the literature on workplace learning and the older worker pertains to big picture outcomes of older workers' participation in learning. In other words, what impacts beyond skill mastery are evident when older workers participate in nonformal or informal learning activities? In 2015, Cummins et al. used 2012 PIAAC data, "to examine the relationship in the U.S. between participation in AET [adult education and training] programs and employment, labor force participation, income, and net worth for adults aged 45 to 65" (p.

1). Overall participation rates in formal and nonformal education in the U.S., “were 55.8% and 50.4% for the respective age groups [45-54 and 55-65]” (p. 10). Participation rates in nonformal and informal workplace learning are described for Baby Boomers in this study in Chapter Four.

Chapter One introduced the ways society benefits from the longer working lives of Baby Boomers. Importantly, Cummins et al. (2015) found, “there was a significant relationship between participation in all categories of AET and employment status for the 55 to 65 age group, but none in any AET category for the 45 to 54 age group” (p. 12). After age 55, if the goal is to maintain the employment of older workers, then participation in adult education and training (formal and/or nonformal learning) becomes important. Females were less likely than males to remain employed after participating in AET. Those males who participated in AET, though, also improved their log odds of moving up an income quintile, which prompted the authors to reinforce the importance of making training opportunities available to those in low income groups.

In a similar study, Berg et al. (2017) used data from the German Institute for Employment Research to study, “the relationship between employer-provided training and the retention and wages of older workers” (p. 496). Older workers in this study were those between age 50-65. In the literature review, the authors establish that training specifically targeted at and designed for older workers is more effective for them. In their survey, then, they distinguish between training targeted to older workers and standard training and examine the impact of both on worker retention. Overall, the authors found that companies that employ larger numbers of workers were also more likely to offer training and higher wages. The authors conclude, “training establishments may be better places to work overall” (p. 502).

Although Berg et al. (2017) did not find a relationship overall between training participation and retirement, the probability of delayed retirement (established at the outset of the article as a desirable outcome) among older female workers increased when the organization offered training targeted to older workers. This difference was the most significant among women whose wages were in the bottom 20th percentile.

Interest in big picture outcomes of learning participation extends beyond employment. Jenkins and Mostafa (2015) sought to determine whether participation in different types of learning activities was associated with higher wellbeing among adults age 50 or older in England. Wellbeing was measured using Wiggins et al.'s (2008) CASP-19 quality of life index. The CASP-19 asks 19 questions categorized into four areas: control (c) over one's environment; autonomy (a), which is the ability to do the things you want to do; self-realization (s), which is a sense of satisfaction and optimism for the future; and pleasure (p), or enjoyment of life. One overall score is awarded. There were four measures of learning which Jenkins and Mostafa categorized into formal (seeking a qualification or attending training) and informal (membership in an educational group or in fitness classes). Participation in training had no impact on wellbeing, but "the findings show strong evidence that both music/art groups or evening classes and gym/exercise classes and sports clubs had a positive and significant impact on wellbeing" (p. 2061). Females were more inclined to participate in informal learning activities. The authors note a decline in wellbeing over the four time periods measured, but informal learning generally prevented the decline for participants.

As we saw with training effectiveness (Zwick, 2015), gender is an important moderator in the relationship between training participation and outcomes. In the U.S., older males were more likely to remain employed and raise their income after participating in adult education

(Cummins et al., 2015). In Germany, however, when organizations offered training that accommodated the needs of older workers, it was the female employees who were more likely to delay retirement (Berg et al., 2017). Older females in England were more likely to participate in informal learning opportunities such as art groups, and participants in these activities were found to have higher quality of life (Jenkins & Mostafa, 2015). These differences in learning outcomes by gender reinforce the need to engage gender as a control variable in the present study when its main effects are not being investigated.

Summary

Development of the older worker is clearly a complex subject. Figure 2 captures some of the factors influencing training participation and training outcomes of older workers. Of many key influences, it is important to note that stereotypes are the only factor with the potential to directly influence both older workers' participation in training and the outcomes of training for these workers. In the current study, the threat of stereotypes influencing the way workers are assessed is removed because PIAAC is a standardized assessment—there is no discretion involved in assigning scores. However, the findings of McCausland et al. (2015) should be kept in mind as development professionals consider ways to facilitate learning about technology for older workers.

Motivation to learn is a key factor in determining training participation among older workers (Yamashita et al., 2019), and has been shown to be lower among older adults (Roessger et al., 2020). There is some evidence that a workplace can influence older workers' motivation to learn through by emphasizing learning goals (Setti et al., 2015) and the intrinsic benefits of training (Truxillo et al., 2015). More research is called for in this area, though, because Lopina et

al. (2019) demonstrated that significant differences in training motivation between generations are not present in all settings.

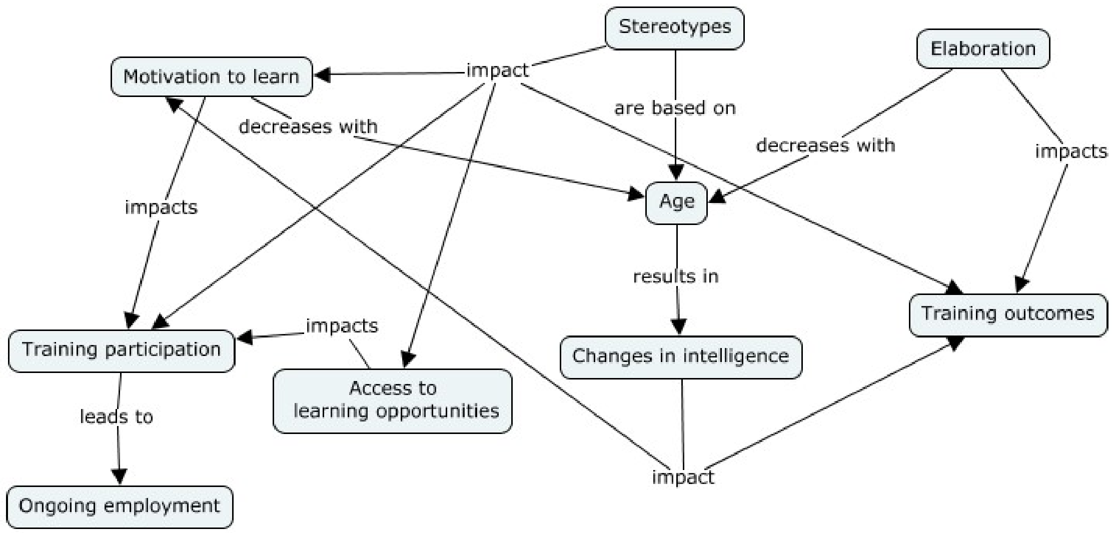


Figure 2: Factors Influencing Training Participation and Training Outcomes of Older Workers

Changes in intelligence over the lifespan impact both workers' motivation to learn new skills and the success of learning interventions in some training environments (Salthouse, 2012). This known problem has recently resulted in a great deal of literature on improving training outcomes for older workers, and may be especially important to consider in situations where workplace training is needed to increase technology competency (Kanfer & Ackerman, 2004; Salthouse, 2012). Let us turn now to a review of literature that enables a fuller understanding of the complex relationship between older workers and technology.

Older Workers in Technology-Rich Environments

Becker (2019) writes that Baby Boomers are, "digital immigrants; they came to age in a time when fax machines were the fastest way to transmit documents. When they were in the workplace they went from typewriters to word processors and computers" (p. 30). The adjustment of Baby Boomers to technology in the workplace interested researchers and has been

studied extensively since the 1990s. A review of the last five years of literature in this area resulted in the identification of four overarching themes. First, several large studies consider differences between age groups regarding attitudes and use of technology. Second, an extensive literature utilizing the Unified Theory of Acceptance and Use of Technology (UTAUT) by Venkatesh et al. (2003) was identified. The model is reviewed, and a few selected studies using UTAUT are presented. Third, some current literature considers how these trends impact the daily working practices of older workers. Finally, two studies explore the impact of technostress on older workers.

Attitudes and Use of Technology Across the Lifespan

A large, frequently cited early study in age and technology adoption was done by Czaja et al. in 2006. The purpose of their study was to explore the relationships between multiple variables—age, education, attitude, and cognitive ability—and use of technology among a large sample of 1,204 people between age 18-91 in the U.S. Participants were divided into three groups: those aged 18-39, 40-59, and 60-91. The article does not state when data were collected but, given the publication date, Baby Boomers were most likely largely represented in the middle age group reported.

As you may recall from Salthouse (2012), fluid intelligence tends to decline as we age, whereas crystalized intelligence continues to increase. Fluid intelligence impacts one's ability to learn new skills. This lead Czaja et al. (2006) to hypothesize, "the relationship between age and technology adoption would be mediated by cognitive abilities" (p. 334). Their findings confirm a positive relationship between fluid intelligence and technology adoption. The authors found, "younger adults performed better than did the middle-aged adults, who performed better than did the older adults, on the perceptual speed, memory, fluid intelligence, and psychomotor speed

factors" (p. 337). Older adults, however, outperformed the other two groups on measures of crystalized intelligence.

Across all age groups in Czaja et al.'s (2006) study, gender impacted computer anxiety and attitude. Women "reported higher computer anxiety, lower computer self-efficacy, lower general computer attitudes, and less interest in computers than did men" (p. 339). Interestingly, women in the youngest and oldest age groups also had less computer experience, but this was not true for the middle age group. Several trends are ultimately noted in technology use, with younger, better educated people who have less computer anxiety being more likely to report general technology use, computer use, and Web use. Race is noted to impact all these trends, with African Americans using less types of technology, having less experience with computers, and having less experience with the Web.

It is only a small mention in the article, but (due to the focus of the present study on learning and technology competency) it is worth noting that Czaja et al. (2006) also asked participants how they learned to use the Web. Only 19% of all respondents indicated they learned to use the Web by attending a class. Among middle-aged participants, 70% indicated learning to use the Web through trial and error. Unfortunately, we do not know whether the informal trial and error method was more successful in terms of outcomes compared to the nonformal, in-class method.

Usually technology acceptance is treated as an outcome variable, but Elias et al. (2012) turned this around by asking how technology acceptance impacts motivation and job satisfaction. The authors collected data from two generations, Gen X and Baby Boomers, via the 1997 International Social Survey Program; 612 U.S. employees were in the sample. The authors found that age acts as a moderator in the relationship between attitude toward technology and

motivation at work. For example, those age 44 or greater who had positive attitudes toward technology enjoyed the highest overall job satisfaction while those who had a low attitude toward technology had the lowest overall job satisfaction. Offering support to the suggestion of Truxillo et al. (2015) to emphasize the intrinsic value of training, age in Elias et al.'s study was negatively related to extrinsic motivation.

Noting a disagreement in the literature regarding whether age was positively related, negatively related, or unrelated to technology acceptance, Hauk et al. (2018) completed a meta-analysis of quantitative studies that used Davis's (1989) Technology Acceptance Model. Although their search yielded over 6,000 articles, after exclusion criteria were applied, 144 studies were included in the analysis. As hypothesized, older adults in the studies found technology less easy to use. Importantly, though, the perceived usefulness of technology by older people varied by the type of technology. The authors emphasize "the importance of considering the type of technology as a boundary condition for the negative association between age and technology acceptance" (p. 311). Age was negatively related to growth-related technologies such as those that improve workplace efficiency. The authors note that technologies facilitative of successful aging, however, are perceived as useful by older people. Just as Truxillo et al. (2015) recommended that training incorporate SOC Theory, Hauk et al. suggest that technology which embraces the tenants of this theory will be adopted by older adults. The authors suggest that workplaces focus on interventions such as special training opportunities that address older workers' ease of use perceptions.

Most recently, using a sample of 3,917 adults from age 18-98, Lee et al. (2019) set out to learn more about individual differences in attitude toward computers. The authors found that males and people who had higher levels of education and computer experience showed

significantly more interest in computers, computer efficacy, and computer comfort than other participants. Interestingly, greater interest levels and efficacy for males decreased in later age groups. Also of importance, younger people reported significantly higher computer efficacy and comfort with computers, but not significantly more interest in computers. Finally, race impacted these relationships, but in different ways than we saw in the earlier study by Czaja et al. (2006). In Lee et al.'s study, African Americans reported significantly more interest in computers, computer efficacy, and computer comfort than Caucasians.

Broadly speaking, then, we can tell from these studies that younger people outperform older people on measures of fluid intelligence and are more likely to use computers and other technology (Czaja et al., 2006). Across age groups, women experience higher computer anxiety, lower computer self-efficacy, lower general attitudes toward computers, and less interest in computers (Czaja et al., 2006). There may, however, be reason to believe that the strength of these trends decreases in later age (Lee et al., 2019), which reiterates the importance of exploring gender as a moderator in the present study. Additionally, we have evidence from previous large-scale studies that race can impact computer interest and experience (Czaja et al., 2006; Lee et al., 2019). Race is, therefore, used as a control variable in this study. For additional evidence regarding the roles of age and gender on technology acceptance, let us turn now to studies that use UTAUT as a theoretical frame.

Unified Theory of Acceptance and Use of Technology (UTAUT) and UTAUT Studies

Venkatesh et al. (2003) built UTAUT based on eight previous models of technology acceptance including Davis's (1989) Technology Acceptance Model. The authors noted that the presence of so many competing models for understanding acceptance of new technologies was creating confusion for researchers. They identified similarities between the models and created

and validated UTAUT which outperformed all the models on which it was based. In their initial tests, UTAUT accounted for 70% of the variance in individuals' intention to use new technology.

UTAUT (Venkatesh et al., 2003) proposes that four elements impact a person's intent to adopt technology or its actual adoption. Determinants are:

- Performance expectancy: "the degree to which an individual believes that using the system will help him or her to attain gains in job performance" (p. 447).
- Effort expectancy: "the degree of ease associated with the use of the system" (p. 450).
- Social influence: "the degree to which an individual perceives that important others believe he or she should use the new system" (p. 451).
- Facilitating conditions: "the degree to which an individual believes that an organizational and technical infrastructure exists to support use of the system" (p. 453).

Performance expectancy, effort expectancy, and social influence impact a person's intent to adopt technology (which in turn influences its actual adoption), whereas facilitating conditions directly impact the actual adoption of technology. These relationships are, however, moderated, with different groups having different outcomes. Age, gender, years of work experience, and voluntary use (can the individual decide to use the technology?) are the moderators, with each impacting different determinants/outcome relationships. For performance expectancy, Venkatesh et al. (2003) found that the model demonstrated stronger effects for men and younger workers. For effort expectancy, social influence, and facilitating conditions, stronger effects were found for older workers, with effort expectancy and social influence also having stronger effects for women.

UTAUT is important in this study because it is the foundation of a great deal of research testing the assumption that age and gender impact technology adoption. A recent review by

Williams et al. (2015) identified 174 articles using UTAUT from 2004-2011. The authors classified articles into four types of technology systems, with 52% being about general systems such as personal computers, Windows, the Internet, etc. Specialized business systems, many from the medical field, were the second most examined (28%), followed by communication systems (14%, many studies involving mobile phones). Office systems, such as remote desktop applications, were the least common at 6%. Most studies were cross-sectional, prompting the authors to call for more longitudinal research using UTAUT. The authors also performed a weight analysis to identify the best predictors of technology use, defined as those with a weight of 0.80 or more. Only two predictors met this criteria, performance expectancy and behavioral intention. Social influence came close at 0.74. The authors call for more research on the performance of the relationships within the model. To pick up where Williams et al. left off, highlights from several studies conducted since 2012 are covered in Table 3.

A quick review of the findings of these selected studies supports the call by Williams et al. (2015) for more research on the relationships proposed in UTAUT. The main effects generally seem reliable, but the moderators are less so. Each of these five studies (Afonso et al., 2012; Alkhasawneh & Alanazy, 2015; Bawack & Kala Kamdjoug, 2018; Moryson & Moeser, 2016; Šumak & Šorgo, 2016) reports moderation effects on fewer relationships than anticipated by the model. Two recent studies using UTAUT have been selected to discuss in greater detail given their relevance to the present study. Let us see how the expectations of the Theory hold up in these examples.

Table 3

Overview of Selected Empirical Workplace Studies Using UTAUT

Author(s), Year	*Purpose*	*Salient Points*
Afonso et al., 2012	“Testing the moderating effects of Gender on the UTAUT model in a study on users of EDMS [electronic document management system] in Portuguese municipalities” (p. 2).	N = 2,715 Only one relationship reached significance. Performance expectancy had a stronger positive effect on intention to use EDMS for men than for women.
Alkhasawneh & Alanazy, 2015	“This study examined factors affecting the behavioral intention to use ICT [information and communication technology] among academic staff at Al Jouf University” (p. 490).	N = 60, sample includes people up to age 59 The authors found positive correlations between the four main effects and intention to use ICT, but no significance by age or gender.
Bawack & Kala Kamdjoug, 2018	“Investigating the adequacy of UTAUT in determining factors that influence the adoption of HIS [health information systems] by clinicians in developing countries, based on the case of Cameroon” (p. 15).	N = 228 The authors note the UTAUT model performed poorly in this context, but younger clinicians were more likely to adopt the health information system than older clinicians.
Moryson & Moeser, 2016	“To better understand the adoption criteria of German cloud computing users” (p. 15).	N = 1047, sample includes people aged 14-64 All direct measures of UTAUT were fully supported, but there was less support for moderators. Regarding gender, the effect of performance expectancy was significantly stronger among women, whereas the effect of effort expectancy was stronger among men. Age only moderated the effect of facilitating conditions, leading the authors to suggest, “related to the UTAUT core model there seems to be less need to divide consumers based on age” (p. 28). They do, however, note the need for older users to receive facilitative aids such as knowledge resources.

Table 3 (Cont.)

Author(s), Year	*Purpose*	*Salient Points*
Šumak & Šorgo, 2016	"To investigate differences in the UTAUT determinants between pre- and post-adopters of IWBs [interactive whiteboards]" (p. 602).	N = 898, sample includes people aged less than 25 to over 54 The authors were interested in how teachers who used interactive whiteboards differed from teachers who do not use interactive whiteboards in terms of UTAUT. The authors found several significant differences between groups for main effects. For example, the effect of facilitating conditions on behavioral intention was stronger among people who use interactive whiteboards. However, only partial support was found for moderators. For example, the effect of performance expectancy on intention to use interactive whiteboards was, "stronger for male, younger pre-adopters [non-users]. Stronger for male, older post-adopters [users]" (p. 615).

Magsamen-Conrad et al. (2015) surveyed 899 people between the ages of 19-99 regarding their intention to use tablets. Of especial relevance to the present study, the authors divided respondents by generations, and Baby Boomers made up 36.9% of their total sample. Tablet users reported higher mean scores in the four main determinants of the Model. The authors also found significant mean differences between generations "for effort expectancy, followed by facilitating conditions, with differences between both Builders and Boomers and younger generations" (p. 192). This leads the authors to conclude that age is a moderator of technology use with greater differences being evident between the oldest and youngest generations.

Dutta and Borah (2018) conducted a study to test whether UTAUT moderators hold true among postal workers in India. The authors divided participants into three age groups:

respondents below age 25; respondents aged 25-50; and respondents age 50 and above. The authors do not indicate when data were collected, but it is probable that Indian Baby Boomers would have fallen into the age 50+ category.

Key findings from Dutta and Borah (2018) regarding age are interesting, as they defy many common age-related stereotypes about older workers. Older postal workers in this study were the most likely to welcome IT-related changes in the workplace and, “greatly believe that IT has improved their work performance” (p. 392). Anxiety and attitude about IT were not significant between age groups, and the only area where younger workers fared more positively was in their confidence to learn and adopt new technologies. However, years of experience in postal work adds some interesting flavor to the findings regarding age. The authors found that, while older workers were more likely to welcome IT changes, those with more years of work experience also felt higher anxiety about working with information technology. The authors also confirmed the moderating role of gender, finding that males were more confident in their ability to learn new technology and expressed more positive attitudes about technology, whereas females were more ready to embrace technological change. As with age, anxiety about technology did not vary by gender.

It seems fair to conclude, then, that despite efforts by to Venkatesh et al. (2003) to unify and clarify the variables impacting individuals’ acceptance of technology, the reality of these relationships is still somewhat murky. Although evidence is, in some cases, clear that age impacts technology adoption (Bawack & Kala Kamdjoug, 2018; Magsamen-Conrad et al., 2015) occasionally a study either yields surprising findings as in Dutta and Borah’s (2018) study of postal workers, or age simply has no impact as in Alkhasawneh and Alanazy’s (2015) study of academic staff. As with age, one cannot say based on these studies that males (or females)

always have greater technology acceptance. It varies, in some cases even within the same measure as seen in differences between users and non-users of interactive whiteboards in Šumak & Šorgo's (2016) study. UTAUT is not, however, the only way to study older workers and technology acceptance. Let us turn now to articles that examine more closely the daily decisions of older workers regarding use of technology in their workplaces.

Everyday Decisions of Older Workers Regarding Use of Technology

Everyday decisions regarding technology in the workplace might entail whether a worker uses a computer at work, whether a worker uses technology to facilitate communication, or whether a worker utilizes technology during a meeting. Fernández-de-Álava et al. (2017) used the PIAAC background questionnaire to examine generational differences in the use of different computer applications in Spanish workplaces. They used 2012 PIAAC data and categorized respondents into three groups: digital natives (age 16-32 in PIAAC), digital immigrants (age 33-45 in PIAAC), and a new construct they created and labeled "pre-digital immigrants" (p. 124), who were age 46-65 in PIAAC. Digital natives are those for whom computer technology has been part of the educational process. Digital immigrants are those, "who were born before the digital age and had to adapt" (p. 124). Pre-digital immigrants are those for whom, "partial onset of technology arrived with their descendants and often led them to adapt to ICTs [information and communication technologies] subsequently" (p. 124). The authors note that, in Spain, 2012 PIAAC data were collected from 2011-2012. Spanish Baby Boomers, therefore, would have been between age 47-66 at the time of data collection, placing them in the pre-digital immigrant group.

Interestingly, in the study by Fernández-de-Álava et al. (2017), Baby Boomers were found to use email and word processors more frequently than the younger age group. Only

49.9% of the Baby Boomers reported using a computer at work, but this is perhaps not astonishing since only 58.5% of digital immigrants used them. Similarly, 48% of Baby Boomers reported needing only basic computer skills to do their jobs, but 15.4% indicate they, "need more knowledge on computer tools to perform their jobs" (p. 129). Although they report needing more computer knowledge, they also report that lack of knowledge has not hindered their careers. The authors point this out as a key incongruence discovered in the study because it is difficult to get people to see the value in learning if the decision not to learn does not have negative consequences. Knowing whether U.S. Baby Boomers experience the same incongruence would be useful when considering implications of this study in Chapter Five. Therefore, average responses from Baby Boomers in this study are reported in Chapter Four for the following questions from the PIAAC background questionnaire:

- G_Q07: Do you think you have the computer skills you need to do your job well?
- G_Q08: Has a lack of computer skills affected your chances of being hired for a job or getting a promotion or pay raise?

Although, in Spain, Baby Boomers were more frequent users of email than younger generations (Fernández-de-Álava et al., 2017) there is reason to believe this tendency could vary by country or culture. In India, Singh (2014) engaged older employees in the oil and gas sectors in a qualitative study to learn about participants' attitudes regarding using technology for communication. Singh spoke with thirty employees whose mean age was 52. Participants reported ability to use technology to communicate, but preferred face-to-face communication so they could visualize body language, etc. They also, however, noted the benefits of technology for communicating urgent messages. It seems from Singh's study, then, that even the unique context

of a specific relationship or situation in the workplace could influence an older worker's decision to utilize technology.

In the modern workplace, though, communication technologies extend far beyond email. Jarrahi and Eshraghi (2019) recently interviewed 58 workers from management consulting firms about communication practices. They wanted to know if there were generational differences in ways workers used technology to share knowledge and communicate. Their article does not specify where the consulting firms were located, but the authors are from universities in the United States and Australia. The authors only explored two groups, digital natives (born after 1980) and digital immigrants (born before 1980). It is unspecified whether any Baby Boomers were interviewed as digital immigrants, but it would be unusual for them not to be. In addition to interviews, the authors connected with their participants on LinkedIn and Twitter to observe the use of these sites for knowledge-sharing. The authors discovered generational differences in how technology was used to share knowledge.

Key findings from Jarrahi and Eshraghi (2019) indicate digital natives in the study were more likely to connect with coworkers through social networks such as Facebook and more likely to utilize tools like instant messaging to facilitate communication in the workplace. The authors indicate a major difference between digital natives and digital immigrants, "may revolve around the applicability of social technologies for work-related knowledge practices. For older knowledge workers, face-to-face interactions are seen as a more preferential mode of social interaction" (p. 1057). When face-to-face interactions are not practical, digital immigrants were more likely to turn to phone or email to facilitate learning.

Finally, Sox et al. (2016) used a partial least squares analysis to study generational differences in workers' use of technology during meetings. The authors used online

crowdsourcing to obtain survey responses. From 431 completed surveys, the authors randomly selected participants in order to ensure equal representation of respondents for each generation (Baby Boomers, Generation X, and Generation Y) to yield a total of 420 responses. Respondents were disproportionately male (63.5%), and mostly from the United States (64.4%) and India (32.7%). The authors utilized a novel theoretical framework, combining Generational Cohort Theory with the Technology Acceptance Model. According to Generational Cohort Theory, a generation is influenced by events that occurred during their formative years of upbringing. The authors asked participants which of several influences (friends, family values, society values) from their formative years influenced their “behavior toward the use of technology within meetings today” (p. 168). For each generation measured, the authors found that these formative items significantly influenced perceived usefulness and ease of use of technology within meetings, as well as attitude toward technology, intention to use technology, and actual use of technology in meetings. Perceived ease of use had a particularly strong significant relationship with generational formative items. Since experiences from formative years are different for each generation, the implication is that one’s generation significantly influences how technology is viewed and utilized in meetings.

As we saw in the UTAUT studies, older workers in these studies are generally found to use technology less than younger generations. This was the case, for example, regarding overall computer use at work in Spain (Fernández-de-Álava et al., 2017), and in communication practices among managers (Jarrahi & Eshraghi, 2019). Taken together, these studies reinforce that there are differences between generations in terms of workplace technology use. Interestingly, older workers in two studies (Jarrahi & Eshraghi, 2019; Singh, 2014) preferred

face-to-face interactions in the workplace, a trend which could conceivably impact learning preferences as well.

Technostress and Older Workers

Although only two studies are included in this final category, it introduces an important lens beyond technology acceptance through which to view the relationship of older workers and technology. Berg-Beckhoff et al. (2017) and Hauk et al. (2019) studied a concept called technostress. Hauk et al. say, "technostress refers to perceived threatening situations involving ICTs [information and communication technologies] that may result in technology-related strain" (p. 3). Berg-Beckhoff et al. provide an excellent overview of these threats, emphasizing there are negative psychosocial consequences related to the use of information and communication technologies. For example, while information and communication technology can improve productivity, expectations regarding productivity also increase, sometimes to unhealthy levels. Similarly, while technology improves communication, some employees also experience an unhealthy inability to disconnect from work.

Berg-Beckhoff et al. (2017) establish a lack of clarity regarding the impact of age on these circumstances. They conducted a meta-analysis of quantitative studies to examine whether age modified the association between information communication technology use with stress and burnout. The authors reviewed 42 articles from several countries including the United States. The authors find multiple studies showing that, among all employees, there is a clear relationship between ICT use and burnout. However, older employees—defined as those over the age of 45—were not found to experience *more* stress or burnout than others when using information communication technology. In fact, it is the middle age group (aged 35-45) that suffers the worst impacts of technostress. The authors propose that the life experience of older workers may better

equip them to handle stress. Interestingly, then, the same cognitive changes that make it more difficult for older workers to *learn* technology may also provide a buffer when it comes to widely acknowledged detrimental health impacts of *using* technology.

Building on this idea, Hauk et al. (2019) hypothesized that age would be negatively correlated with technology-related strain and found this to be the case. As age increased, technostress decreased. Their study collected data from 1,216 workers in Germany, Austria, and Switzerland over three cycles to answer the question, "how do workers cope with technostress across the age span in a digitalized work environment?" (p. 2). Also of importance here, based on research connecting aging with improved social skills (similar to the idea of positive personality changes associated with aging as discussed by Truxillo et al., 2015), the authors hypothesized that age would be positively correlated with help-seeking behavior. This was not the case: "social coping decreased as age increased" (p. 10). This is important because informal learning strategies—seeking help from colleagues—are at play in this scenario, and the authors found that as people aged, they were less likely to engage in this type of behavior.

In many of these studies, the same basic stressors associated with losses in fluid intelligence are thought to influence the outcomes. Older workers are less likely to use technology because of losses in fluid intelligence. However, the studies of Berg-Beckhoff et al. (2017) and Hauk et al. (2019) show that, when using technology, gains associated with crystallized intelligence decrease known negative impacts of technology use for these workers. It seems reasonable then that if technology adoption could be increased through better learning interventions for older workers, workplaces could benefit from having older workers more engaged in technology-heavy tasks.

Summary

In their widely cited article on age and use of technology, Czaja et al. (2006) conclude: “Our findings suggest that adoption of technology is a complex issue and is influenced by a variety of factors…people’s choices about using a particular technology cannot be explained solely by their age” (p. 349). Without a doubt, this statement is still applicable today. Based on the discussion in this literature review, Figure 3 demonstrates the multitude of interconnected factors that have been shown to either directly or indirectly (through relationships with other variables) influence technology adoption. For the most part, these can be grouped into demographic variables (age, gender, race, and educational background) and personal traits (interest, attitude, anxiety or comfort, self-efficacy). Two of the traits, computer interest and computer self-efficacy are especially interesting in the context of the present study.

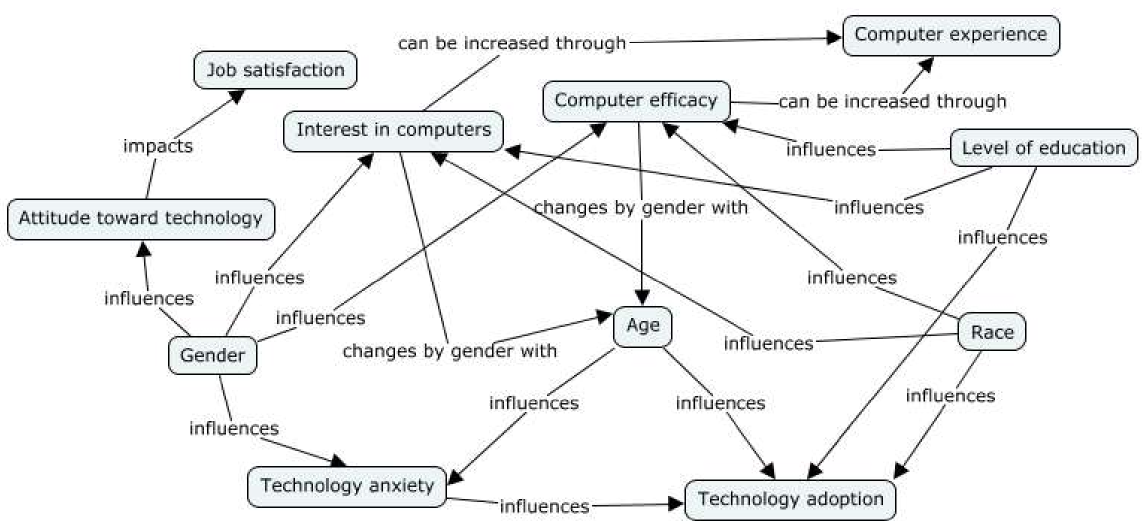


Figure 3: Interconnected Factors Influencing Older Workers in Technology-Rich Environments

Despite a widely acknowledged impact of gender as a moderator influencing technology adoption (Venkatesh et al., 2003), Lee et al. (2019) reported that greater self-efficacy and higher computer interest seen in younger males disappeared in older age. This makes it especially

interesting to determine whether gender moderates the relationship between learning strategies and PS-TRE competency for Baby Boomers. This finding is also important, though, because interest and self-efficacy are two of the factors that can be influenced by something our workplaces can provide: computer experience. As we have seen, organizations might leave workers to self-manage their experience and learning informally, or the experience could be organized by the institution to achieve certain objectives (nonformal learning). Which strategy would be more effective? The next section provides some insight into that question.

Intersections of Workplace Learning and Technology for the Older Worker

So far this literature review has considered the main variables in this study as separate entities. We have reviewed studies addressing workplace learning among older workers, and we have reviewed trends pertaining to older workers and technology. We turn now to a group of studies wherein these variables meet. Studies highlighting the intersection of workplace learning and technology for the older worker tend to fall into three categories. Two categories are somewhat opposite. In some cases, articles discuss learning interventions intended to help employees learn to use technology. This review focused largely on literature from the last five years, and this line of research was largely evident in studies of mentoring. Therefore, a few key historical works and studies of mentoring are reviewed. In another group of studies, authors discuss how technology can be used to facilitate learning and how older workers fare in these technological learning environments. Finally, a couple of articles specifically address informal learning and technology among older workers.

Older Workers Learning to Use Technology

Czaja and Sharit (1998) are key authors in this field, and they conducted an early empirical study on aging and technology use. Participants ranging in age from 20-75 were

trained to complete a data entry task. One noteworthy finding was that all participants were able to perform the task after training, even though most of the older participants had not used computers before. Participants completed the task over a three-day period. Older adults input significantly less data than younger and middle-aged participants, but there were no age group differences in accuracy of input.

Ng and Feldman (2008) serendipitously provide another interesting historical view on this topic. Their meta-analysis looked at ten dimensions of job performance in which it was commonly believed that age had an influence, including performance of older workers in training programs. The authors reviewed studies that had an explicit training intervention followed by post-training performance measures (N = 9,228). Most of the studies reviewed for their meta-analysis were conducted on technology training. The authors found that older workers had slightly lower performance than younger workers following the training intervention. Essentially, the authors inadvertently asked if nonformal workplace learning led to improved skills in technology and found that nonformal education worked slightly better for younger workers than for older workers.

Using a mixed-methods approach involving both questionnaires and focus groups, Lee et al. (2009) set out to learn about the training needs and preferences of older job-seekers. Participants in the study ranged in age from 51-76 and all were seeking employment. The researchers specifically wanted to know what training these older job seekers needed and what training format they preferred. All focus group participants indicated that lack of computer-related skills was one of the biggest obstacles they faced while searching for work. Most participants had worked previously in occupations like truck driving that did not require computer skills. Unsurprisingly, then, computer use was the most requested training topic. Most

participants indicated they would prefer to receive this training in an in-person class so that knowledge could be shared with peers. One-on-one training was also noted as an acceptable training format.

A recent trend in workplace learning worth noting is the use of reverse mentoring to help older employees learn technology skills. An early contributor in the literature on reverse mentoring is Murphy (2012), who proposed a model of reverse mentoring variables and outcomes. Murphy described reverse mentoring as a relationship wherein a junior employee (the mentor) is paired with a senior colleague (the mentee). According to the author, “the purpose is knowledge sharing, with the mentee focused on learning from the mentor’s updated subject or technological expertise and generational perspective. In addition, there is an emphasis on the leadership development of the mentors” (p. 549). Murphy credits Jack Welch, former CEO of General Electric, as the originator of the method, but indicates it has been used in various settings since the late 90s.

Murphy (2012) discusses differences between reverse mentoring and traditional mentoring and emphasizes benefits to both mentor and mentee as well as positive outcomes for the organization when reverse mentoring is utilized. Clearly, two benefits are gains in technology competency (for Baby Boomers) and leadership development (for Millennials). By pairing members of these generations, positive unanticipated outcomes are also evident. For example, increased communication and collaboration between generations might lead to, “new approaches to problems and suggestions for implementing solutions” (p. 556), thereby helping organizations remain competitive in ever-changing landscapes.

Morris (2017) considers several potential benefits of using reverse mentoring in higher education. For example, as a mentor, a student could have both the opportunity to teach and,

"practice leadership skills while gaining insight into the academy as a unique educational and social organization" (p. 286). On the other hand, for faculty, reverse mentoring could enhance teaching as new technology skills are gained and as they gain insight into a younger generation.

As we have seen, motivation to learn is extremely important among older workers. Kaše et al. (2019) studied the motivations in the young mentors and the older mentees in these relationships. The authors were able to survey 457 young mentors and 293 older mentees (mostly retired) during a national, week-long reverse mentoring initiative in a European country. The authors found opposite motivational trends. Young mentors were externally motivated by things like goal attainment. For the older mentees, digital skill development was, "primarily driven by intrinsic motivation" (p. 57), which reinforces the recommendation of Truxillo et al. (2015) to emphasize the intrinsic value of training among older workers.

For those with interest in establishing these programs, Chaudhuri (2019) recently wrote about implementing reverse mentoring programs. The author provides ten key principles for success in these programs. Principles include:

- Programs are more successful if tied to a strategic goal of the organization.
- Organizational culture is important—it must be one that supports learning and innovation.
- Support and involvement of senior leadership sets a good precedent for others to follow.
- Participation should be optional and, "early career high potential top performing employees with strong communication, technical, and social media skills will be ideal candidates for being the reverse mentors" (p. 68).
- Training before and during mentoring is important for both mentors (in communication skills, giving feedback) and mentees (in being good listeners).

- Mentors and mentees should have common interests, and they should not be from the same line of supervision.
- Start with a small number of pairs.
- Typically the relationship lasts for a year with monthly meetings for the first six months. Goals are helpful (indicating a nonformal learning approach to the relationship might be more effective).
- Trust between mentor and mentee is essential.
- Share success stories, especially those of senior leaders who participate.

Satterly et al. (2018), however, return us to a message we have seen before: interventions are not always right for all settings. They propose that intergenerational mentoring is superior to both traditional and reverse mentoring in academia. A problem with reverse mentoring is that it involves only two generations, Baby Boomers and Millennials. This excludes other workers from important learning opportunities. The authors note that intergenerational mentoring is derived from reverse mentoring, but "is based upon the notion that *everyone leads, and everyone learns*" (p. 446, emphasis in original). The authors focus mentoring efforts on the three-legged stool of academic promotion: teaching, service, and research/scholarship. Considering scholarship, for example, the idea is that each generation brings an important contribution from which the others can learn. A Baby Boomer might be well-connected to editors of potential journals. A GenXer is well poised to help develop the research agenda. The Millennial team member might have new ideas regarding researching with technology. Unlike Kaše et al. (2019) who suggest highly structured mentoring relationships, Satterly et al. suggest leaving the relationship flexible so that it can be structured (or not) by each team.

What, then, can we conclude from this series of works about helping older workers increase competency with technology? One thing to point out is a shift in the literature. Far fewer studies involving current employees are starting from scratch (as Czaja and Sharit did in 1998) with people who have not used a computer before. Today, as we see with trends in reverse mentoring, the story is more about keeping up with technological advances. Lee et al.'s (2009) study is a sobering reminder, though, that there are still plenty of people out there in certain professions who need significant development in computer skills.

We also have evidence that nonformal learning approaches—training in workshops or one-on-one—are at least somewhat effective (Czaja & Sharit, 1998; Ng & Feldman, 2008). Notably, while mentoring is clearly the popular topic in current literature for achieving competency gains in this area, none of the studies reviewed tested the outcomes of these relationships. Mentoring is more difficult to categorize as either nonformal or informal, and there are differing opinions about which format is more impactful. Chaudhuri (2019) and Kaše et al. (2019) suggest an organized (nonformal) structure for reverse mentoring, but Satterly et al. (2018) indicate an informal structure would be preferred for intergenerational mentoring among academics. It seems, then, that there is a need to move mentoring discussions beyond concepts into the brass tacks of outcomes measures. Although the current study is not able to specifically identify whether Baby Boomers participated in a mentoring relationship, it does provide fresh insight into nonformal and informal workplace learning participation and how these are associated with technology competency for this generation.

Using Technology to Facilitate Learning

As we have seen, some discussions about learning and technology are focused on improving technological competency. Other studies, however, flip that mindset and consider how

technology might facilitate learning. Charness and Czaja (2018) and Lowell and Morris (2019) provide recent discussions about the use of technology during training involving older workers. In their discussion of technology for work for older workers, Charness and Czaja (2018) suggest ideas for training design that incorporates the unique needs of this population. The authors emphasize that self-paced formats are the preferred training model. Online training is one self-paced format which has the benefits of enabling the learner to control the pace, font size and volume, and to potentially minimize distractions. Sections may be repeated if needed. However, the authors emphasize that learners must have the basic skills needed to utilize this format and that technical support must be provided.

Lowell and Morris (2019) conducted a narrative literature review on "generational attitudes towards learning and technology within professional training" (p. 113). In line with generational theory, the authors propose that the lifelong experiences of a generation impact their preferences at work, including learning preferences. The authors reviewed 70 sources and then described the unique experiences of three generations. The authors describe how these experiences influence each generation's general preferences and experiences regarding learning and technology. Regarding Baby Boomers, the authors point out that Baby Boomers witnessed the introduction of personal computers as adults, and therefore may be less likely than younger generations to embrace or utilize technology. They also say that, in their youth, Baby Boomers generally experienced more lecture as an instructional strategy. The authors propose that this experience will influence Baby Boomers' preference for technology instruction, making nonformal learning through structured training a more effective strategy.

Ultimately, though, to isolate one generation into a training experience may not be practical. Lowell and Morris (2019) focus most of their article on finding ways trainers can

incorporate approaches that appeal to Baby Boomers as well as Gen X and Gen Y. They provide 11 guidelines for designing training for multigenerational learners. A couple of interest here are, "be purposeful when using technology" (p. 127), and, "offer training by generational format and methods if needed" (p. 129). The authors suggest that technology be used during training only if participants are clearly told what value it brings to the experience. They also express that, especially in cases where training involves heavy use of technology, different presentation formats should be offered so that participants can choose whether to attend face-to-face, online, etc. As we have seen previously, other suggestions include emphasizing the value of the training, giving people choices during training, and incorporating flexible timing into training design.

We can see from these authors that online training is, theoretically, a useful strategy for older workers, but it is also important to know how older workers perceive these interventions. Fleming et al. (2017) provide insight into this important question. The authors surveyed workers in the Australian rail industry (N = 979) who had completed at least two e-learning courses. The purpose of their study was, "to examine the factors affecting employees' acceptance and future use of e-learning" (p. 77). Although the authors hypothesized that age would be negatively related to both satisfaction with and future intent to use e-learning, neither of these hypotheses were supported by the data. Factors that were found to positively impact employees' intent to use e-learning in the future included user-friendliness (not perceived to require a lot of effort), the use of real-world situations (authenticity), and the availability of technical support. The authors warn of the dangers of age stereotyping in the workplace, and call for, "a more informed discussion around the learning needs of older workers" (p. 84). It seems, then, that online learning in general is ok for older workers, but what happens when the topic to be learned is also technical in nature?

Two studies were identified wherein technology was used to facilitate learning about technology. Fritzsche et al. (2009) had 51 older adults, ranging in age from 61-91, complete a library training and then complete post training exercises. Although, due to its age, findings from this study should be interpreted cautiously, it is included because it tests the much-lauded (Jeske et al., 2015; Kraiger, 2017; Taylor & Bisson, 2020; Truxillo et al., 2015) concept of self-paced training. The study intended to test the effect of self-paced (in a computer lab) training and stereotype threat on older adults' performance on a library training exercise. In this experimental design, some participants were told that previous research demonstrated a difference in training outcomes related to age, thus introducing a stereotype threat. In an unexpected outcome, this group performed significantly better than the no-threat group on both practice exercises and the post-test, but no support was found to support the hypothesis that self-paced training would improve performance on the subsequent computer-based task.

Taha et al. (2016) developed an interest in testing the efficacy of e-learning (watching recorded videos) to teach Microsoft Excel skills to 35 U.S. job-seekers age 50 or higher. E-learning, the authors contend, is superior to in-class formats because practicing the skills can be incorporated into the learning (as opposed to learned in class and then practiced later), and trainees can set their own pace for training completion. Although only 12 out of 35 participants ultimately performed well on the task, the authors conclude that the training was successful since so many participants started with limited skills. More than 80% of participants reported feeling that the training was beneficial.

It seems, then, that in situations where adequate technical support is provided and older workers have already achieved a baseline technology competency, using technology to deliver training is a promising format. It enables adjustment to cognitive and physical outcomes of aging

(Charness & Czaja, 2018), and workers, at least in certain industries, seem to like it (Fleming et al., 2017). In one study, while the outcome measures were not stellar, both trainers and participants felt like the experience was a success (Taha et al., 2016). While Lowell and Morris (2019) suggest that this might not be the ideal learning strategy for Baby Boomers, they acknowledge the improbability of organizations being able to design training specifically for each generational group represented and note the benefit of self-paced training for older workers.

Informal Learning and Technology Among Older Workers

This section on learning and technology among older workers has considered ways these variables interact for older workers. The section concludes with two studies in which informal learning strategies are the focus. In line with the previous group of studies wherein older workers used technology to learn, Jin et al. (2019) conducted a literature review to learn what theoretical perspectives had been used in studies involving older adults, informal learning, and mobile phone use, and how the devices facilitated informal learning. The authors identified 118 empirical studies published between 2005—2017 that included people over age 50 and that focused on one of three types of informal learning: "self-directed, incidental, or tacit" (p. 122). Tacit learning is defined as both "unintentional and unconscious" (p.121) on the part of the learner. Findings seem largely geared toward retirees but are included here because some studies reviewed included working-age Baby Boomers. Four main frameworks were identified: technology acceptance model or UTAUT; experiential learning theory; social cognitive theory; and activity theory.

Jin et al. (2019) also identified six themes "that characterize older adults' informal learning using mobile devices" (p. 129). First, older adults use mobile devices to seek information related to health. Second, mobile devices were associated with "affective and

emotional dimensions" (p. 131), such as spirituality or mindfulness. Third, the authors note that technical support and awareness of benefits are "preconditions" (p. 131) for older adults to adopt mobile technology. Fourth, certain studies addressed specific practical uses associated with mobile phone use such as using the phone for shopping, transacting, accessing Facebook, etc. Fifth, "both qualitative and quantitative findings showed the value of mobile device use for the social aspects of learning" (p. 132), essentially through online communication tools. Finally, the authors note the potential for "collaborative learning experiences" (p. 132) wherein older adults can share knowledge and resources and form or maintain relationships.

Lopes et al. (2020) took a different approach. These authors developed an interest in understanding, "*the extent to which cooperation/collaboration at work and sharing work-related information, considered here as two distinct activities, are associated with cognitive skills, as measured by the PIAAC 2012/2014 U.S. data set*" (p. 2, emphasis in original). The authors hypothesized that collaborating and sharing information at work would lead to higher competency in the three PIAAC skill domains, literacy, numeracy, and problem solving in technology-rich environments. Although their study did not focus on Baby Boomers, they were included in the U.S. averages reported. The authors used a measure from the PIAAC background questionnaire that asks people how often their jobs involve sharing work related information with coworkers. The present study uses a similar question that asks how often a person learns new work-related things from supervisors or coworkers. Lopes et al. found that, across all industries and levels of education studied, "those who share work-related information once a week or more can expect to have higher literacy, numeracy, and PS-TRE scores" (p. 16). Scores were only significantly higher in certain industries. Nevertheless, consider, for a moment, the implication here for development professionals. Technology competency across all age groups is

higher among people who simply take the time to exchange information—not necessarily even information *about* technology—with their coworkers. By including measures of informal learning, the present study helps capture similar information about the kind of learning environment that facilitates technology competency among Baby Boomers in different settings.

We can easily see how these two works align with the previous categorizations in this section (learning associated with technology, and technology associated with learning).First, using technology can result in different forms of informal learning, as noted in the review of mobile phone use by Jin et al. (2019). At the same time, participating in certain informal learning activities—information-sharing—is associated with greater PS-TRE competency (Lopes et al., 2020). Notably, though, the number of studies considering informal learning and technology competency is small, and studies measuring the relationship between these two variables specifically among Baby Boomers are nonexistent based on the parameters established at the outset of this review. Some of the studies reviewed by Jin et al. fit topically, but the participants are largely retired which places them outside of our present interest. This study helps fill the hole in the literature by addressing the relationship between informal learning and technology competency specifically for older workers.

Summary

Considering all the works herein addressing how the concepts of workplace learning and technology competency interact for older workers, a couple of trends are identified. First, this section was heavier on conceptual works than the other background sections have been. Mentoring especially seems to be an intervention that people are excited about (theorists and participants alike), but we need to know more about the actual gains made as a result of these relationships. Table 4 recaps key takeaways regarding competency gains from the studies

reviewed. Similarly, this is an area where a few names dominate the literature: Sara Czaja, Neil Charness, Joseph Sharit, and Chin Chin Lee are household names in the study of older workers and technology competency. Their work is phenomenal and of tremendous historical value, but a lot of their *current* research pertains to retirees or large-scale studies across multiple age groups. Given that trends in learning preferences change by generations (Lowell & Morris, 2019), there is a need to keep introducing fresh data and results into these discussions. This study fills the need for more current, empirical, large-scale research in workplace learning and technology competency for older workers. To ground the study in a solid theoretical framework for competency development, I turned to the Dreyfus Model of Skill Acquisition.

Table 4

Learning Strategies and Technology Competency: What Works for Older Workers?

Author(s), Year	*Learning Strategy*	*Competency Gains*
Czaja & Sharit, 1998	In-person training	Older adults input less data but were equally accurate in their entries
Ng & Feldman, 2008	Training (format unknown)	Older workers had slightly lower performance than younger workers following training
Murphy, 2012; Chaudhuri, 2019	Reverse mentoring	Reportedly high, but empirical evidence lacking in sources identified for this review
Satterly et al., 2018	Intergenerational mentoring	Reportedly high, but empirical evidence lacking in sources identified for this review
Taha et al., 2016	E-learning (recorded video)	Only 12 of 35 performed well on the task, but more than 80% of participants reported feeling the training was beneficial
Lopes et al., 2020	Informal learning—information sharing	Sharing work-related information at least once/week is associated with higher PS-TRE scores in PIAAC

Theoretical Framework: The Dreyfus Model of Skill Acquisition

One key concept to understand in a study using PIAAC is what is meant by the idea of competency. The OECD (2019b) explains that competency refers to, “the ability or capacity of

an agent to act appropriately in a given situation" (p.17). Whereas many assessments measure the mastery of certain concepts, a competency assessment asks if a person can take his or her knowledge and apply it in various realistic scenarios. Proficiency, then, is not something a person either possesses or lacks, but is instead viewed on a continuum. Some people can demonstrate competency in more challenging or complex scenarios than others, but that does not mean that people who obtain lower scores lack ability—they just are at a different stage of development (OECD, 2019b). Of concern here is the question of which workplace learning strategies are associated with Baby Boomers moving significantly further along on the technology proficiency continuum.

The Dreyfus Model of Skill Acquisition is highly relevant to this discussion because it considers how, through instruction and experience, a person progresses toward greater skill proficiency (Dreyfus & Dreyfus, 1980a; Dreyfus, 1981; Dreyfus et al., 1986; Dreyfus, 2004). It also suggests how training should be designed to help people gain higher-level skills (Dreyfus, 2004; Dreyfus & Dreyfus, 1980a, b). According to Dreyfus et al., "a person usually passes through at least five stages of qualitatively different perceptions of his task and/or mode of decision-making as his skill improves" (1986, p. 19). The Dreyfus Model proposes that people begin to learn new skills through instruction and conscious deliberation but eventually transition to a heavier reliance on experience and intuition as their skills develop (Dreyfus & Dreyfus, 1980a; Dreyfus, 1981; Dreyfus et al., 1986; Dreyfus, 2004). In other words, both nonformal and informal learning are involved in the process of skill acquisition, but the instructional approaches best utilized depend on where a person is on the skill development continuum. The history, stages, and training implications of the Model are presented in the sections that follow. The section concludes with a review of what is known about the performance of Baby Boomers in the

PIAAC PS-TRE assessment and of what the Dreyfus Model suggests regarding their skill development.

History of the Dreyfus Model of Skill Acquisition

The Dreyfus brothers, Stuart and Hubert, first introduced their five-stage Model in 1980. The authors note that their five-stage Model expands on two of their earlier works which are not reviewed here (see Dreyfus, H. & Dreyfus, S., 1979, and Dreyfus, S. & Dreyfus, H., 1979). At that time, the authors were conducting United States Air Force sponsored research on the skill development of pilots. Their study also included chess players, automobile drivers, and second-language learners. They sought to describe, “changes in the perception of the task environment reported by performers in the course of acquiring complex skills” (1980a, p. 1). The authors emphasize the importance of problem solving in the development of higher-level skills, and argue that, “concrete experience plays a paramount role” (1980a, p. 5). Through life experience, people naturally encounter problems of varying complexity to solve. Their study (1980a) resulted in the identification of five distinct stages of development: novice, competence, proficiency, expertise, and mastery.

In 1981, Stuart Dreyfus introduced a revision to the Model of Skill Acquisition. In this unpublished manuscript, Dreyfus set out to, “investigate the development of the intuitive thought process of the expert [business] manager in detail, showing how it evolves from, and transcends, analytic thought” (p. 2). Dreyfus reinforces an interest in understanding how decision-making changes as a person’s skill develops: “When is decision-making abstract and analytical and when concrete and intuitive?. . . When is it slow and laborious and when fast and easy?” (p. 6). Dreyfus asserts it is the changed perception of the task coupled with instinctive ability that produces excellent decision-makers in business management.

Dreyfus's 1981 manuscript incorporates a significant change to the earlier (1980a) Model. In 1981, the five stages presented by Dreyfus are: novice, advanced beginner, competence, proficiency, and expertise. Advanced beginner has been added, and mastery removed, since the earlier (1980a) iteration of the Model. No justification is offered regarding these changes, and there is not a publication in which the reasons for these changes are addressed. In a personal communication (April 21, 2020), however, Stuart Dreyfus explained the addition of advanced beginner:

> I found the ability to recognize something, based on experience but not rules, just as in stages 4 and 5 of the final model, important. Of course in advanced beginner it is just used as an input into rules while in stages 4 and 5 it is the whole non-rule event.

Regarding mastery, in the original expression of the Model (1980a), Dreyfus and Dreyfus indicate mastery is not a level, but rather a state into which an expert occasionally enters. Stuart Dreyfus (personal communication, April 21, 2020) indicates, "I also was uncomfortable with the speculation about mastery based on no evidence in the original model." Mastery was, therefore, removed in 1981. In 1982, Dreyfus published the manuscript in a journal called *Office Technology and People*—no changes were noted between this article and the unpublished manuscript.

In 1986, Dreyfus et al. provided the most robust description of the revised Model in their book, *Mind over Machine*. The premise of the book is, "computers as reasoning machines can't match human intuition and expertise" (p. xi). In short, the authors were writing about the failure of artificial intelligence to achieve the expectations people had for it at the time. The authors argued that through understanding the complexity of human skill acquisition, one could better estimate how far a computer could progress along that path.

In 2004, Dreyfus recapped the revised Model in the *Bulletin of Science, Technology & Society*. The 2004 article provides perhaps the most readily accessible summary of the revised Model. Otherwise there are no substantial differences between the 1981, 1986, and 2004 Model descriptions.

Stages of Development in the Dreyfus Model (1981/1986/2004)

How does a person transition from being completely new at something to being proficient in it, to being a resource that others call upon for advice or guidance? This section details the five stages of development proposed by Dreyfus et al. (1986). To keep the discussion relevant, I will incorporate a vignette about Sally, a Baby Boomer and college professor who found herself suddenly transitioned into a fully remote teaching environment due to the Covid-19 pandemic.

A novice is described by Dreyfus (2004) as a beginner, someone who is learning a skill for the first time. At this stage, a person is taught to follow rules pertaining to the skill being learned. When learning to drive a stick shift, for example, one might hear, "shift to second gear when the speedometer needle points to 10" (p. 177). Importantly, this initial period of learning takes place outside of the actual learning environment.

In our vignette, it is the middle of March, 2020. In the space of about one week, suddenly the whole country is in confusion and panic over the rapid spread of Covid-19 with cases in multiple states and community spread in Washington and California. Sally has only ever taught face-to-face classes, but her university decides it is in the best interest of students, faculty, and staff to transition to online learning after Spring Break. With some trepidation, Sally reads an email indicating that the University has purchased licenses for the web conferencing platform Zoom for all faculty, and she needs to be ready to teach through Zoom starting in two weeks. The IT Department has provided a Guide to Zoom and has arranged numerous training dates in

the next several weeks. Sally signs up for a few training sessions and starts reading the guide. One rule she learns from the guide is that you click the icon that looks like a microphone in order to talk.

The second stage of development in the Dreyfus Model is that of the advanced beginner. Dreyfus et al. (1986) describe the advanced beginner as a person who is attempting the skill in the real world for the first time. Through this initial exposure, the learner adds a cadre of situational rules to the context-free rules of the novice. The authors say, for example, “the advanced beginner automobile driver uses situational engine sounds as well as context-free speed in his gear-shifting rules” (p. 23). The advanced beginner develops sensitivity to the context of the situation in which the skill is practiced—the sounds, smells, and other circumstances that influence decisions but are difficult to put into words.

Sally clicks the link in the email she received from IT and enters her first Zoom meeting. She can hear the presenter, but when she clicks the microphone to ask a question, nothing happens. The presenter says she may need to choose her audio source and explains where to click to do so. Later in the meeting, another participant takes a call and does not mute herself. Everyone hears her brainstorm with her husband about another grocery store they might visit to try and secure toilet paper (which is sold out everywhere, along with most canned goods). The presenter mutes the woman so that the rest of the participants can continue. Sally writes a note to herself to make sure to mute when she isn’t speaking.

Eventually, according to Dreyfus et al. (1986), the seemingly endless contextual elements of the skill environment overwhelm the advanced beginner. At this point, Dreyfus (2004) says, “to cope with this overload, and to achieve competence, people learn, through instruction or experience, to devise a plan or choose a perspective that then determines those elements of the

situation or domain that must be treated as important" (p. 178). Whereas people in earlier stages of development simply follow rules, a person who is competent in a skill begins to organize stimuli, choose which elements are the most important, and act from the perspective of those important elements. For the first time, ownership in the outcome is felt because the decision is not based on a rule, but rather is made by the learner. Along with that ownership, the learner experiences the emotional swings of success and failure. Dreyfus (2004) emphasizes the importance of the learner reflecting on "one's successful and unsuccessful choices, even brooding over them—not just feeling good or bad…but replaying one's performance in one's mind" (p. 179) in order to progress to the next stage of development.

Over the last 10 days, Sally has attended the Zoom beginner's workshop, the advanced beginner's workshop, an advanced skills workshop, and a Zoom webinar workshop. Three days remain until her first class, and she is flipping anxiously through her notebook trying to remember how to set up polls. Her anxiety peaks and, frustrated, Sally steps away from her computer. She takes a moment to regroup, asking herself what she and the students would be doing if they met in-person. She would lecture using PowerPoint, and they would have a large group discussion at a few points during the presentation. Sally decides to keep things simple on the first night of Zoom class. All she has to do is screen share her presentation and adjust her view so she can see the participants' panel and call on students. She is incredibly nervous when she initiates the session, but the students can hear her and see the slides, and she realizes about ten minutes in that things feel more normal than she expected. She reflects on the class a lot over the next several days with pride for having done it, but she feels like student engagement was low. She decides to try incorporating some questions using the chat feature next time in case some students lack the ability to participate through audio.

In reference to one of one of Shakespeare's iconic characters, Dreyfus et al. (1986) refer to the thought process of the competent performer as a, "Hamlet model of decision-making—the detached, deliberative, and sometimes agonizing selection among alternatives" (p. 28). The key change that takes place as a person becomes a proficient performer is the loss of the conscious organization of stimuli. The change in performance that takes place between competence and proficiency is so notable that Dreyfus (2016) later refers to it as a "transformation" (p. xii). The learner who has achieved proficiency, according to Dreyfus et al., has experienced enough situations to intuitively recognize similarity between past and present sets of circumstances and to intuitively prioritize those stimuli. The proficient performer does, however, still consciously consider how to respond to a problem. The authors describe this as, "involved, intuitive understanding followed by detached decision-making" (p. 29). The authors give the example of a driver intuitively recognizing the need to slow down for a curve on a rainy day, but then consciously deciding between the alternative responses of applying the brake or of simply removing their foot from the gas pedal.

It is the first week of May and Sally is teaching her 10th class through Zoom. Although the energy of students increased steadily until about mid-April, by now the students have had so many virtual classes that they are fatigued and not responding to her questions. Sally realizes in the middle of the class that she needs to mix things up. She announces that she wants to do a think-pair-share exercise using the Zoom breakout rooms. She poses a question to students and tells them to think individually about their answers while she sets up the rooms. Then she realizes that she has not actually tested this feature, but she understands how it works from having watched a video tutorial about it. She follows the prompts and sends the students off to chat with their partners. She calls them back five minutes later and asks one person from each

pair to share highlights of the discussion with the rest of the group. Energy in the class is restored, and the rest of the time passes quickly.

What separates the expert from the proficient performer, according to Dreyfus et al. (1986), is that, for experts, decision-making also becomes intuitive. The authors say, "*when things are proceeding normally, experts don't solve problems and don't make decisions; they do what normally works*" (p. 30, emphasis in original). Dreyfus (2004) explains that, through additional experience, the expert can perceive subtle differences between situations that the proficient learner still views as similar. It is this level of discrimination that enables the expert to act using intuition. Dreyfus et al. also clarify that, when things are not proceeding normally, the expert does still consciously consider options before acting. The difference is that this decision process for experts is no longer based on solving the problem, but rather on critically reflecting on their own intuition. For reference, the Five Stage Model of Skill Acquisition by Dreyfus et al. (1986) is summarized in Table 5.

Table 5

Dreyfus Model of Skill Acquisition

Skill Level	*Components*	*Perspective*	*Decision*	*Commitment*
1. Novice	Context-free	None	Analytical	Detached
2. Advanced beginner	Context-free and situational	None	Analytical	Detached
3. Competent	Context-free and situational	Chosen	Analytical	Detached understanding and deciding. Involved in outcome
4. Proficient	Context-free and situational	Experienced	Analytical	Involved understanding. Detached deciding
5. Expert	Context-free and situational	Experienced	Intuitive	Involved

Note. From H.L. Dreyfus, S.E. Dreyfus, and T. Athanasiou, 1986, *Mind over machine: The power of human intuition and expertise in the era of the computer*, p. 50. Copyright 1986 by Hubert L. Dreyfus and Stuart E. Dreyfus.

The key to expertise is a lot of practice. Although Sally has achieved incredible technology competency gains in a short amount of time through both nonformal and informal learning, a few months are probably not going to be enough to get her to the point where she operates Zoom like it is a natural extension of her own mind. She might not ever reach the level of intuitive expertise as it is discussed in the Dreyfus model, and that is fine. We do not all become experts in every skill we set out to learn.

Workplace Learning Implications from the Dreyfus Model

As the Dreyfus Model has been adopted for use in other fields, implications for training are noted in the literature. Arguably the best-known verification of the Dreyfus Model was conducted by Patricia Benner. Through interviews and participant observation, Benner set out "to evaluate the practicality of applying the Dreyfus model to nursing and to clarify the characteristics of nurse performance at different stages of skill acquisition" (1982, p. 402). Benner notes that the advanced beginner nurse benefits from a mentor pointing out meaningful aspects of real situations—discerning between breath sounds for example—and providing guidelines for recognizing those aspects as the learner moves ahead. Benner emphasizes that the advanced beginner can only demonstrate, "marginally acceptable performance" (p. 403) due to inability to discern situational priorities, and therefore needs to be supported by more advanced practitioners in the clinical setting.

One important point from Benner's (1982) work pertains to the development of competency. Benner describes the competent nurse as one who, "begins to see his or her actions in terms of long-range goals or plans" (p. 405). Simulations or decision-making games are helpful at this stage because they provide the nurse with practice organizing goals in patient care. Benner emphasizes the role of time in the development of competency for nurses, noting that

most competent nurses have been in practice for 2-3 years. While not every skill is likely to follow the same timeline, and not every person will follow the same timeline for a given skill, it is helpful to note that the development of expertise in some skills is a lengthy process. Benner also indicates that many nurses do not progress beyond competency because the idea of standard procedures reinforces the competent mindset, and much ongoing education is targeted at this level. Finally, Benner suggests case studies as the best educational material for proficient nurses. Proficient nurses are those who have begun grasping situations as wholes rather than as combinations of individual elements, so the case study approach is less frustrating for them than training that relies on decision-making rules.

In 1999, Daley expanded on the work of Benner (1982) and Dreyfus et al. (1986) by specifically comparing the learning processes and preferences of ten novice and ten expert nurses. All participants were female, aged 23-62 (potentially including Baby Boomers who would have been aged 35-53 in 1999). Novice nurses were found to be so overwhelmed in their new roles that they relied heavily on other people—physicians or staff—to tell them what to go and learn more about. Experts, on the other hand, were able to determine their own learning needs and were also able to seek out the help of other experts in order to fulfill those needs. Novices indicated a preference for organized learning, indicating that they relied on classes, conferences, or textbooks for learning. Experts preferred to learn informally, through dialogue with others. Interestingly, experts also indicated that they felt compelled to learn so that they would be ready to engage in these dialogues if people came to them. In this way, informal learning through dialogue with peers was found to be both a motivator and a resource for learning among expert nurses.

In the 2004 recap of the revised Model, Dreyfus includes a few additional notes about the role of the instructor in the early stages of skill development. As we have come to understand, the novice learner of any skill is learning the basics of the skill before undertaking it. At this stage, then, the learner benefits from an instructor presenting information about the skill, "decomposing the task environment into context-free features" (p. 177) that the novice can begin to recognize. When a learner seeks instruction through organized workplace training, the OECD (2011b) refers to this as nonformal learning. Clearly, then, nonformal learning has an important role in the skill development of the novice. This is the case regardless of the skill under review, so it is safe to hypothesize the following:

> H_1: Baby Boomers who participate in nonformal workplace learning will have significantly stronger PS-TRE scores than those who do not participate.

To move from novice to advanced beginner and to a state of competency, the Dreyfus Model acknowledges the role of real-world experience (informal learning). This is also the case regardless of the skill under review, so the following hypothesis is offered:

> H_2: Baby Boomers who participate in informal workplace learning will have significantly stronger PS-TRE scores than those who do not participate.

One might wonder, though, how to best support the movement of someone further along the skill continuum?

In 2016, Dreyfus discussed the role of the mentor in helping a person progress from competency to proficiency. Dreyfus emphasizes the importance of this transition, saying, "the most important learning event is now at hand. This involves the transformation of the mentee from an analytical thinker into an intuitive *sense-maker*. Many skill-learners fail to take this leap" (p. xii, emphasis in original). Much of the thinking the learner has used up until this point

has been rule based with emphasis on how to act in certain situations. Now, to encourage proficiency, Dreyfus encourages the mentor to point out unique aspects of the situation. Dreyfus encourages mentors to reiterate, “an effortless intuitive sense-making perceptive ability comes about only through sufficient experience with a particular type of situation” (p. xiii). Learning through personal experience is, according to Marsick and Watkins (1990), a defining feature of informal learning. We can see, then, that to facilitate this transformation from analytic thinking to reliance on intuition inherent in the movement from competency to proficiency, a change in instructional approach is required. To move from competency to proficiency, informal learning must replace nonformal learning as the crucial learning strategy for ongoing skill development. This concept is demonstrated in Figure 4.

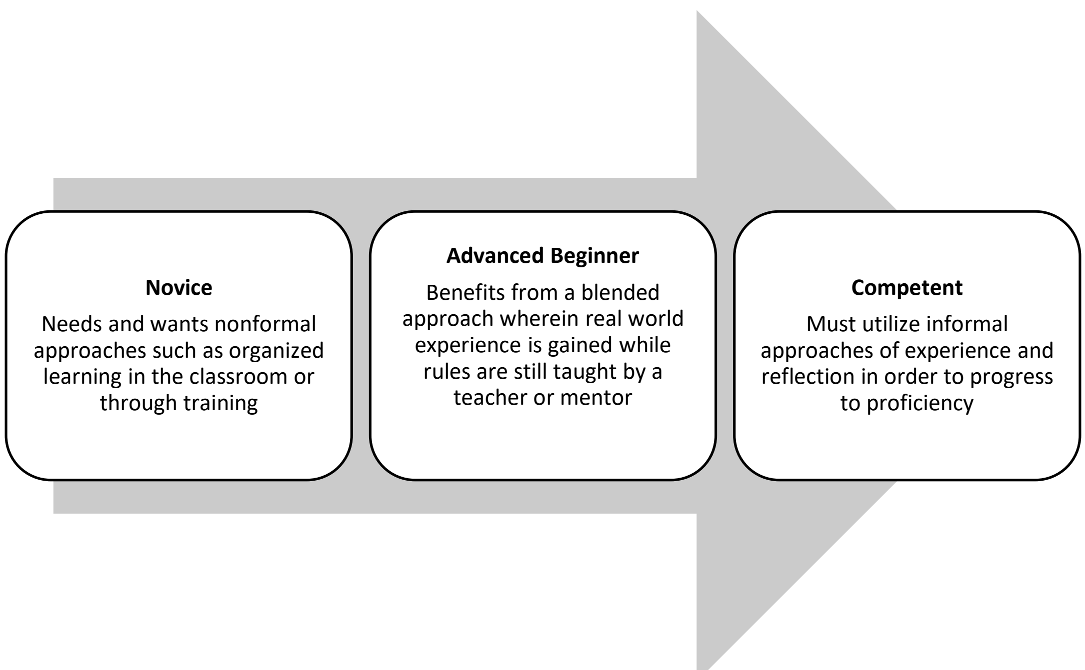


Figure 4: Aligning Workplace Learning Strategies with the Dreyfus Model

In one of their earliest works, the Dreyfus brothers also provide insight into the training needs of experts. In a companion paper (1980b) to their original Model (1980a), Dreyfus and Dreyfus engage their Model to critique a proposed pilot training program. The companion paper

(1980b) suggests how a pilot should be trained to respond to an emergency. In an emergency influenced by several complex factors, "no single appropriate response presents itself" (1980b, p. 7). Dreyfus and Dreyfus (1980b) were critiquing a training model proposed by a company called Perceptronics. The Perceptronics training model proposed that the pilot in this situation should be taught to consider all the relevant factors and the perspective each factor suggests before selecting their response. What solutions, for example, do the terrain and weather conditions suggest when an airplane's engine fails?

Dreyfus and Dreyfus (1980b) contest this approach for three reasons. First, they point out that this reduces the expert to a state of proficiency wherein their behavior is "based on the application of decision procedures" (1980b, p. 11). This approach also makes all factors appear to be equally important, thereby ignoring the natural context of the situation. Finally, they argue that experienced pilots must fight their own intuition in order to employ this model, and they say this tension could lead to indecision in a dangerous situation. Instead, Dreyfus and Dreyfus suggest, "what the expert pilot needs is to be both decisive and open-minded" (p. 14). If the pilot's instinct suggests one perspective, that is the one that should be taken. If several perspectives seem equally urgent, the pilot should pick one and proceed from that perspective. In either case, the pilot should be taught to remain open to changing their perspective depending on what happens next.

PIAAC PS-TRE and the Dreyfus Model

To tie these topics together, let us review what is known about the technology competency of Baby Boomers in PIAAC, and consider what that means regarding their stage of development according to the Dreyfus Model (Dreyfus et al., 1986). We have seen that skill development stages are associated with specific nonformal, informal, or blended learning

strategies. Identifying a specific Dreyfus stage describing the current overall technology competency of Baby Boomers will enable us to apply the Model and identify which learning strategies the Model suggests are likely to have the most significant impact on improving technology competency.

The OECD (2019b) describes the process for summarizing PS-TRE data into proficiency levels. PS-TRE has three levels, plus a level that is assigned to participants who fall below the cutoff for Level 1. The levels each encompass a wide range of skills, with people at the low-end showing ability in the level about half of the time and people at the upper end achieving accuracy at that level most of the time. The OECD (2019a) reports, “On average, across the OECD countries participating in the Survey of Adult Skills, around one-third of adults (29.7%) are proficient at the two highest levels (Level 2 or 3)” (p. 56). An additional 28.3% of all adults across participating countries attained Level 1 scores, making Level 1 the most common proficiency level for PS-TRE. In line with the OECD average, in 2012/2014, 29% of all U.S. adults aged 16-65 attained Level 2 or 3 scores. That level rose to 31% in 2017.

We know from the work of Rampey et al. (2016), however, that among U.S. Baby Boomers, only 23-26% achieved Level 2 scores, whereas 35% of respondents aged 16-24 and 37% of respondents aged 25-34 attained Level 2. We also know from Rampey et al. that 41-44% of all U.S. Baby Boomers achieved Level 1 scores. To add clarity to understanding this important piece, in Chapter Four the PS-TRE scores of participants of this study (employed Baby Boomers in PIAAC 2017) are compared to those of younger employees in PIAAC 2017 in order to determine specific average scores and Levels, thereby enabling a more nuanced understanding of the skill gap between these groups.

The next logical question might be, what does it mean to score at Level 1? Given the importance of this definition, the description provided by the OECD (2019a) is fully quoted in the following passage:

> At this level, tasks typically require the use of widely available and familiar technology applications, such as e-mail software or a web browser. There is little or no navigation required to access the information or commands required to solve the problem. The problem may be solved regardless of the respondent's awareness and use of specific tools and functions (e.g. a sort function). The tasks involve few steps and a minimal number of operators. At the cognitive level, the respondent can readily infer the goal from the task statement, the problem resolution requires the respondent to apply explicit criteria, and there are few monitoring demands (e.g. the respondent does not have to check whether he or she has used the appropriate procedure or made progress towards the solution). Identifying content and operators can be done through simple matches. Only simple forms of reasoning, such as assigning items to categories, are required; there is no need to contrast or integrate information. (p. 57)

The passage is fairly self-explanatory up until the discussion of the cognitive level of the task.

According to the PIAAC Expert Group who designed the PS-TRE assessment, PS-TRE tasks have three key components: a task or problem statement; cognitive dimensions; and technologies (laptops and the software installed on them). The cognitive dimensions are, "the mental structures and processes by which a person actually performs problem solving. These include goal setting and monitoring progress; planning; locating, selecting and evaluating information; and organizing and transforming information" (2009, p. 11). Planning involves organizing one's response to a problem—these plans are called "operators" (2009, p. 12). Finally, the cognitive dimensions require a person to acquire and use information. Acquiring information includes an evaluative component—is the information reliable, and does it meet your needs? If information is from several sources, to use it, one must integrate it. Integration also involves resolving discrepancies between sources.

At Level 1, then, the test-takers do not have to consider and set their own goals from understanding the problem; the goal is clear from the statement of the task, as is the appropriate response. There is no need to evaluate or reconcile sources of information. Key differences between Level 1 and Level 2 scores are that, in Level 2, some goal definition by the respondent is required, and some use of inferential reasoning is required in order to solve the problems (OECD, 2019b).

A quick example of inferential reasoning might be useful to help clarify that concept. Streumer (2007) indicates that most philosophers would recognize the following as an example of inferential reasoning:

(Belief:) If it is going to rain, the streets will get wet.

(Belief:) It is going to rain.

So, (Belief:) The streets will get wet. (p. 2)

Notice that the association of rain with wet streets is dependent on the individual having *experienced* these phenomena together. When reasoning by inference, a person is assimilating new data with prior experience and using that experience to make a little mental leap in judgment. In PS-TRE, to achieve Level 2, the individual must be able to tap into a reservoir of experience in order to solve the problem.

The combination of goal setting and more experience in the skill environment are key features of the competency stage of development according to Dreyfus et al. (1986). Level 2 PS-TRE performance, then, aligns with the Dreyfus et al. definition of competency. Dreyfus et al. reinforce this conclusion, stating that when cognitive scientists refer to problem solving, "they have in mind the thought processes that characterize competence" (p. 26). We also know that Dreyfus et al. define the novice as a person who is so new at a skill that they are not yet

attempting it in the real world. In PIAAC, most Baby Boomers can attain a Level 1 score in PS-TRE (Rampey et al., 2016), so they are not novices as defined by Dreyfus et al. (1986). We must, therefore, conclude that, overall, Baby Boomers in PIAAC are performing at what Dreyfus et al. (1986) would call an advanced beginner level of PS-TRE performance. To move to Level 2/Competency, then, according to the Dreyfus Model, Baby Boomers would benefit from a blend of nonformal and informal learning strategies. Knowing what to expect regarding main effects based on the Dreyfus Model, let us consider how other variables might color these relationships based on previous findings from the empirical literature.

Research Questions and Hypotheses

Six research questions guide this study. In this section, each question is restated along with its attendant hypothesis. Hypotheses for the primary research questions are based on the Dreyfus Model of Skill Acquisition (Dreyfus et al., 1986). Hypotheses regarding moderation effects are based on the Dreyfus Model and on previous findings from the empirical literature covered in this review. The empirical literature also alludes to numerous variables that impact either workplace learning or technology adoption for Baby Boomers, so the study includes several control variables. Variables that are controlled in the consideration of each relationship include completion of a college degree, self-reported health, and race. Age and gender are controlled when their main effects are not being considered. Empirical justification for control variables is outlined in Table 6.

Table 6

Empirical Justification for Variables Controlled in this Study

Variable	*Reason for Controlling*
Higher education	Yamashita et al. (2019) found, in PIAAC, participants in formal or nonformal learning were more likely to have higher education
	Jeong et al. (2018) found the amount of effort a person put into informal learning efforts varied by education level attained
	Roessger et al. (2020) found internationally, in PIAAC, that people with more than a high school diploma scored higher on *motivation to learn* and *elaboration* constructs
	Czaja et al. (2006) found that better educated people reported more general technology use, computer use, and Web use
Self-reported health	Becker Patterson (2018) found, in PIAAC, people who did not participate in nonformal learning were more likely to report poor health
	Yamashita et al. (2019) found, in PIAAC, participants in formal or nonformal learning were more likely to be healthier
	Zwick (2015) found that bad health impacts training effectiveness
Race	Yamashita et al. (2019) found, in PIAAC, participants in formal or nonformal learning were more likely to be White
	Race has been shown over time to impact technology use in different ways. Czaja et al. (2006) found African Americans used less types of technology, had less experience with computers, and had less experience with the Web. In 2019, however, Lee et al. found African Americans reported significantly more interest in computers, computer efficacy, and computer comfort than Caucasians.
Age	Fluid intelligence declines with age, and is important for learning new skills (Salthouse, 2012).
	Motivation to learn and the use of elaboration strategies decrease with age (Roessger et al., 2020).
	Age groups impact outcomes of technology acceptance in the UTAUT Model (Venkatesh et at., 2003).
Gender	Gender impacts computer anxiety and attitude (Czaja et al., 2006; Dutta & Borah, 2018).
	Gender impacts outcomes of technology acceptance in the UTAUT Model (Venkatesh et at., 2003).
	Gender impacts motivation to learn and the use of elaboration strategies (Roessger et al., 2020).
	Gender impacted participation in informal learning in Spain (Pineda-Herrero et al., 2017).

Research Question One

Q_1: Is participation in nonformal workplace learning associated with significantly higher PS-TRE performance among U.S. Baby Boomers?

Four specific categories of nonformal workplace learning are measured in PIAAC (OECD, 2011b), two of which will be used in this study. Question one is, therefore, broken down into two sub-questions:

Q_{1a}: Is participation in organized sessions for on-the-job training or training by supervisors or co-workers associated with significantly higher PS-TRE performance among U.S. Baby Boomers?

Q_{1b}: Is participation in seminars or workshops associated with significantly higher PS-TRE performance among U.S. Baby Boomers?

The Dreyfus Model of Skill Acquisition (Dreyfus et al., 1986) emphasizes the importance of learning from an instructor during the early stages of skill development. It is, therefore, hypothesized:

H_1: Baby Boomers who participate in nonformal workplace learning will have significantly stronger PS-TRE scores than those who do not participate.

Research Question Two

Q_2: Is participation in informal workplace learning associated with significantly higher PS-TRE performance among U.S. Baby Boomers?

Only certain indicators of informal workplace learning have been studied in PIAAC (Pineda-Herrero et al., 2017). Question two is, therefore, broken down into two sub-questions:

Q_{2a}: Is learning-by-doing associated with significantly higher PS-TRE performance among U.S. Baby Boomers?

Q_{2b}: Is learning new work-related things from co-workers or supervisors associated with significantly higher PS-TRE performance among U.S. Baby Boomers?

The Dreyfus Model of Skill Acquisition (Dreyfus et al., 1986) emphasizes the importance of learning from experience and mentors (Dreyfus, 2016) as a person progresses beyond the novice competency level. It is, therefore, hypothesized:

H_2: Baby Boomers who participate in informal workplace learning will have significantly stronger PS-TRE scores than those who do not participate.

Research Question Three

According to Field (2018), "moderation occurs when the relationship between two variables changes as a function of a third variable" (p. 746). This literature review has demonstrated that several variables impact outcomes relating to workplace learning and/or technology competency among Baby Boomers. It stands to reason, then, that the relationships between learning and technology competency may be less direct than the Dreyfus Model (Dreyfus et al., 1986) suggests. The remainder of the research questions in this study address moderating variables that may impact the relationships between nonformal or informal workplace learning and technology competency for Baby Boomers. The first of these potential moderators is supervisory status.

Q_3: Does supervisory status influence the relationship between workplace learning and PS-TRE competency among U.S. Baby Boomers?

It is common knowledge that supervisors receive more training (nonformal learning) than workers who do not supervise others. In their study of informal learning in Spain, Pineda-Herrero et al. (2017) found that men and respondents who were supervisors were more likely to learn from colleagues and learn by doing than other participants. This tendency for supervisors to

utilize informal learning techniques is reiterated by Warhurst and Black (2015) who documented the extensive use of informal learning strategies by managers in the U.K. Over time, then, supervisors may experience more workplace learning than non-supervisors. Participation in nonformal and informal learning are causally related to competency gain in the Dreyfus Model (Dreyfus et al., 1986), so it is reasonable to expect that supervisors may have higher PS-TRE scores than those seen among non-supervisors. Since the appropriateness and effectiveness of learning strategy changes by competency level according to the Dreyfus Model, it is hypothesized:

H_3: The relationship between workplace learning and PS-TRE is different between supervisors and non-supervisors.

Research Question Four

Q_4: Does economic sector influence the relationship between workplace learning and PS-TRE competency among U.S. Baby Boomers?

Jeong et al. (2018) note that organizational characteristics (size of business, economic sector, type of organization) impact informal learning opportunities within a given organization. Economic sector impacts nonformal learning opportunities as well according to Silvennoinen and Nori (2017) and Olsen and Tikkanen (2018). According to the Dreyfus Model (Dreyfus et al., 1986), participation in nonformal and informal learning are both important for competency gains. It is therefore hypothesized:

H_4: Workplace learning formats leading to significantly stronger PS-TRE competency will vary by economic sector.

Research Question Five

Q_5: Does size of the organization influence the relationship between workplace learning and PS-TRE competency among U.S. Baby Boomers?

As above, Jeong et al. (2018) note that organizational characteristics (size of business, economic sector, type of organization) impact informal learning opportunities within a given organization. Similarly, Berg et al. (2017) found that companies that employ larger numbers of workers were also more likely to offer training. According to the Dreyfus Model (Dreyfus et al., 1986), participation in nonformal and informal learning are both important for competency gains. It is therefore hypothesized:

H_5: Workplace learning formats leading to significantly stronger PS-TRE competency will vary by size of the organization.

Research Question Six

Q_6: Does the relationship between gender, workplace learning, and PS-TRE vary as a function of age among U.S. Baby Boomers?

This research question reflects a three-way interaction between gender, workplace learning, and age. To make sense of this, a summary of what we have learned from this literature review about the relationships between gender and learning and gender and technology competency is in order. Regarding gender and learning, we have seen that, internationally, men have higher motivation to learn (Roessger et al., 2020). We also have evidence that motivation to learn directly impacts training participation (Yamashita et al., 2019), and participation in nonformal learning is necessary for competency gains according to the Dreyfus Model (Dreyfus et al., 1986). At the same time, however, we have some evidence that older women (Jenkins & Mostafa, 2015) and experienced female nurses (Daley, 1999) may be more inclined to seek out

informal learning opportunities. Increased age, then, may change the relationship between gender, workplace learning, and PS-TRE.

Regarding gender and technology competency, Lee et al. (2019) reported that greater self-efficacy and higher computer interest seen in younger males disappeared in older age. The interaction graphs in the article by Lee et al. show the differences disappearing between males and females around age 80, which raises a question about whether gender differences are significant for Baby Boomers. It could also be possible that gender becomes insignificant somewhere within this generation. As above, gender alone as a moderator does not get close enough to the point of interest—we need to know if age matters in the relationship between gender, workplace learning, and technology competency. Given this background, the following hypothesis is offered:

H_6: Age weakens the influence that gender has on workplace learning and PS-TRE.

Summary

It has been a long journey, so let us recap. The purpose of this study is to describe the relationship of workplace learning with Baby Boomers' skills in problem solving in technology-rich environments. Workplace learning can be nonformal (through seminars, workshops, or structured on-the-job training) or informal (things we learn by doing a job or things we learn from coworkers). Problem solving in technology-rich environments is an especially interesting competency to study with this generation for several reasons. Many Baby Boomers did not receive formal education in these skills, and research has documented a skill gap in this competency measure between generations (Rampey et al., 2016). Losses in fluid intelligence make it more difficult for older workers to learn new skills in this area (Salthouse, 2012). Much of the recent work specifically addressing learning interventions leading to technology

competency for older workers remains theoretical as seen in the literature on reverse mentoring (Murphy, 2012) and intergenerational mentoring (Satterly et al., 2018). Due to the uptick in remote work resulting from the Covid-19 pandemic, perhaps now more than ever it is important to determine empirically how best to facilitate technology competency gains through learning interventions for Baby Boomers.

A great deal of literature addresses training design for older workers. Reoccurring themes are that older workers should either be given more time to complete training or allowed to self-pace their training experiences (Czaja & Sharit, 2013; Jeske et al., 2015; Kraiger, 2017; Taylor & Bisson, 2020; Truxillo et al., 2015). Fleming et al. (2017) found that e-learning was a successful way of offering self-paced training to older workers in the Australian rail industry.

Despite this interest in training design, older workers face difficulties regarding training that may not be shared by younger employees. For example, their access to training might be limited by stereotypes (Posthuma & Campion, 2009), which have also been shown to impact their scores in training (McCausland et al., 2015). Perceived (North & Fiske, 2016) or actual (Warhurst & Black, 2015) resource scarcity also impact training opportunities for older workers.

If training is not or cannot be offered, it becomes especially important to know which informal learning strategies work well for the development of technology competency. This, unfortunately, is an area where empirical evidence is scant. We know that informal learning in the form of sharing information is associated with higher PS-TRE scores in PIAAC (Lopes et al., 2020), but there is a definite need for additional research in this area specifically for the Baby Boomer generation.

According to the Dreyfus Model of Skill Acquisition (Dreyfus et al., 1986), where a person is in terms of skill development determines which learning strategies are likely to be the

most beneficial to them. We have determined that Baby Boomers in PIAAC largely align with the Dreyfus advanced beginner stage, indicating that they will benefit from a blend of nonformal and informal learning approaches. This study, therefore, examines both types of learning to determine the best possible combinations of learning in different employment settings that lead to gains in technology competency for this generation. Chapter Three introduces the research model used to accomplish this.

Chapter 3: Methodology

We turn now to the methodology of this study. In this chapter, this study's six guiding research questions are re-stated along with their substantive and statistical hypotheses. This study is reliant on existing 2017 data from the Programme for the International Assessment of Adult Competencies (PIAAC) Survey of Adult Skills. The PIAAC Survey is described in detail, including its history and the U.S. sampling and data collection procedures undertaken by the National Center for Education Statistics (NCES) in collaboration with Westat. I identify the PIAAC measures specifically used in this study and describe the data analysis procedure. The section concludes with a discussion of threats to the internal and external validity of this study.

The Quantitative Paradigm

Before delving into details regarding the methodology of this study, it may be useful to pause and reinforce a couple of key points from Chapters One and Two. The workplace learning and technology skills of Baby Boomers are subjects that have been studied extensively both in the United States and internationally. To study these phenomena is not novel, but some lack of clarity remains regarding the best learning approach to promote development of higher levels of technology competency among Baby Boomers. To find that clarity, a quantitative comparison of methods using a large, national dataset is warranted, and PIAAC meets that need. Studying these concepts in PIAAC might also be useful due to international interest in extending the working lives of Baby Boomers. A PIAAC study can be replicated throughout member countries of the Organisation for Economic Co-operation and Development (OECD) in order to identify gaps and facilitate better discussions about policies that support workplace learning for the Baby Boomer generation.

Creswell and Creswell (2018) explain that the research problem should drive the subsequent decisions the researcher makes regarding the research approach, methods of data collection, etc. In this case, while in general there is a need to better understand the relationship of nonformal and informal workplace learning to technology competency for the Baby Boomer generation, another significant component of the need is to conduct this study using PIAAC. A PIAAC study necessitates a quantitative approach due to the design of the Survey of Adult Skills (described in detail later in this chapter).

Creswell and Creswell (2018) suggest that most quantitative research has been conducted by researchers who approach the inquiry from a postpositivist view. Creswell and Poth (2018) summarize, “postpositivism has the elements of being reductionistic, logical, empirical, cause-and-effect oriented, and deterministic based on a priori theories” (p. 23). Postpositivism diverges from a purely positivistic orientation because, although both approaches acknowledge that reality is observable and measurable, postpositivists also believe that knowledge is relative, not absolute (Merriam & Tisdell, 2016). As a researcher conducting a study using numerical data from PIAAC, I can take an objective stance and use the deductive process described in this chapter to answer my research questions.

Research Questions and Hypotheses

There are six research questions guiding this study. In this section, each research question is restated along with its substantive and statistical hypothesis. For each research question, the population is employed U.S. adults ranging in age from 50-70 in 2017 when the PIAAC Survey was completed (Baby Boomers). Additional control variables to be added to each research question include completion of a college degree, self-reported health, and race. Age and gender

are controlled in research questions 1-5. These control variables are potential confounders, known to influence the independent and/or dependent variables in this study.

Research Question One

Q_1: Is participation in nonformal workplace learning associated with significantly higher PS-TRE performance among U.S. Baby Boomers?

Q_{1a}: Is participation in organized sessions for on-the-job training or training by supervisors or co-workers associated with significantly higher PS-TRE performance among U.S. Baby Boomers?

Q_{1b}: Is participation in seminars or workshops associated with significantly higher PS-TRE performance among U.S. Baby Boomers?

H_1: Baby Boomers who participate in nonformal workplace learning will have significantly stronger PS-TRE scores than those who do not participate.

The null hypothesis, H_0, is $b_{(\text{nonformal measure})} = 0$. Therefore, $b_{(\text{on-the-job training})} = 0$; and $b_{(\text{seminars or workshops})} = 0$. The alternative hypothesis, H_1, is $b_{(\text{nonformal measure})} > 0$. Therefore, $b_{(\text{on-the-job training})} > 0$; and $b_{(\text{seminars or workshops})} > 0$.

Research Question Two

Q_2: Is participation in informal workplace learning associated with significantly higher PS-TRE performance among U.S. Baby Boomers?

Q_{2a}: Is learning-by-doing associated with significantly higher PS-TRE performance among U.S. Baby Boomers?

Q_{2b}: Is learning new work-related things from co-workers or supervisors associated with significantly higher PS-TRE performance among U.S. Baby Boomers?

H_2: Baby Boomers who participate in informal workplace learning will have significantly stronger PS-TRE scores than those who do not participate.

The null hypothesis, H_0, is $b_{(\text{informal measure})} = 0$. Therefore, $b_{(\text{learning-by-doing})} = 0$; and $b_{(\text{learning from coworkers})} = 0$. The alternative hypothesis, H_1, is $b_{(\text{informal measure})} > 0$. Therefore, $b_{(\text{learning-by-doing})} > 0$; and $b_{(\text{learning from coworkers})} > 0$.

Research Question Three

Q_3: Does supervisory status influence the relationship between workplace learning and PS-TRE competency among U.S. Baby Boomers?

Q_{3a}: Does supervisory status influence the relationship between on-the-job training and PS-TRE competency among U.S. Baby Boomers?

Q_{3b}: Does supervisory status influence the relationship between seminar or workshop participation and PS-TRE competency among U.S. Baby Boomers?

Q_{3c}: Does supervisory status influence the relationship between learning-by-doing and PS-TRE competency among U.S. Baby Boomers?

Q_{3d}: Does supervisory status influence the relationship between learning from coworkers or supervisors and PS-TRE competency among U.S. Baby Boomers?

H_3: The relationship between workplace learning and PS-TRE is different between supervisors and non-supervisors.

The null hypothesis, H_0, is $b_{(\text{supervisor x learning participation})} = 0$. Therefore, $b_{(\text{supervisor x on-the-job training})} = 0$; and $b_{(\text{supervisor x seminars or workshops})} = 0$; and $b_{(\text{supervisor x learning-by-doing})} = 0$; and $b_{(\text{supervisor x learning from coworkers})} = 0$. The alternative hypothesis, H_1, is $b_{(\text{supervisor x learning participation})} > 0$. Therefore, $b_{(\text{supervisor x on-the-job training})} > 0$; and $b_{(\text{supervisor x seminars or workshops})} > 0$; and $b_{(\text{supervisor x learning-by-doing})} > 0$; and $b_{(\text{supervisor x learning from coworkers})} > 0$.

Research Question Four

Q_4: Does economic sector influence the relationship between workplace learning and PS-TRE competency among U.S. Baby Boomers?

Q_{4a}: Does economic sector influence the relationship between on-the-job training and PS-TRE competency among U.S. Baby Boomers?

Q_{4b}: Does economic sector influence the relationship between seminar or workshop participation and PS-TRE competency among U.S. Baby Boomers?

Q_{4c}: Does economic sector influence the relationship between learning-by-doing and PS-TRE competency among U.S. Baby Boomers?

Q_{4d}: Does economic sector influence the relationship between learning from coworkers or supervisors and PS-TRE competency among U.S. Baby Boomers?

H_4: Workplace learning formats leading to significantly stronger PS-TRE competency will vary by economic sector.

The null hypothesis, H_0, is $b_{\text{(sector x learning participation)}} = 0$. Therefore, $b_{\text{(sector x on-the-job training)}} = 0$; and $b_{\text{(sector x seminars or workshops)}} = 0$; and $b_{\text{(sector x learning-by-doing)}} = 0$; and $b_{\text{(sector x learning from coworkers)}} = 0$. The alternative hypothesis, H_1, is $b_{\text{(sector x learning participation)}} \neq 0$. Therefore, $b_{\text{(sector x on-the-job training)}} \neq 0$; and $b_{\text{(sector x seminars or workshops)}} \neq 0$; and $b_{\text{(sector x learning-by-doing)}} \neq 0$; and $b_{\text{(sector x learning from coworkers)}} \neq 0$.

Research Question Five

Q_5: Does size of the organization influence the relationship between workplace learning and PS-TRE competency among U.S. Baby Boomers?

Q_{5a}: Does size of the organization influence the relationship between on-the-job training and PS-TRE competency among U.S. Baby Boomers?

Q_{5b}: Does size of the organization influence the relationship between seminar or workshop participation and PS-TRE competency among U.S. Baby Boomers?

Q_{5c}: Does size of the organization influence the relationship between learning-by-doing and PS-TRE competency among U.S. Baby Boomers?

Q_{5d}: Does size of the organization influence the relationship between learning from coworkers or supervisors and PS-TRE competency among U.S. Baby Boomers?

H_5: Workplace learning formats leading to significantly stronger PS-TRE competency will vary by size of the organization.

The null hypothesis, H_0, is $b_{\text{(size x learning participation)}} = 0$. Therefore, $b_{\text{(size x on-the-job training)}} = 0$; and $b_{\text{(size x seminars or workshops)}} = 0$; and $b_{\text{(size x learning-by-doing)}} = 0$; and $b_{\text{(size x learning from coworkers)}} = 0$. The alternative hypothesis, H_1, is $b_{\text{(sizer x learning participation)}} \neq 0$. Therefore, $b_{\text{(size x on-the-job training)}} \neq 0$; and $b_{\text{(size x seminars or workshops)}} \neq 0$; and $b_{\text{(size x learning-by-doing)}} \neq 0$; and $b_{\text{(size x learning from coworkers)}} \neq 0$.

Research Question Six

Q_6: Does the relationship between gender, workplace learning, and PS-TRE vary as a function of age among U.S. Baby Boomers?

Q_{6a}: Does the relationship between gender, on-the-job training, and PS-TRE vary as a function of age among U.S. Baby Boomers?

Q_{6b}: Does the relationship between gender, seminar or workshop participation, and PS-TRE vary as a function of age among U.S. Baby Boomers?

Q_{6c}: Does the relationship between gender, learning-by-doing, and PS-TRE vary as a function of age among U.S. Baby Boomers?

Q_{6d}: Does the relationship between gender, learning from coworkers or supervisors, and PS-TRE vary as a function of age among U.S. Baby Boomers?

H_6: Age weakens the influence that gender has on workplace learning and PS-TRE. The null hypothesis, H_0, is $b_{(\text{age x gender x learning participation})} = 0$. Therefore, $b_{(\text{age x gender x on-the-job training})} = 0$; and $b_{(\text{age x gender x seminars or workshops})} = 0$; and $b_{(\text{age x gender x learning-by-doing})} = 0$; and $b_{(\text{age x gender x learning from coworkers})} = 0$. The alternative hypothesis, H_1, is $b_{(\text{age x gender x learning participation})} \neq 0$. Therefore, $b_{(\text{age x gender x on-the-job training})} \neq 0$; and $b_{(\text{age x gender x seminars or workshops})} \neq 0$; and $b_{(\text{age x gender x learning-by-doing})} \neq 0$; and $b_{(\text{age x gender x learning from coworkers})} \neq 0$.

Methods

Study Design

The PIAAC Survey of Adult Skills is a cross-sectional study. Field (2018) defines cross-sectional research as, "a form of research in which you observe what naturally goes on in the world without directly interfering with it by measuring several variables at a single time point" (p. 739). The NCES (2019) specifies the variables measured in PIAAC, indicating, "PIAAC measures relationships between individuals' educational background, workplace experiences and training, skill-used at work and home, occupational attainment, income, health, use of information and communications technology, and cognitive skills in the areas of literacy, numeracy, and digital problem solving" (p. 1). Since cross-sectional research does not entail any manipulation of circumstances by the researcher, this type of research is also correlational. When using correlational research methods, important relationships between variables can be identified, but causality cannot be determined (Field, 2018).

Study Setting

PIAAC is a household survey, meaning that trained interviewers visited a participant's home or another agreed upon location to administer the background questionnaire and cognitive assessments (OECD, 2019b). The NCES (2019) specifies that only households or group quarters

were eligible testing sites. The 2017 (Round 3) study used criteria similar to the U.S. Round 1 study, which excluded “those living in shelters, the incarcerated, military personnel who lived in barracks or bases, or persons who lived in institutionalized group quarters, such as hospitals or nursing homes” (p. 4). Although household surveys are somewhat common—consider, for example, the decennial census—conducting a cognitive assessment in the home poses certain challenges.

Maddox (2018) undertook an observational study of PIAAC administration in Slovenia. The author documents the case of one forty-year-old female participant, writing, “like the other PIAAC assessments that I observed in Slovenia, the completion of the BQ [background questionnaire] took place in the kitchen-dining room…the respondent answered questions while she tidied the room and washed some dishes” (p. 186). The participant’s three children entered during the computer-based cognitive assessment. Maddox says their presence, “introduced new challenges for the interviewer as the children inquired about the assessment and offered their suggestions and help” (p. 189). This glimpse into one testing situation offers important insights into the home as a testing environment. For some, this assessment was undertaken with distraction and noise, without privacy, while having to care for family members. Maddox calls these circumstances a threat to the integrity of the assessment. In the present study, it could be viewed as a limitation that I have no control over decisions about the study setting, or over how these assessments were verbally administered. At a minimum, it is worth noting that the home-based testing environment would have had considerable variation. These variable testing conditions may not have given all participants an equal starting point from which to measure their skills in the cognitive domains.

Participants and Placement

Through PIAAC, this study utilizes a nationally representative sample of U.S. Baby Boomers. In the United States, PIAAC was administered to people between ages 16-74 who were living in the U.S. at the time of data collection. U.S. citizenship was not required (OECD, 2019b).

In the technical report for PIAAC 2017, Krenzke et al. (2019) describe the sample design. Data were collected, "through a four-stage area sample, consisting of 80 primary sampling units (PSUs), 698 segments, 8,576 dwelling units (DUs), and 4,769 sampled persons, resulting in 3,660 respondents to the survey" (p. 3-2). Moving from a broad picture to a narrow view, then, imagine a map of the United States. A PSU is a county within a state. A segment is made up of U.S. Census blocks or block groups. Blocks are the smallest geographic areas studied in the Census and typically represent streets but could also be bounded by something like a stream or railroad (Rossiter, 2011). According to Krenzke et al. (2019), following this selection process, the final 80 PSUs, "were diverse in terms of literacy skills, geographic region of the country, and urbanicity of the PSU, as well as diverse in educational attainment, spoken-English ability, race/ethnicity, and poverty status" (p. 3-6).

Once a residence (dwelling unit) on a block had been identified for inclusion, a screening tool was used to enumerate the number of people who lived in the dwelling. The screening tool enabled researchers to identify which prospective participants were eligible, and then a sampling algorithm was used to select participants (Krenzke et al., 2019).

One important point is that there are more sampled people than respondents in PIAAC (Krenzke et al., 2019). According to the OECD (2019b), since the PIAAC Survey is intended to provide information about population groups, individual respondents only completed certain

subsets of test items in the assessments. To complete the full assessment would have been too time consuming. In the case reported by Maddox (2018), for example, the interviewer spent 2.5 hours with the respondent to complete her background questionnaire and subset of assessments.

The OECD (2019b) describes the possible pathways through the PIAAC assessments. All participants began by completing the background questionnaire. From there, those who reported having at least some computer experience were given a basic assessment to confirm their ability to use the computer's features, such as the mouse, necessary for navigating the computer-based assessments. Those who demonstrated proficiency then completed a computer-based assessment core of three literacy and three numeracy tasks. If the core assessment was passed, then the person moved ahead into two rounds of testing in the three PIAAC competency domains: literacy, numeracy, and PS-TRE. If the person was first randomly assigned a literacy assessment (for example), then the second random assignment could have either directed him or her to a numeracy assessment or to a PS-TRE assessment. For a full description of the PIAAC Survey administration workflow, see Figure 5.

Partial individual responses were combined into aggregated cases using a complex weighting procedure. According to the NCES, "the purpose of calculating sample weights for PIAAC was to permit inferences from sampled persons to the populations from which they were drawn and to allow tabulations to reflect estimates of the population parameters" (2019, p. 7). For a full description of the PIAAC weighting process, see the *U.S. Program for the International Assessment of Adult Competencies (PIAAC) 2012/2014/2017: Main Study, National Supplement, and PIAAC 2017 Technical Report* (Krenzke et al., 2019). The aggregated cases reflect completion of the full PIAAC assessment for each line of data. Therefore, if you examine the 2017 public use data file, there are 3,660 lines of data, but these are not individual

responses. They are aggregate cases which were created from a larger pool of data gathered from 4,769 total participants.

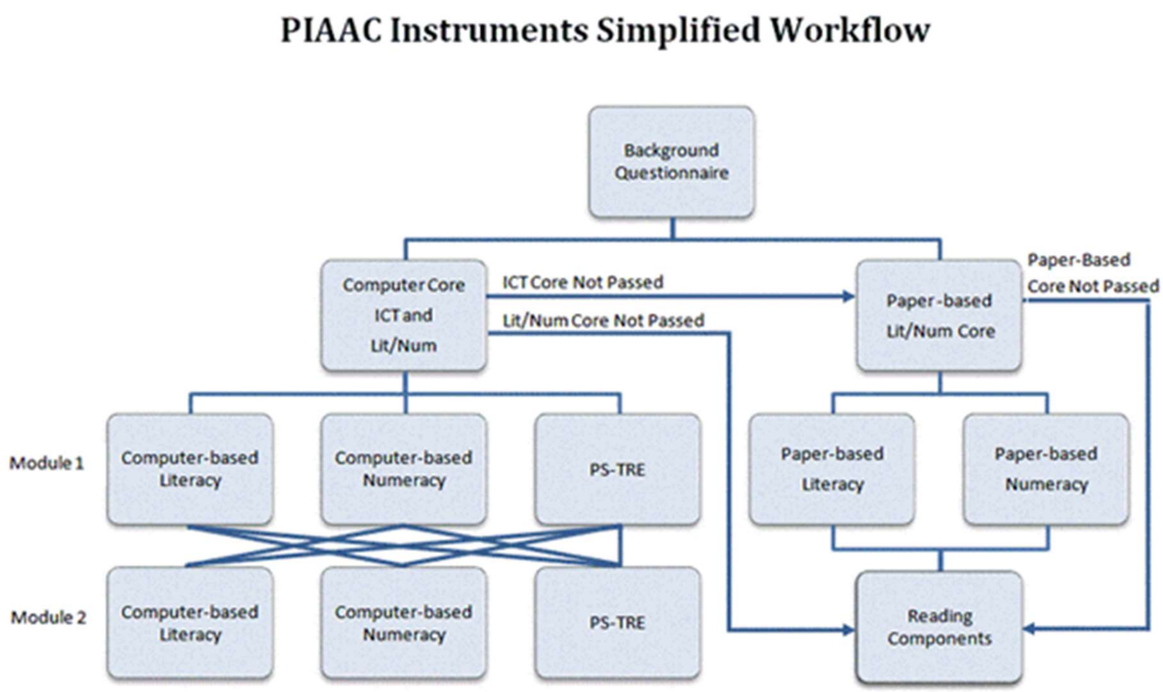


Figure 5: PIAAC Survey Administration Workflow. This figure is copied from the U.S. National Center for Education Statistics website (https://nces.ed.gov/surveys/piaac/admin.asp#fig_a).

This study utilized only the aggregated data for employed workers who were between ages 50-70 at the time of data collection (Baby Boomers). The SPSS version of the 2017 U.S. PIAAC Household Study Public-Use File was downloaded and opened using IBM SPSS Statistics Version 25. Cases were sorted by five-year age bands using variable AGEG5LFSEXT. Cases younger than 50 and older than 70 were cleared, leaving 1,378 cases. Then that data was sorted by employment status using variable C_D05. Those cases who were in any category other than employed were removed, leaving 838 cases in the data set which represents the total of employed Baby Boomers in PIAAC. However, it was also crucial that respondents in this study have PS-TRE scores and, because of the way the PIAAC Survey was administered (see Figure

5), not all participants completed this assessment. Cases that were missing plausible values for the PS-TRE competency measures were removed, leaving a total of 701 cases in the dataset.

As suggested by Field (2018), a power analysis was conducted using *G*Power* to estimate the necessary sample size for this study. Input parameters were as follows: ability to find medium-sized effects ($f^2 = 0.15$); Type I error probability (α -level) = 0.05; power (Type II error probability, $1-\beta$) = 0.8. In a study using multiple linear regression, normally the researcher would conduct a *G*Power* analysis by first inputting an initial number of predictors and running the calculation using an R^2 deviation from zero. Then the calculation would be repeated using an R^2 increase that takes new predictors into account. Due to the complexity of this model, only an R^2 deviation from zero was calculated. With 213 total predictors, the analysis indicated a total sample size of 519 participants is needed. Table 7 in the Measures section includes a column showing how the number of predictors was calculated. Although more cases than needed are in the data set, all 701 were included in the analysis because a high total number of cases is needed in order to meet the NCES sample size standards for analyses involving plausible values.

Materials

This cross-sectional study used existing data from the PIAAC Survey of Adult Skills. Specifically, data from PIAAC's U.S. Cycle 1, Round 3 Household Study (2017) was utilized. The public-use files are available for download from the NCES at https://nces.ed.gov/surveys/piaac/datafiles.asp.

Stein (2017) describes the history of the PIAAC Survey, indicating that it grew out of an earlier OECD initiative, the Defining and Selecting Key Competencies (DeSeCo) project. DeSeCo helped OECD member countries come to a common definition of a successful life and of the key competencies needed in order to achieve success. The key competencies identified

through DeSeCo included: “acting autonomously, using tools interactively, and interacting in socially heterogenous groups” (p. 31). Stein indicates that the three PIAAC assessments and background questionnaire were developed with these competencies in mind. One can see the relationship to DeSeCo in the main dimensions of measure utilized by each PIAAC assessment: content, cognitive strategies, and context. Content encompasses the tools people must interact with. Cognitive strategies are the areas of knowledge that the adult must bring to solve a problem. Contexts are the different situations in which adults must utilize their skills (OECD, 2019b).

According to the OECD (2019b), international groups of experts were convened to design the PIAAC Survey’s background questionnaire and the assessments in literacy, numeracy, and PS-TRE. International expertise and collaboration in instrument design were important in terms of the PIAAC Survey’s content validity because the goal was to deploy the same assessments in multiple countries and be able to compare the results. According to Krenzke et al. (2019), U.S. representatives for this initiative came from the U.S. Department of Education’s NCES and the U.S. Department of Labor.

Krenzke et al. (2019) describe the field test of the PIAAC Survey, which yielded important information about the validity of the background questionnaire. The PIAAC Survey was field tested in the U.S. in 2010 using a sample of 1,510 adults. A master version of the background questionnaire created by the PIAAC Consortium was used in the field test. The Consortium is responsible for the international quality control of PIAAC—this group establishes the standards to which individual countries must adhere. Based on results of the field test, the background questionnaire was updated “to eliminate problematic items and to reduce the overall length” (p. 2-3). There is, however, always the possibility that a respondent could respond

dishonestly or misunderstand and then incorrectly respond to a question, so that threat to validity remains.

Since 2011, the PIAAC Survey has been used in 38 countries (Krenzke et al., 2019). In the key competencies measured, PIAAC enables researchers to compare competency levels both across countries and between population subgroups within a given country. This study takes the latter approach, using PIAAC to look specifically at employed Baby Boomers as a subgroup of the U.S. population.

While the PIAAC Survey contains three assessments, this study only used U.S. data from the background questionnaire and the PS-TRE assessment. According to the OECD (2019b), it is through the background questionnaire that researchers can examine skill levels among population sub-groups and explore what factors lead to the acquisition of specific skills. The OECD indicates, "items were expected to measure concepts that had a strong theoretical underpinning, had been measured in other studies, and would be comparable across countries and groups within countries" (p. 36). The background questionnaire collects demographic data such as age, gender, and residential information. It asks about the attainment of formal education and participation in nonformal education including distance education, on the job training, seminars, or private lessons. Current and past employment information is collected, as are data about the characteristics of those workplaces. The focus on job requirements in the background questionnaire enables researchers to ask how frequently certain skills are used at work and in everyday life (Krenzke et al., 2019). Individual countries were permitted to add a small number of country-specific questions to the overall questionnaire.

The OECD (2011b) published a report on the conceptual framework of the background questionnaire. The report indicates that questions were selected for inclusion if they met the

following criteria: clear theoretical relationship to skills; good measurement properties; items are able to be compared within and across countries; questions are applicable to the general population (not small subgroups); items are comparable to other international surveys such as the International Adult Literacy Survey; and national adaptations of questions are minimal. The full U.S. PIAAC 2017 Background Questionnaire can be viewed on the NCES website: https://nces.ed.gov/surveys/piaac/questionnaires.asp.

According to the PIAAC PS-TRE Expert Group (2009), problem solving in technology-rich environments is defined as, "using digital technology, communication tools and networks to acquire and evaluate information, communicate with others and perform practical tasks" (p. 9). Note that this definition encompasses much more than simply operating a computer. PS-TRE measures a person's ability to operate a computer in order to solve specific information-related problems necessary for success in knowledge-based economies. In the PS-TRE assessment, adults are asked to apply skills in the use of spreadsheets, email, and webpage navigation in order to solve scenario-based problems that vary in difficulty. The assessment relies solely on prior knowledge—participants are not taught how to use the applications.

The PS-TRE assessment was comprised of sixteen scenario-based items which required participants to utilize web, spreadsheet, and email applications. The problem presented in each scenario varied in complexity, with each scenario taking an anticipated 5-15 minutes to complete. The OECD (2019b) provides an example of a PS-TRE measure. The authors describe a scenario in which a participant is looking for a job and must evaluate various webpages to determine which of the websites charge a fee for their use. As with other PIAAC competencies, ability in PS-TRE is not dichotomous (something one either does or does not possess), but rather is measured on a continuum of ability (OECD, 2019b) resulting in a score from 0-500.

Yamamoto et al. (2019) describe the reliability of PIAAC competency measures and report the U.S. reliability for the PS-TRE measure at .866 during Round 1 of data collection, which Field (2018) indicates is acceptable when using Cronbach's α for reliability analysis.

Data Collection

In the technical report for PIAAC 2017, Krenzke et al. (2019) indicate that the NCES contracted with Westat, a research services company based in Maryland, to conduct PIAAC data collection in the United States. Although PIAAC data has been collected in the United States through two full rounds and one supplementary round of data collection since 2011 (Krenzke et al., 2019), this study only used data from PIAAC's U.S. Cycle 1, Round 3 Household Study. Round 3 data were collected in the United States from March-November 2017 (Krenzke et al., 2019), so this data provides the most current measure of Baby Boomers' overall PS-TRE competency.

According to the OECD (2019b), the PIAAC Survey was "conceived primarily as a computer-based assessment" (p. 48), and indeed, interviewers took laptop computers with them to households in order to administer the assessments. However, those participants who had no computer experience, or who failed an initial assessment, were provided a paper-based assessment. Those who had to be directed to the paper-based survey were unable to complete the PS-TRE assessment, as were those who failed a brief subsequent test of basic literacy and numeracy skills (the computer-based assessment core). As the PIAAC PS-TRE Expert Group (2009) explains, "achievement of PS-TRE tasks presupposes the mastery of foundational ICT skills" (p. 16) such as use of the mouse, keyboard, etc. This adds some complexity to the consideration of the PS-TRE measure because, although the competency scale starts at zero,

there are participants who could be viewed as having scores that are realistically lower than the lowest proficiency level indicated.

Once an individual was identified for participation, according to the OECD (2019b) a trained interviewer first administered the background questionnaire. The interviewer verbalized the questions and recorded responses on a laptop. The background questionnaire was expected to take about 45 minutes to complete, with an additional five minutes allotted for questions added by individual countries.

Interviewers underwent extensive training. According to Krenzke et al. (2019), interviewers received at least 33 hours of training before administering the Main Study. Training topics included skills specifically related to PIAAC such as administering the background questionnaire, but also included general interviewing techniques and practice through role-playing and practice interviews. Once an interviewer began work in the field, two interviews were fully audio recorded and reviewed by the interviewer's supervisor, who provided feedback for ongoing improvement. The work of interviewers was validated to ensure the validity of the PIAAC Survey. Each interviewer had at least ten percent of his or her work checked for completeness and potential falsification of data. If it was determined that data had been falsified in any way (if, for example, the interviewer allowed someone other than the selected respondent to complete the Survey), then all the work of that interviewer underwent verification to ensure its validity for inclusion.

Next, the cognitive assessments were administered. As indicated above, the ideal was for the participant to complete the cognitive assessments on a laptop provided by the interviewer. For those participants who were selected for the PS-TRE competency measure, the laptops had software installed that simulated applications including email, word processing, spreadsheets,

and websites for use in the PS-TRE assessment. According to the PIAAC PS-TRE Expert Group (2009), each assessment used one or more of these applications to assess various cognitive dimensions such as gathering and evaluating information. An incentive of $50 was paid to each respondent upon completion of the background questionnaire and cognitive assessments (Krenzke et al., 2019).

Measures

Table 7 provides operational definitions of this study's independent, dependent, moderating, and control variables in PIAAC and directs the reader to the corresponding question numbers from the 2017 background questionnaire. It also notes how the number of predictors used in the power analysis was determined. While reviewing these operational definitions, it might be useful to refer to some of the main variables' conceptual definitions. Conceptual definitions are provided in the Key Terms and Concepts section of Chapter One.

Table 7

Variable Operationalization in PIAAC and Predictor Determination

Variable	*PIAAC BQ Reference*	*PIAAC Variable Label*	*PIAAC Categories*	*Number of Predictors*
		Independent Variables		
On-the-job Training	B_Q12D_C	Activities - Last year - On the job training - Count (top-coded at 5)	0: 0 times 1: 1 time 2: 2 times 3: 3 times 4: 4 times 5: 5 or more times	5
Seminar or Workshop Participation	B_Q12F_C	Activities - Last year - Seminars or workshops - Count (top-coded at 5)	1: 1 time 2: 2 times 3: 3 times 4: 4 times 5: 5 or more times	4
Learning-by-Doing	D_Q13B	Current work - Learning - Learning-by-doing	1: Never 2: Less than once a month 3: Less than once a week but at least once a month 4: At least once a week but not every day 5: Every day	4

Table 7 (Cont.)

Variable	*PIAAC BQ Reference*	*PIAAC Variable Label*	*PIAAC Categories*	*Number of Predictors*
Learning from Coworkers or Supervisors	D_Q13A	Current work - Learning - Learning from co-workers/supervisors	1: Never 2: Less than once a month 3: Less than once a week but at least once a month 4: At least once a week but not every day 5: Every day	4
		Dependent Variable		
PS-TRE Score	Not applicable	PIAAC (2009) defines PS-TRE as, "using digital technology, communication tools and networks to acquire and evaluate information, communicate with others and perform practical tasks" (p. 9).	A score from 0-500 is awarded	Not applicable
		Moderating Variables		
Supervisor	D_Q08A	Current work - Managing other employees	1: Yes 2: No	1 (x 17 = 17 additional interaction terms)
Economic Sector	D_Q03US	Current work - Economic sector	1: Private 2: Public 3: Non-profit	2 (x 17 = 34 additional interaction terms)
Size of Organization	D_Q06A	Current work - Amount of people working for employer	1: 1-10 people 2: 11-50 people 3: 51-250 people 4: 251-1000 people 5: More than 1000 people	4 (x 17 = 68 additional interaction terms)
Age[a]	AGEG5LFSEXT	Age in 5 year bands extended to include ages over 65 (derived)	8: 50-54 9: 55-59 10: 60-65 11: 66-70	3 (x 17 =51 additional interaction terms)
Gender[a]	GENDER_R	Person resolved gender from BQ and QC check (derived)	1: Male 2: Female	1 (x 17 = 17 additional interaction terms)

Table 7 (Cont.)

Variable	*PIAAC BQ Reference*	*PIAAC Variable Label*	*PIAAC Categories*	*Number of Predictors*
		Control Variables		
College Degree	B_Q01AUS_C	Education - highest qualification - level (3 categories) (derived from B_Q01aUS)	1: Less than high school diploma 2: High school diploma/some college but no degree 3: College degree or higher (associate, bachelor, doctorate)	2
Race	RACETHN_4CAT	Background - race/ethnicity (derived, 4 categories)	1: Hispanic 2: White 3: Black 4: Other race	3
Health	I_Q08	About yourself - Health - State	1: Excellent 2: Very good 3: Good 4: Fair 5: Poor	4
				Total predictors = 213

Note. PIAAC = Programme for the International Assessment of Adult Competencies; BQ = background questionnaire.

[a] Age and gender are controlled when moderation effects are not being investigated.

Data Analysis

Multiple linear regression was used to answer this study's six research questions. Multiple linear regression permits the researcher to examine differences between individuals, which is important here because this study seeks to determine what types of workplace learning are associated with a person being more likely to do well in PS-TRE in different circumstances. According to Field (2018), multiple linear regression allows for two or more independent variables which can either be continuous or categorical. It requires a continuous dependent variable, and it also allows the researcher to consider moderating variables while controlling for variables that are either continuous or categorical.

This study used four independent variables (measures of nonformal and informal workplace learning), all of which are categorical with up to five levels. The continuous dependent variable in this study is problem solving in technology-rich environments, which is a

score from 0-500. Five moderating variables—supervisory role, economic sector, size of business, gender, and age—were all categorical with between 2-5 levels. Finally, categorical control variables used in this study included college degree, self-rated health, and race, all of which had more than two levels. Due to the presence of more than two independent variables, a continuous dependent variable, plus numerous moderating and control variables, multiple linear regression was the best statistical test to use in this study. Figure 6 provides a diagram of the research design.

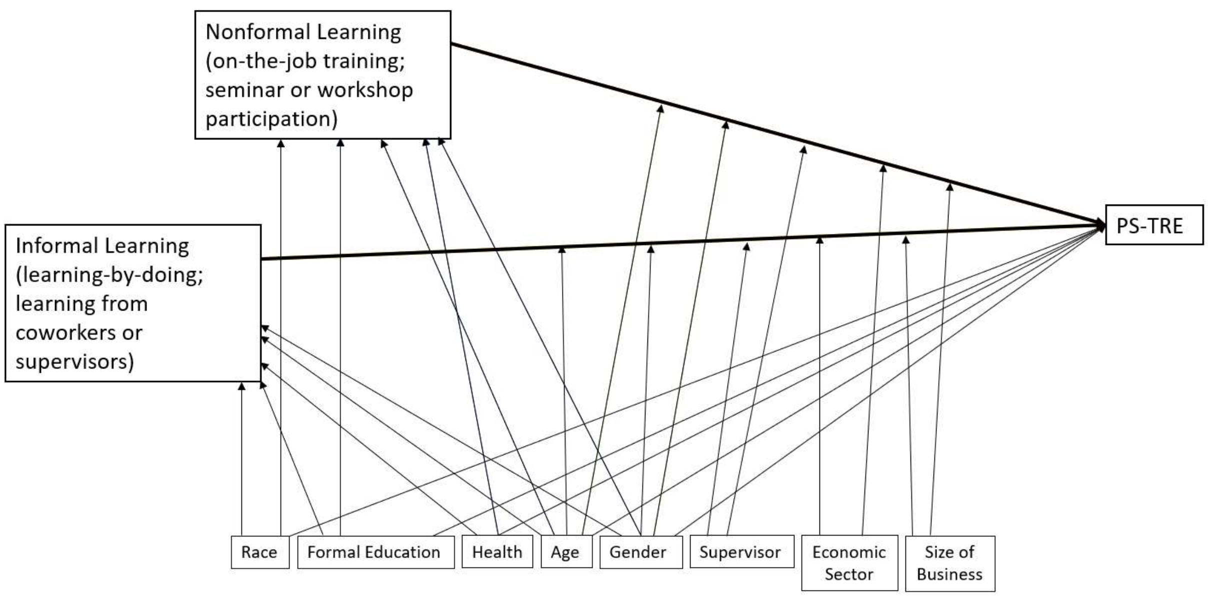


Figure 6: Research Design. PS-TRE = problem solving in technology-rich environments. Gender and age are control variables in this study when they are not being considered as moderators.

Typically in this type of study, several checks for potential sources of bias would occur before undertaking data analysis. Field (2018) explains that data is biased if the estimates produced through analysis do not reflect the true values of the population for which an estimate is being made, or when assumptions inherent to the function of the linear model are violated. As described previously, however, PIAAC utilized a *complex* survey design. One key difference in a

complex survey design is that a simple random sample is not utilized. Complex survey designs break many traditional assumptions of statistical analyses, and therefore analysis procedures must be adjusted to handle the unique structure of the sample (Johnson & Rust, 1992). The necessary adjustments in a PIAAC study are made by following published NCES guidelines for sample size, use of sampling weights, use of plausible values when literacy, numeracy, or PS-TRE are included in the analysis, and by checking the coefficient of variation (CV) for significant predictors (AIR PIAAC Team, 2019). The CV is a calculation of the standard error divided by the estimate; that number is then converted to a percentage for ease of interpretation. This draws attention to dispersion within the variable; CVs between 30-50% should be interpreted with caution, and CVs greater than 50% do not meet reporting standards of the NCES because they indicate the model may be a poor fit (AIR PIAAC Team, 2019). Adjustments made in this study to align with NCES reporting standards are outlined in Chapter Four.

Due to the complex sampling procedures used in PIAAC, a special software called the International Database (IDB) Analyzer was used to convert the data for analysis in SPSS. The IDB Analyzer can be accessed through the OECD's website, http://www.oecd.org/skills/piaac/publicdataandanalysis/. IBM SPSS Statistics v. 25 was used in conjunction with the IDB Analyzer to conduct the multiple regression analyses.

Ethical Considerations

Due to the complex design of PIAAC and the need to use the IDB Analyzer along with SPSS for analysis, specialized training offered by Educational Testing Service (ETS) is recommended for those who are interested in undertaking studies in PIAAC. Training dates and resources are noted on the U.S. PIAAC Gateway website, http://piaacgateway.com/researchers-corner. I attended an ETS PIAAC workshop in October 2019. Before the workshop, a description

of this study was submitted to the University of Arkansas Institutional Review Board. In September 2019, the IRB determined that review of this study was not required. The IRB outcome letter is available in Appendix A.

This study uses PIAAC public use datafiles. Before posting for public use, extensive measures are taken to protect the identity of participants. Krenzke et al. (2019) describe the process of reducing the risk for data disclosure in PIAAC. Before posting for public use, all personal identifiers—such as name and address—and all geographic identifiers such as primary sampling unit (county) were removed. Additional data went through a process called “data coarsening” (p. 6-3) wherein, for example, continuous variables were categorized. Due to data coarsening, PIAAC reports ages in five-year bands instead of as a continuous variable. Restricted use files containing data that has not been coarsened are available by request from the NCES, but researchers must apply for a special license in order to receive access to restricted use data.

Internal and External Validity

O’Dwyer and Bernauer (2014) say that internal validity is, “the function of the degree to which extraneous variables are controlled and possible alternative explanations for the results observed are minimized” (p. 136). The authors discuss several common threats to internal validity, and one that might apply in a PIAAC study is instrumentation threat. Instrumentation threat indicates that the person collecting the data and the site of data collection can influence the data itself. The PIAAC Survey attempts to account for problems arising from the person collecting the data through extensive training of the interviewers. Krenzke et al. (2019), however, report that of the 120 interviewers trained to administer PIAAC 2017, nine interviewers were ultimately fired for falsifying data. Regarding the site of data collection, Maddox’s (2018) study showed that household surveys are undertaken in different testing

environments depending on the presence of others, noise level, and other circumstances. In this study, the concern of instrumentation threat is somewhat alleviated because PS-TRE was only offered as a computer-based assessment. Therefore, the concerns associated with calculating and reporting scores on the paper-based version of the PIAAC numeracy and literacy components did not apply.

External validity refers to the generalizability of the study (O'Dwyer & Bernauer, 2014). While the complexity of the sampling procedure described by Krenzke et al. (2019) alleviates the usual concern over whether the sample studied was not representative of the population, one point of concern regarding generalizability remains. In this particular study, as time continues to pass since the data were collected, it will become harder to confidently generalize the results. Technology changes rapidly, and people adapt to those changes through acquiring new skills and by utilizing new approaches to learning.

Summary

This chapter has outlined the methodology used to study the research questions in this study. For clarity, the research questions and hypotheses guiding the study were stated up front. Then the PIAAC survey was described in detail and links to retrieve data were provided in case a researcher would wish to replicate this study. Variables—independent, dependent, moderating, and control—were fully delineated with references to the specific PIAAC background questionnaire elements used in this study. This study requires the use of multiple linear regression to answer its research questions, but as with all PIAAC studies, additional steps are needed. Readers have been directed to appropriate sources for accessing PIAAC analysis software and training. Results of the analysis are reported in the next chapter.

Chapter 4: Results

The primary purpose of this study was to describe the relationship of workplace learning with Baby Boomers' skills in problem solving in technology-rich environments (PS-TRE). Two types of nonformal workplace learning (participation in on-the-job training and participation in seminars or workshops) and two types of informal workplace learning (learning by doing and learning from coworkers or supervisors) were investigated. A secondary purpose of the study was to determine whether supervisory status, economic sector, or size of business moderated the relationships between workplace learning and PS-TRE competency. Finally, this study investigated whether the relationship between gender, workplace learning, and PS-TRE varied as a function of age. This chapter presents the findings of the study. First, steps taken to prepare the 2017 U.S. Programme for the International Assessment of Adult Competencies (PIAAC) Household Study Public-Use File for analysis are described. Next, data demographics are presented to provide insight into the sample of U.S. Baby Boomers in this PIAAC dataset. As indicated in the literature review, this section includes a summary of the overall PS-TRE performance of employed Baby Boomers in comparison to other employed individuals in PIAAC. It also includes summary statistics for the background questions regarding whether Baby Boomers have the necessary computer skills to do their jobs and whether lack of skill has impacted promotion opportunities. Missing data methods are discussed, and then findings are presented for each of the study's six hypotheses. Finally, reliability and validity of the findings are reconsidered, and the chapter concludes with a summary of key findings.

Preparing the Dataset

As indicated in Chapter Three, the SPSS version of the 2017 U.S. PIAAC Household Study Public-Use File was downloaded and opened using IBM SPSS Statistics Version 25. Cases

that were not in the population of interest (employed Baby Boomers) were removed, as were Baby Boomers who lacked PS-TRE scores, which left 701 cases in the dataset. Frequencies were then examined in SPSS for each variable of interest. When running regression analysis using PIAAC data, each variable of interest must contain 62 cases at each level of the category for the National Center for Education Statistics (NCES) reporting standards to be met (AIR PIAAC Team, 2019). So, for example, in a regression of gender and learning-by-doing on PS-TRE, the dataset must contain at least 62 males, 62 females, 62 participants who never learned by doing, 62 participants who learned by doing less than once a month, and so on for the other levels of learning by doing. Reporting standards are important because the complex survey design of PIAAC breaks many traditional assumptions of statistical analyses, and therefore analysis procedures must be adjusted to handle the unique structure of the sample (Johnson & Rust, 1992). These adjustments are made by following the guidelines for sample size, use of sampling weights, use of plausible values when literacy, numeracy, or PS-TRE are included in the analysis, and by checking the coefficient of variation (CV) for significant predictors (AIR PIAAC Team, 2019).

To answer the six research questions of this study required the use of 42 distinct models. At various points, different subgroups failed to meet the criteria of 62 cases per subgroup when using the predetermined PIAAC sub-categories. Additionally, it was desirable to have at least thirty cases per subgroup when considering interactions since this is generally accepted as the point at which the central limit theorem ensures normality of the sampling distribution (Field, 2018). Therefore, new variables were created that combined small categories with others in the dataset. The goal throughout was to maintain as much ability as possible to detect subgroup differences, so subgroups were not always combined in the same way. For example, when age is

used as a control variable, all four categories are included. When age is used as a moderator, however, the variable was collapsed into two or three categories depending on sample size in the interaction term. These changes are documented in Table 8. Frequency analyses were repeated using the new variables, and demographics from this analysis are reported in the next section.

Changes made to the non-formal learning measures (on-the-job training and seminar or workshop participation) may require additional clarification. The PIAAC background questionnaire first asks if a person participated in the non-formal learning activity—yes or no. Then, if yes, it asks how many times the person participated. The count variable is a scale from 1-5 with 5 as the maximum possible score. In this study, I was interested in comparing participation to no participation, so I created new categorical variables for on-the-job training and seminar or workshop participation. First, the original variables were visually inspected side-by-side in SPSS. The "no" responses on B_Q12C and B_Q12E (the PIAAC variables for yes/no participation in on-the-job training and seminars or workshops) corresponded to "valid skip" entries on the scale variables (B_Q12D_C and B_Q12F_C). The scale variables were recoded into different variables using the transform menu in SPSS. Valid skips were re-coded as no participation. The categories for participation three times and participation four times did not meet the sample size limit, so they were combined. The new categorical variables have five levels: 1) never participated 2) participated one time 3) participated two times 4) participated three or four times and 5) participated five or more times. These were then further collapsed in some of the interactions depending on sample size.

Table 8
New Variables Created for This Analysis

PIAAC Variable	*PIAAC Variable Label*	*PIAAC Categories*	*New Categories*	*Used in Research Question*
B_Q01AUS_C	Education - highest qualification - level (3 categories) (derived from B_Q01aUS)	1: Less than high school diploma 2: High school diploma/some college but no degree 3: College degree or higher (associate, bachelor, doctorate)	1: High school diploma or less 2: College degree (associate or higher)	1a, 1b, 2a, 2b, 3a, 3b, 3c, 3d, 4a, 4b, 4c, 4d, 5a, 5b, 5c, 5d, 6a, 6b, 6c, 6d
RACETHN_4CAT	Background - race/ethnicity (derived, 4 categories)	1: Hispanic 2: White 3: Black 4: Other race	1: White 2: Black 3: Other race	1a, 1b, 2a, 2b, 3a, 3b, 3c, 3d, 4a, 4b, 4c, 4d, 5a, 5b, 5c, 5d, 6a, 6b, 6c, 6d
I_Q08	About yourself - Health - State	1: Excellent 2: Very good 3: Good 4: Fair 5: Poor	1: Excellent 2: Very good 3: Good 4: Fair or Poor	1a, 1b, 2a, 2b, 3a, 3b, 3c, 3d, 4a, 4b, 4c, 4d, 5a, 5b, 5c, 5d, 6a, 6b, 6c, 6d
AGEG5LFSEXT	Age in 5 year bands extended to include ages over 65 (derived)	8: 50-54 9: 55-59 10: 60-65 11: 66-70	1: 50-59 2: 60-70	6a, 6b
AGEG5LFSEXT	Age in 5 year bands extended to include ages over 65 (derived)	8: 50-54 9: 55-59 10: 60-65 11: 66-70	1: 50-54 2: 55-59 3: 60-70	6c, 6d
D_Q03US	Current work - Economic sector	1: Private 2: Public 3: Non-profit	1: Private 2: Public or Non-profit	4a, 4b, 4c, 4d
D_Q06A	Current work - Amount of people working for employer	1: 1-10 people 2: 11-50 people 3: 51-250 people 4: 251-1000 people 5: More than 1000 people	1: 1-50 people 2: 51-250 people 3: 251 or more people	5a, 5b, 5c, 5d

Table 8 (Cont.)

PIAAC Variable	*PIAAC Variable Label*	*PIAAC Categories*	*New Categories*	*Used in Research Question*
D_Q13A	Current work - Learning - Learning from co-workers/supervisors	1: Never 2: Less than once a month 3: Less than once a week but at least once a month 4: At least once a week but not every day 5: Every day	1: Never or less than once a month 2: Less than once a week but at least once a month 3: At least once a week but not every day 4: Every day	2b, 3d, 4d, 5d
D_Q13A	Current work - Learning - Learning from co-workers/supervisors	1: Never 2: Less than once a month 3: Less than once a week but at least once a month 4: At least once a week but not every day 5: Every day	1: Less than once a week 2: At least once a week	6d
D_Q13B	Current work - Learning - Learning-by-doing	1: Never 2: Less than once a month 3: Less than once a week but at least once a month 4: At least once a week but not every day 5: Every day	1: Never or less than once a month 2: Less than once a week but at least once a month 3: At least once a week but not every day 4: Every day	2a, 3c, 4c, 5c
D_Q13B	Current work - Learning - Learning-by-doing	1: Never 2: Less than once a month 3: Less than once a week but at least once a month 4: At least once a week but not every day 5: Every day	1: Less than once a week 2: At least once a week but not every day 3: Every day	6c
B_Q12C and B_Q12D_C	Activities - Last year - On the job training Activities - Last year - On the job training - Count (top-coded at 5)	B_Q12C categories were 1: Yes; 2: No.	1: Never 2: One time 3: Two times 4: Three or four times 5: Five or more times	1a

Table 8 (Cont.)

PIAAC Variable	*PIAAC Variable Label*	*PIAAC Categories*	*New Categories*	*Used in Research Question*
B_Q12C and B_Q12D_C	Activities - Last year - On the job training Activities - Last year - On the job training - Count (top-coded at 5)	B_Q12C categories were 1: Yes; 2: No.	1: Never 2: One or two times 3: Three or four times 4: Five or more times	3a, 4a
B_Q12C and B_Q12D_C	Activities - Last year - On the job training Activities - Last year - On the job training - Count (top-coded at 5)	B_Q12C categories were 1: Yes; 2: No.	1: Never 2: One or two times 3: Three or more times	5a, 6a
B_Q12E and B_Q12F_C	Activities - Last year - Seminars or workshops Activities - Last year - Seminars or workshops - Count (top-coded at 5)	B_Q12E categories were 1: Yes; 2: No.	1: Never 2: One time 3: Two times 4: Three or four times 5: Five or more times	1b, 4b
B_Q12E and B_Q12F_C	Activities - Last year - Seminars or workshops Activities - Last year - Seminars or workshops - Count (top-coded at 5)	B_Q12E categories were 1: Yes; 2: No.	1: Never 2: One or two times 3: Three or more times	3b, 5b, 6b

Note. PIAAC = Programme for the International Assessment of Adult Competencies

Descriptive Statistics

Although 2017 U.S. PIAAC data were collected from 80 sampling units across the country intended to reflect diversity among participants in educational attainment, race, etc. (Krenzke et al., 2019), the subgroup of employed Baby Boomers was found to be over-representative of certain groups. For example, while the cases were fairly evenly split between male and female (n = 338 and n = 363, respectively), the oldest Baby Boomers in the sample (those between age 66-70) were far fewer in number than those Baby Boomers in the other three age groups. Similarly, the White race accounted for 77% of the sample with other subgroups being so small that only the categories White, Black, and Other could be used in analysis. About 60% of the sample possessed an associate degree or higher. Participants were fairly evenly

distributed among organizations of different size. As may be expected, non-supervisors outnumbered supervisors (n = 378 and n = 192, respectively), and the majority of participants were employed in the private sector, meaning that they worked for companies that are not publicly owned. Table 9 provides the full demographic characteristics of the sample of employed U.S. Baby Boomers in PIAAC 2017. The IDB Analyzer was used to conduct a percentages and means analysis of the sample using the PS-TRE plausible values and 80 replicate weights. This allows the mean PS-TRE score to be included for each subgroup, but the percent indicated includes the weights which can be confusing at first glance. For example, while the total case count of females outnumbers males, their weighted values are closer to a 50/50 split.

A few trends are worth noting regarding mean differences in PS-TRE scores. PS-TRE scores can range from 0-500 and are broken down into four levels. Levels are defined as follows. Below Level 1 = below 241 points. Level 1 = 241 to less than 291. Level 2 = 291 to less than 341. Level 3 = 341 or higher. Reviewing these demographics, the overall mean PS-TRE score for the entire sample is 260.86, which is a Level One score. None of the subgroups achieved mean scores in the Level Two or Level Three range, but one subgroup—those whose race is Black—had a mean PS-TRE score in the Below Level One category. Subgroups with mean PS-TRE scores above the overall sample mean include those who have earned college degrees, those between ages 55-65, those who are male, those who are White, those whose health is excellent or very good, those who supervise others, those who work in organizations with more than 1,000 employees, and those who work in the public or non-profit sectors.

Table 9

Demographic Characteristics of Sample

Demographic	*n*	Weighted Sample %	Mean PS-TRE	Standard Error
Total Cases	701	100	260.86	2.04
Age				
50-54	211	33.44	258.36	3.28
55-59	214	31.69	265.14	3.18
60-65	213	26.18	261.03	3.84
66-70	63	8.69	254.41	6.95
Gender				
Male	338	50.43	262.34	3.32
Female	363	49.57	259.36	2.74
Race				
White	540	75.63	267.12	2.21
Black	74	10.75	229.80	5.26
Other race	84	13.18	250.31	6.73
Missing data	3	‡	‡	‡
Education level				
High school diploma or less	282	45.15	244.10	2.94
College degree (associate or higher)	419	54.85	274.66	2.65
Self-rated health				
Excellent	138	19.69	262.20	6.32
Very good	265	37.96	266.11	3.45
Good	221	29.37	257.48	3.08
Fair or Poor	76	12.91	251.15	5.65
Missing data	1	‡	‡	‡
Supervises others				
Yes	192	27.08	266.61	4.15
No	378	54.84	257.56	2.57
Missing data	131	18.09	262.29	5.21
Size of organization				
1-10 people	109	14.82	257.19	4.88
11-50 people	136	19.63	259.22	4.96
51-250 people	164	25.31	259.65	4.02
251-1000 people	71	9.00	260.29	9.28
More than 1000 people	88	12.95	268.51	5.03
Missing data	133	18.29	262.15	5.14
Economic sector				
Private	467	68.16	260.05	2.56
Public	165	22.51	263.38	4.35
Non-Profit	66	8.75	262.25	5.44
Missing data	3	‡	‡	‡

Note. PS-TRE = problem solving in technology-rich environments. Demographic data were compiled using the IDB Analyzer which utilizes the PS-TRE plausible values and replicate weights.
‡ NCES reporting standards are not met.

The mean difference in PS-TRE scores among participants in the four types of learning activity in this study are also important to consider. Tables 10-11 provide this information for the

nonformal learning measures. As above, the IDB Analyzer was used to conduct a percentages and means analysis of the sample using the PS-TRE plausible values and 80 replicate weights, so the percent indicated includes the weights. All mean PS-TRE scores are Level One scores. Table 10 indicates that the mean PS-TRE score overall was higher among people who participated in on-the-job training than among those who did not. Interestingly, though, participating more times does not consistently result in a higher mean PS-TRE score. We see this trend repeated in Table 11 which shows the mean PS-TRE scores for seminar or workshop participants. In both nonformal learning measures, then, the highest overall PS-TRE scores are seen among those who participated two times in the type of learning activity.

Table 10

Mean PS-TRE for Non-Formal Learning: Participation in On-the-Job Training Last Year

Participation	*n*	Weighted Sample %	Mean PS-TRE	Standard Error
Yes	342	48.78	267.72	2.87
No	359	51.22	254.33	3.07
If yes, times participated				
0 [a]	1	‡	‡	‡
1	75	10.03	267.50	5.03
2	72	9.65	276.51	5.99
3	40	5.71!	257.11!	7.93!
4	41	6.22!	267.74!	10.55!
5 or more	113	17.08	266.30	4.59

Note. PS-TRE = problem solving in technology-rich environments. Demographic data were compiled using the IDB Analyzer which utilizes the PS-TRE plausible values and replicate weights.

[a] Zero times participated was treated as no participation during analysis.

‡ NCES reporting standards are not met.

! Interpret data with caution. The sample size for this estimate is between 30 and 61 cases.

Table 11

Mean PS-TRE for Non-Formal Learning: Participation in Seminars or Workshops Last Year

Participation	*n*	Weighted Sample %	Mean PS-TRE	Standard Error
Yes	303	43.46	272.05	2.95
No	398	56.54	252.26	2.88
If yes, times participated				
1	79	10.20	272.12	5.17
2	83	12.08	276.64	5.05
3	45	6.79!	262.45!	8.07!
4	28	‡	‡	‡
5 or more	68	10.61	271.73	5.80

Note. PS-TRE = problem solving in technology-rich environments. Demographic data were compiled using the IDB Analyzer which utilizes the PS-TRE plausible values and replicate weights.
‡ NCES reporting standards are not met.
! Interpret data with caution. The sample size for this estimate is between 30 and 61 cases.

Percentages and means for the informal learning variables are presented in Tables 12-13. Due to low sample size, the category "never" was not able to be used by itself in analysis, so "never" and "less than once a month" were combined. The IDB Analyzer was used to conduct a percentages and means analysis of the sample using the PS-TRE plausible values and 80 replicate weights, so the percent indicated includes the weights. All mean PS-TRE scores are Level One scores. As with the nonformal learning measures, higher participation in informal learning does not consistently lead to higher mean PS-TRE scores. Table 12 indicates that among those who learned by doing, the highest PS-TRE scores were among those who learned by doing at least once a week but not every day. Interestingly, those who reported learning by doing every day had the worst overall mean PS-TRE scores. We see this trend repeated in Table 13 which shows the mean PS-TRE scores for learning informally from coworkers or supervisors. In both learning measures, those who reported learning informally every day had worse mean PS-TRE scores than those who never or rarely learned informally.

Table 12

Mean PS-TRE for Informal Learning: Participation in Learning by Doing

Participation	*n*	Weighted Sample %	Mean PS-TRE	Standard Error
Never or less than once a month	155	22.48	262.90	4.08
Less than once a week but at least once a month	120	17.64	269.95	5.00
At least once a week but not every day	156	21.29	270.71	3.67
Every day	268	38.45	249.97	3.00
Missing data	2	‡	‡	‡

Note. PS-TRE = problem solving in technology-rich environments. Demographic data were compiled using the IDB Analyzer which utilizes the PS-TRE plausible values and replicate weights.
‡ NCES reporting standards are not met.

Table 13

Mean PS-TRE for Informal Learning: Participation in Learning from Co-workers or Supervisors

Participation	*n*	Weighted Sample %	Mean PS-TRE	Standard Error
Never or less than once a month	189	27.55	256.45	4.10
Less than once a week but at least once a month	138	19.17	267.66	4.44
At least once a week but not every day	161	22.54	268.30	3.87
Every day	125	19.85	250.20	5.61
Missing data	88	10.88	264.08	5.37

Note. PS-TRE = problem solving in technology-rich environments. Demographic data were compiled using the IDB Analyzer which utilizes the PS-TRE plausible values and replicate weights.

To gain a better understanding of PS-TRE performance within the sample, I used the IDB Analyzer to run a benchmark analysis using the PS-TRE plausible values and 80 replicate weights. The percent of participants indicated includes the weights. Figure 7 shows the outcome of the PS-TRE benchmark analysis. Essentially this analysis confirms that there are differences in PS-TRE ability within the sample. Although the overall mean PS-TRE score for the entire sample (N = 701) of employed Baby Boomers is a Level 1 score with 284 cases scoring in this

range, 194 cases had scores in the Level 2 or 3 range. More participants, however, scored Below Level 1 (*n* = 223) than scored above it.

With about one-third of the sample scoring Below Level 1 in PS-TRE, one might wonder if the employment prospects of these participants have been impacted by difficulty in this competency area. As indicated in Chapter Two, Table 14 shows the results of the following two questions from the PIAAC Background Questionnaire:

- G_Q07: Do you think you have the computer skills you need to do your job well?
- G_Q08: Has a lack of computer skills affected your chances of being hired for a job or getting a promotion or pay raise?

The majority of respondents (*n* = 561) felt that they have the computer skills needed to do their jobs well and only 65 reported that a lack of skills has impacted their chance at being hired, promoted, or given a raise. Notably, however, there is only about a 10-point difference in the mean PS-TRE scores of those who report having the necessary computer skills and those who do not. All mean PS-TRE scores reported are Level 1 scores.

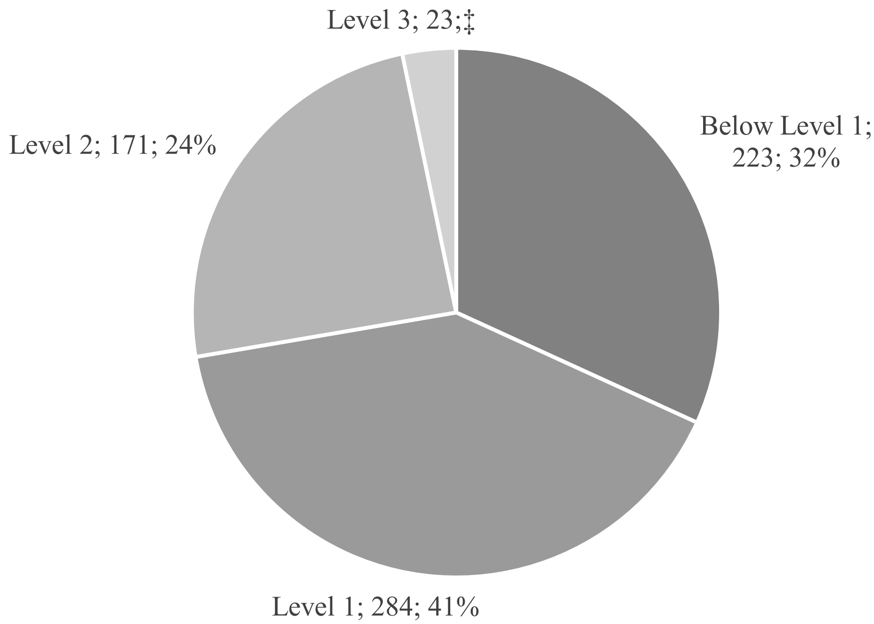


Figure 7: PS-TRE Benchmarks for Employed Baby Boomers in PIAAC 2017. N = 701. PS-TRE = problem solving in technology-rich environments. PIAAC = Programme for the International Assessment of Adult Competencies PS-TRE scores range from 0-500 and levels are defined as follows. Below Level 1 = below 241 points. Level 1 = 241 to less than 291. Level 2 = 291 to less than 341. Level 3 = 341 or higher. Benchmark data were compiled using the IDB Analyzer which utilizes the PS-TRE plausible values and replicate weights.
‡ NCES reporting standards for percentage are not met.

Table 14
Computer Skills and Employment Outcomes for Employed U.S. Baby Boomers

Question	Response	N of Cases	Weighted Sample %	Mean PS-TRE Score (SE)
Do you think you have the computer skills you need to do your job well?	Yes	561	89.68	265.21 (2.44)
	No	59	10.32!	255.00 (6.36)!
Has a lack of computer skills affected your chances of being hired for a job or getting a promotion or pay raise?	Yes	65	10.71	251.59 (6.50)
	No	554	89.29	265.55 (2.36)

Note. PS-TRE = problem solving in technology-rich environments; SE = standard error. Demographic data were compiled using the IDB Analyzer which utilizes the PS-TRE plausible values and replicate weights. Missing data were excluded from analysis.
! Interpret data with caution. The sample size for this estimate is between 30 and 61 cases.

One final point of interest regarding PS-TRE scores is the question of how this sample of employed Baby Boomers performs in PS-TRE in comparison to other U.S. employees in the 2017 PIAAC dataset. To answer this question required the use of the full dataset (N = 3,660) which was sorted only by employment status using variable C_D05. Those respondents who were in any category other than employed were removed, leaving 2,510 cases in the data set. The IDB Analyzer was used to conduct a percentages and means analysis using the PS-TRE plausible values and 80 replicate weights, so the percent indicated includes the weights. Table 15 provides a breakdown of the scores by 5-year age groups and Figure 8 shows a line graph of these results. As a reminder, Baby Boomers are those between ages 50-70 in this dataset. No mean PS-TRE scores were Below Level 1 for any age group, and no age groups achieved PS-TRE means of Level 3. Those between ages 25-29 achieved a mean PS-TRE score in Level 2. All other groups had scores in the Level 1 range.

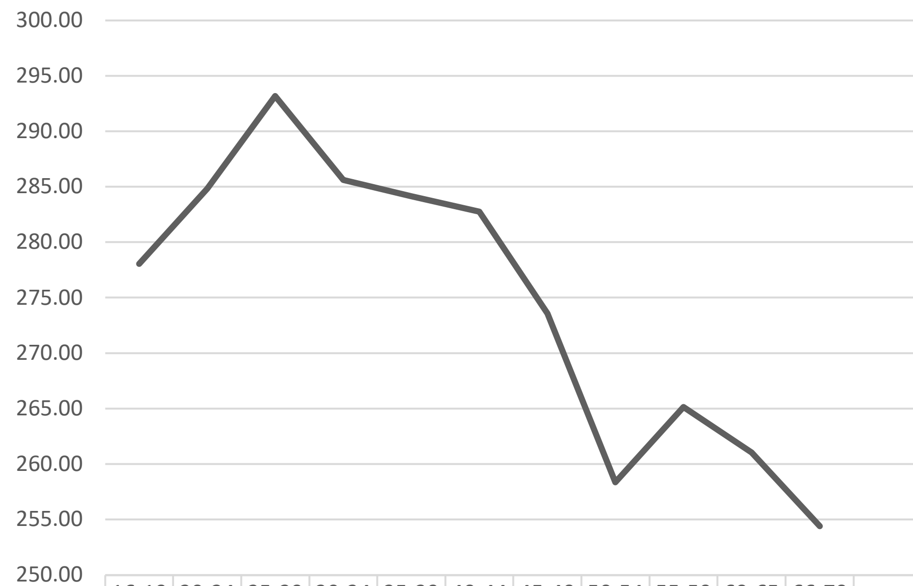
Table 15

Average PS-TRE Scores of All U.S Employees in PIAAC 2017

Age	N of Cases	Weighted Sample %	Mean PS-TRE Score (SE)
16-19	103	5.93	278.04 (4.89)
20-24	212	12.02	284.84 (4.78)
25-29	230	10.14	293.20 (4.02)
30-34	260	11.68	285.60 (3.57)
35-39	258	10.67	284.14 (3.85)
40-44	217	9.52	282.75 (3.61)
45-49	200	9.25	273.57 (3.82)
50-54	211	10.01	258.36 (3.28)
55-59	214	9.48	265.14 (3.18)
60-65	213	7.83	261.03 (3.84)
66-70	63	2.60	254.41 (6.95)
71 plus	22	‡	‡

Note. PS-TRE = problem solving in technology-rich environments; PIAAC = Programme for the International Assessment of Adult Competencies; SE = standard error. Demographic data were compiled using the IDB Analyzer which utilizes the PS-TRE plausible values and replicate weights. Missing data were excluded from analysis.

‡ NCES reporting standards are not met.



	16-19	20-24	25-29	30-34	35-39	40-44	45-49	50-54	55-59	60-65	66-70
Mean PS-TRE Score	278.04	284.84	293.20	285.60	284.14	282.75	273.57	258.36	265.14	261.03	254.41

Figure 8: Line Graph of Average PS-TRE Scores of All U.S Employees in PIAAC 2017

The final set of descriptive statistics is provided to help us identify trends in nonformal and informal learning participation within the sample. Table 16 provides crosstabulations of on-the-job training, learning from coworkers, and learning by doing. Notably, there were many cases who reported never receiving on-the-job training and never learning from coworkers (n = 34) or never learning by doing (n = 33). Numbers of those who never received on-the-job training and learned from coworkers or learned by doing less than once a month (n = 72 and n = 70, respectively) were also high. All participants in on-the-job training were most likely to learn by doing every day. The majority trends in on-the-job training and learning from coworkers, though, follow a different pattern. Those who did not participate in on-the-job training or who participated once were most likely to learn from coworkers less than once a month. Those who experienced on-the-job training twice were tied between being most likely to learn from coworkers at least once a month and at least once a week. Those who had on-the-job training

three or four times were most likely to learn from coworkers every day. Those who had on-the-job training five or more times were most likely to learn from coworkers at least once a week.

Table 16

Crosstabulations of On-the-Job Training and Informal Learning

Nonformal (horizontal) and Informal (vertical)	On-the-Job Training					
	Participation	Did not participate	One time	Two times	Three or four times	Five or more times
Learning from Coworkers or Supervisors	Never	34	2	1	4	2
	Less than once a month	72	24	16	13	21
	Less than once a week but at least once a month	61	18	18	15	25
	At least once a week but not every day	70	17	18	22	34
	Every day	51	8	14	23	29
Learning by Doing	Never	33	2	1	5	2
	Less than once a month	70	10	8	10	14
	Less than once a week but at least once a month	54	21	11	19	15
	At least once a week but not every day	69	14	24	21	27
	Every day	132	27	28	26	55

Table 17 provides crosstabulations of seminar or workshop participation, learning from coworkers, and learning by doing. As above, many reported never participating in seminars or workshops and never learning from coworkers (n = 36) or never learning by doing (n = 39). Almost 14% of the sample (n = 98) never participated in a seminar or workshop and learned from coworkers less than once a month. On the other hand, no cases reported never learning informally if they participated in seminars or workshops three or four times. As we saw with on-the-job training, all who had participated in seminars or workshops were most likely to learn by

doing every day, but majority trends for learning from coworkers follow a different pattern. Those who did not participate in seminars were most likely to learn from coworkers less than once a month. Those who participated in one seminar or workshop were most likely to learn from coworkers at least once a week. Those who participated twice were most likely to learn from coworkers at least once a month. Those who participated three or four times were most likely to learn from coworkers every day, and those who participated five or more times were most likely to learn from coworkers at least once a week or every day.

Table 17

Crosstabulations of Seminar or Workshop Participation and Informal Learning

Nonformal (horizontal) and Informal (vertical)	Seminar or workshop participation					
	Participation	Did not participate	One time	Two times	Three or four times	Five or more times
Learning from coworkers or supervisors	Never	36	1	3	0	3
	Less than once a month	98	14	16	8	10
	Less than once a week but at least once a month	72	17	22	14	13
	At least once a week but not every day	82	23	20	17	19
	Every day	55	15	16	20	19
Learning by doing	Never	39	2	2	0	0
	Less than once a month	74	11	14	4	9
	Less than once a week but at least once a month	64	13	17	15	11
	At least once a week but not every day	73	23	20	20	20
	Every day	148	28	30	34	28

Analysis

This section describes the analysis procedures used to answer the six research questions of this study. All multiple regression analyses were conducted in the IDB Analyzer. The International Association for the Evaluation of Educational Achievement (IEA, 2018) describes the IDB Analyzer as a software application that allows researchers to analyze data from their large-scale assessment studies. The IDB Analyzer interfaces with SPSS or SAS—I used SPSS version 25. After opening the IDB Analyzer and selecting the Analysis Module, the researcher first selects the SPSS file that is to be used in the analysis. PIAAC was selected as the study type, and linear regression was selected as the statistic type. From there, independent and dependent variables are selected from a menu. The ten PS-TRE plausible values were always the dependent variables in this study, and the final full sample weight was always utilized.

In the remainder of this section, the first subsection describes the method for dealing with missing data. The second subsection describes the analysis procedures for answering this study's primary research questions regarding the impact of nonformal and informal workplace learning participation on PS-TRE scores. Finally, the third subsection describes the analysis procedures for answering this study's research questions pertaining to moderation.

Missing Data

Review of the demographic statistics indicates several variables in this study had missing data. The IDB Analyzer offers three options for dealing with missing data when running multiple linear regression analyses. The options are pairwise, listwise, or mean substitution. Pairwise exclusion was selected for all multiple regression analyses used in this study. Of the three, Field (2018) indicates pairwise exclusion is preferable because it utilizes as much data as possible

while maintaining an accurate standard error estimate. Multiple imputation procedures for replacing missing data are not available for complex survey data sets such as PIAAC.

Analysis Procedure for Primary Research Questions

Model One: Control Variables

Research questions 1-5 utilize the same group of control variables: age, education level, gender, self-rated health, and race. A linear regression model, Model One, was run to determine the impact of these variables on PS-TRE competency. To meet the NCES reporting standards (AIR PIAAC Team, 2019) the PIAAC variables for education, race, and health were collapsed as indicated in Table 8. Age (AGEG5LFSEXT) and gender (GENDER_R) variables were utilized as-is. Model One is represented by the following equation:

$$PS\text{-}TRE = b_0 + b_1\text{Age} + b_2\text{Education} + b_3\text{Gender} + b_4\text{Health} + b_5\text{Race} + e$$

Research Question One

Research question one asks if participation in nonformal workplace learning is associated with significantly higher PS-TRE performance among U.S. Baby Boomers. As measures of nonformal workplace learning, Question 1a asks specifically about on-the-job training while Question 1b asks about participation in seminars or workshops. After running Model One as indicated, Model Two was run for Question 1a, and Model Two was run for Question 1b. As indicated in Table 8, new categorical variables were created for on-the-job training and seminar or workshop participation. Model Two for Question 1a (on-the-job training) is represented by the following equation:

$$PS\text{-}TRE = b_0 + b_1 Age + b_2 Education + b_3 Gender + b_4 Health + b_5 Race + b_6 On\text{-}the\text{-}job\ Training + e$$

Model Two for Question 1b (seminar or workshop participation) is represented by the following equation:

$$PS\text{-}TRE = b_0 + b_1 Age + b_2 Education + b_3 Gender + b_4 Health + b_5 Race + b_6 Seminar + e$$

Research Question Two

Research question two asks if participation in informal workplace learning is associated with significantly higher PS-TRE performance among U.S. Baby Boomers. As measures of informal workplace learning, Question 2a asks specifically about learning-by-doing while Question 2b asks about learning from coworkers. After running Model One as indicated, Model Two was run for Question 2a, and Model Two was run for Question 2b. As indicated in Table 8, new categorical variables were created for learning-by-doing and learning from coworkers. Model Two for Question 2a (learning-by-doing) is represented by the following equation:

$$PS\text{-}TRE = b_0 + b_1 Age + b_2 Education + b_3 Gender + b_4 Health + b_5 Race + b_6 Learning\text{-}by\text{-}Doing + e$$

Model Two for Question 2b (learning from coworkers) is represented by the following equation:

$$PS\text{-}TRE = b_0 + b_1 Age + b_2 Education + b_3 Gender + b_4 Health + b_5 Race + b_6 Learning\text{-}from\text{-}Coworkers + e$$

Analysis Procedure for Moderation Research Questions

Creating and Interpreting Interaction Terms

When regression involves categorical predictors, as is the case here, dummy coding is used to define the interaction terms. The dummy coding process described by Field (2018) has eight steps and utilizes a sequence of 0s and 1s as values. PIAAC variables all start with 1 by default, so several data transformations were needed in order to compute the interaction terms.

First, the case count for each interaction was reviewed to determine how many participants fell into the subcategory. Table 18 shows the interaction counts for the learning terms and supervisory status, economic sector, and size of the organization. Table 19 shows the interaction counts for the learning terms, gender, and age. Due to the Central Limit Theorem, it was desirable to have at least 30 cases in each subcategory. In most cases, variables were collapsed in order to accomplish that goal. Table 8 outlines how variables were collapsed for each research question. Any dummy variables with fewer than 30 cases are flagged to interpret with caution in the results tables.

Second, the collapsed categories for each variable of interest in a given interaction were recoded to include a 0 category as the reference group using the transform menu in SPSS. These two variables were then multiplied using the compute variable option in the transform menu in SPSS. The result was a variable including values ranging from 0-6 depending on the number of categories in the interaction terms. This variable was then recoded to drop the 0 and replace it with 1 using the transform menu in SPSS—this resulted in an interaction term that could be used in the IDB Analyzer. One full example of this process is shown in Appendix B.

Research Question Three

Research question three asks if supervisory status influences the relationship between workplace learning and PS-TRE performance among U.S. Baby Boomers. As measures of workplace learning, Question 3a asks about on-the-job training, Question 3b asks about participation in seminars or workshops, Question 3c asks about learning-by-doing, and Question 3d asks about learning from coworkers. Model One was run as indicated. Then Model Two for each of these questions added the main effects of the learning term and the main effects of supervisory status. As indicated in Table 8, new categorical variables were created for the

learning terms. The PIAAC supervisory status variable (D_Q08A) was utilized as-is. Model Two for Question 3a (on-the-job training) is represented by the following equation:

$$PS\text{-}TRE = b_0 + b_1 Age + b_2 Education + b_3 Gender + b_4 Health + b_5 Race + b_6 On\text{-}the\text{-}job\ Training + b_7 Supervisor + e$$

Model Two for Question 3b (seminar or workshop participation) is represented by the following equation:

$$PS\text{-}TRE = b_0 + b_1 Age + b_2 Education + b_3 Gender + b_4 Health + b_5 Race + b_6 Seminar + b_7 Supervisor + e$$

Model Two for Question 3c (learning-by-doing) is represented by the following equation:

$$PS\text{-}TRE = b_0 + b_1 Age + b_2 Education + b_3 Gender + b_4 Health + b_5 Race + b_6 Learning\text{-}by\text{-}Doing + b_7 Supervisor + e$$

Model Two for Question 3d (learning from coworkers) is represented by the following equation:

$$PS\text{-}TRE = b_0 + b_1 Age + b_2 Education + b_3 Gender + b_4 Health + b_5 Race + b_6 Learning\text{-}from\text{-}Coworkers + b_7 Supervisor + e$$

Model Three for each of these questions included controls, plus main effects, plus the interaction term. Model Three for Question 3a (on-the-job training) is represented by the following equation:

$$PS\text{-}TRE = b_0 + b_1 Age + b_2 Education + b_3 Gender + b_4 Health + b_5 Race + b_6 On\text{-}the\text{-}job\ Training + b_7 Supervisor + b_8 OTJTxSupervisor + e$$

Model Three for Question 3b (seminar or workshop participation) is represented by the following equation:

$$PS\text{-}TRE = \mathrm{b}_0 + \mathrm{b}_1 Age + \mathrm{b}_2 Education + \mathrm{b}_3 Gender + \mathrm{b}_4 Health + \mathrm{b}_5 Race + \mathrm{b}_6 Seminar + b_7 Supervisor + b_8 SeminarxSupervisor + e$$

Model Three for Question 3c (learning-by-doing) is represented by the following equation:

$$PS\text{-}TRE = b_0 + b_1 Age + b_2 Education + b_3 Gender + b_4 Health + b_5 Race + b_6 Learning\text{-}by\text{-}Doing + b_7 Supervisor + b_8 LBDxSupervisor + e$$

Model Three for Question 3d (learning from coworkers) is represented by the following equation:

$$PS\text{-}TRE = b_0 + b_1 Age + b_2 Education + b_3 Gender + b_4 Health + b_5 Race + b_6 Learning\text{-}from\text{-}Coworkers + b_7 Supervisor + b_8 LFCxSupervisor + e$$

Research Question Four

Research question four asks if economic sector influences the relationship between workplace learning and PS-TRE performance among U.S. Baby Boomers. As measures of workplace learning, Question 4a asks about on-the-job training, Question 4b asks about participation in seminars or workshops, Question 4c asks about learning-by-doing, and Question 4d asks about learning from coworkers. Model One was run as indicated. Then Model Two for each of these questions added the main effects of the learning term and the main effects of economic sector. As indicated in Table 8, new categorical variables were created for the learning terms and for economic sector. Model Two for Question 4a (on-the-job training) is represented by the following equation:

$$PS\text{-}TRE = b_0 + b_1 Age + b_2 Education + b_3 Gender + b_4 Health + b_5 Race + b_6 On\text{-}the\text{-}job\ Training + b_7 Sector + e$$

Model Two for Question 4b (seminar or workshop participation) is represented by the following equation:

$$PS\text{-}TRE = \mathrm{b}_0 + \mathrm{b}_1 Age + \mathrm{b}_2 Education + \mathrm{b}_3 Gender + \mathrm{b}_4 Health + \mathrm{b}_5 Race + \mathrm{b}_6 Seminar + b_7 Sector + e$$

Model Two for Question 4c (learning-by-doing) is represented by the following equation:

$$PS\text{-}TRE = b_0 + b_1Age + b_2Education + b_3Gender + b_4Health + b_5Race + b_6Learning\text{-}by\text{-}Doing + b_7Sector + e$$

Model Two for Question 4d (learning from coworkers) is represented by the following equation:

$$PS\text{-}TRE = b_0 + b_1Age + b_2Education + b_3Gender + b_4Health + b_5Race + b_6Learning\text{-}from\text{-}Coworkers + b_7Sector + e$$

Model Three for each of these questions included controls, plus main effects, plus the interaction term. Model Three for Question 4a (on-the-job training) is represented by the following equation:

$$PS\text{-}TRE = b_0 + b_1Age + b_2Education + b_3Gender + b_4Health + b_5Race + b_6On\text{-}the\text{-}job\ Training + b_7Sector + b_8OTJTxSector + e$$

Model Three for Question 4b (seminar or workshop participation) is represented by the following equation:

$$PS\text{-}TRE = b_0 + b_1Age + b_2Education + \mathrm{b}_3Gender + b_4Health + b_5Race + b_6Seminar + b_7Sector + b_8SeminarxSector + e$$

Model Three for Question 4c (learning-by-doing) is represented by the following equation:

$$PS\text{-}TRE = b_0 + b_1Age + b_2Education + b_3Gender + b_4Health + b_5Race + b_6Learning\text{-}by\text{-}Doing + b_7Sector + b_8LBDxSector + e$$

Model Three for Question 4d (learning from coworkers) is represented by the following equation:

$$PS\text{-}TRE = b_0 + b_1Age + b_2Education + b_3Gender + b_4Health + b_5Race + b_6Learning\text{-}from\text{-}Coworkers + b_7Sector + b_8LFCxSector + e$$

Table 18

Workplace Learning Participation: Total Cases by Supervisor, Sector, and Size of Organization

Variable	Supervisor Yes	Supervisor No	Private Sector	Public Sector	Non-profit Sector	Small Businesses	Medium-Sized Businesses	Large Businesses
On the job training								
Never	80	176	268	61	28	134	71	50
1 time	24	43	50	17	8	30	19	18
2 times	20	44	43	24	4	23	20	21
3 times	13	23	20	14	6	12	12	12
4 times	13	27	26	13	2	10	11	19
5 or more times	41	65	60	35	18	36	30	39
Seminars or Workshops								
Never	88	230	300	69	26	164	81	71
1 time	24	44	42	27	10	26	18	24
2 times	33	40	45	22	16	21	28	24
3 times	9	24	29	9	7	8	15	10
4 times	9	12	13	15	0	5	10	6
5 or more times	29	28	38	23	7	21	12	95
Learning by doing								
Never	8	22	34	7	1	16	7	7
Less than once a month	34	54	75	27	10	42	21	25
Less than once a week but at least once a month	35	68	81	28	11	40	36	26
At least once a week but not every day	52	76	101	41	14	48	35	45
Every day	63	156	175	61	30	98	65	55

Table 18 (Cont.)

Variable	Supervisor Yes	Supervisor No	Private Sector	Public Sector	Non-profit Sector	Small Businesses	Medium-Sized Businesses	Large Businesses
Learning from coworkers or supervisors								
Never	8	29	32	10	1	19	9	8
Less than once a month	51	87	97	31	18	63	38	36
Less than once a week but at least once a month	48	84	86	36	16	55	44	33
At least once a week but not every day	51	98	101	46	13	60	45	44
Every day	34	79	73	36	15	47	28	38

Table 19

Workplace Learning Participation: Total Cases by Gender and Age

Variable	Male	Female	Age 50-54	Age 55-59	Age 60-65	Age 66-70
On the job training						
Never	188	171	108	100	111	40
1 time	40	35	15	28	23	9
2 times	35	37	22	25	21	4
3 times	16	24	11	11	15	3
4 times	18	23	13	16	9	3
5 or more times	41	72	41	34	34	4
Seminars or Workshops						
Never	197	201	124	119	111	44
1 time	38	41	25	22	25	7
2 times	38	45	23	27	29	4
3 times	20	25	12	15	15	3
4 times	16	12	8	7	11	2
5 or more times	29	39	19	24	22	3
Learning by doing						
Never	15	28	10	10	16	7
Less than once a month	49	63	35	32	32	13
Less than once a week but at least once a month	64	56	33	42	35	10
At least once a week but not every day	81	75	53	50	41	12
Every day	127	141	79	80	88	21
Learning from coworkers or supervisors						
Never	18	25	9	13	14	7
Less than once a month	66	80	49	45	39	13
Less than once a week but at least once a month	60	78	48	41	40	9
At least once a week but not every day	77	84	49	48	54	10
Every day	67	58	41	38	37	9

Research Question Five

Research question five asks if the size of an organization influences the relationship between workplace learning and PS-TRE performance among U.S. Baby Boomers. As measures of workplace learning, Question 5a asks about on-the-job training, Question 5b asks about participation in seminars or workshops, Question 5c asks about learning-by-doing, and Question 5d asks about learning from coworkers. Model One was run as indicated. Then Model Two for each of these questions added the main effects of the learning term and the main effects of organizational size. As indicated in Table 8, new categorical variables were created for the learning terms and for size of the organization. Model Two for Question 5a (on-the-job training) is represented by the following equation:

$$PS\text{-}TRE = b_0 + b_1 Age + b_2 Education + b_3 Gender + b_4 Health + b_5 Race + b_6 On\text{-}the\text{-}job\ Training + b_7 Size + e$$

Model Two for Question 5b (seminar or workshop participation) is represented by the following equation:

$$PS\text{-}TRE = \mathrm{b}_0 + \mathrm{b}_1 Age + \mathrm{b}_2 Education + \mathrm{b}_3 Gender + \mathrm{b}_4 Health + \mathrm{b}_5 Race + \mathrm{b}_6 Seminar + b_7 Size + e$$

Model Two for Question 5c (learning-by-doing) is represented by the following equation:

$$PS\text{-}TRE = b_0 + b_1 Age + b_2 Education + b_3 Gender + b_4 Health + b_5 Race + b_6 Learning\text{-}by\text{-}Doing + b_7 Size + e$$

Model Two for Question 5d (learning from coworkers) is represented by the following equation:

$$PS\text{-}TRE = b_0 + b_1 Age + b_2 Education + b_3 Gender + b_4 Health + b_5 Race + b_6 Learning\text{-}from\text{-}Coworkers + b_7 Size + e$$

Model Three for each of these questions included controls, plus main effects, plus the interaction term. Model Three for Question 5a (on-the-job training) is represented by the following equation:

$$PS\text{-}TRE = b_0 + b_1 Age + b_2 Education + b_3 Gender + b_4 Health + b_5 Race + b_6 On\text{-}the\text{-}job\ Training + b_7 Size + b_8 OTJTxSize + e$$

Model Three for Question 5b (seminar or workshop participation) is represented by the following equation:

$$PS\text{-}TRE = b_0 + b_1 Age + b_2 Education + b_3 Gender + b_4 Health + b_5 Race + b_6 Seminar + b_7 Size + b_8 SeminarxSize + e$$

Model Three for Question 5c (learning-by-doing) is represented by the following equation:

$$PS\text{-}TRE = b_0 + b_1 Age + b_2 Education + b_3 Gender + b_4 Health + b_5 Race + b_6 Learning\text{-}by\text{-}Doing + b_7 Size + b_8 LBDxSize + e$$

Model Three for Question 5d (learning from coworkers) is represented by the following equation:

$$PS\text{-}TRE = b_0 + b_1 Age + b_2 Education + b_3 Gender + b_4 Health + b_5 Race + b_6 Learning\text{-}from\text{-}Coworkers + b_7 Size + b_8 LFCxSize + e$$

Research Question Six

Research question six asks whether the relationship between gender, workplace learning, and PS-TRE varies as a function of age among U.S. Baby Boomers. Since age and gender are main effects in this model, this research question utilizes a new controls model for sub questions 6a, 6b, 6c, and 6d. Control variables in this research question include: education level, self-rated health, and race. A linear regression model, Model One, was run to determine the impact of these variables on PS-TRE competency. To meet the NCES reporting standards (AIR PIAAC Team,

2019) the PIAAC variables for education, race, and health were collapsed as indicated in Table 8. Model One is represented by the following equation:

$$PS\text{-}TRE = b_0 + b_1 Education + b_2 Health + b_3 Race + e$$

As measures of workplace learning, Question 6a asks about on-the-job training, Question 6b asks about participation in seminars or workshops, Question 6c asks about learning-by-doing, and Question 6d asks about learning from coworkers. Model One was run as indicated. Then Model Two for each of these questions added the main effects of the learning term, gender, and age. As indicated in Table 8, new categorical variables were created for the learning terms and age. The PIAAC gender variable (GENDER_R) was utilized as-is. Model Two for Question 6a (on-the-job training) is represented by the following equation:

$$PS\text{-}TRE = b_0 + b_1 Education + b_2 Health + b_3 Race + b_4 On\text{-}the\text{-}job\ training + b_5 Gender + b_6 Age + e$$

Model Two for Question 6b (seminar or workshop participation) is represented by the following equation:

$$PS\text{-}TRE = b_0 + b_1 Education + b_2 Health + b_3 Race + b_4 Seminar + b_5 Gender + b_6 Age + e$$

Model Two for Question 6c (learning-by-doing) is represented by the following equation:

$$PS\text{-}TRE = b_0 + b_1 Education + b_2 Health + b_3 Race + b_4 Learning\text{-}by\text{-}Doing + b_5 Gender + b_6 Age + e$$

Model Two for Question 6d (learning from coworkers) is represented by the following equation:

$$PS\text{-}TRE = b_0 + b_1 Education + b_2 Health + b_3 Race + b_4 Learning\text{-}from\text{-}coworkers + b_5 Gender + b_6 Age + e$$

Model Three for each of these questions included controls, plus main effects, plus the interaction terms for gender x learning and age x learning. Model Three for Question 6a (on-the-job training) is represented by the following equation:

$$PS\text{-}TRE = b_0 + b_1 Education + b_2 Health + b_3 Race + b_4 On\text{-}the\text{-}job\ training + b_5 Gender + b_6 Age + b_7 OTJTxGender + b_8 OTJTxAge + e$$

Model Three for Question 6b (seminar or workshop participation) is represented by the following equation:

$$PS\text{-}TRE = b_0 + b_1 Education + b_2 Health + b_3 Race + b_4 Seminar + b_5 Gender + b_6 Age + b_7 SeminarxGender + b_8 SeminarxAge + e$$

Model Three for Question 6c (learning-by-doing) is represented by the following equation:

$$PS\text{-}TRE = b_0 + b_1 Education + b_2 Health + b_3 Race + b_4 Learning\text{-}by\text{-}Doing + b_5 Gender + b_6 Age + b_7 LBDxGender + b_8 LBDxAge + e$$

Model Three for Question 6d (learning from coworkers) is represented by the following equation:

$$PS\text{-}TRE = b_0 + b_1 Education + b_2 Health + b_3 Race + b_4 Learning\text{-}from\text{-}coworkers + b_5 Gender + b_6 Age + b_7 LFCxGender + b_8 LFCxAge + e$$

Model Four for each of these questions included controls, plus main effects, plus the interaction terms for gender x learning and age x learning, plus the 3-way interaction terms for learning x gender x age. Model Four for Question 6a (on-the-job training) is represented by the following equation:

$$PS\text{-}TRE = b_0 + b_1 Education + b_2 Health + b_3 Race + b_4 On\text{-}the\text{-}job\ training + b_5 Gender + b_6 Age + b_7 OTJTxGender + b_8 OTJTxAge + b_9 OTJTxGenderxAge + e$$

Model Four for Question 6b (seminar or workshop participation) is represented by the following equation:

$$PS\text{-}TRE = b_0 + b_1 Education + b_2 Health + b_3 Race + b_4 Seminar + b_5 Gender + b_6 Age + b_7 SeminarxGender + b_8 SeminarxAge + b_9 SeminarxGenderxAge + e$$

Model Four for Question 6c (learning-by-doing) is represented by the following equation:

$$PS\text{-}TRE = b_0 + b_1 Education + b_2 Health + b_3 Race + b_4 Learning\text{-}by\text{-}Doing + b_5 Gender + b_6 Age + b_7 LBDxGender + b_8 LBDxAge + b_9 LBDxGenderxAge + e$$

Model Four for Question 6d (learning from coworkers) is represented by the following equation:

$$PS\text{-}TRE = b_0 + b_1 Education + b_2 Health + b_3 Race + b_4 Learning\text{-}from\text{-}coworkers + b_5 Gender + b_6 Age + b_7 LFCxGender + b_8 LFCxAge + b_9 LFCxGenderxAge + e$$

Results

Control Variables Model for Research Questions 1-5

As indicated in the literature review, previous empirical studies allude to numerous variables that impact either workplace learning or technology adoption for Baby Boomers. Therefore, a linear regression analysis was conducted to determine the impact of age, education level, gender, self-rated health, and race on PS-TRE scores. This analysis serves as Model One for Research Questions 1-5. Table 20 shows the results of this analysis. Findings from the previous literature were partially supported. Possession of a college degree (b = 29.26, p < 0.001, 95% CI (35.46, 23.06), CV = 10.81%), Black race (b = -35.97, p < 0.001, 95% CI (-25.02, -46.92), CV = -15.53%) and Other race (b = -16.83, p < 0.05, 95% CI (-2.85, -30.82), CV = -42.38%) were unique predictors of PS-TRE performance. There were no significant relationships between age, gender, or health and PS-TRE. The total R^2 = 0.20 which reflects a small-medium effect.

Table 20
Control Variables Model (Model One) for Research Questions 1-5

Variable	Model 1		
	b_i	SE	t
Constant	249.03***	6.92	35.98
Age			
50-54 (ref)			
55-59	4.47	4.47	1.00
60-65	-1.01	4.87	-0.21
66-70	-5.31	6.68	-0.79
Education level			
HS diploma or less (ref)			
College degree	29.26***	3.16	9.25
Gender			
Male (ref)			
Female	-1.74	4.34	-0.40
Self-rated health			
Excellent (ref)			
Very good	5.76	6.59	0.87
Good	1.03	6.43	0.16
Fair or Poor	-3.07	7.77	-0.40
Race			
White (ref)			
Black	-35.97***	5.59	-6.44
Other race	-16.83*!	7.13!	-2.36!
R^2	0.20		

Note. N = 697. PS-TRE = problem solving in technology-rich environments; HS = high school; SE = standard error; Ref = reference.
! Interpret data with caution. The coefficient of variation (CV) for this estimate is between 30 and 50 percent.
* $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$

Hypothesis 1

Hypothesis 1 stated that Baby Boomers who participate in nonformal workplace learning will have significantly stronger PS-TRE scores than those who do not participate. To test this hypothesis, a linear regression, Model Two, was conducted that added the nonformal workplace learning measures to the controls model, Model One. This was done for both on-the-job training and seminar or workshop participation. Results of Model Two (on-the-job training) are in Table

21, and results of Model Two (seminar or workshop participation) are in Table 22. Hypothesis 1 is partially supported for both measures of nonformal workplace learning.

In Model Two for on-the-job training, participating two times in on-the-job training (b = 16.31, $p < 0.01$, 95% CI (28.53, 4.09), CV = 38.23%) was a unique predictor of PS-TRE performance. The other levels of on-the-job training (one time, three or four times, or five or more times) did not reach statistical significance, but all had positive coefficients. Those who participated twice in on-the-job training scored an average of 16.31 points higher in PS-TRE than those who did not participate. The total $R^2 = 0.21$ which reflects a small-medium effect, and the $\Delta R^2 = 0.01$ for step two.

Table 21
Main Effects of Controls and On-the-Job Training on PS-TRE

Variable	Model 2		
	b_i	SE	t
Constant	244.87***	7.32	33.47
Age			
50-54 (ref)			
55-59	3.76	4.44	0.85
60-65	-0.72	4.91	-0.15
66-70	-3.94	6.85	-0.57
Education level			
HS diploma or less (ref)			
College degree	28.63***	3.09	9.26
Gender			
Male (ref)			
Female	-2.15	4.31	-0.50
Self-rated health			
Excellent (ref)			
Very good	5.51	6.44	0.86
Good	1.19	6.18	0.19
Fair or Poor	-1.14	7.77	-0.15
Race			
White (ref)			
Black	-35.56***	5.50	-6.47
Other race	-15.92*!	6.66!	-2.39!

Table 21 (Cont.)

Variable	Model 2		
	b_i	SE	t
On-the-job training			
Never (ref)			
One time	10.30	5.56	1.85
Two times	16.31**!	6.23!	2.62!
Three or four times	3.98	5.45	0.73
Five or more times	7.29	5.06	1.44
R^2	0.21		

Note. N = 696. PS-TRE = problem solving in technology-rich environments; HS = high school; SE = standard error; Ref = reference. ΔR^2 = 0.01 for Step 2.
! Interpret data with caution. The coefficient of variation (CV) for this estimate is between 30 and 50 percent.
* $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$

In Model Two for seminar or workshop participation, participating two times in seminars or workshops (b = 16.05, $p < 0.01$, 95% CI (27.87, 4.23), CV = 37.58%) was a unique predictor of PS-TRE performance. The other levels of seminar or workshop participation (one time, three or four times, or five or more times) did not reach statistical significance, but all had positive coefficients. Those who participated twice in seminars or workshops scored an average of 16.05 points higher in PS-TRE than those who did not participate. The total R^2 = 0.22 which reflects a small-medium effect, and the ΔR^2 = 0.02 for step two.

Table 22
Main Effects of Controls and Seminar or Workshop Participation on PS-TRE

Variable	Model 2		
	b_i	SE	t
Constant	244.53***	7.37	33.19
Age			
50-54 (ref)			
55-59	3.45	4.32	0.80
60-65	-1.78	4.92	-0.36
66-70	-4.57	6.42	-0.71
Education level			
HS diploma or less (ref)			
College degree	26.23***	3.50	7.50
Gender			
Male (ref)			
Female	-1.25	4.33	-0.29

Table 22 (Contd.)

Variable	Model 2		
	b_i	SE	t
Self-rated health			
Excellent (ref)			
Very good	7.01	6.63	1.06
Good	3.11	6.79	0.46
Fair or Poor	-0.51	7.92	-0.06
Race			
White (ref)			
Black	-36.14***	5.38	-6.71
Other race	-16.72*!	6.87!	-2.43!
Seminar or workshop participation			
Never (ref)			
One time	10.19	6.37	1.60
Two times	16.05**!	6.03!	2.66!
Three or four times	8.52	6.73	1.26
Five or more times	10.03	6.70	1.50
R^2	0.22		

Note. $N = 697$. PS-TRE = problem solving in technology-rich environments; HS = high school; SE = standard error; Ref = reference. $\Delta R^2 = 0.02$ for Step 2.
! Interpret data with caution. The coefficient of variation (CV) for this estimate is between 30 and 50 percent.
* $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$

Hypothesis 2

Hypothesis 2 stated that Baby Boomers who participate in informal workplace learning will have significantly stronger PS-TRE scores than those who do not participate. To test this hypothesis, a linear regression, Model Two, was conducted that added the informal workplace learning measures to the controls model, Model One. This was done for both learning-by-doing and learning from coworkers or supervisors. Results of Model Two (learning-by-doing) are in Table 23, and results of Model Two (learning from coworkers) are in Table 24. Findings failed to support Hypothesis 2 for either measure of informal workplace learning.

In Model Two for learning-by-doing, participating every day in learning-by-doing (b = -12.23, $p < 0.01$, 95% CI (-3.43, -21.02), CV = -36.69%) was a unique predictor of PS-TRE

performance. The other levels of learning-by-doing did not reach statistical significance, but those who learned by doing every day had significantly worse PS-TRE performance than those who never or rarely learned by doing. The total $R^2 = 0.22$ which reflects a small-medium effect, and the $\Delta R^2 = 0.02$ for step two.

Table 23

Main Effects of Controls and Learning-by-Doing on PS-TRE

Variable	Model 2		
	b_i	SE	*t*
Constant	254.38***	7.07	35.97
Age			
50-54 (ref)			
55-59	4.58	4.41	1.04
60-65	-0.22	4.84	-0.05
66-70	-6.23	6.51	-0.96
Education level			
HS diploma or less (ref)			
College degree	27.91***	3.32	8.40
Gender			
Male (ref)			
Female	-1.28	4.37	-0.29
Self-rated health			
Excellent (ref)			
Very good	4.48	6.15	0.73
Good	-0.08	6.09	-0.01
Fair or Poor	-4.46	7.70	-0.58
Race			
White (ref)			
Black	-34.15***	5.83	-5.86
Other race	-16.22*!	6.82!	-2.38!
Learning-by-doing			
Never or less than once a month (ref)			
Less than once a week but at least once a month	0.29	5.14	0.06
At least once a week but not every day	1.76	4.89	0.36
Every day	-12.23**!	4.49!	-2.73!
R^2	0.22		

Note. $N = 695$. PS-TRE = problem solving in technology-rich environments; HS = high school; SE = standard error; Ref = reference. $\Delta R^2 = 0.02$ for Step 2.
! Interpret data with caution. The coefficient of variation (CV) for this estimate is between 30 and 50 percent.
* $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$

In Model Two for learning from coworkers, no amount of learning from coworkers resulted in a significant relationship with PS-TRE performance. The total $R^2 = 0.24$ which reflects a small-medium effect, and the $\Delta R^2 = 0.04$ for step two.

Table 24
Main Effects of Controls and Learning from Coworkers or Supervisors on PS-TRE

Variable	Model 2		
	b_i	SE	t
Constant	244.42***	7.02	34.82
Age			
50-54 (ref)			
55-59	3.02	4.43	0.68
60-65	-1.77	5.04	-0.35
66-70	-13.94*!	6.00!	-2.32!
Education level			
HS diploma or less (ref)			
College degree	30.11***	3.18	9.46
Gender			
Male (ref)			
Female	-3.23	4.65	-0.69
Self-rated health			
Excellent (ref)			
Very good	8.30	6.68	1.24
Good	3.91	6.79	0.58
Fair or Poor	-3.81	8.20	-0.46
Race			
White (ref)			
Black	-35.24***	5.97	-5.91
Other race	-14.89*!	7.33!	-2.03!
Learning from coworkers or supervisors			
Never or less than once a month (ref)			
Less than once a week but at least once a month	7.51	5.43	1.38
At least once a week but not every day	10.08	5.64	1.79
Every day	-3.15	5.88	-0.54
R^2	0.24		

Note. $N = 610$. PS-TRE = problem solving in technology-rich environments; HS = high school; SE = standard error; Ref = reference. $\Delta R^2 = 0.04$ for Step 2.
! Interpret data with caution. The coefficient of variation (CV) for this estimate is between 30 and 50 percent.
* $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$

Hypothesis 3

Hypothesis 3 stated that the relationship between workplace learning and PS-TRE is different between supervisors and non-supervisors. This hypothesis was tested using linear regression for each of the four workplace learning measures. Model Two adds the main effects of the learning term and supervisory status to the control model, Model One. Model Three adds the interaction term learning x supervisor. Findings failed to support Hypothesis 3 for any of the learning measures. Although supervisors consistently had higher PS-TRE scores than non-supervisors, the difference was never significant. Similarly, although a non-supervisor who participated in workplace learning usually earned a higher PS-TRE score than a supervisor who did not participate, the difference between scores was never significant.

Results of Model Two and Three for on-the-job training are reported in Appendix C. In Model Two, participating once or twice in on-the-job training (b = 15.69, $p < 0.001$, 95% CI (24.71, 6.67), CV = 29.33%) was a unique predictor of PS-TRE performance. In Model Two, people who participated once or twice in on-the-job training scored an average of 15.69 points higher in PS-TRE than those who never participated. There was no significant relationship between supervisory status and PS-TRE. The total $R^2 = 0.25$ which reflects a small-medium effect, and the $\Delta R^2 = 0.05$ for step two. In Model Three, there was no significant relationship between the on-the-job training x supervisor interaction and PS-TRE. The total $R^2 = 0.26$ which reflects a small-medium effect, and the $\Delta R^2 = 0.01$ for step three.

Results of Model Two and Three for seminar or workshop participation are reported in Appendix D. In Model Two, there were no significant relationships between seminar or workshop participation or supervisory status and PS-TRE. The total $R^2 = 0.24$ which reflects a small-medium effect, and the $\Delta R^2 = 0.04$ for step two. In Model Three, there was no significant

relationship between the seminar participation x supervisor interaction and PS-TRE. The total R^2 = 0.24 which reflects a small-medium effect, and there is no change in R^2 for step three.

Results of Model Two and Three for learning-by-doing are reported in Appendix E. In Model Two, there were no significant relationships between learning-by-doing or supervisory status and PS-TRE. The total $R^2 = 0.24$ which reflects a small-medium effect, and the $\Delta R^2 = 0.04$ for step two. In Model Three, there was no significant relationship between the learning-by-doing x supervisor interaction and PS-TRE. The total $R^2 = 0.25$ which reflects a small-medium effect, and the $\Delta R^2 = 0.01$ for step three.

Results of Model Two and Three for learning from coworkers or supervisors are reported in Appendix F. In Model Two, there were no significant relationships between learning from coworkers or supervisory status and PS-TRE. The total $R^2 = 0.24$ which reflects a small-medium effect, and the $\Delta R^2 = 0.04$ for step two. In Model Three, there was no significant relationship between the learning from coworkers x supervisor interaction and PS-TRE. The total $R^2 = 0.25$ which reflects a small-medium effect, and the $\Delta R^2 = 0.01$ for step three.

To summarize, then, this study failed to find any significant findings regarding supervisory status or its interaction with workplace learning. In Model 2 for each of the learning terms, supervisors did not have significantly different overall PS-TRE scores than non-supervisors. In Model 3, there were no significant findings for the interaction effect of supervisory status and workplace learning on PS-TRE.

Hypothesis 4

Hypothesis 4 stated that workplace learning formats leading to significantly stronger PS-TRE competency will vary by economic sector. This hypothesis was tested using linear regression for each of the four workplace learning measures. Model Two adds the main effects of

the learning term and economic sector to the control model, Model One. Model Three adds the interaction term learning x sector. Findings failed to support Hypothesis 4 for any of the learning measures. Overall PS-TRE scores between workers in the private sector versus workers in the public or non-profit sector were similar. PS-TRE scores of workers in the public or non-profit sector who participated in workplace learning were not significantly different than PS-TRE scores of workers in the private sector who did not participate or had minimal participation in workplace learning.

Results of Model Two and Three for on-the-job training are reported in Appendix G. In Model Two, participating once or twice in on-the-job training (b = 13.00, $p < 0.01$, 95% CI (22.17, 3.84), CV = 35.97%) was a unique predictor of PS-TRE performance. In Model Two, people who participated once or twice in on-the-job training scored an average of 13 points higher in PS-TRE than those who never participated. There was no significant relationship between economic sector and PS-TRE. The total $R^2 = 0.21$ which reflects a small-medium effect, and the $\Delta R^2 = 0.01$ for step two. In Model Three, there was no significant relationship between the on-the-job training x sector interaction and PS-TRE. The total $R^2 = 0.22$ which reflects a small-medium effect, and the $\Delta R^2 = 0.01$ for step three.

Results of Model Two and Three for seminar or workshop participation are reported in Appendix H. In Model Two, participation in two seminars or workshops (b = 15.69, $p < 0.05$, 95% CI (27.74, 3.65), CV = 39.14%) was a unique predictor of PS-TRE performance. In Model Two, people who participated two times in seminars or workshops scored an average of 15.69 points higher in PS-TRE than those who never participated. There was no significant relationship between economic sector and PS-TRE. The total $R^2 = 0.22$ which reflects a small-medium effect, and the $\Delta R^2 = 0.02$ for step two. In Model Three, there was no significant relationship between

the seminar participation x sector interaction and PS-TRE. The total $R^2 = 0.23$ which reflects a small-medium effect, and the $\Delta R^2 = 0.01$ for step three.

Results of Model Two and Three for learning-by-doing are reported in Appendix I. In Model Two, learning by doing every day ($b = -11.76$, $p < 0.01$, 95% CI (-2.95, -20.57), CV = -38.24%) was a unique predictor of PS-TRE performance. In Model Two, people who learned by doing every day scored an average of 11.76 points lower in PS-TRE than those who never or rarely participated. There was no significant relationship between economic sector and PS-TRE. The total $R^2 = 0.22$ which reflects a small-medium effect, and the $\Delta R^2 = 0.02$ for step two. In Model Three, there was no significant relationship between the learning-by-doing x sector interaction and PS-TRE. The total $R^2 = 0.22$ which reflects a small-medium effect, and there is no change in R^2 for step three.

Results of Model Two and Three for learning from coworkers or supervisors are reported in Appendix J. In Model Two, there were no significant relationships between learning from coworkers or economic sector and PS-TRE. The total $R^2 = 0.24$ which reflects a small-medium effect, and the $\Delta R^2 = 0.04$ for step two. In Model Three, there was no significant relationship between the learning from coworkers x sector interaction and PS-TRE. The total $R^2 = 0.24$ which reflects a small-medium effect, and there is no change in R^2 for step three.

To summarize, then, this study failed to find any significant findings regarding economic sector or its interaction with workplace learning. In Model 2 for each of the learning terms, workers in the private sector did not have significantly different overall PS-TRE scores than workers in the public or non-profit sector. In Model 3, there were no significant findings for the interaction effect of economic sector and workplace learning on PS-TRE.

Hypothesis 5

Hypothesis 5 stated that workplace learning formats leading to significantly stronger PS-TRE competency will vary by size of organization. This hypothesis was tested using linear regression for each of the four workplace learning measures. Model Two adds the main effects of the learning term and organizational size to the control model, Model One. Model Three adds the interaction term learning x size. Apart from one significant interaction term in Model Three for learning-by-doing, findings failed to support Hypothesis 5. Overall PS-TRE scores between workers in small, medium, and large organizations were similar. PS-TRE scores of workers in medium and large organizations who participated in nonformal workplace learning or learning from coworkers were not significantly different than PS-TRE scores of workers in small organizations who did not participate or had minimal participation in nonformal workplace learning or learning from coworkers.

Results of Model Two and Three for on-the-job training are reported in Appendix K. In Model Two, participating once or twice in on-the-job training (b = 16.13, p < 0.001, 95% CI (25.41, 6.86), CV = 29.33%) was a unique predictor of PS-TRE performance. In Model Two, people who participated once or twice in on-the-job training scored an average of 16.13 points higher in PS-TRE than those who never participated. There was no significant relationship between size of the organization and PS-TRE. The total R^2 = 0.25 which reflects a small-medium effect, and the ΔR^2 = 0.05 for step two. In Model Three, there was no significant relationship between the on-the-job training x size interaction and PS-TRE. The total R^2 = 0.26 which reflects a small-medium effect, and the ΔR^2 = 0.01 for step three.

Results of Model Two and Three for seminar or workshop participation are reported in Appendix L. In Model Two, there were no significant relationships between seminar or

workshop participation or size of the organization and PS-TRE. The total $R^2 = 0.24$ which reflects a small-medium effect, and the $\Delta R^2 = 0.04$ for step two. In Model Three, there was no significant relationship between the seminar participation x size interaction and PS-TRE. The total $R^2 = 0.24$ which reflects a small-medium effect, and there is no change in R^2 for step three.

Results of Model Two and Three for learning-by-doing are reported in Appendix M. In Model Two, there were no significant relationships between learning-by-doing or size of the organization and PS-TRE. The total $R^2 = 0.25$ which reflects a small-medium effect, and the $\Delta R^2 = 0.05$ for step two. In Model Three, membership in the group of people who worked in a large organization (250 or more employees) and who learned by doing at least once a week but not every day ($b = 30.43$, $p < 0.05$, 95% CI (57.60, 3.26), CV = 45.56%) was a unique predictor of PS-TRE performance. In Model Three, the reference group for the interaction term was people in small organizations who learned by doing less than once a month. Those who worked in a large organization and who learned by doing at least once a week but not every day scored an average of 30.43 points higher in PS-TRE than those in the reference group. The total $R^2 = 0.27$ which reflects a small-medium effect, and the $\Delta R^2 = 0.02$ for step three.

Results of Model Two and Three for learning from coworkers or supervisors are reported in Appendix N. In Model Two, there were no significant relationships between learning from coworkers or size of the organization and PS-TRE. The total $R^2 = 0.24$ which reflects a small-medium effect, and the $\Delta R^2 = 0.04$ for step two. In Model Three, there was no significant relationship between the learning from coworkers x size interaction and PS-TRE. The total $R^2 = 0.26$ which reflects a small-medium effect, and the $\Delta R^2 = 0.02$ for step three.

To summarize, then, this study found one significant interaction for organizational size. In Model 3 for learning-by-doing, workers in large organizations (251+ people) who learned by

doing at least once a week but not every day had significantly better PS-TRE scores than workers in small organizations (1-50 people) who learned by doing less than once a month.

The study failed to find any significant interactions between size of organization and on-the-job training, seminar or workshop participation, or learning from coworkers or supervisors.

Control Variables Model for Research Question 6

In research question six, the main effects of age and gender are considered. Therefore, the control variables model changes. A linear regression analysis was conducted to determine the impact of education level, self-rated health, and race on PS-TRE scores. This analysis serves as Model One for the interactions considered in sub-questions 6a, 6b, 6c, and 6d. Table 25 shows the results of this analysis. Possession of a college degree (b = 29.35, p < 0.001, 95% CI (35.66, 23.05), CV = 10.96%), Black race (b = -36.24, p < 0.001, 95% CI (-25.50, -46.99), CV = -15.13%) and Other race (b = -16.64, p < 0.05, 95% CI (-2.77, -30.51), CV = -42.52%) were unique predictors of PS-TRE performance. There were no significant relationships between health and PS-TRE. The total R^2 = 0.19 which reflects a small-medium effect.

Table 25

Control Variables Model (Model One) for Research Question 6

Variable	Model 1		
	b_i	SE	t
Constant	249.10***	5.48	45.44
Education level			
HS diploma or less (ref)			
College degree	29.35***	3.22	9.12
Self-rated health			
Excellent (ref)			
Very good	5.45	6.48	0.84
Good	0.71	6.31	0.11
Fair or Poor	-3.65	7.82	-0.47

Table 25 (Cont.)

Variable		Model 1		
		b_i	SE	t
Race				
White (ref)				
Black		-36.24***	5.48	-6.61
Other race		-16.64*!	7.08!	-2.35!
R^2	0.19			

Note. N = 697. PS-TRE = problem solving in technology-rich environments; HS = high school; SE = standard error; Ref = reference.

! Interpret data with caution. The coefficient of variation (CV) for this estimate is between 30 and 50 percent.

* $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$

Hypothesis 6

The final research question of this study asks whether the relationship between gender, workplace learning, and PS-TRE varies as a function of age among U.S. Baby Boomers. This reflects a three-way interaction between age x gender x learning. To build this model requires two lower-level interaction terms, age x learning and gender x learning. Hypothesis six stated that age weakens the influence that gender has on learning and PS-TRE. This hypothesis was tested using linear regression for each of the four workplace learning measures. Model Two adds the main effects of the learning term, gender, and age to the control model, Model One. Model Three adds the two-way interaction terms learning x age and learning x gender. Model Four tests hypothesis six by adding the three-way interaction, age x gender x learning.

Findings failed to support Hypothesis 6, but one significant interaction was noted in the two-way interaction of age x on-the-job training. Older Baby Boomers who participated in informal workplace learning or seminars/workshops had similar scores to younger Baby Boomers who did not participate or who rarely participated. Females who participated in workplace learning had similar scores to males who did not participate or who rarely

participated. Older female Baby Boomers who participated in workplace learning had similar scores to younger male Baby Boomers who did not participate or who rarely participated.

Results of Model Two, Three, and Four for on-the-job training are reported in Appendix O. In Model Two, participating once or twice in on-the-job training (b = 13.63, $p < 0.01$, 95% CI (22.77, 4.49), CV = 34.21%) was a unique predictor of PS-TRE performance. In Model Two, people who participated once or twice in on-the-job training scored an average of 13.63 points higher in PS-TRE than those who never participated. There were no significant relationships between gender or age and PS-TRE. The total $R^2 = 0.21$ which reflects a small-medium effect, and the $\Delta R^2 = 0.02$ for step two. In Model 3, membership in the group of people aged 60-70 who participated in on-the-job training once or twice (b = -21.13, $p < 0.05$, 95% CI (-2.10, -40.16), CV = -45.95%) was a unique predictor of PS-TRE performance. In Model Three, older Baby Boomers (age 60-70) who participated once or twice in on-the-job training earned PS-TRE scores that were an average of 21.13 points lower than the PS-TRE scores of younger Baby Boomers (age 50-59) who never participated. There was no significant relationship between the interaction of on-the-job training x gender and PS-TRE. The total $R^2 = 0.22$ which reflects a small-medium effect, and the $\Delta R^2 = 0.01$ for step three. In Model Four, there was no significant relationship between the three-way interaction of learning x age x gender and PS-TRE. The total $R^2 = 0.22$ which reflects a small-medium effect, and there is no change in R^2 for step four.

Results of Model Two, Three, and Four for seminar or workshop participation are reported in Appendix P. In Model Two, participating once or twice in seminars or workshops (b = 13.68, $p < 0.05$, 95% CI (24.22, 3.14), CV = 39.31%) was a unique predictor of PS-TRE performance. In Model Two, people who participated once or twice in seminars or workshops scored an average of 13.68 points higher in PS-TRE than those who never participated. There

were no significant relationships between gender or age and PS-TRE. The total $R^2 = 0.21$ which reflects a small-medium effect, and the $\Delta R^2 = 0.02$ for step two. In Model 3, there were no significant relationships between the interaction of seminar x age or the interaction of seminar x gender and PS-TRE. The total $R^2 = 0.22$ which reflects a small-medium effect, and the $\Delta R^2 = 0.01$ for step three. In Model Four, there was no significant relationship between the three-way interaction of learning x age x gender and PS-TRE. The total $R^2 = 0.22$ which reflects a small-medium effect, and there is no change in R^2 for step four.

Results of Model Two, Three, and Four for learning-by-doing are reported in Appendix Q. In Model Two, participating every day in learning-by-doing ($b = -12.07$, $p < 0.01$, 95% CI (-4.10, -20.04), CV = -33.69%) was a unique predictor of PS-TRE performance. In Model Two, people who learned by doing every day scored an average of 12.07 points lower in PS-TRE than those who learned by doing less than once a week. There were no significant relationships between gender or age and PS-TRE. The total $R^2 = 0.22$ which reflects a small-medium effect, and the $\Delta R^2 = 0.03$ for step two. In Model Three, there were no significant relationships between the interaction of learning-by-doing x age or the interaction of learning-by-doing x gender and PS-TRE. The total $R^2 = 0.23$ which reflects a small-medium effect, and the $\Delta R^2 = 0.01$ for step three. In Model Four, there was no significant relationship between the three-way interaction of learning x age x gender and PS-TRE. The total $R^2 = 0.23$ which reflects a small-medium effect, and there is no change in R^2 for step four.

Results of Model Two, Three, and Four for learning from coworkers or supervisors are reported in Appendix R. In Model Two, there were no significant relationships between gender, age, or learning from coworkers or supervisors and PS-TRE. The total $R^2 = 0.22$ which reflects a small-medium effect, and the $\Delta R^2 = 0.03$ for step two. In Model Three, there were no significant

relationships between the interaction of learning from coworkers x age or the interaction of learning from coworkers x gender and PS-TRE. The total $R^2 = 0.22$ which reflects a small-medium effect, there is no change in R^2 for step three. In Model Four, there was no significant relationship between the three-way interaction of learning x age x gender and PS-TRE. The total $R^2 = 0.22$ which reflects a small-medium effect, and there is no change in R^2 for step four.

To summarize, then, this study failed to find any significant findings regarding gender or its interaction with workplace learning. In Model 2 for each of the learning terms, female workers did not have significantly different overall PS-TRE scores than male workers. In Model 3, there were no significant findings for the interaction of gender and workplace learning. This study found one significant interaction for age. In Model 3 for on-the-job training, workers age 60-70 who participated in on-the-job training once or twice earned significantly worse PS-TRE scores than workers age 50-59 who never experienced on-the-job training. Finally, this study failed to find any significant findings regarding the three-way interaction of workplace learning x age x gender and PS-TRE.

Validity and Reliability

Chapter Three presented some overall considerations regarding validity and reliability in a PIAAC study. The specific changes to the dataset outlined in this chapter introduce a few additional concerns regarding threats to external validity. Many variables were collapsed to meet the case-count requirements, which means the ability to distinguish between certain subgroups was lost. This is perhaps most apparent in the models for research questions four and six. In the question of whether economic sector impacted the relationship of workplace learning with PS-TRE, the non-profit and public sectors were always collapsed and then compared to the private sector. Results, therefore, may not be fully generalizable to Baby Boomers who work in the

nonprofit sector or the public sector. Similarly, in the question of whether the relationship between gender, workplace learning, and PS-TRE varies as a function of age, it was arguably the most important to be able to distinguish the impact for the oldest group of Baby Boomers, those age 66-70. Yet, this group always had to be collapsed with those age 60-65 due to low case count. Results, therefore, may not be fully generalizable for Baby Boomers who are age 60-70.

Summary

This study found evidence to partially support the hypothesis that Baby Boomers who participate in nonformal workplace learning will have significantly stronger PS-TRE scores than those who do not participate. Specifically, those who participated two times in either type of nonformal learning had significantly stronger PS-TRE scores than those who did not participate, but other participation levels did not result in significant improvement. An unexpected finding from the analysis of Hypothesis 6, however, was regarding the impact of age on the relationship between on-the-job training and PS-TRE. In that scenario, a person age 60-70 who participated in on-the-job training once or twice earned an average PS-TRE score 21.13 points lower than a person age 50-59 who never participated in on-the-job training.

Although the hypothesis that informal learning participation would be associated with stronger PS-TRE scores was not supported, organizational size was found to matter in the relationship between learning-by-doing and PS-TRE which offers partial evidence in support of Hypothesis 5. In general, informal learning participation did not lead to significantly stronger PS-TRE scores, and learning by-doing every day resulted in significantly lower PS-TRE scores. People who worked in a large organization and who learned by doing at least once a week, however, scored an average of 30.43 points higher in PS-TRE than people in small organizations who learned by doing less than once a month.

The study failed to find any evidence to support Hypothesis 3, Hypothesis 4, or Hypothesis 6. There were no significant differences in the relationship between workplace learning and PS-TRE by supervisory status, economic sector, or in the three-way interaction of learning x age x gender. Findings are discussed in Chapter Five.

Chapter 5: Discussion

This chapter accomplishes several goals. A brief summary of the full study is provided which recaps the problem and purpose, research questions, literature review, methodology, and findings. Conclusions are drawn for each of the study's six research questions, and limitations of the study are identified. Then I discuss this study's findings in comparison to previous literature and consider implications regarding use of the Dreyfus Model of Skill Acquisition (Dreyfus et al., 1986) to improve problem solving in technology-rich environments (PS-TRE) proficiency among U.S. Baby Boomers. The chapter concludes with recommendations for practice and future research.

Summary

Problem and Purpose

Although it is economically desirable to promote the delayed retirement of Baby Boomers (Dong et al., 2017), the ability to solve problems using technology has been identified by the Organisation for Economic Co-operation and Development (OECD, 2019a) as a skill crucial for success in the globalized world, and this generation has been shown to struggle in this competency area (Rampey et al., 2016). Workplace training has been suggested as a solution to bring older employees up to speed (Elias et al., 2012; Hämäläinen et al., 2017), yet access to training for older workers can be limited by economic conditions (Olsen & Tikkanen, 2018; Warhurst & Black, 2015) and by negative stereotypes about older workers (Posthuma & Campion, 2009). Since Baby Boomers' access to training could be limited, it is important to utilize that time efficiently. Identifying which workplace learning approaches are associated with significant gains in technology competency for Baby Boomers could help those who oversee workplace learning opportunities for this generation.

Although some studies have indicated that nonformal learning approaches such as participation in seminars or workshops are somewhat effective in improving the technology skills of older workers (Czaja & Sharit, 1998; Ng & Feldman, 2008), recent empirical studies in this area in the field of adult learning are limited. It is important to have ongoing research in this area because technology is constantly changing. Similarly, few if any studies examine the impact that engaging in informal workplace learning has on PS-TRE in this generation. Therefore, the purpose of this study is to describe the relationship of nonformal and informal workplace learning with Baby Boomers' skills in problem solving in technology-rich environments.

Research Questions

1. Is participation in nonformal workplace learning associated with significantly higher PS-TRE performance among U.S. Baby Boomers?

   1a: Is participation in organized sessions for on-the-job training or training by supervisors or co-workers associated with significantly higher PS-TRE performance among U.S. Baby Boomers?

   1b: Is participation in seminars or workshops associated with significantly higher PS-TRE performance among U.S. Baby Boomers?

2. Is participation in informal workplace learning associated with significantly higher PS-TRE performance among U.S. Baby Boomers?

   2a: Is learning-by-doing associated with significantly higher PS-TRE performance among U.S. Baby Boomers?

   2b: Is learning new work-related things from co-workers or supervisors associated with significantly higher PS-TRE performance among U.S. Baby Boomers?

3. Does supervisory status influence the relationship between workplace learning and PS-TRE competency among U.S. Baby Boomers?

3a: Does supervisory status influence the relationship between on-the-job training and PS-TRE competency among U.S. Baby Boomers?

3b: Does supervisory status influence the relationship between seminar or workshop participation and PS-TRE competency among U.S. Baby Boomers?

3c: Does supervisory status influence the relationship between learning-by-doing and PS-TRE competency among U.S. Baby Boomers?

3d: Does supervisory status influence the relationship between learning from coworkers or supervisors and PS-TRE competency among U.S. Baby Boomers?

4. Does economic sector influence the relationship between workplace learning and PS-TRE competency among U.S. Baby Boomers?

4a: Does economic sector influence the relationship between on-the-job training and PS-TRE competency among U.S. Baby Boomers?

4b: Does economic sector influence the relationship between seminar or workshop participation and PS-TRE competency among U.S. Baby Boomers?

4c: Does economic sector influence the relationship between learning-by-doing and PS-TRE competency among U.S. Baby Boomers?

4d: Does economic sector influence the relationship between learning from coworkers or supervisors and PS-TRE competency among U.S. Baby Boomers?

5. Does size of the organization influence the relationship between workplace learning and PS-TRE competency among U.S. Baby Boomers?

5a: Does size of the organization influence the relationship between on-the-job training and PS-TRE competency among U.S. Baby Boomers?

5b: Does size of the organization influence the relationship between seminar or workshop participation and PS-TRE competency among U.S. Baby Boomers?

5c: Does size of the organization influence the relationship between learning-by-doing and PS-TRE competency among U.S. Baby Boomers?

5d: Does size of the organization influence the relationship between learning from coworkers or supervisors and PS-TRE competency among U.S. Baby Boomers?

6. Does the relationship between gender, workplace learning, and PS-TRE vary as a function of age among U.S. Baby Boomers?

6a: Does the relationship between gender, on-the-job training, and PS-TRE vary as a function of age among U.S. Baby Boomers?

6b: Does the relationship between gender, seminar or workshop participation, and PS-TRE vary as a function of age among U.S. Baby Boomers?

6c: Does the relationship between gender, learning-by-doing, and PS-TRE vary as a function of age among U.S. Baby Boomers?

6d: Does the relationship between gender, learning from coworkers or supervisors, and PS-TRE vary as a function of age among U.S. Baby Boomers?

Literature Review

Workplace learning for the older worker is a complex topic. Learning in the workplace can be nonformal—organized learning that is often instructor led (Merriam & Bierema, 2014)—or informal. Marsick and Watkins (1990) describe informal learning as more experiential and less structured than the training that is usually provided by an organization. For older workers,

access to both nonformal and informal learning opportunities could be impacted by negative stereotypes. Posthuma and Campion's (2009) work, for example, identified stereotypes that older workers are more difficult to train and have less ability to learn than younger employees. If a supervisor of an older worker adopts these beliefs, an older worker's access to nonformal learning opportunities may be limited. North and Fiske's (2016) research shows that informal learning opportunities for older workers could also be impacted by the beliefs of younger employees. The authors found that networking opportunities can be withheld from older workers when younger workers perceive that jobs are scarce and when older workers express the intent to keep working.

When older workers do participate in workplace learning, though, does this result in increased technology competency? According to the Dreyfus Model of Skill Acquisition (Dreyfus et al., 1986), to make competency gains, the right type or blend of learning activities needs to be matched to the current ability of the individual in the competency domain. Someone brand-new to the skill (a novice) will need more structured (nonformal) learning. As their skills develop, though, to achieve expertise requires a heavier reliance on experience (informal learning) and intuition. What does previous literature say, then, about the competency level of Baby Boomers in problem solving in technology-rich environments?

Rampey et al. (2016) used 2012/2014 data from the Programme for the International Assessment of Adult Competencies (PIAAC) to examine PS-TRE skills by age group. PS-TRE skills are categorized into three levels, with an additional level for people who score Below Level 1 (OECD, 2019a). Rampey et al. found that the majority of Baby Boomers, 41-44%, attained Level 1 scores. As a group, then, they are not so new at the skill as to be considered novices according to the Dreyfus Model (Dreyfus et al., 1986). Nor are they advanced enough to

demonstrate ability to routinely set goals and use inferential reasoning, which is how the OECD (2019a) describes Level 2 PS-TRE proficiency. Goal setting is an important component of the competent level of performance according to the Dreyfus Model. It seems, therefore, that Level 1 scores align best with the advanced beginner level of proficiency according to the Dreyfus Model. As an advanced beginner, an individual benefits from a blend of nonformal and informal learning strategies in order to advance to the competent level of proficiency.

One might ask, how does this theoretical approach to proficiency gain align with past empirical findings regarding improving technology competency for older workers? No studies from the last five years were identified that empirically examined the impact of a blend of nonformal and informal approaches on technology competency. One recent study by Taha et al. (2016) indicated that nonformal learning may be at least somewhat impactful. The authors used recorded videos to teach Microsoft Excel skills to a group of older workers. Only about 34% of the participants ultimately performed well on the task, but more than 80% of the participants reported that the training was beneficial. Similarly, Lopes et al. (2020) recently found that informal learning in the form of information-sharing produced significant PS-TRE gains for workers in certain industries. Their study was not focused on older workers but did include Baby Boomers in the overall pool of participants. Literature identified for this review, then, did not address how informal learning impacts technology competency specifically within this generation.

Methodology

This study used multiple linear regression to answer its six research questions. Data came from the PIAAC Survey of Adult Skills; specifically, data came from the PIAAC U.S. Cycle 1, Round 3 Household Study (2017) which is available for download from the National Center for

Education Statistics. Baby Boomers would have ranged from age 53-71 at the time of survey completion between March-November, 2017. PIAAC, however, only reports age in five or 10-year intervals (not as a continuous variable). Therefore, in this analysis, employed people ranging in age from 50-70 at the time of PIAAC survey completion were considered Baby Boomers. Within the dataset, 701 cases met the criteria of being employed Baby Boomers with PS-TRE scores. Data were collected from 80 different U.S. counties (Krenzke et al., 2019), making findings of this study nationally representative.

Findings

This study did not find evidence to support four of its six hypotheses. In general, participating in informal learning did not lead to significantly stronger PS-TRE scores; in fact, learning-by-doing every day was associated with PS-TRE scores significantly lower than the scores earned by individuals who rarely learned by doing. There were no significant differences in the relationship between workplace learning and PS-TRE by supervisory status or economic sector. Age did not change the relationship between gender, workplace learning, and PS-TRE.

Two hypotheses were partially supported. First, hypothesis one indicated that Baby Boomers who participate in nonformal workplace learning will have significantly stronger PS-TRE scores than those who do not participate. On-the-job training and workshop or seminar participation were only significant for those individuals who participated two times in the year leading up to completion of the PIAAC Survey. Individuals who participated any other number of times (one, three or four, or five or more) did not have significantly higher PS-TRE scores than those who never participated. However, an unexpected finding from the investigation of hypothesis six indicates that age significantly influenced the relationship between on-the-job training and PS-TRE. A person age 60-70 who participated in on-the-job training once or twice

earned an average PS-TRE score 21.13 points lower than a person age 50-59 who never participated in on-the-job training. An optimal amount of on-the-job training, therefore, may not be equally beneficial for all Baby Boomers.

Second, hypothesis five indicated that workplace learning formats leading to significantly stronger PS-TRE would vary by size of the organization. One significant interaction was found for learning-by-doing. Those who worked in a large organization (251 + employees) and who learned by doing at least once a week scored an average of 30.43 points higher in PS-TRE than people in small organizations who learned by doing less than once a month. Therefore, although learning-by-doing every day resulted in lower PS-TRE scores for Baby Boomers overall, there is some evidence that the effectiveness of this learning strategy could vary for Baby Boomers who work in different sizes of organizations.

Conclusions

Conclusion 1

Research question one asked: Is participation in nonformal workplace learning associated with significantly higher PS-TRE performance among U.S. Baby Boomers? This study found evidence that Baby Boomers who participated two times in either measure of nonformal learning had significantly stronger PS-TRE scores than those who did not participate. Those who participated twice in on-the-job training earned an average PS-TRE score 16.31 points higher than those who did not participate, and those who participated twice in seminars or workshops earned an average PS-TRE score 16.05 points higher than those who did not participate. However, other participation levels (participating one time, three or four times, or five or more times) did not significantly improve PS-TRE scores. Therefore, these findings suggest that Baby Boomers who participate in an optimal amount of nonformal learning may make significant

gains in PS-TRE. Since we do not know anything about what was taught in these activities, though, this finding invites additional research.

Conclusion 2

Research question two asked: Is participation in informal workplace learning associated with significantly higher PS-TRE performance among U.S. Baby Boomers? This study did not find evidence that learning informally from coworkers or supervisors significantly improved PS-TRE performance. PS-TRE scores of those who reported learning from coworkers at least once a month, at least once a week, or every day were not significantly different than the scores of those who never learned in this way, or who learned in this way less than once a month. Therefore, learning informally from coworkers or supervisors might not significantly increase PS-TRE performance among U.S. Baby Boomers.

This study also did not find evidence that learning-by-doing significantly improved PS-TRE performance. Importantly, however, those who learned by doing every day had significantly *worse* scores than those who rarely or never learned in this way. As we saw with nonformal learning, then, it could be that the amount of participation matters in this learning activity. Therefore, these findings suggest that while occasionally learning by doing might not significantly impact PS-TRE scores, the PS-TRE proficiency of Baby Boomers may be significantly reduced if they have an overreliance on this informal learning strategy.

Conclusion 3

Research question three asked: Does supervisory status influence the relationship between workplace learning and PS-TRE competency among U.S. Baby Boomers? This study did not find significant results to support a main effect of supervisory responsibility on PS-TRE scores. Supervisors did not have significantly different PS-TRE scores than non-supervisors.

This study also did not find a moderating effect of supervisory status on the relationship between learning and PS-TRE for any of the four workplace learning measures. Therefore, the responsibility of managing other employees may not play a significant role in the relationship between workplace learning and PS-TRE proficiency among U.S. Baby Boomers.

Conclusion 4

Research question four asked: Does economic sector influence the relationship between workplace learning and PS-TRE competency among U.S. Baby Boomers? This study did not find significant results to support a main effect of economic sector on PS-TRE scores. Workers in the private sector did not have significantly different PS-TRE scores than workers in the public/non-profit sectors. This study also did not find significant results to support a moderating effect of economic sector on the relationship between learning and PS-TRE for any of the four workplace learning measures. Therefore, the sector in which a person works may not play a significant role in the relationship between workplace learning and PS-TRE proficiency among U.S. Baby Boomers.

Conclusion 5

Research question five asked: Does size of the organization influence the relationship between workplace learning and PS-TRE competency among U.S. Baby Boomers? This study did not find significant results to support a main effect of organizational size on PS-TRE scores. Workers in small organizations did not have significantly different PS-TRE scores than workers in mid-sized or large organizations. This study also did not find significant results to support a moderating effect of organizational size for any of the workplace learning measures except learning-by-doing. Therefore, the size of the organization in which a person works may not play a significant role in the relationship between nonformal workplace learning and PS-TRE

proficiency among U.S. Baby Boomers. Size of the organization also may not play a significant role in the relationship between learning from coworkers or supervisors and PS-TRE proficiency among U.S. Baby Boomers.

Regarding learning-by-doing, this study found evidence that Baby Boomers who worked in large organizations (251 or more employees) and who learned by doing at least once a week but not every day had PS-TRE scores an average of 30.43 points higher than Baby Boomers who worked in small organizations (1-50 employees) and who learned by doing less than once a month. Therefore, the size of the organization in which a person works could play a significant role in the relationship between learning-by-doing and PS-TRE proficiency among U.S. Baby Boomers. Remember, overall, Baby Boomers in this study who participated in learning-by-doing every day were found to have significantly worse PS-TRE scores than those who rarely learned this way, so this finding demonstrates that the effectiveness of learning-by-doing may be nuanced by organizational size. It is not, however, clear from these results how well Baby Boomers in small organizations who participated in learning-by-doing at least once a week performed. Previous literature suggests that employees who lack access to nonformal learning may rely more heavily on informal learning (Warhurst & Black, 2015), and that people who work in small businesses could lack access to certain forms of nonformal learning (Twyford et al., 2016). It could be possible that the significance here is attributable to differences in the amount of learning participation, not to difference in the size of the organization. Additional research is, therefore, needed to confirm this conclusion.

Conclusion 6

Research question six asked: Does the relationship between gender, workplace learning, and PS-TRE vary as a function of age among U.S. Baby Boomers? To answer a question

involving a three-way interaction of age x gender x learning required me to first investigate whether the relationship between workplace learning and PS-TRE varied as a function of age or of gender. This study did not find significant results to support main effects of age or gender on PS-TRE scores. This study also did not find significant results to support a moderating effect of gender for any of the workplace learning measures. Therefore, these findings suggest that gender may not play a significant role in the relationship between workplace learning and PS-TRE proficiency among U.S. Baby Boomers.

This study did not find significant results to support a moderating effect of age for any of the workplace learning measures except on-the-job training. Therefore, age of the individual may not play a significant role in the relationship between informal workplace learning and PS-TRE proficiency among U.S. Baby Boomers. Age of the individual also may not play a significant role in the relationship between seminar or workshop participation and PS-TRE proficiency among U.S. Baby Boomers.

Regarding on-the-job training, this study found evidence that Baby Boomers between ages 60-70 who participated in on-the-job training once or twice had PS-TRE scores an average of 21.13 points lower than Baby Boomers between ages 50-59 who never participated in on-the-job training. Therefore, age might play a significant role in the relationship between on-the-job training and PS-TRE proficiency among U.S. Baby Boomers. Conclusion One indicated that on-the-job training has a positive overall effect on PS-TRE if a person participates an optimal number of times per year. This finding regarding the interaction of age indicates it may be possible that the positive overall effect of on-the-job training is reversed for those between ages 60-70.

This study did not find significant results to support a moderating effect of age on the relationship between gender, workplace learning, and PS-TRE for any of the four workplace learning measures. Therefore, the relationship between gender, workplace learning, and PS-TRE may not be significantly influenced by the age of the individual learning participant among U.S. Baby Boomers.

Limitations

Although studying the technology competency of Baby Boomers using PIAAC is beneficial due to the large number of people in the dataset and because the data are nationally representative, there are specific limitations that should be kept in mind when considering results and implications of this study. First, this study examines the association between different types of workplace learning activity and PS-TRE proficiency. We do not, however, have any information about what was taught or learned during these activities. For example, the results here cannot attest to whether a seminar *about* PS-TRE will lead to improvements in PS-TRE; all we know is that people who attended an optimal number of seminars or workshops tended to do better in PS-TRE than those who did not attend seminars or workshops at all.

Similarly, regarding nonformal learning, although the PIAAC Background Questionnaire asks whether participation in nonformal learning was job-related and whether the activity took place during working hours, this study did not take these responses into account. This study cannot differentiate, then, between people who participated in nonformal learning during business hours for work-related reasons and people who pursued nonformal learning outside of business hours for reasons of personal interest. This was concerning, so, using the full 2017 PIAAC dataset, I examined the total number of employed Baby Boomers who responded to the question (B_Q14a) of whether the nonformal learning activity was job-related (N = 295). About

19% (n = 55) of respondents indicated the activity was *not* job-related. This variable is tricky because the survey logic indicates that not all individuals were asked this question, and it is possible that the nonformal activity in question was one of the two not used in this study. Interpreting this outcome, then, becomes complicated. However, this may establish enough of a trend to warrant future research to determine whether there are significant differences in PS-TRE competency between those Baby Boomers who participate in job-related nonformal learning versus those Baby Boomers who participate in nonformal learning out of personal interest.

The problem solving in technology-rich environments competency measure also has some inherent limitations. You might recall from Chapter Three that, although there were 838 cases of employed Baby Boomers in PIAAC, only 701 had PS-TRE scores. According to the OECD (2019b), some cases would have lacked PS-TRE scores because not all PIAAC participants were routed into the PS-TRE assessment. Some, however, probably lacked PS-TRE scores because they failed the computer core assessment and were routed into paper-based versions of the literacy and numeracy competency measures, instead. The findings of this study, therefore, can generalize to Baby Boomers with limited computer skills, but not to those who are severely deficient in this area—a significant limitation since that group is arguably the most in need of workplace learning interventions.

As described in Chapter One, PS-TRE as a competency measure is also limited by its failure to incorporate social media, cell phones, tablet use, etc. PIAAC has been administered since 2012, and its competency measures did not change in rounds one, two, or three of the first cycle. It is possible that someone performed poorly using the technology designed for PIAAC but could perform better at the same task using a more intuitive app, for example. Over time, PS-TRE as a competency measure has arguably failed to keep up with current workplace

technology. The OECD has indicated on its website (https://www.oecd.org/skills/piaac/about/secondcycle/) that PS-TRE has been discontinued in the second cycle of PIAAC, initial results of which are expected to be released in 2023. An additional limitation of this study, then, is that it is only replicable using 2012, 2014, or 2017 PIAAC data.

Given the high significance of race and education as predictors of PS-TRE in this study, it is a limitation that more information was not able to be gleaned from these variables. Race is documented in five categories in the full 2017 dataset; it just had to be collapsed into White, Black, and Other in this study due to low case count among Baby Boomers. Given that definitions of older workers vary and can extend even down to those age 40 and above (Ng & Feldman, 2008), future researchers might choose to expand the age groups of this study to see if other categories of race could meet the criteria to be studied. Similarly, since education was only intended as a control variable in this study, for simplicity the education variable with the fewest number of predictors was chosen. However, the variable used here (B_Q01AUS_C) groups people who have completed associate degrees with those who have completed bachelor's degrees or above. This study showed that those with associate degrees or above had significantly higher PS-TRE scores than those with a high school diploma or less. Given that several states are now offering free community college, selecting a different education variable could have led to better understanding regarding how much of a difference earning an associate degree versus earning a bachelor's degree makes in PS-TRE competency for this generation. It would be useful to know whether organizations should encourage workers, even later in life, to earn associate degrees for development of this competency when the opportunity is provided by the state.

Finally, as is common in instruments relying on self-reported data, one important limitation is that there could be differences in how people understood or interpreted questions, or in the level of honesty in their responses. For example, as someone who has studied informal learning, if I was asked how often I learn informally from coworkers, I would be perhaps more likely to say, "every day," than someone who has not read about the many ways this type of learning could manifest. The same could be true of how someone responds regarding their level of health, or of several other variables in this study.

Discussion

Discussion of Descriptive Statistics

The workplace learning participation, computer skills, and PS-TRE proficiency of Baby Boomers in this study add valuable new data to previous literature. Regarding participation rates in nonformal learning activities such as seminars or on-the-job training, Baby Boomers in this study largely aligned with Baby Boomers studied in the 2012/2014 dataset. For example, using 2012/2014 PIAAC data, Yamashita et al. (2019) had indicated about 44% of people over age 50 had participated in formal or nonformal learning in the year leading up to completion of the PIAAC Survey. In the present study, using 2017 U.S. PIAAC data and looking only at participation in nonformal learning, about 49% of Baby Boomers had participated in on-the-job training and about 43% had participated in seminars or workshops.

This study adds important new insight regarding the participation of Baby Boomers in informal workplace learning. Merriam and Bierema (2014) call informal learning, "by far the most prevalent of the three forms of learning in the Coombs typology" (p. 17). Marsick and Watkins (1990) advocate that, since informal learning opportunities are more prevalent in the workplace than organized training opportunities, more attention should be given to capitalizing

on these moments. From these and other discussions in adult learning literature, I had formed the opinion that the dominance of informal learning was a foregone conclusion. For older workers in this study, that conclusion is inaccurate. Baby Boomers in this study were fairly evenly disbursed in their informal learning participation with similar numbers reporting limited use of informal learning strategies and daily use of informal learning. Figure 9 visually captures these trends for learning-by-doing, and Figure 10 visually captures these trends for learning from coworkers or supervisors. Although a majority, about 38%, of Baby Boomers reported learning by doing every day (n = 268), about 22% reported learning by doing never or less than once a month (n = 155). Importantly, this trend is reversed when informally learning from coworkers or supervisors; a slight majority, about 28%, of Baby Boomers reported they never or rarely (less than once a month) learn from coworkers or supervisors (n = 189).

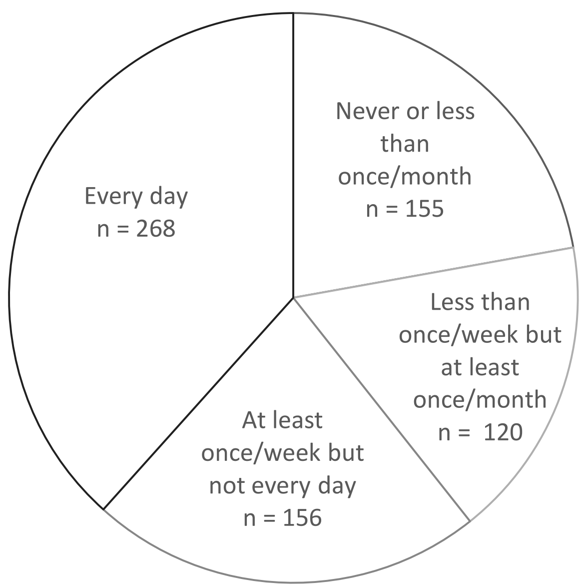


Figure 9: Baby Boomer Participation in Learning-by-Doing

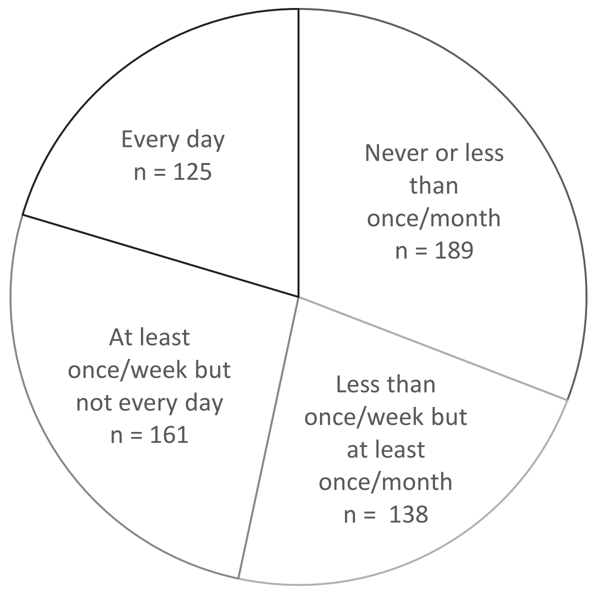


Figure 10: Baby Boomer Participation in Learning from Coworkers or Supervisors

A great deal of research in adult learning relies on the idea that people learn from their interactions with one-another. Indeed, any research built on social cognitive learning theory (Bandura, 1986) or social constructivism (Vygotsky, 1978) posits that people learn through observing one another or through engaging socially. These ideas dominate the workplace learning literature. Billett (2001), for example, presents a workplace curriculum model intended to help people capitalize on informal learning, but the model relies on an individual learning from expert coworkers. Similarly, Wenger et al. (2002) discuss fostering communities of practice in the workplace—groups of people who share a concern or passion and develop their knowledge on the topic through regular interaction. Data from this study suggests that these and other key strategies in adult learning might not be reaching the oldest workers in today's organizations.

This study also provides important new insights about overall workplace learning trends among older workers. In this study, in the year leading up to completion of the PIAAC Survey, the majority of Baby Boomers never participated in a seminar or workshop, never participated in

on-the-job training, and never or rarely (less than once a month) learned informally from coworkers or supervisors. Importantly, though, increased participation in nonformal learning occasionally seems linked to increased learning from coworkers or supervisors. Consider, for example, Figure 11, which shows a line graph of the crosstabulation of seminar or workshop participation and learning from coworkers. This demonstrates that those workers who participate twice in seminars or workshops are most likely to report learning from coworkers or supervisors less than once a week. Those who participate three or four times, though, are most likely to report learning from coworkers or supervisors every day. This aligns with the suggestion of Jeong et al. (2018) that formal training promotes informal learning.

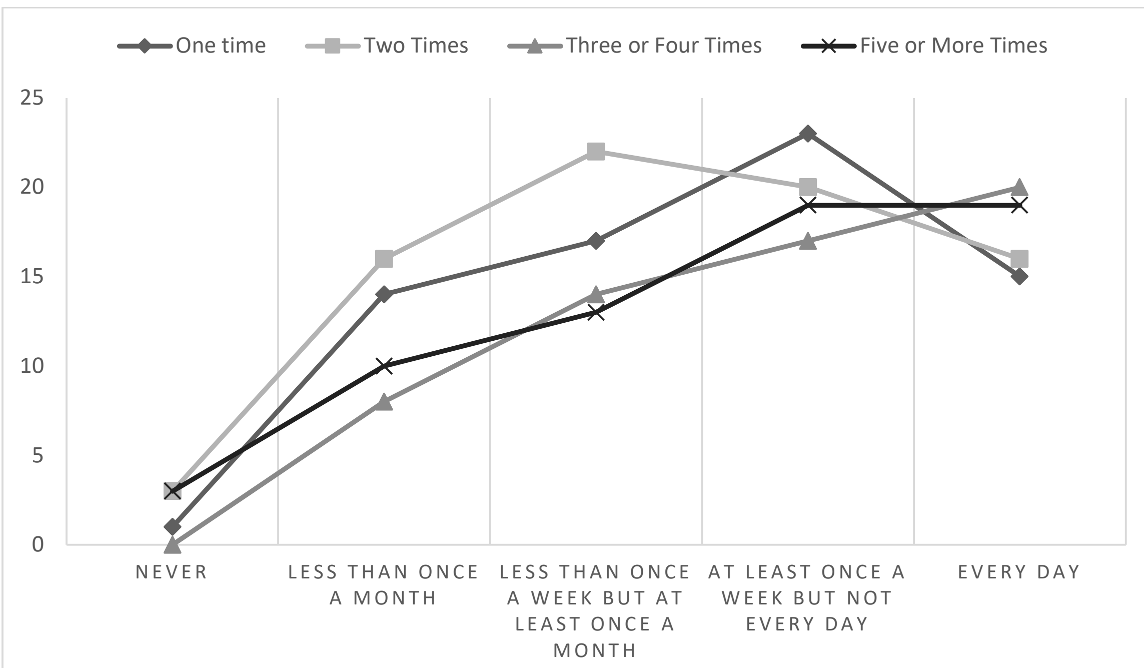


Figure 11: Trends in Seminar or Workshop Participation and Learning from Coworkers or Supervisors

Computer skills and problem solving in technology-rich environments competency are other findings from demographic statistics that warrant further discussion. Results from two questions from the PIAAC Background Questionnaire regarding computer skills among Baby

Boomers were reported in Chapter Four. In contrast to the findings of Fernández-de-Álava et al. (2017) in Spain, the majority of U.S. Baby Boomers in this study reported having the computer skills needed to do their jobs well. The majority also indicated that a lack of computer skills has not impacted their chances of being hired, promoted, or given a pay raise. This seems incongruent with the finding in this study that so many U.S. Baby Boomers—32%—earned PS-TRE scores Below Level 1. Salthouse (2012) theorizes that cognitive tests such as the PS-TRE assessment may be harder than the typical proficiency a person generally needs in real life. It could be, then, that although as a generation Baby Boomers earn worse PS-TRE scores than any other group of younger employees in PIAAC, this difference does not ultimately impact performance in the workplace.

If the ability to solve problems using technology the way it is measured in PIAAC is truly necessary for success in 21st century economies as the OECD suggests (2019a), then the fact that the majority of U.S. employees score at Level 1 indicates this is an area where U.S. employees of all ages have room to grow. We are in good company since this majority Level 1 PS-TRE trend is repeated throughout OECD countries. The OECD (2019a) reports that only eight countries outperform the U.S. in PS-TRE competency: Canada, Finland, England (UK), Norway, Denmark, the Netherlands, Sweden, and New Zealand. This puts us in about the middle of the pack of countries that score above the OECD average in this competency domain.

One explanation for this homogeneity of PS-TRE scores could be that an over-emphasis on technology acceptance in the literature impacts the design of workplace training. The literature is dominated by models that examine processes leading up to a person deciding to use or adopt technology. Two examples previously noted in this dissertation are Davis's (1989) Technology Acceptance Model and Venkatesh et al. (2003)'s Unified Theory of Acceptance and

Use of Technology (UTAUT). While it is undeniably important for organizations to have models that help them convince employees of the value of implementing new technology tools, there is a gap between a person deciding to use technology and then being able to use it to solve problems as measured in PIAAC. It may be that, when new technologies are introduced, the learning objectives for the consequent workplace training are not taking people past the application level of Bloom’s Taxonomy (Bloom, 1956). To solve problems using technology would be more in the realm of analysis or synthesis because to do so requires people to strategize about the problem—formulate a plan and set goals to achieve it. Simply stated, we might not be teaching people PS-TRE through nonformal workplace learning.

Discussion of Control Variables

Several variables were controlled in this study due to suggestions from previous literature. Some trends in results in this study were surprising, so discussion about these variables could be worthwhile for future scholars. All models in this study controlled for completion of a college degree, race, and self-rated health. Age and gender were controlled when they were not being considered as main effects.

Formal higher education was the only variable that performed completely as expected based on previous research. Prior research had indicated that people with a college degree have higher motivation to learn (Roessger et al., 2020), are more likely to participate in nonformal learning (Yamashita et al., 2019), and report more general technology use (Czaja et al., 2006). In this study, U.S. Baby Boomers who possessed associate degrees or higher had significantly higher PS-TRE scores than those who had a high school diploma or less.

Race was controlled because two prior large-scale studies had indicated a significant relationship between race and technology (Czaja et al., 2006; Lee et al., 2019), and Yamashita et

al. (2019) had found that race was also a significant predictor in nonformal learning participation. In contrast to the finding of Lee et al. (2019) that African Americans reported higher computer efficacy than Caucasians, this study found that Black Baby Boomers earned significantly lower PS-TRE scores than White Baby Boomers. Part of this proficiency gap may be explained by differences in educational attainment. I conducted a crosstabulation analysis in SPSS to find out how the three different racial groups in this study compared in terms of educational attainment. About 61% of White participants (n = 328) had a college degree, whereas only about 54% of Black participants (n = 40) had a college degree. This example also provides an important reminder that White participants were highly over-represented in this study. Findings about race, then, should be interpreted with sample size and educational attainment in mind.

Findings regarding self-rated health were surprising. Health was controlled because previous research indicated that poor health impacts training participation and effectiveness (Becker Patterson, 2018; Yamashita et al., 2019; Zwick, 2015). Since this study hypothesized that workplace learning participation would be associated with higher PS-TRE proficiency, it seemed reasonable to control for the expected impact of health. However, self-rated health had no significant relationship with PS-TRE proficiency among U.S. Baby Boomers. PS-TRE scores of those Baby Boomers who reported fair or poor health did not differ significantly from scores of those who reported excellent health.

Age as a control variable in this study also yields some interesting results. When age was only in a model with the other control variables—education, gender, health, and race—there were no significant differences in PS-TRE competency between the control group (age 50-54) and the three other age groups in this study. This was also the case when the main effects of on-

the-job training, seminar or workshop participation, learning-by-doing, and economic sector were added to the model. However, when learning from coworkers or supervisors, supervisor status, and organizational size were added as main effects, then age group 66-70 became significantly different than the control group (age 50-54) in terms of PS-TRE proficiency. Conceptually, this scenario indicates a suppression effect could be happening. Field (2018) provides the following definition of suppressor effect: “a situation where a predictor has a significant effect but only when another variable is held constant” (p. 753). In other words, if suppression was happening, then a person could not see the true relationship between age and PS-TRE unless the third variable (learning from coworkers, supervisory status, or organizational size) was in the model.

Normally, in a linear regression study outside of PIAAC, tests for multicollinearity would help identify in advance instances where suppression could occur. Since those normality checks cannot be performed using the IDB Analyzer, chi square analyses were conducted in SPSS to get a general sense for whether age was highly associated with learning from coworkers, supervisor status, or organizational size. Weights were not used, so results should be interpreted with caution. Nevertheless, the chi square test was not significant for age and learning from coworkers (x^2 (9) = 4.32, p = .889), for age and supervisor status (x^2 (3) = 2.30, p = .513), or for age and size of the organization (x^2 (6) = 8.78, p = .187). In instances like this, Warner (2021) suggests it is fine not to attempt to explain results that do not make sense, so I will simply say that the occasional significance of age in this study is a curiosity that future researchers might wish to explore.

Finally, gender was not a significant predictor of PS-TRE competency among Baby Boomers in this study. Lee et al. (2019) reported that greater computer self-efficacy among

younger males disappeared in older age. The current study adds important new information by demonstrating that differences in PS-TRE proficiency by gender are insignificant among U.S. Baby Boomers. Future research could better explain this outcome. It is possible that significant PS-TRE difference by gender disappears before workers reach the age of older workers in this study (50-70 years of age). An alternative explanation could be that there are differences by gender in how people report computer efficacy as an attitudinal measure like the one used in the study by Lee et al., but those differences are not significant in an actual competency measure such as PS-TRE.

Discussion of Conclusions

Results of this study indicate that, among Baby Boomers, participating in an optimal amount of nonformal workplace learning—either through on-the-job training or seminar or workshop attendance—is associated with significant gains in PS-TRE competency. It might seem odd at first to consider whether a sweet spot exists for training participation when it comes to development of this competency. The idea that there is a sweet spot associated with learning, however, is not unique. Csikszentmihalyi (1990), for example, studies optimal human experience, or *flow*. Csikszentmihalyi defines flow as, “the state in which people are so involved in an activity that nothing else seems to matter” (p. 4). According to the author, people describe eight common themes of the flow experience. Of importance here, the first common element of flow is that the activity offers the appropriate amount of challenge to engage the person’s skills. Csikszentmihalyi writes, “enjoyment appears at the boundary between boredom and anxiety, when the challenges are just balanced with the person’s capacity to act” (p. 52). In this, we can see a conceptual sweet spot where conditions must be right for learning to occur. Could training frequency be a condition that has to be right in certain subject matter?

Researchers are exploring this possibility for cardiopulmonary resuscitation (CPR) training. Noting a problem in provider retention of skills when training is only attended annually, Anderson et al. (2019) sought to determine whether brief refresher sessions at one, three, six, or 12-month intervals improved CPR performance among nurses. The training format was identical among groups; the only difference was its frequency. Participants who trained monthly achieved a significantly higher rate of excellent CPR performance than those in all other groups. Interestingly, there were no significant differences between the three, six, and 12-month groups. As in the current study, nonformal learning participation had a definite sweet spot, and the other amounts of training did not matter.

It is very challenging in the present study to suggest a reason for this outcome. In the CPR study by Anderson et al. (2019), more training led to better skills—that outcome is intuitive. Here, when Baby Boomers participated three times in seminars or workshops, it resulted in no better PS-TRE skills than a lack of participation; only participating twice mattered. I might be tempted to call it a fluke if the pattern had not repeated with on-the-job training. Since the pattern did repeat, I would offer that a possible explanation could be found in the concepts of elaboration and fluid intelligence.

Elaboration is a long-term memory process wherein a person relates new skills to prior experience or forms associations. Roessger et al. (2020) found that Baby Boomers scored 6.9-8.0% lower than those aged 16-24 on elaboration items in PIAAC. Salthouse (2012) proposes that, in real life, older people are not harmed by losses in fluid intelligence because, as they age, they encounter fewer novel situations and can rely on knowledge they have gained through experience (crystalized intelligence). In nonformal workplace learning situations, however, older workers may encounter novel ideas and then find themselves struggling to connect the new ideas

to previous experience. It could be that those Baby Boomers who attend nonformal learning activities more than twice in a year enjoy the experience but fail to elaborate. If they fail to elaborate, then more participation might not matter in skill acquisition because the deep work is not happening to lodge the skills in long-term memory. Since fluid intelligence decreases with age, this idea could also account for the finding in this study that participating in on-the-job training once or twice was detrimental for the oldest Baby Boomers (those age 60-70). A training experience could be detrimental if a person realized that they were struggling with the subject matter and it resulted in a high-stress experience. In both of these scenarios, though, if it is true that Baby Boomers are struggling to elaborate, then development professionals should see greater competency gains for this generation if they intentionally build opportunities for elaboration into training exercises.

In this study, the PS-TRE competency of Baby Boomers was not impacted by informally learning from coworkers or supervisors. This contrasts with the findings of Lopes et al. (2020), who recently reported that informal learning in the form of information-sharing produced significant PS-TRE gains for U.S. workers in certain industries. It seems, therefore, that it may be important to account for generational differences in future studies of informal learning and PS-TRE competency. PIAAC includes employment classification codes based on the International Standard Classification of Occupations. Although the present study did not find significant PS-TRE differences between Baby Boomers by economic sector or many differences by organizational size, future researchers could further explore potential differences among Baby Boomers by specific occupational groups such as craft and trade workers, service and sales workers, etc. to more fully identify similarities and differences with the findings of Lopes et al.

This study also provides important new information regarding the impact of learning-by-doing on PS-TRE competency. U.S. Baby Boomers who learned by doing every day earned significantly *worse* PS-TRE scores than those who never or rarely learned by doing. Reviewing the crosstabulations of learning participation, many participants in this study (n = 132) who reported learning by doing every day also never participated in on-the-job training, or never participated in seminars or workshops (n = 148). Out of curiosity, I ran another crosstabulation to get a sense for how often people who learned by doing every day reported learning informally from coworkers or supervisors. Of respondents who reported learning by doing every day, 36% reported learning from coworkers less than once a week. Full results of the crosstabulation of learning by doing and learning from coworkers or supervisors are in Appendix S. We can see, then, that more than 1/3 of Baby Boomers who spend a lot of time learning by doing also do not spend very much time engaging in social forms of learning.

Consider, for a moment, what the Dreyfus Model of Skill Acquisition (Dreyfus et al., 1986), suggests about skill development. Although the Model proposes that learning from experience has a crucial role in moving people from novice to expert, Dreyfus et al. do not propose that a person be given some initial training and then left to sink or swim on their own in the task environment. Instead, the role of the instructor changes as the individual's skills develop. As the person moves from novice to advanced beginner, Dreyfus (2004) describes the role of the instructor as one who provides instruction and examples, helping the less skilled individual recognize situational elements that influence decision-making. Data from this study indicate that many Baby Boomers who learn by doing every day are also those who do not report learning from coworkers or supervisors either non-formally or informally. It is really not surprising, then, that they would also have worse PS-TRE skills; interactions with more

knowledgeable peers are crucial for skill development, and they might be having those interactions less frequently than other workers.

One last conclusion from this study regarding learning-by-doing warrants additional discussion. In the question of whether the size of an organization impacted the relationship between workplace learning and PS-TRE competency among Baby Boomers, one significant interaction was identified. This study found that Baby Boomers who worked in large organizations (251+ employees) and who learned by doing at least once a week earned significantly higher PS-TRE scores than those in small organizations (1-50 employees) who learned by doing less than once a month. In Chapter Two, I proposed that Level 1 PS-TRE scores align best with the advanced beginner level of proficiency according to the Dreyfus Model (Dreyfus et al., 1986). As an advanced beginner, an individual benefits from a blend of nonformal and informal learning strategies in order to advance to the competent level of proficiency. In Chapter Four, results of this study confirmed the previous finding of Rampey et al. (2016) that 41% of Baby Boomers attained Level 1 PS-TRE scores. Also in Chapter Four, the crosstabulations of workplace learning participation by size of the organization indicate that about 55% of Baby Boomers who work in small businesses never participate in on-the-job training and about 67% never participate in seminars or workshops. In large organizations, on the other hand, only 31% never received on-the-job training and only 31% never participated in seminars or workshops. It seems, then, that workers in large organizations could be more likely to receive the blend of nonformal and informal learning approaches that lead to increased proficiency among advanced beginners according to the Dreyfus Model.

Implications for Use of the Dreyfus Model in this Context

When I first read through the Dreyfus Model of Skill Acquisition (Dreyfus, 2004), I remember thinking that the crucial role of learning through experience made it easy to hypothesize that informal learning leads to increased competency. As I spent more time with the Model, though, I came to realize that the key is not experience alone, but rather (for those early in skill development) the coupling of experience with instruction in the task environment. Dreyfus et al. (1986) are not abundantly clear regarding what that instruction in the task environment should look like in order to maximize gains. Maybe the best type of instruction varies by the skill being taught, or maybe it varies by who the learners are. Dreyfus et al. also do not suggest a recipe for success in blending learning strategies; they do not say, for example, attend two seminars and learn by doing on a weekly basis to produce competency. Just as the Model itself implies, a person should not get too caught up in rules, but rather should utilize the Model as a mindset.

Since not many Baby Boomers attain Level 2 or 3 PS-TRE scores (moving beyond advanced beginner), it is difficult to fully explore the implications of the Dreyfus Model (Dreyfus et al., 1986) in the context of PS-TRE proficiency in PIAAC. Some might argue that the finding of this study that informal learning does not routinely lead to PS-TRE competency gains for U.S. Baby Boomers is evidence against the accuracy of the Dreyfus Model. However, I also anticipated based on the Dreyfus Model and the known skill level of Baby Boomers in PS-TRE that Baby Boomers would benefit from a blend of nonformal and informal learning strategies to achieve competency gain. In the interaction of size of the organization and learning by doing, this study provided at least some evidence in support of that idea.

One place where the Dreyfus Model (Dreyfus et al., 1986) might have faltered in this study is in the finding that, in the interaction of age and on-the-job training, older participants earned worse PS-TRE scores than younger nonparticipants. Since on-the-job training is arguably the variable most aligned with mentoring, and Dreyfus (2016) describes mentoring as one desirable form of instruction in the task environment, this is concerning. Even this, though, could potentially be inaccurate because, as indicated previously, the relationship between age and PS-TRE merits further exploration due to inconsistencies noted in this study.

In summary, then, it seems that further exploration may be warranted regarding the use of the Dreyfus Model (Dreyfus et al., 1986) in predicting PS-TRE skill acquisition among the oldest members of our workforce. Since the Model suggests that a blend of instruction and informal learning through experience in the task environment is needed for people in the early stages of skill development, it seems reasonable that both nonformal and informal learning should result in skill gain. In this study, skill gain in PS-TRE was not guaranteed when participating in non-formal learning, and too much learning-by-doing was harmful. As previously discussed, it is unknown whether the problem is with learning-by-doing as a learning strategy, or with the trend noted in this data that many people who rely heavily on learning-by-doing also do not report receiving the other half of the Dreyfus Model equation—instruction in the task environment. It may be that, if we can take steps to foster a blended approach to instruction in PS-TRE for this generation, the Dreyfus Model would perform as expected.

Recommendations for Research and Practice

Ever since Senge (1990) brought the concept of a learning organization into popular literature, the idea has been widely acknowledged that staying competitive in a globalized world requires organizations to facilitate learning among employees. In this study, out of four types of

workplace learning, the only learning activity engaged in regularly by a majority Baby Boomers was learning-by-doing, a strategy which might not require interaction with others. How can we possibly foster learning organizations if the majority of an entire generation of workers—the very people who we want to keep employed past a traditional retirement age for economic reasons—rarely or never participate in social learning activities?

If we truly desire learning organizations, then development professionals need to adopt an intentionally inclusive mindset about this generation, and they need support from their organizations to document the efficacy of the engagement strategies they attempt through research and scholarship. Chapter Two documents a wide exchange of ideas in the literature regarding optimizing training for older workers. There are not, however, many reports of empirical tests of these ideas, and there are mixed results regarding efficacy in the tests that have been conducted (see, for example, Lopina et al., 2019). There is a huge opportunity and need evident here for future research in the field of adult and lifelong learning to find out what works for motivating older workers to participate in workplace learning and what works to increase the efficacy of these learning experiences for older workers. To design a training with the unique needs of older workers in mind, though, requires resources of time, personnel, and funding. This means not only do development professionals need to develop an intentionally inclusive mindset about this generation, but that same asset-mindset must extend to those in organizational leadership.

The lack of significant findings in many areas of this study interestingly helps create clarity in the path forward. An optimal amount of participation in nonformal workplace learning (either through seminar/workshop attendance or through on-the-job training) was associated with PS-TRE competency gains among U.S. Baby Boomers. Differences between gender, supervisory

status, economic sector, or organizational size and PS-TRE were not detected, nor did any of these significantly moderate the relationship between nonformal learning and PS-TRE. This provides a strong, widely applicable argument for ensuring older workers are offered nonformal workplace learning opportunities if organizations wish to improve competency in PS-TRE. Some caution may be warranted, however, in using on-the-job training to promote PS-TRE competency among Baby Boomers age 60 or older.

The present study uses cross-sectional data and therefore cannot determine causality. The finding here that attending an optimal amount of nonformal workplace learning is associated with significant improvement in PS-TRE among Baby Boomers is one that invites additional testing. Remember, too, that we do not know anything about the training events that were attended. To clarify these findings, a randomized controlled trial testing the effect of on-the-job training on PS-TRE could be set up using a design like the one used in the CPR study by Anderson et al. (2019). In the study by Anderson et al., all participants began with a baseline measure of proficiency and ended with a 12-month measure of proficiency. In-between, participants received different amounts of CPR refresher sessions. Those refresher sessions could be replaced with on-the-job training. The present study indicates that, in one year, there may be a specific amount of training participation that results in PS-TRE gains for this generation. In theory a test could be done with seminars or workshop participation, too, but it might be more challenging to secure the attendance of groups of Baby Boomers in multiple seminars or workshops. An added benefit to testing the effect of on-the-job training with control groups could be the ability to determine whether age has the same moderating effect noted in this study where on-the-job training was only beneficial for younger Baby Boomers (age 50-59). In this study, older participants (those age 60-70) who participated in on-the-job training once or twice

ended up with significantly worse PS-TRE scores than those age 50-59 who never participated. A randomized controlled trial that could confirm or shed new light on these correlational findings could provide extremely useful information for human resource and development professionals who plan and deliver these learning opportunities.

Although Baby Boomers have lower PS-TRE scores than other U.S. employees, they still perform on average at the same level of PS-TRE competency—Level 1. To further explore the differences between these scores, I ran a regression analysis using the IDB Analyzer and the 2017 U.S. data. Age group 30-34 served as the reference group since theirs were the highest scores in the Level 1 range (one age group scored in Level 2). Table 26 provides the results of the analysis for Baby Boomers.

Table 26
Difference in PS-TRE Performance between Baby Boomers and Age Group 30-34

Age Group	b_i	SE	95% CI		t	CV
			UL	LL		
50-54	-28.45***	4.53	-19.57	-37.33	-6.28	-15.93%
55-59	-21.68***	4.74	-12.38	-30.98	-4.57	-21.88%
60-65	-25.65***	5.16	-15.54	-35.75	-4.97	-20.10%
66-70	-32.15***	7.22	-18.00	-46.29	-4.45	-22.45%

Note. $N = 2510$. PS-TRE = problem solving in technology-rich environments; SE = standard error; CI = confidence interval; UL = upper level; LL = lower level; CV = coefficient of variation.
*** $p < 0.001$

The difference between scores for each age group of employed Baby Boomers and the reference group was highly significant ($p < 0.001$). Baby Boomers on average scored between 21.68-32.15 points lower in PS-TRE than employees in age group 30-34. Future researchers could further explore significant differences between Level 1 scores and interpret what within-level differences mean in terms of PS-TRE proficiency. This information could help guide development of nonformal learning opportunities for this generation.

The finding of this study that the majority of Baby Boomers—about 27%—report infrequently learning informally from coworkers or supervisors contrasts with the findings of two qualitative studies reviewed in Chapter Two. Warhurst and Black (2015) documented the extent that older managers tend to learn from coworkers. Daley (1999) discussed how expert nurses learned from coworkers. In both studies, participants had at least some expertise in their areas. Could it be, then, that informal learning is not only needed to progress to higher levels of proficiency as the Dreyfus Model (Dreyfus et al., 1986) suggests, but also only *becomes* a dominant and effective learning strategy after a certain point of skill development? Or could it be that, as experts in their fields, some older workers identify more with the role of teacher than that of learner in workplace relationships and so fail to report learning from coworkers? An entirely different explanation for this phenomenon is that this trend could indicate an issue of access—it could be that younger workers are excluding older workers from these interactions under certain conditions (North & Fiske, 2016). Future research is needed to disentangle this unexpected finding. It might be useful to replicate Pineda-Herrero et al.'s (2017) Spanish PIAAC study to examine informal learning more thoroughly among all U.S. employees to develop a broader understanding of whether this trend among Baby Boomers is unique.

The extent to which formal training promotes informal learning among members of this generation provides another interesting area for future quantitative and qualitative inquiry. This study only utilized crosstabulations to look at numbers in participation trends. It could be useful to follow up with testing to find out if these relationships in participation are statistically significant. Although in this study participating in three seminars resulted in more frequent informal learning from coworkers than participating in two seminars, that trend was not the same for all levels of participation. Why do Baby Boomers who only attend one seminar or workshop,

for example, report learning from coworkers on a weekly basis—more often than those who attend two seminars or workshops? The relationships between learning strategies among older workers could prove to be a useful new line of inquiry in the study of lifelong learning.

Summary

This study used multiple linear regression to explore the association between four different types of workplace learning and PS-TRE competency in a national sample of U.S. Baby Boomers. Results indicate that participating in an optimal amount of on-the-job training, seminars, or workshops was associated with stronger PS-TRE scores, but some caution may be warranted in use of on-the-job training with workers age 60-70. Learning informally from coworkers or supervisors did not impact PS-TRE performance, and participating in learning-by-doing every day was associated with worse PS-TRE scores. Participating in an optimal amount of learning-by-doing, however, may be associated with PS-TRE gains for workers in large organizations (250+ employees). Future research should test these correlational findings using experimental designs, and future research in adult and lifelong learning should explore the social learning experiences of older workers in order to better understand these outcomes.

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Appendices

Appendix A: IRB Outcome

UNIVERSITY OF ARKANSAS

To:	Julie M. Galliart
From:	Chair, Douglas James Adams IRB Committee
Date:	09/16/2019
Action:	**Review Not Required**
Action Date:	09/16/2019
Protocol #:	1908212097
Study Title:	Baby Boomers in Technology-Rich Environments: Using PIAAC to Study Skill Acquisition

Please keep this form for your records. Investigators are required to notify the IRB if any changes are made to the referenced study that may change the status of this determination. Please contact your IRB Administrator if you have any questions regarding this determination or future changes to this determination.

Page 1 of 1

Appendix B: Dummy Coding Process for Seminar Participation x Supervisory Status

First, review case counts for each interaction.

Seminar never (1) x supervisor yes (1) = 88

Seminar once or twice (2) x supervisor yes (1) = 57

Seminar three or more times (3) x supervisor yes (1) = 47

Seminar never (1) x supervisor no (2) = 230

Seminar once or twice (2) x supervisor no (2) = 84

Seminar three or more times (3) x supervisor no (2) = 64

Second, recode variables to include zeros.

1 » 0

2 » 1

3 » 2

Third, compute interactions using new categories. Multiply the new categories using the compute variable option in the transform menu in SPSS. The outcome will be a new variable with values as follows. Define the dummy coded variables that will appear in the output.

0 x 0 = 0

0 x 1 = 0

1 x 0 = 0

1 x 1 = 1 this is dummy 1. It represents someone who is not a supervisor who participated in one or two seminars or workshops

2 x 0 = 0

2 x 1 = 2 this is dummy 2. It represents someone who is not a supervisor who participated in three or more seminars or workshops

Fourth, recode the new variable to include the value of 1. This is the term used in the IDB Analyzer.

0 » 1

1 » 2 now represents someone who is not a supervisor who participated in one or two seminars or workshops

2 » 3 now represents someone who is not a supervisor who participated in three or more seminars or workshops

Appendix C: Results Table for Research Question 3a

Table 27

Interaction Effect of Supervisory Status and On-the-Job Training on PS-TRE

Variable	Model 2			Model 3		
	b_i	SE	t	b_i	SE	t
Constant	246.49***	7.41	33.27	249.74***	7.68	32.51
Age						
50-54 (ref)						
55-59	-0.34	4.83	-0.07	0.08	4.84	0.02
60-65	-2.00	5.21	-0.38	-1.09	5.37	-0.20
66-70	-15.26*!	6.64!	-2.30!	-14.74*!	6.60!	-2.23!
Education level						
HS diploma or less (ref)						
College degree	28.64***	3.14	9.11	28.47***	3.06	9.31
Gender						
Male (ref)						
Female	-2.94	4.86	-0.61	-3.40	4.77	-0.71
Self-rated health						
Excellent (ref)						
Very good	6.93	7.37	0.94	7.10	7.38	0.96
Good	4.70	7.38	0.64	4.61	7.29	0.63
Fair or Poor	-7.15	9.71	-0.74	-6.27	9.62	-0.65
Race						
White (ref)						
Black	-36.92***	5.64	-6.54	-37.07***	5.64	-6.57
Other race	-15.17*!	7.20!	-2.11!	-14.57*!	7.14!	-2.04!
On-the-job training						
Never (ref)						
Once or twice	15.69***	4.60	3.41	15.63	8.76	1.78
Three or four times	6.73	5.61	1.20	-2.13	10.35	-0.21
Five or more times	9.48	5.44	1.74	0.03	7.60	0.00

Table 27 (Cont.)

Variable	Model 2			Model 3		
	b_i	SE	t	b_i	SE	t
Supervisor						
Yes (ref)						
No	-3.16	4.83	-0.65	-8.27	6.46	-1.28
OTJTxSupervisor						
OTJTxSupervisor (ref) [a]						
OTJTxSupervisor _D2 [b]				-0.06	11.73	0.00
OTJTxSupervisor_D3 [c]				13.08	12.32	1.06
OTJTxSupervisor_D4 [d]				15.11	10.87	1.39
R^2	0.25			0.26		

Note. N = 566. PS-TRE = problem solving in technology-rich environments; HS = high school; OTJT = on-the-job training; SE = standard error; Ref = reference. $\Delta R^2 = 0.05$ for Step 2. $\Delta R^2 = 0.01$ for Step 3.

[a] The reference category is a supervisor who never participated in on-the-job training.

[b] D2 = person who is not a supervisor and who participated in on-the-job training once or twice.

[c] D3 = person who is not a supervisor and who participated in on-the-job training three or four times.

[d] D4 = person who is not a supervisor and who participated in on-the-job training five or more times.

! Interpret data with caution. The coefficient of variation (CV) for this estimate is between 30 and 50 percent.

* $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$

Appendix D: Results Table for Research Question 3b

Table 28

Interaction Effect of Supervisory Status and Seminar or Workshop Participation on PS-TRE

Variable	Model 2			Model 3		
	b_i	SE	*t*	b_i	SE	*t*
Constant	249.96***	7.71	32.42	253.41***	7.21	35.16
Age						
50-54 (ref)						
55-59	0.34	4.62	0.07	0.22	4.53	0.05
60-65	-2.92	5.26	-0.56	-2.84	5.30	-0.54
66-70	-14.81*!	6.64!	-2.23!	-14.90*!	6.55!	-2.28!
Education level						
HS diploma or less (ref)						
College degree	26.72***	3.54	7.55	26.83***	3.60	7.45
Gender						
Male (ref)						
Female	-2.26	4.91	-0.46	-2.03	4.95	-0.41
Self-rated health						
Excellent (ref)						
Very good	7.74	7.82	0.99	7.70	7.78	0.99
Good	5.87	8.09	0.73	5.49	7.91	0.69
Fair or Poor	-7.21	10.09	-0.71	-7.09	10.01	-0.71
Race						
White (ref)						
Black	-37.62***	5.63	-6.68	-37.80***	5.67	-6.67
Other race	-16.75*!	7.70!	-2.18!	-16.58*!	7.57!	-2.19!
Seminar or workshop participation						
Never (ref)						
Once or twice	10.33	5.40	1.91	4.02	7.38	0.55
Three or more times	3.89	5.06	0.77	-2.97	7.69	-0.39
Supervisor						
Yes (ref)						
No	-3.21	4.87	-0.66	-8.04	6.72	-1.20

Table 28 (Cont.)

Variable	Model 2			Model 3		
	b_i	SE	t	b_i	SE	t
SeminarXSupervisor						
SeminarxSupervisor (ref) [a]						
SeminarxSupervisor_D2 [b]				9.22	9.71	0.95
SeminarxSupervisor_D3 [c]				10.56	11.51	0.92
R^2	0.24			0.24		

Note. N = 567. PS-TRE = problem solving in technology-rich environments; HS = high school; SE = standard error; Ref = reference. $\Delta R^2 = 0.04$ for Step 2.
[a] The reference category is a supervisor who never participated in seminars or workshops.
[b] D2 = person who is not a supervisor and who participated in one or two seminars or workshops.
[c] D3 = person who is not a supervisor and who participated in three or more seminars or workshops.
! Interpret data with caution. The coefficient of variation (CV) for this estimate is between 30 and 50 percent.
* $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$

Appendix E: Results Table for Research Question 3c

Table 29
Interaction Effect of Supervisory Status and Learning-by-Doing on PS-TRE

Variable	Model 2			Model 3		
	b_i	SE	*t*	b_i	SE	*t*
Constant	254.18***	7.84	32.43	259.88***	9.50	27.35
Age						
50-54 (ref)						
55-59	0.83	4.80	0.17	1.37	4.91	0.28
60-65	-1.41	5.29	-0.27	-1.23	5.31	-0.23
66-70	-15.37*!	6.68!	-2.30!	-15.32*!	6.68!	-2.29!
Education level						
HS diploma or less (ref)						
College degree	27.36***	3.41	8.03	27.74***	3.59	7.72
Gender						
Male (ref)						
Female	-1.90	4.88	-0.39	-2.28	4.75	-0.48
Self-rated health						
Excellent (ref)						
Very good	5.91	7.23	0.82	5.16	7.11	0.73
Good	3.38	7.51	0.45	2.94	7.49	0.39
Fair or Poor	-10.14	9.85	-1.03	-10.66	9.84	-1.08
Race						
White (ref)						
Black	-35.74***	6.12	-5.84	-35.48***	6.17	-5.75
Other race	-16.08*!	7.65!	-2.10!	-15.76*!	7.81!	-2.02!
Learning-by-doing						
Never or less than once a month (ref)						
Less than once a week but at least once a month	4.57	5.55	0.82	-6.14	10.82	-0.57
At least once a week but not every day	4.92	5.32	0.92	-2.74	9.21	-0.30
Every day	-6.62	5.23	-1.26	-11.07	10.29	-1.08

Table 29 (Cont.)

Variable	Model 2			Model 3		
	b_i	SE	t	b_i	SE	t
Supervisor						
Yes (ref)						
No	-3.04	4.91	-0.62	-11.23	7.94	-1.41
LBDxSupervisor						
LBDxSupervisor (ref) [a]						
LBDxSupervisor_D2 [b]				15.72	13.28	1.18
LBDxSupervisor_D3 [c]				11.73	11.84	0.99
LBDxSupervisor_D4 [d]				6.70	14.11	0.47
R^2	0.24			0.25		

Note. $N = 565$. PS-TRE = problem solving in technology-rich environments; HS = high school; LBD = learning-by-doing; SE = standard error; Ref = reference. $\Delta R^2 = 0.04$ for Step 2. $\Delta R^2 = 0.01$ for Step 3.

[a] The reference category is a supervisor who learned by doing less than once a month.

[b] D2 = person who is not a supervisor and who learned by doing less than once a week but at least once a month.

[c] D3 = person who is not a supervisor and who learned by doing at least once a week but not every day.

[d] D4 = person who is not a supervisor and who learned by doing every day.

! Interpret data with caution. The coefficient of variation (CV) for this estimate is between 30 and 50 percent.

* $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$

Appendix F: Results Table for Research Question 3d

Table 30

Interaction Effect of Supervisory Status and Learning from Coworkers or Supervisors on PS-TRE

Variable	Model 2			Model 3		
	b_i	SE	*t*	b_i	SE	*t*
Constant	249.43***	7.60	32.81	248.34***	8.25	30.09
Age						
50-54 (ref)						
55-59	1.36	4.74	0.29	1.35	4.66	0.29
60-65	-2.18	5.39	-0.40	-2.60	5.27	-0.49
66-70	-15.66*!	6.55!	-2.39!	-14.33*!	6.82!	-2.10!
Education level						
HS diploma or less (ref)						
College degree	28.58***	3.14	9.10	29.01***	3.08	9.42
Gender						
Male (ref)						
Female	-2.87	4.86	-0.59	-2.57	4.88	-0.53
Self-rated health						
Excellent (ref)						
Very good	7.37	7.32	1.01	8.12	7.13	1.14
Good	4.72	7.58	0.62	5.38	7.38	0.73
Fair or Poor	-8.61	9.47	-0.91	-7.52	9.13	-0.82
Race						
White (ref)						
Black	-35.73***	5.94	-6.01	-35.48***	5.89	-6.02
Other race	-15.76*!	7.71!	-2.04!	-16.75*!	7.65!	-2.19!

Table 30 (Cont.)

Variable	Model 2			Model 3		
	b_i	SE	t	b_i	SE	t
Learning from coworkers or supervisors						
Never or less than once a month (ref)						
Less than once a week but at least once a month	6.81	5.71	1.19	17.19	9.06	1.90
At least once a week but not every day	8.89	5.85	1.52	3.47	8.32	0.42
Every day	-2.60	5.78	-0.45	-5.59	9.28	-0.60
Supervisor						
Yes (ref)						
No	-3.69	4.81	-0.77	-3.41	6.89	-0.49
LFCxSupervisor						
LFCxSupervisor (ref) [a]						
LFCxSupervisor _D2 [b]				-15.34	11.16	-1.37
LFCxSupervisor _D3 [c]				8.22	10.56	0.78
LFCxSupervisor _D4 [d]				4.46	11.53	0.39
R^2	0.24			0.25		

Note. N = 566. PS-TRE = problem solving in technology-rich environments; HS = high school; LFC = learning from coworkers; SE = standard error; Ref = reference. $\Delta R^2 = 0.04$ for Step 2. $\Delta R^2 = 0.01$ for Step 3.

[a] The reference category is a supervisor who learned from coworkers less than once a month.

[b] D2 = person who is not a supervisor and who learned from coworkers less than once a week but at least once a month.

[c] D3 = person who is not a supervisor and who learned from coworkers at least once a week but not every day.

[d] D4 = person who is not a supervisor and who learned from coworkers every day.

! Interpret data with caution. The coefficient of variation (CV) for this estimate is between 30 and 50 percent.

* $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$

Appendix G: Results Table for Research Question 4a

Table 31
Interaction Effect of Economic Sector and On-the-Job Training on PS-TRE

Variable	Model 2			Model 3		
	b_i	SE	*t*	b_i	SE	*t*
Constant	244.87***	7.22	33.93	243.82***	7.68	31.75
Age						
50-54 (ref)						
55-59	3.87	4.48	0.86	3.77	4.50	0.84
60-65	-0.73	4.92	-0.15	-0.59	4.88	-0.12
66-70	-4.07	6.76	-0.60	-4.31	7.12	-0.61
Education level						
HS diploma or less (ref)						
College degree	28.84***	3.14	9.20	28.93***	3.09	9.37
Gender						
Male (ref)						
Female	-2.61	4.35	-0.60	-2.25	4.38	-0.51
Self-rated health						
Excellent (ref)						
Very good	5.70	6.47	0.88	5.93	6.43	0.92
Good	1.20	6.22	0.19	1.08	6.15	0.18
Fair or Poor	-1.73	7.69	-0.22	-1.68	7.65	-0.22
Race						
White (ref)						
Black	-35.84***	5.54	-6.46	-36.11***	5.36	-6.74
Other race	-14.95*!	6.71!	-2.23!	-14.85*!	6.65!	-2.23!
On-the-job training						
Never (ref)						
Once or twice	13.00**!	4.68!	2.78!	12.54*!	6.21!	2.02!
Three or four times	3.71	5.62	0.66	10.80	8.00	1.35
Five or more times	6.98	5.34	1.31	8.28	7.09	1.17

Table 31 (Cont.)

Variable	Model 2			Model 3		
	b_i	SE	t	b_i	SE	t
Sector						
Private (ref)						
Public or Non-profit	0.72	4.26	0.17	4.20	6.08	0.69
OTJTxSector						
OTJTxSector (ref) [a]						
OTJTxSector _D2 [b]				0.20	11.39	0.02
OTJTxSector _D3 [c]				-18.86	12.79	-1.47
OTJTxSector _D4 [d]				-4.66	10.12	-0.46
R^2	0.21			0.22		

Note. N = 693. PS-TRE = problem solving in technology-rich environments; HS = high school; OTJT = on-the-job training; SE = standard error; Ref = reference. $\Delta R^2 = 0.01$ for Step 2. $\Delta R^2 = 0.01$ for Step 3.

[a] The reference category is a person in the private sector who never participated in on-the-job training.

[b] D2 = person in the public or non-profit sector who participated in on-the-job training once or twice.

[c] D3 = person in the public or non-profit sector who participated in on-the-job training three or four times.

[d] D4 = person in the public or non-profit sector who participated in on-the-job training five or more times.

! Interpret data with caution. The coefficient of variation (CV) for this estimate is between 30 and 50 percent.

* $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$

Appendix H: Results Table for Research Question 4b

Table 32

Interaction Effect of Economic Sector and Seminar or Workshop Participation on PS-TRE

Variable	Model 2			Model 3		
	b_i	SE	*t*	b_i	SE	*t*
Constant	244.41***	7.39	33.08	243.60***	7.67	31.77
Age						
50-54 (ref)						
55-59	3.76	4.39	0.86	3.49	4.38	0.80
60-65	-1.68	4.96	-0.34	-2.76	4.85	-0.57
66-70	-4.47	6.42	-0.70	-5.53	6.22	-0.89
Education level						
HS diploma or less (ref)						
College degree	26.60***	3.52	7.56	27.56***	3.59	7.68
Gender						
Male (ref)						
Female	-1.65	4.39	-0.38	-0.88	4.41	-0.20
Self-rated health						
Excellent (ref)						
Very good	7.28	6.66	1.09	6.97	6.53	1.07
Good	3.06	6.83	0.45	3.08	6.80	0.45
Fair or Poor	-0.98	7.86	-0.12	-0.84	7.70	-0.11
Race						
White (ref)						
Black	-36.05***	5.40	-6.67	-36.15***	5.50	-6.57
Other race	-15.54*!	6.96!	-2.23!	-16.69*!	6.88!	-2.43!
Seminar or workshop participation						
Never (ref)						
One time	9.80	6.51	1.51	17.12*!	8.37!	2.04!
Two times	15.69*!	6.14!	2.55!	13.00	8.25	1.58
Three or four times	8.30	6.77	1.23	15.66	8.19	1.91
Five or more times	9.66	6.88	1.40	5.33	9.04	0.59

Table 32 (Cont.)

Variable	Model 2			Model 3		
	b_i	SE	t	b_i	SE	t
Sector						
Private (ref)						
Public or Non-profit	0.05	3.95	0.01	3.05	5.50	0.55
SeminarxSector						
SeminarxSector (ref) [a]						
SeminarxSector _D2 [b]				-19.61	10.94	-1.79
SeminarxSector _D3 [c]				4.80	11.85	0.41
SeminarxSector _D4 [d]				-20.53	11.78	-1.74
SeminarxSector _D5 [e]				7.71	10.91	0.71
R^2	0.22			0.23		

Note. $N = 694$. PS-TRE = problem solving in technology-rich environments; HS = high school; SE = standard error; Ref = reference. $\Delta R^2 = 0.02$ for Step 2. $\Delta R^2 = 0.01$ for Step 3.

[a] The reference category is a person in the private sector who never participated in seminars or workshops.

[b] D2 = person in the public or non-profit sector who participated in one seminar or workshop.

[c] D3 = person in the public or non-profit sector who participated in two seminars or workshops.

[d] D4 = person in the public or non-profit sector who participated in three or four seminars or workshops.

[e] D5 = person in the public or non-profit sector who participated in five or more seminars or workshops.

! Interpret data with caution. The coefficient of variation (CV) for this estimate is between 30 and 50 percent.

* $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$

Appendix I: Results Table for Research Question 4c

Table 33

Interaction Effect of Economic Sector and Learning-by-Doing on PS-TRE

Variable	Model 2			Model 3		
	b_i	SE	*t*	b_i	SE	*t*
Constant	253.57***	7.12	35.62	253.64***	7.86	32.28
Age						
50-54 (ref)						
55-59	4.98	4.49	1.11	5.08	4.47	1.14
60-65	-0.21	4.89	-0.04	-0.28	4.88	-0.06
66-70	-5.93	6.50	-0.91	-5.97	6.69	-0.89
Education level						
HS diploma or less (ref)						
College degree	27.99***	3.38	8.29	28.19***	3.30	8.54
Gender						
Male (ref)						
Female	-1.89	4.39	-0.43	-1.73	4.42	-0.39
Self-rated health						
Excellent (ref)						
Very good	4.91	6.20	0.79	4.84	6.25	0.77
Good	0.05	6.14	0.01	0.07	6.19	0.01
Fair or Poor	-4.43	7.70	-0.58	-4.52	7.69	-0.59
Race						
White (ref)						
Black	-34.47***	5.87	-5.87	-34.60***	5.88	-5.88
Other race	-15.26*!	6.89!	-2.21!	-15.48*!	6.92!	-2.23!
Learning-by-doing						
Never or less than once a month (ref)						
Less than once a week but at least once a month	0.31	5.16	0.06	0.37	6.44	0.06
At least once a week but not every day	1.81	4.94	0.37	0.01	5.85	0.00
Every day	-11.76**!	4.50!	-2.62!	-11.23	5.83	-1.93

Table 33 (Cont.)

Variable	Model 2			Model 3		
	b_i	SE	t	b_i	SE	t
Sector						
Private (ref)						
Public or Non-profit	1.65	3.80	0.43	1.05	7.04	0.15
LBDxSector						
LBDxSector (ref) [a]						
LBDxSector _D2 [b]				-0.24	10.34	-0.02
LBDxSector _D3 [c]				5.95	10.68	0.56
LBDxSector _D4 [d]				-1.64	9.63	-0.17
R^2	0.22			0.22		

Note. N = 692. PS-TRE = problem solving in technology-rich environments; HS = high school; LBD = learning-by-doing; SE = standard error; Ref = reference. $\Delta R^2 = 0.02$ for Step 2.

[a] The reference category is a person in the private sector who learned by doing less than once a month.

[b] D2 = person in the public or non-profit sector who learned by doing less than once a week but at least once a month.

[c] D3 = person in the public or non-profit sector who learned by doing at least once a week but not every day.

[d] D4 = person in the public or non-profit sector who learned by doing every day.

! Interpret data with caution. The coefficient of variation (CV) for this estimate is between 30 and 50 percent.

* $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$

Appendix J: Results Table for Research Question 4d

Table 34

Interaction Effect of Economic Sector and Learning from Coworkers or Supervisors on PS-TRE

Variable	Model 2			Model 3		
	b_i	SE	*t*	b_i	SE	*t*
Constant	243.35***	6.98	34.88	242.65***	7.25	33.46
Age						
50-54 (ref)						
55-59	3.64	4.42	0.82	4.16	4.45	0.94
60-65	-1.77	5.13	-0.35	-1.21	5.20	-0.23
66-70	-13.69*!	6.02!	-2.27!	-13.20*!	6.30!	-2.10!
Education level						
HS diploma or less (ref)						
College degree	29.96***	3.17	9.45	30.21***	3.27	9.24
Gender						
Male (ref)						
Female	-3.93	4.72	-0.83	-3.90	4.66	-0.84
Self-rated health						
Excellent (ref)						
Very good	8.86	6.72	1.32	9.07	6.68	1.36
Good	4.12	6.86	0.60	4.25	7.05	0.60
Fair or Poor	-3.34	8.22	-0.41	-2.83	8.38	-0.34
Race						
White (ref)						
Black	-35.90***	6.02	-5.96	-35.24***	5.92	-5.95
Other race	-13.83	7.35	-1.88	-13.64	7.25	-1.88
Learning from coworkers or supervisors						
Never or less than once a month (ref)						
Less than once a week but at least once a month	7.34	5.50	1.33	4.16	7.06	0.59
At least once a week but not every day	10.12	5.70	1.77	10.23	7.35	1.39
Every day	-2.45	5.91	-0.41	-0.02	8.68	0.00

Table 34 (Cont.)

Variable	Model 2			Model 3		
	b_i	SE	t	b_i	SE	t
Sector						
Private (ref)						
Public or Non-profit	2.72	4.02	0.68	2.51	7.60	0.33
LFCxSector						
LFCxSector (ref) [a]						
LFCxSector _D2 [b]				8.05	10.51	0.77
LFCxSector _D3 [c]				-0.27	10.77	-0.02
LFCxSector _D4 [d]				-7.66	13.06	-0.59
R^2	0.24			0.24		

Note. PS-TRE = problem solving in technology-rich environments; HS = high school; LFC = learning from coworkers; SE = standard error; Ref = reference. $\Delta R^2 = 0.04$ for Step 2.

[a] The reference category is a person in the private sector who learned from coworkers less than once a month.

[b] D2 = person in the public or non-profit sector who learned from coworkers less than once a week but at least once a month.

[c] D3 = person in the public or non-profit sector who learned from coworkers at least once a week but not every day.

[d] D4 = person in the public or non-profit sector who learned from coworkers every day.

! Interpret data with caution. The coefficient of variation (CV) for this estimate is between 30 and 50 percent.

* $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$

Appendix K: Results Table for Research Question 5a

Table 35

Interaction Effect of Size of Organization and On-the-Job Training on PS-TRE

Variable	Model 2			Model 3		
	b_i	SE	*t*	b_i	SE	*t*
Constant	246.71***	7.87	31.33	249.16***	7.27	34.30
Age						
50-54 (ref)						
55-59	-0.61	4.75	-0.13	-0.77	4.73	-0.16
60-65	-2.25	5.11	-0.44	-2.41	5.10	-0.47
66-70	-16.71*!	6.83!	-2.45!	-17.73**!	6.75!	-2.63!
Education level						
HS diploma or less (ref)						
College degree	29.91***	3.21	9.32	29.55***	3.19	9.25
Gender						
Male (ref)						
Female	-3.67	4.77	-0.77	-3.83	4.79	-0.80
Self-rated health						
Excellent (ref)						
Very good	7.02	7.32	0.96	6.70	7.33	0.91
Good	4.65	7.20	0.64	4.24	7.29	0.58
Fair or Poor	-8.01	9.14	-0.88	-8.76	9.00	-0.97
Race						
White (ref)						
Black	-37.18***	5.65	-6.58	-36.93***	5.71	-6.46
Other race	-14.89*!	7.08!	-2.10!	-14.49*!	6.92!	-2.09!
On-the-job training						
Never (ref)						
Once or twice	16.13***	4.73	3.41	16.88*!	7.70!	2.19!
Three or more times	9.41	4.82	1.95	2.10	7.91	0.27

Table 35 (Cont.)

Variable	Model 2			Model 3		
	b_i	SE	t	b_i	SE	t
Size of Organization						
Small (ref)						
Medium	-3.63	4.85	-0.75	-6.61	6.75	-0.98
Large	-6.27	6.14	-1.02	-10.60	10.98	-0.97
OTJTxSize						
OTJTxSize (ref) [a]						
OTJTxSize _D2 [b]				-1.91	11.52	-0.17
OTJTxSize _D3 [c]				0.79	14.27	0.06
OTJTxSize _D4 [d]				11.54	11.70	0.99
OTJTxSize _D5 [e]				12.33	14.03	0.88
R^2	0.25			0.26		

Note. N = 564. PS-TRE = problem solving in technology-rich environments; HS = high school; OTJT = on-the-job training; Small organization = 1-50 people; Medium organization = 51-250 people; Large organization = 251 or more people; SE = standard error; Ref = reference. $\Delta R^2 = 0.05$ for Step 2. $\Delta R^2 = 0.01$ for Step 3.

[a] The reference category is a person in a small organization who never participated in on-the-job training.

[b] D2 = person in a mid-sized organization who participated in on-the-job training once or twice.

[c] D3 = person in a large organization who participated in on-the-job training once or twice.

[d] D4 = person in a mid-sized organization who participated in on-the-job training three or more times.

[e] D5 = person in a large organization who participated in on-the-job training three or more times.

! Interpret data with caution. The coefficient of variation (CV) for this estimate is between 30 and 50 percent.

* $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$

Appendix L: Results Table for Research Question 5b

Table 36

Interaction Effect of Size of Organization and Seminar or Workshop Participation on PS-TRE

Variable	Model 2			Model 3		
	b_i	SE	*t*	b_i	SE	*t*
Constant	249.74***	8.18	30.52	250.31***	7.77	32.20
Age						
50-54 (ref)						
55-59	0.09	4.53	0.02	0.35	4.57	0.08
60-65	-3.15	5.19	-0.61	-3.16	5.23	-0.60
66-70	-16.02*!	6.89!	-2.33!	-16.02*!	6.79!	-2.36!
Education level						
HS diploma or less (ref)						
College degree	27.88***	3.45	8.07	27.65***	3.47	7.96
Gender						
Male (ref)						
Female	-2.88	4.79	-0.60	-3.30	4.94	-0.67
Self-rated health						
Excellent (ref)						
Very good	8.08	7.92	1.02	8.50	7.95	1.07
Good	6.08	8.04	0.76	6.38	8.02	0.80
Fair or Poor	-7.77	9.67	-0.80	-7.48	9.83	-0.76
Race						
White (ref)						
Black	-37.67***	5.59	-6.74	-37.52***	5.63	-6.67
Other race	-16.63*!	7.64!	-2.18!	-16.68*!	7.81!	-2.14!
Seminar or workshop participation						
Never (ref)						
Once or twice	‡	‡	‡	7.09	8.22	0.86
Three or more times	5.09	5.35	0.95	5.85	7.68	0.76

Table 36 (Cont.)

Variable	Model 2			Model 3		
	b_i	SE	t	b_i	SE	t
Size of Organization						
Small (ref)						
Medium	-3.38	4.78	-0.71	-5.56	6.91	-0.80
Large	-5.69	6.33	-0.90	-5.65	10.45	-0.54
SeminarxSize						
SeminarxSize (ref) [a]						
SeminarxSize _D2 [b]				8.63	12.45	0.69
SeminarxSize _D3 [c]				3.15	15.01	0.21
SeminarxSize _D4 [d]				0.58	12.60	0.05
SeminarxSize _D5 [e]				-2.14	12.85	-0.17
R^2	0.24			0.24		

Note. N = 565. PS-TRE = problem solving in technology-rich environments; HS = high school; Small organization = 1-50 people; Medium organization = 51-250 people; Large organization = 251 or more people; SE = standard error; Ref = reference. ΔR^2 = 0.04 for Step 2.

[a] The reference category is a person in a small organization who never participated in seminars or workshops.

[b] D2 = person in a mid-sized organization who participated in one or two seminars or workshops.

[c] D3 = person in a large organization who participated in one or two seminars or workshops.

[d] D4 = person in a mid-sized organization who participated in three or more seminars or workshops.

[e] D5 = person in a large organization who participated in three or more seminars or workshops.

! Interpret data with caution. The coefficient of variation (CV) for this estimate is between 30 and 50 percent.

‡ NCES reporting standards are not met.

* $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$

Appendix M: Results Table for Research Question 5c

Table 37
Interaction Effect of Size of Organization and Learning-by-Doing on PS-TRE

Variable	Model 2			Model 3		
	b_i	SE	*t*	b_i	SE	*t*
Constant	254.23***	8.08	31.45	262.79***	10.09	26.03
Age						
50-54 (ref)						
55-59	0.64	4.71	0.14	-0.14	4.84	-0.03
60-65	-1.50	5.24	-0.29	-2.33	5.18	-0.45
66-70	-16.65*$	6.87$	-2.42$	-18.21**$	7.00$	-2.60$
Education level						
HS diploma or less (ref)						
College degree	28.67***	3.48	8.23	28.62***	3.45	8.30
Gender						
Male (ref)						
Female	-2.51	4.74	-0.53	-2.32	4.79	-0.48
Self-rated health						
Excellent (ref)						
Very good	6.02	7.22	0.83	6.17	6.82	0.90
Good	3.44	7.36	0.47	2.14	6.99	0.31
Fair or Poor	-10.96	9.32	-1.18	-11.21	8.96	-1.25
Race						
White (ref)						
Black	-35.76***	6.06	-5.90	-34.83***	5.87	-5.93
Other race	-15.95*$	7.62$	-2.09$	-16.57*$	7.87$	-2.11$
Learning-by-doing						
Never or less than once a month (ref)						
Less than once a week but at least once a month	4.54	5.63	0.81	-8.94	9.90	-0.90
At least once a week but not every day	5.33	5.31	1.00	-11.09	8.38	-1.32
Every day	-6.83	5.33	-1.28	-12.34	7.25	-1.70

Table 37 (Cont.)

Variable	Model 2			Model 3		
	b_i	SE	t	b_i	SE	t
Size of Organization						
Small (ref)						
Medium	-2.66	4.78	-0.56	‡	‡	‡
Large	-5.59	6.07	-0.92	-17.96	10.84	-1.66
LBDxSize						
LBDxSize (ref) [a]						
LBDxSize _D2 [b]				22.67	17.55	1.29
LBDxSize _D3 [c]				27.88!	17.80!	1.57!
LBDxSize _D4 [d]				20.07	12.66	1.59
LBDxSize _D5 [e]				30.43*$	13.86$	2.20$
LBDxSize _D6 [f]				26.35	13.62	1.94
LBDxSize _D7 [g]				-0.06	14.65	0.00
R^2	0.25			0.27		

Note. $N = 563$. PS-TRE = problem solving in technology-rich environments; HS = high school; LBD = learning-by-doing; Small organization = 1-50 people; Medium organization = 51-250 people; Large organization = 251 or more people; SE = standard error; Ref = reference. $\Delta R^2 = 0.05$ for Step 2. $\Delta R^2 = 0.02$ for Step 3.

[a] The reference category is a person in a small organization who learned by doing less than once a month

[b] D2 = person in a mid-sized org who learned by doing less than once a week but at least once a month

[c] D3 = person in a large org who learned by doing less than once a week but at least once a month

[d] D4 = person in a mid-sized org who learned by doing every day

[e] D5 = person in a large org who learned by doing at least once a week but not every day

[f] D6 = person in a mid-sized org who learned by doing at least once a week but not every day

[g] D7 = person in a large org who learned by doing every day

! Interpret data with caution. The sample size for this estimate is between 20 and 30 cases.

$ Interpret data with caution. The coefficient of variation (CV) for this estimate is between 30 and 50 percent.

‡ NCES reporting standards are not met.

* $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$

Appendix N: Results Table for Research Question 5d

Table 38

Interaction Effect of Size of Organization and Learning from Coworkers or Supervisors on PS-TRE

Variable	Model 2			Model 3		
	b_i	SE	*t*	b_i	SE	*t*
Constant	248.92***	7.87	31.65	248.69***	8.99	27.66
Age						
50-54 (ref)						
55-59	1.21	4.67	0.26	1.58	4.70	0.33
60-65	-2.34	5.33	-0.44	-2.47	5.37	-0.46
66-70	-16.90*$	6.76$	-2.50$	-17.96**$	6.97$	-2.58$
Education level						
HS diploma or less (ref)						
College degree	29.88***	3.27	9.14	30.20***	3.33	9.08
Gender						
Male (ref)						
Female	-3.56	4.77	-0.75	-3.80	4.81	-0.79
Self-rated health						
Excellent (ref)						
Very good	7.62	7.38	1.03	7.33	7.21	1.02
Good	4.81	7.50	0.64	4.44	7.41	0.60
Fair or Poor	-9.26	9.08	-1.02	-9.86	8.85	-1.12
Race						
White (ref)						
Black	-35.87***	5.87	-6.11	-36.72***	5.91	-6.22
Other race	-15.68*$	7.72$	-2.03$	-17.80*$	7.79$	-2.29$
Learning from coworkers or supervisors						
Never or less than once a month (ref)						
Less than once a week but at least once a month	6.81	6.00	1.14	2.75	9.40	0.29
At least once a week but not every day	9.29	5.93	1.57	10.47	8.77	1.19
Every day	-2.31	5.73	-0.40	5.30	7.16	0.74

Table 38 (Cont.)

Variable	Model 2			Model 3		
	b_i	SE	t	b_i	SE	t
Size of Organization						
Small (ref)						
Medium	-3.27	4.64	-0.70	-6.98	8.71	-0.80
Large	-5.06	5.89	-0.86	2.86	8.44	0.34
LFCxSize						
LFCxSize (ref) [a]						
LFCxSize _D2 [b]				14.65	12.97	1.13
LFCxSize _D3 [c]				-4.74	12.03	-0.39
LFCxSize _D4 [d]				-0.92!	14.54!	-0.06!
LFCxSize _D5 [e]				-5.53	10.36	-0.53
LFCxSize _D6 [f]				0.47	14.26	0.03
LFCxSize _D7 [g]				-24.33	14.95	-1.63
R^2	0.24			0.26		

Note. N = 564. PS-TRE = problem solving in technology-rich environments; HS = high school; LFC = learning from coworkers; Small organization = 1-50 people; Medium organization = 51-250 people; Large organization = 251 or more people; SE = standard error; Ref = reference. $\Delta R^2 = 0.04$ for Step 2. $\Delta R^2 = 0.02$ for Step 3.

[a] The reference category is a person in a small organization who learned from coworkers less than once a month

[b] D2 = person in a mid-sized organization who learned from coworkers less than once a week but at least once a month

[c] D3 = person in a large organization who learned from coworkers less than once a week but at least once a month

[d] D4 = person in a mid-sized organization who learned from coworkers every day

[e] D5 = person in a large organization who learned from coworkers at least once a week but not every day

[f] D6 = person in a mid-sized organization who learned from coworkers at least once a week but not every day

[g] D7 = person in a large organization who learned from coworkers every day

! Interpret data with caution. The sample size for this estimate is between 20 and 30 cases.

$ Interpret data with caution. The coefficient of variation (CV) for this estimate is between 30 and 50 percent.

* $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$

Appendix O: Results Table for Research Question 6a

Table 39

Interaction Effect of Age, Gender, and On-the-Job Training on PS-TRE

Variable	Model 2			Model 3			Model 4		
	b_i	SE	*t*	b_i	SE	*t*	b_i	SE	*t*
Constant	247.09***	6.63	37.28	242.85***	8.16	29.76	242.99***	8.23	29.52
Education level									
HS diploma or less (ref)									
College degree	28.53***	3.11	9.16	28.35***	3.06	9.28	28.23***	3.05	9.25
Self-rated health									
Excellent (ref)									
Very good	5.20	6.39	0.81	6.15	6.32	0.97	6.08	6.35	0.96
Good	0.95	6.14	0.15	1.93	6.15	0.31	1.81	6.21	0.29
Fair or poor	-1.98	7.72	-0.26	-0.70	7.46	-0.09	-0.72	7.46	-0.10
Race									
White (ref)									
Black	-36.19***	5.54	-6.54	-35.48***	5.62	-6.31	-35.45***	5.67	-6.25
Other race	-16.50*$	6.72$	-2.46$	-16.14*$	6.54$	-2.47$	-16.27*$	6.51$	-2.50$
Age									
50-59 (ref)									
60-70	-3.53	3.70	-0.95	2.23	4.95	0.45	2.23	4.95	0.45
Gender									
Male (ref)									
Female	-2.12	4.32	-0.49	0.56	6.01	0.09	0.55	6.02	0.09
On-the-job training									
Never (ref)									
Once or twice	13.63**$	4.66$	2.92$	26.77**$	8.58$	3.12$	27.07**$	9.08$	2.98$
Three or more times	6.18	4.18	1.48	9.01	8.98	1.00	7.80	9.64	0.81
OTJTxAge									
OTJTxAge (ref) [a]									
OTJTxAge_D2 [b]				-21.13*$	9.71$	-2.18$	-21.99	12.49	-1.76
OTJTxAge_D3 [c]				-6.88	9.22	-0.75	-3.02	13.02	-0.23
OTJTxGender									
OTJTxGender (ref) [d]									
OTJTxGender_D2 [e]				-12.88	9.77	-1.32	-13.44	11.15	-1.21
OTJTxGender_D3 [f]				-0.95	9.43	-0.10	1.31	10.73	0.12

Table 39 (Cont.)

Variable	Model 2			Model 3			Model 4		
	b_i	SE	t	b_i	SE	t	b_i	SE	t
OTJTxAgexGender									
OTJTxAgexGender (ref) [g]									
OTJTxAgexGender D2 [h]							1.92!	13.96!	0.14!
OTJTxAgexGender D3 [i]							-6.78	13.15	-0.52
R^2	0.21			0.22			0.22		

Note. N = 696. PS-TRE = problem solving in technology-rich environments; HS = high school; OTJT = on-the-job training; SE = standard error; Ref = reference. ΔR^2 = 0.02 for Step 2. ΔR^2 = 0.01 for Step 3.

[a] OTJTxAge (ref) = a person age 50-59 who never participated in on-the-job training

[b] OTJTxAge _D2 = a person age 60-70 who participated in on-the-job training once or twice

[c] OTJTxAge_D3 = a person age 60-70 who participated in on-the-job training three or more times

[d] OTJTxGender (ref) = a male who never participated in on-the-job training

[e] OTJTxGender _D2 = a female who participated in on-the-job training once or twice

[f] OTJTxGender_D3 = a female who participated in on-the-job training three or more times

[g] OTJTxAgexGender (ref) = a male age 50-59 who never participated in on-the-job training

[h] OTJTxAgexGender _D2 = a female age 60-70 who participated in on-the-job training once or twice

[i] OTJTxAgexGender_D3 = a female age 60-70 who participated in on-the-job training three or more times

! Interpret data with caution. The sample size for this estimate is between 20 and 30 cases.

$ Interpret data with caution. The coefficient of variation (CV) for this estimate is between 30 and 50 percent.

* $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$

Appendix P: Results Table for Research Question 6b

Table 40

Interaction Effect of Age, Gender, and Seminar or Workshop Participation on PS-TRE

Variable	Model 2			Model 3			Model 4		
	b_i	SE	*t*	b_i	SE	*t*	b_i	SE	*t*
Constant	246.25***	6.84	36.03	245.61***	7.83	31.37	245.82***	7.69	31.95
Education level									
HS diploma or less (ref)									
College degree	26.12***	3.48	7.50	26.27***	3.32	7.91	25.95***	3.31	7.83
Self-rated health									
Excellent (ref)									
Very good	7.15	6.70	1.07	6.86	6.52	1.05	6.84	6.46	1.06
Good	3.18	6.76	0.47	3.87	6.76	0.57	3.90	6.70	0.58
Fair or poor	-0.86	7.94	-0.11	-1.14	7.84	-0.15	-1.06	7.76	-0.14
Race									
White (ref)									
Black	-36.22***	5.34	-6.78	-36.39***	5.36	-6.79	-36.71***	5.37	-6.84
Other race	-17.16*!	6.97!	-2.46!	-17.06*!	6.92!	-2.46!	-17.48*!	6.84!	-2.56!
Age									
50-59 (ref)									
60-70	-4.35	3.67	-1.19	-4.65	4.63	-1.00	-4.67	4.63	-1.01
Gender									
Male (ref)									
Female	-1.29	4.35	-0.30	-0.08	6.18	-0.01	-0.06	6.16	-0.01
Seminar or workshop participation									
Never (ref)									
Once or twice	13.68*!	5.38!	2.54!	19.14*!	8.61!	2.22!	20.03*!	8.43!	2.38!
Three or more times	9.59	5.23	1.83	5.85	8.63	0.68	2.57	8.86	0.29
SeminarxAge									
SeminarxAge (ref) [a]									
SeminarxAge_D2 [b]				-12.67	7.72	-1.64	-15.06	10.27	-1.47
SeminarxAge_D3 [c]				13.93	9.55	1.46	23.11	12.33	1.87

Table 40 (Cont.)

Variable	Model 2			Model 3			Model 4		
	b_i	SE	t	b_i	SE	t	b_i	SE	t
SeminarxGender									
SeminarxGender (ref) [d]									
SeminarxGender D2 [e]				-2.65	8.45	-0.31	-4.26	8.13	-0.52
SeminarxGender D3 [f]				-3.38	9.81	-0.34	4.04	11.46	0.35
SeminarxAgexGender									
SeminarxAgexGender (ref) [g]									
SeminarxAgexGender D2 [h]							4.95	12.08	0.41
SeminarxAgexGender D3 [i]							-19.14	15.51	-1.23
R^2	0.21			0.22			0.22		

Note. N = 697. PS-TRE = problem solving in technology-rich environments; HS = high school; SE = standard error; Ref = reference. ΔR^2 = 0.02 for Step 2. ΔR^2 = 0.01 for Step 3.

[a] SeminarxAge (ref) = a person age 50-59 who never participated in seminars or workshops

[b] SeminarxAge _D2 = a person age 60-70 who participated in one or two seminars or workshops

[c] SeminarxAge_D3 = a person age 60-70 who participated in three or more seminars or workshops

[d] SeminarxGender (ref) = a male who never participated in seminars or workshops

[e] SeminarxGender _D2 = a female who participated in one or two seminars or workshops

[f] SeminarxGender_D3 = a female who participated in three or more seminars or workshops

[g] SeminarxAgexGender (ref) = a male age 50-59 who never participated in seminars or workshops

[h] SeminarxAgexGender _D2 = a female age 60-70 who participated in one or two seminars or workshops

[i] SeminarxAgexGender_D3 = a female age 60-70 who participated in three or more seminars or workshops

! Interpret data with caution. The coefficient of variation (CV) for this estimate is between 30 and 50 percent.

* $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$

Appendix Q: Results Table for Research Question 6c

Table 41

Interaction Effect of Age, Gender, and Learning-by-Doing on PS-TRE

Variable	Model 2			Model 3			Model 4		
	b_i	SE	*t*	b_i	SE	*t*	b_i	SE	*t*
Constant	254.21***	6.55	38.84	259.43***	7.14	36.32	259.45***	7.10	36.55
Education level									
HS diploma or less (ref)									
College degree	27.97***	3.30	8.47	27.50***	3.17	8.68	27.50***	3.14	8.75
Self-rated health									
Excellent (ref)									
Very good	4.64	6.16	0.75	4.96	5.91	0.84	4.93	5.87	0.84
Good	-0.20	6.10	-0.03	-0.36	6.01	-0.06	-0.43	5.96	-0.07
Fair or poor	-4.47	7.72	-0.58	-4.20	7.58	-0.55	-4.25	7.69	-0.55
Race									
White (ref)									
Black	-34.30***	5.82	-5.89	-34.17***	5.88	-5.82	-34.03***	6.04	-5.63
Other race	-16.15*$	6.86$	-2.35$	-16.03*$	7.01$	-2.29$	-15.96*$	6.95$	-2.30$
Age									
50-54 (ref)									
55-59	4.60	4.40	1.04	6.15	7.11	0.86	6.14	7.12	0.86
60-70	-1.72	4.30	-0.40	-3.16	6.83	-0.46	-3.15	6.82	-0.46
Gender									
Male (ref)									
Female	-1.09	4.34	-0.25	-10.73	6.01	-1.79	-10.74	6.01	-1.79
Learning-by-doing									
Less than once/week (ref)									
At least once/week	1.78	4.59	0.39	-0.01	8.40	0.00	1.62	9.86	0.16
Every day	-12.07**$	4.07$	-2.97$	-23.25**$	8.58$	-2.71$	-25.16*$	10.15$	-2.48$
LBDxAge									
LBDxAge (ref) [a]									
LBDXAge_D2 [b]				-9.49	11.38	-0.83	-14.68	14.71	-1.00
LBDXAge_D3 [c]				-7.74	11.03	-0.70	-6.68	14.63	-0.46
LBDXAge_D4 [d]				2.29	9.99	0.23	6.35	13.15	0.48
LBDXAge_D5 [e]				6.39	10.35	0.62	7.92	13.52	0.59

Table 41 (Cont.)

Variable	Model 2			Model 3			Model 4		
	b_i	SE	t	b_i	SE	t	b_i	SE	t
LBDxGender									
LBDxGender (ref) [f]									
LBDXGender_D2 [g]				15.85	8.47	1.87	12.21	12.08	1.01
LBDXGender_D3 [h]				15.66	8.53	1.84	19.34	12.45	1.55
LBDxAgexGender									
LBDxAgexGender (ref) [i]									
LBDxAgexGender_D2 [j]							13.60!	16.03!	0.85!
LBDxAgexGender_D3 [k]							-8.28	15.58	-0.53
LBDxAgexGender_D4 [l]							-3.02!	17.30!	-0.17!
LBDxAgexGender_D5 [m]							-3.03	13.70	-0.22
R^2	0.22			0.23			0.23		

Note. N = 695. PS-TRE = problem solving in technology-rich environments; HS = high school; SE = standard error; LBD = learning-by-doing; Ref = reference. $\Delta R^2 = 0.03$ for Step 2. $\Delta R^2 = 0.01$ for Step 3.

[a] LBDxAge (ref) = a person age 50-54 who learned by doing less than once a week

[b] LBDXAge_D2 = a person age 55-59 who learned by doing at least once a week but not every day

[c] LBDXAge_D3 = a person age 60-70 who learned by doing at least once a week but not every day

[d] LBDXAge_D4 = a person age 55-59 who learned by doing every day

[e] LBDXAge_D5 = a person age 60-70 who learned by doing every day

[f] LBDxGender (ref) = a male who learned by doing less than once a week

[g] LBDXGender_D2 = a female who learned by doing at least once a week but not every day

[h] LBDXGender_D3 = a female who learned by doing every day

[i] LBDxAgexGender (ref) = a male age 50-54 who learned by doing less than once a week

[j] LBDxAgexGender_D2 = a female age 55-59 who learned by doing at least once a week but not every day

[k] LBDxAgexGender_D3 = a female age 55-59 who learned by doing every day

[l] LBDxAgexGender_D4 = a female age 60-70 who learned by doing at least once a week but not every day

[m] LBDxAgexGender_D5 = a female age 60-70 who learned by doing every day

! Interpret data with caution. The sample size for this estimate is between 20 and 30 cases.

$ Interpret data with caution. The coefficient of variation (CV) for this estimate is between 30 and 50 percent.

* $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$

Appendix R: Results Table for Research Question 6d

Table 42

Interaction Effect of Age, Gender, and Learning from Coworkers or Supervisors on PS-TRE

Variable	Model 2			Model 3			Model 4		
	b_i	SE	*t*	b_i	SE	*t*	b_i	SE	*t*
Constant	247.47***	7.03	35.18	249.46***	7.12	35.05	249.61***	7.18	34.76
Education level									
HS diploma or less (ref)									
College degree	30.55***	3.25	9.41	30.24***	3.30	9.15	30.17***	3.36	8.99
Self-rated health									
Excellent (ref)									
Very good	8.25	6.98	1.18	8.07	6.91	1.17	7.99	6.92	1.15
Good	3.21	6.99	0.46	3.10	6.97	0.44	3.02	7.06	0.43
Fair or poor	-4.28	8.59	-0.50	-4.97	8.54	-0.58	-5.29	8.48	-0.62
Race									
White (ref)									
Black	-37.84***	5.89	-6.43	-38.04***	5.66	-6.73	-38.08***	5.71	-6.67
Other race	-15.89*!	7.40!	-2.15!	-15.72*!	7.23!	-2.17!	-15.69*!	7.20!	-2.18!
Age									
50-54 (ref)									
55-59	2.95	4.52	0.65	4.42	5.56	0.80	4.41	5.56	0.79
60-70	-4.56	4.40	-1.04	-4.76	5.74	-0.83	-4.78	5.75	-0.83
Gender									
Male (ref)									
Female	-2.46	4.66	-0.53	-6.24	6.28	-0.99	-6.25	6.28	-0.99
Learning from coworkers or supervisors									
Less than once/week (ref)									
Once/week or more	1.15	3.68	0.31	-2.02	9.03	-0.22	-3.10	11.62	-0.27
LFCxAge									
LFCxAge (ref) [a]									
LFCxAge_D2 [b]				-3.32	11.23	-0.30	-2.02	15.94	-0.13
LFCxAge _D3 [c]				0.57	9.15	0.06	2.37	12.31	0.19
LFCxGender									
LFCxGender (ref) [d]									
LFCxGender _D2 [e]				8.05	8.66	0.93	10.29	13.41	0.77

Table 42 (Cont.)

Variable	Model 2			Model 3			Model 4		
	b_i	SE	t	b_i	SE	t	b_i	SE	t
LFCxAgexGender									
LFCxAgexGender (ref) [f]									
LFCxAgexGender D2 [g]							-2.77	15.67	-0.18
LFCxAgexGender D3 [h]							-3.87	12.28	-0.31
R^2	0.22			0.22			0.22		

Note. $N = 610$. PS-TRE = problem solving in technology-rich environments; HS = high school; SE = standard error; LFC = learning from coworker; Ref = reference. $\Delta R^2 = 0.03$ for Step 2.

[a] LFCxAge (ref) = a person age 50-54 who learned from coworkers less than once a week

[b] LFCxAge_D2 = a person aged 55-59 who learned from coworkers once a week or more

[c] LFCxAge _D3 = a person aged 60-70 who learned from coworkers once a week or more

[d] LFCxGender (ref) = a male who learned from coworkers less than once a week

[e] LFCxGender _D2 = a female who learned from coworkers once a week or more

[f] LFCxAgexGender (ref) = a male age 50-54 who learned from coworkers less than once a week

[g] LFCxAgexGender _D2 = a female age 55-59 who learned from coworkers once a week or more

[h] LFCxAgexGender _D3 = a female age 60-70 who learned from coworkers once a week or more

! Interpret data with caution. The coefficient of variation (CV) for this estimate is between 30 and 50 percent.

* $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$

Appendix S: Crosstabulation of Learning-by-Doing and Learning from Coworkers or Supervisors

Table 43

Crosstabulation of Learning-by-Doing and Learning from Coworkers or Supervisors

Learning-by-doing (horizontal) and learning from coworkers (vertical)	Learning-by-Doing				
	Participation	Never or 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	Every day
Learning from Coworkers or Supervisors	Never or less than once a month	74	37	29	48
	Less than once a week but at least once a month	30	37	33	38
	At least once a week but not every day	16	25	51	69
	Every day	7	9	26	83