ABSTRACT

KIRBY, KAMISHA DARDEN. The IT Factor: Exploring Veterans' Success in Registered Apprenticeships Using Propensity Score Matching. (Under the direction of Dr. Michelle Bartlett and Dr. James Bartlett).

There are more jobs in several IT occupational areas that do not require a bachelor's degree for entry. Those jobs outnumber the current supply of labor creating a shortage of workers that is negatively impacting businesses. At the same time, there are veterans exiting military service and transitioning to the civilian workforce. One method to provide training for IT workforce that is emerging is an apprenticeship model. This study sought to examine the impact of veteran status on the successful completion of IT apprenticeships and the impact of veteran status on the salary of the apprentices upon exiting the registered apprenticeship program. Using data from the The Registered Apprenticeship Partners Information Data Systems (RAPIDS) on IT apprentices and the data analysis strategy of propensity score matching as a methodology, balanced groups of veterans and nonveterans were created using various covariates. The findings indicated that there were differences between veterans and nonveterans and matching created more balanced data. After matching, veterans completed at higher rates and had higher salaries at the time of exiting the completed apprenticeship programs.

The IT Factor: Exploring Veterans' Success in Registered Apprenticeships Using Propensity Score Matching

by
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DEDICATION

This work is dedicated to my family, whose constant sacrifice, honorable service, and unwavering support has guided me throughout my life and educational journey.

BIOGRAPHY

Kamisha Kirby serves as Director of the Learning Commons at South Piedmont Community College. Prior to this role, she served as English and Humanities Faculty, where she helped students become confident, competent communicators. Known for her innovative teaching, forward-thinking ideas, and student-centered philosophies, Kamisha feels fortunate to operate in her “calling” of helping learners explore and achieve their possibilities.

In 2019, Kamisha was recognized as a semi-finalist for the Excellence in Teaching Award from the North Carolina Community College System. Her work with students has also earned her "Collaborator of the Year," "Innovator of the Year," and "Faculty of the Year" honors during her tenure at South Piedmont.

Kamisha began her career in higher education at her alma mater, The University of North Carolina at Chapel Hill, where she was a Pogue Scholar and earned a Bachelor of Arts in Journalism, with a second major in Speech & Hearing Sciences. She later earned her master's in English with a focus in Technical and Professional Communication from East Carolina University.

In addition to her work in education, Kamisha spends considerable time serving her community and volunteering with organizations close to her heart, particularly those focused on the mentorship, talent-development, and advocacy of girls and women.

Kamisha is married to her high-school sweetheart, Chris. Together, they have four children.

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Being confident of this very thing, that He who has begun a good work in you will complete it until the day of Jesus Christ- Philippians 1:6

I give all praise and honor to God, who has been my source of strength, confidence, and blessed assurance. During each part of this journey, I was reminded of His presence, His grace, and His care for me that I would have just what I needed when I needed it. His grace is sufficient, and His power was made perfect in my weakness.

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Chapter 1: Introduction

According to the U.S. Bureau of Labor Statistics (2022a), approximately 6.4 million jobs were created in 2021, representing more jobs created than any other year in history. Nevertheless, the American labor force is not equipped to fill the millions of jobs available because many lack the requisite workplace skills needed (McCarthy, 2014). This *skills gap* exists in nearly every industry, from manufacturing to information technology (IT) (Newman & Winston, 2016; Shipps & Howard, 2013). The discussion of the workforce preparation was and continues to be the focus of higher education conversation, specifically in the sector of community colleges, during the Great Recession and its aftermath (D'Amico, 2016).

Researchers have attributed the skills gap to several reasons. Some scholars looked toward the past, offering those changes in traditional vocational education have played their part for the striking 5% of manufacturing positions in the United States and other jobs in the blue-collar sector that go unfilled (Newman & Winston, 2016). High schools, which had historically offered a solid pathway to vocational fields, have suffered from the ambivalence American parents, policymakers, and educational leaders display toward these jobs in favor of promoting more *professional* college for all pathways. Other researchers focused their attention on the future, arguing that advances in technology outpace the availability of talent; after all, it is difficult to learn a job that has not been created yet (Merisotis, 2015). This argument is especially true for the copious occupations found within the IT sector.

Background of the Problem

IT is a dynamic industry with a history defined by a robust narrative (Adomavicius et al., 2008; Haigh, 2011). Although the exact meaning of IT has shifted over time (Kline, 2006), the term is now used to describe the interconnection of the computing, media, and

telecommunications and the technologies in those industries (Haigh, 2011). According to Bennett and Lamback (2020), the demand for skilled IT workers is projected to grow 12% from 2018 to 2028, resulting in 546,000 new jobs as "the increased use of technology to support remote working, virtual learning and training, and efforts to overcome the digital divide could contribute to a greater need for a skilled IT workforce" (p. 2). Additionally, it is projected that up to one-third of the U.S. workforce may need to find work in new occupations by 2030 due to automation and artificial intelligence (McKinsey Global Institute [MGI], 2017, p. 10).

Some of these new skills and new-collar jobs, including entry-level occupations in high-growth sectors, like IT, do not require a 4-year degree (Bennett & Lamback, 2020; Fuller & Sigelman, 2017; Guth, 2019). However, they do require some postsecondary training or credential beyond high school to earn a sustainable living wage (Carnevale et al., 2012; McCarthy, 2014). Americans cannot expect to compete in a global economy and keep up with innovation in the workforce without some education and training beyond high school, particularly for the many middle-skill jobs left unfilled (Merisotis, 2015; Newman & Winston, 2016).

While the argument for greater training has allowed for increased accessibility to higher education, it has not come without consequence. According to Friedman (2020), student loan debt is the second-highest consumer debt category behind mortgages. The historical focus on a college-for-all model that promoted the university pathway for a bachelor's degree has contributed to a $1.6 trillion student loan debt crisis that leaves seven out of 10 college graduates with student loan debt (Friedman, 2020; Smith, 2021). The student loan debt crisis, coupled with dissatisfactory student success data indicating that, on

average, only 62.2 % of students complete their postsecondary pathway after 6 years (National Student Clearinghouse Research Center, 2022), has left many students questioning the value and feasibility of pursuing a bachelor's degree. Consider that a 2017 poll conducted by Education Next (2018) reported that 89% of Americans see the importance of education after high school. In contrast, Pew Research Center (2018) found that "About six-in-ten Americans (61%) say the higher education system in the United States is going in the wrong direction" (p. 1), citing reasons such as affordability and the lack of preparation of graduates for the workforce. The sentiment is further exacerbated when framed from an equity-mindedness lens as marginalized populations do not experience the same levels of postsecondary student success outcomes (National Student Clearinghouse Research Center, 2022).

Today, higher education is not the only pathway to a good job. One popular training model has its roots in history: apprenticeship (Newman & Winston, 2016). Long before classroom instruction entered the workforce equation for many occupations, apprenticeship was the most common means of learning how to be everything from a tailor to a hairdresser and even an attorney (Newman & Winston, 2016). Traditionally, apprenticeships were more commonly used to train workers in trade and blue-collar industries such as manufacturing and construction. Today, however, recent research and dialogue suggest that the apprenticeship model should be used in more white-collar industries and occupations, specifically IT (Guth, 2019; McGregor, 2017).

Fuller and Sigelman (2017) argued that employers may be receptive to white-collar apprenticeships, but public perception may still be an issue in their adoption. Many people consider an apprenticeship to career pathway as only applicable in the industrial and trade

jobs of the past, instead of the high-tech jobs of the future. Though the existing knowledge base should be sufficient to dispel this narrow belief, it may not do enough to influence high-school-aged youth—a traditional recruiting population for career and technical education (Herr & Gray, 1998)—to pursue an apprenticeship to career pathway.

Apprenticeship does make a case for another skilled population—the women and men who have served in the nation's armed forces. These veterans already possess a unique skill set that, when translated and upskilled for the civilian workforce, provides companies with an *honorable* talent pool ready for the job at hand. As Merisotis (2015) indicated, talent is much more than some narrowly framed idea. Talent encompasses knowledge, skills, abilities, values, interests, and personality traits. According to Merisotis, "Talent is rooted in values: a deep belief in discovery, personal fulfillment, and service to others" (p. 8). Often, the women and men who served in the U.S. Armed Forces are highly skilled, dedicated, reliable, and thus, talented; with the leadership and soft skills needed to fill middle-skill jobs. Employers in the technology sector are taking notice by designing *veteran-friendly* (Hunter-Johnson, 2020) and *veteran-ready* (Constantine, 2018) apprenticeship programs for this valuable and talented group (Amazon, n.d).

Significance of the Study

In 2021, 213,000 new IT jobs were created (Sayer, 2022). Some of these IT jobs are considered middle-skill—requiring some education beyond high school, but not necessarily a bachelor's degree. As Fuller and Sigelman (2017) noted:

> A highly dynamic technology environment has been creating whole new categories of jobs in the U.S. economy. For example, today there are almost 100,000 mobile application developers working in the United States. There were none ten years ago.

> Such emerging jobs often prove hard to fill, as companies are eager for workers but lack established talent pipelines. (p. 12)

Due to the destitution of established talent pipelines in some of these growing industries, the government and many employers are investing millions of dollars into training programs and initiatives, like apprenticeship, that seek to train skilled workers. In 2021, the U.S. Department of Labor awarded more than $130 million in grants to support registered apprenticeship programs (U.S. Department of Labor, 2021). Though traditionally reserved for blue-collar sectors, some of today's apprenticeship programs are focused on white-collar industries such as insurance, human resources, and informational technology (Gurchiek, 2019; Guth, 2019; McGregor, 2017).

Furthermore, some of these apprenticeship programs have a veteran focus. Soldiers are transitioning out of the armed forces and looking to leverage the skills learned in the military with their GI Bill to compete in a civilian, middle-class workforce. Accordingly, employers are acknowledging that competency and skill-based training can effectively connect those without a postsecondary credential or prior work experience to high-wage occupations by designing registered apprenticeship programs. With starting wages of at least $25 an hour for three main entry-level pathways in IT: programming, IT support, and cybersecurity (Bennett & Lamback, 2020), companies like IBM and Apprenti have created registered IT apprenticeship programs. These registered IT apprenticeships are robust in their job preparation by providing comprehensive work-based learning and hands-on training (Bennett & Lamback, 2020).

Meanwhile, student loan debt is high and college completion rates are low, causing growing public concern about the value and feasibility of pursing a traditional college degree.

These realizations create strong support and appreciation for low-cost credentials and training programs with a good return on investment, like apprenticeship. And these rationalizations create the environment for a rise in white-collar apprenticeships, with an emerging focus on subpopulations, including veterans.

Given the military's proven training model that incorporates critical thinking, reasoning, and soft skills, veterans make for a natural talent pool. Moreover, these veterans are interested in joining IT as a fast-growing sector (PRWeb, 2018). Likewise, employers, too, are interested in recruiting veterans. For example, Amazon's Technical Apprenticeship program (Amazon, n.d.) targets veterans and their spouses for careers in cloud computing explicitly. The apprenticeship provides paid training courses, followed by up to 12 months of paid, on-the-job training, to best prepare veterans for careers at Amazon (Amazon, n.d.). According to Amazon (n.d.), over 700 apprentices have been trained since the program's start, with 90% of apprentices completing.

Problem Statement

Ever since the first IT Generalist Apprenticeship Program was registered in 2017 by NPower, a nonprofit in New Jersey (PRWeb, 2017), technology giants like Amazon and Microsoft have taken note by investing in similar programs designed to upskill current workers and veterans, specifically. However, though these programs anecdotally contribute to the *sea of goodwill* (Copeland & Sutherland, 2010) research determining the impact of veteran status on the success of an apprentice, as measured by the completion and salary, in registered IT apprenticeships, is exiguous.

Purpose Statement

The purpose of this study was to examine the completion rate and salary of veterans in registered IT apprenticeship programs compared to nonveterans in similar programs using propensity score matching. The researcher matched two equivalent groups of apprentices from these apprenticeship programs, with or without veteran status, using existing data from The Registered Apprenticeship Partners Information Data Systems (RAPIDS, U.S. Department of Labor, 2019).

Theoretical Frameworks

Two frameworks anchored the study theoretically: human capital theory (Becker, 1964; Schultz, 1961) and signaling theory (Spence, 1973). Generally developed a priori in quantitative research designs, theoretical frameworks are derived from validated and tested theories; thus, they serve not only as the researcher's lens in which to view and design the study but specifically, as the researcher's unique application of a lens to their study (Osanloo & Grant, 2014). Each of these perspectives provides a valuable lens to understand the impact of veteran status on the completion and salary of registered IT apprenticeships programs.

Human Capital Theory

Since the 1960s, human capital theory has dominated the understanding and correlation of education and earnings. According to Schultz (1961), education is an investment that becomes an integral part of a person; thus, the investment derives economic benefits for society and can be treated as a form of capital (Sweetland, 1996). Theodore W. Schultz and Gary S. Becker are often referred to as the two most pronounced scholars of human capital theory (Sweetland, 1996), though research supporting the field had been conducted before 1960 (Blaug, 1966; Kiker, 1968).

Human capital theory examines the investment of education and training that creates knowledge and skills in human beings (Benjamin et al., 1998). Generally, the discussion of human capital accumulation is limited to knowledge-reproducing activities; migration, healthcare, and engagement in job search activities have also been considered as investments in human capital (Schultz, 1961; Wang & Holton, 2005). These investments in individuals are thought to create productivity and then, in turn, increase their earnings. Education, then, supplements natural talents that are subsequently sold in labor markets (Bedard, 2001).

At its core, human capital theory stresses that education and training are investments with positive future returns. Individuals decide to acquire learning and training, foregoing current income or benefits, with the expectation that they will experience increased future earnings. Sweetland (1996) described that the literature relating to human capital theory makes distinctions among the types and means of education. For example, there is formalized education (Cohn & Geske, 1990), informal education (Schultz, 1961), specialized vocational education (Corazzini, 1967), and on-the-job training and apprenticeships (Mincer, 1974). It is the latter context that was the focus of this research study.

Signaling Theory

In the most basic terms, a *signal* is defined as an observable indicator of something with unobservable quality (Spence, 1974). According to Bartlett (2004), "signaling refers to the process and strength of the contextual clues that reside in the application, resume, interview, test scores, and other information collected during the recruitment process to determine the applicant's potential worth to the company" (p. 6). Furthermore, to be considered a signal, an observable indicator must meet two criteria: it must be able to be

manipulated by an individual, and the marginal cost of difficulty of obtaining the indicator must be inversely correlated with the individual's ability level (Spence, 1973).

A college degree is a frequently used example—it is a signal of workplace productivity because acquiring a degree is at least partly within one's control and is made more difficult by other productivity-contributed barriers such as skills, motivation, and focus. Employers rely on signals to screen applicants. Some signals are unique to each organization, while others are universal, like credentials and a college degree. Typically, certifications and degrees signal to employers that applicants or employees possess certain qualifications and skills. Veteran status works in a similar way, signaling fidelity and a unique skill set gained through military training. It is unclear, however, what veteran status signals with regard to IT apprenticeships, specifically. The theoretical framework was utilized to answer that pressing question. Using both human capital theory and signaling theory for this research study allowed for a more-informed discussion on whether the military, as a pathway, offers education and training advantages similar to postsecondary education. The theoretical framework also helped determine if military service, in the context of this study, could act as a signal for the IT workforce, and in what ways.

Research Questions

Three research questions guided this study:

RQ1. What are the demographics of the two groups (veteran IT apprentices and nonveteran IT apprentices) prior to matching?

RQ2. After propensity score matching, is there a difference in demographics of the two study groups?

RQ3. Is there a difference in the completion and ending salary of IT apprenticeships between veteran and nonveteran apprentices?

Definition of Key Terms

Apprenticeship.

An apprenticeship is a program that combines classroom instruction with paid on-the-job training to train workers for highly skilled careers (U.S. Department of Labor, n.d-a).

Human Capital.

According to the OECD (n.d.), human capital is broadly defined as the combination of knowledge, skills, and other characteristics represented in people that fuels productivity.

Information Technology.

Information technology is the convergences of the computing, media, and telecommunications industries and their technologies (Haigh, 2011).

Middle-skill Job.

Middle-skill jobs require education or training beyond high school, but not a 4-year degree (Newman & Winston, 2016).

MOS.

Military occupation specialty, or MOS, refers to the term used by some branches of the armed forces to describe the types of jobs servicemembers quality for based on testing (Veteran, n.d.).

Pre-apprenticeship.

Pre-apprenticeship refers to a set of services or program created to prepare individuals to transition into Registered Apprenticeship Programs (U.S. Department of Labor, n.d.-b).

Propensity Score Matching.

Propensity score matching is a provisional technique used to make the groups in a comparison analysis statistically more equivalent, resulting in a stronger foundation for causal inferences (Fan & Nowell, 2011).

RAPIDS.

Registered Apprenticeship Partners Information Data Systems, or RAPIDS, houses data from the Registered Apprenticeship Program (U.S. Department of Labor, 2019).

Registered Apprenticeship Program.

A Registered Apprenticeship Program, or RAP, is an apprenticeship program approved by a State Apprenticeship Agency or U.S. Department of Labor (U.S. Department of Labor, n.d-d).

Signal.

A signal is defined as an observable indicator of something with unobservable quality (Spence, 1974).

Skills Gap.

Skills gap is a term to describe a fundamental mismatch between the skills that employers rely upon in their employees and the skills that job seekers possess (McCarthy, 2014).

Theoretical frameworks.

Theoretical frameworks are tested theories that serve as a lens for a research study (Osanloo & Grant, 2014).

Veteran.

The term veteran refers to a person who has honorably served in the active military, naval, or air service (Veteran's Benefits, 1958).

Veteran-friendly.

Veteran-friendly is a term used to demonstrate the support of veterans in various capacities, including the recruitment of veterans as employees for companies (Hunter-Johnson, 2020).

Veteran-ready.

Veteran-ready is a term used to describe an organization's attempts to intentionally engage, train, and retain veterans in their organizational culture (Constantine, 2018).

White-Collar.

White-collar is a term relating to the class of employees who earn higher than average salaries by doing highly skilled "shirt and tie" administrative work (Hayes, 2021, para. 1).

Workforce development.

Workforce development is the alignment and combination of programs, policies, and activities, to facilitate a more vibrant economy (Haralson, 2010).

Limitations and Delimitations

The researcher acknowledges the potential bias presented by her affiliation with the study's veteran population. Though the researcher did not serve in the military, she recognizes that her military upbringing influenced her perception of veterans and thus presented a limitation of this study.

The study was delimited and confined by the population and sample used, which included veterans and nonveterans participating in registered apprenticeship programs, as reported by the RAPIDS (U.S. Department of Labor, 2019) database.

Organization of the Study

This study is divided and structured into five chapters. Chapter 1 presented an overview of the topic, including the research questions and significance of the study. Chapter 2 provides a highlight and review of the extant literature. Chapter 3 contains a detailed description of the methodology used, including its rationale and benefits for this study. Chapters 4 and 5 contain the presentation of the results, a discussion of the findings for the research study, and implications for practice.

Summary

Chapter 1 included a presentation of the significance of the skills gap crisis facing the United States. The researcher described workforce development strategies used to address the problem, including the intentional recruitment of veterans into registered IT apprenticeship programs. While literature describing the transition of veterans into the civilian workforce is circumstantiated, and research describing the value of apprenticeship as a pathway to a good job is established, research that explicitly explores the impact of veteran status in registered IT apprenticeship programs is scant. As highlighted in Chapter 1, this study used information from the RAPIDS (U.S. Department of Labor, 2019) database to address this gap. Chapter 2 contains a review of the extant literature for the themes and concepts that guided this stud: apprenticeships, veterans, and IT. The chapter also includes an examination of the theoretical underpinnings of the study, including signaling and human capital theories.

Chapter 2: Review of Literature

In 2020, veterans accounted for about 7% of the U.S. civilian noninstitutional population age 18 and over, as 18.5 million men and women identified as having served in the armed forces (U.S. Bureau of Labor Statistics, 2022b). Each year, a quarter of a million service members transition from the military and join the civilian workforce (Constantine, 2018). In doing so, they bring their experience in planning, communication, decision-making, perseverance, and conflict resolution into the workplace (Davis & Minnis, 2017).

Within recent years, civilian organizations have strived to be *veteran-friendly*, a designation that demonstrates the support of veterans in myriad capacities, including the recruitment of veterans as employees (Hunter-Johnson, 2020). While some civilian companies employ active veteran recruitment strategies as goodwill toward these heroes, other companies recruit veterans because they recognize veterans' worthwhile skill set; the distinctive capabilities and skills developed through the military's real-world, high-pressure experience are valuable in the civilian workplace (Davis & Minnis, 2017). Veterans possess soft skills such as flexibility, decision making, leadership, persistence, and attention to detail that, when supplemented by the technology skills obtained in the armed forces, make many veterans well-suited to jobs in the tech ecosystem (Constantine, 2018; Davis & Minnis, 2017).

In 2011, companies such as Verizon, Broadridge Financial Solutions, Cisco Systems, and EMC Corporation committed to hiring 100,000 veterans by 2020. By 2014, this coalition had expanded to include more than 175 companies who had doubled that commitment to 200,000 (Hall et al., 2014). While there is considerable research on veteran employment in civilian contexts, much of it focuses on a veteran's transition to a civilian workforce and

highlights any barriers faced (Davis & Minnis, 2017; Minnis, 2014; Figinski, 2017; Keeling et al., 2019). Very little research examines veterans' success in apprenticeship programs and, specifically, white-collar industries such as IT, despite the rise in these targeted apprenticeship programs. The historical context of workforce development and the themes of veterans in apprenticeships, the expansion of technology apprenticeships, and human capital and signaling theories, which helped provide the underpinnings for this study, are presented in Chapter 2.

Workforce Development: The Need for a Skilled Workforce

One cannot approach examining the success of apprenticeship programs without first understanding the broader context of workforce development and the demand for and availability of a skilled workforce. Workforce development has evolved to describe a wide range of national and international policies and programs related to learning for work (Jacobs & Hawley, 2005). In a more general sense, the term workforce development describes the combination and alignment of programs, activities, and policies to create a more vibrant economy (Haralson, 2010). However, Jacobs and Hawley (2005) offered a more specific definition in that "workforce development is the coordination of public and private-sector policies and programs that provides *individuals* with the opportunity for a sustainable livelihood and helps *organizations* achieve exemplary goals, consistent with the *societal* context" (p. 12). In this way, workforce development can be thought of as an approach to economic development, which, in turn, is an essential factor in any local economy's health. Communities and countries that invest in good workforce development strategies thrive because their citizens can access the resources to help meet their most basic needs and provide them the opportunity to fully participate in their communities.

Workforce development is typically approached from two different perspectives: place-based or sector-based (Social Solutions, 2020). As the name suggests, place-based refers to those workforce strategies confined to a specific geographic location, and they approach development from the supply side by focusing on the people. Place-based strategies identify the employment needs of the people in a defined area, attempt to mitigate barriers experienced by these people, and build programs around these needs and barriers (Social Solutions, 2020). Sector-based is an employee-driven approach that directly aligns occupational skills training to growing industries in efforts to grow the talent pool available for current and emerging jobs (Social Solutions, 2020; Ziegler, 2015). Whereas place-based focuses on the supply side, sector-based focuses on the demand side by preparing a talent pool ready for current and future job opportunities.

According to a report authorized by the Aspen Institute, *Jobs and the Urban Poor* (Clark & Dawson, 1995), sector workforce development strategies are defined by a "distinct employment model that: (a) targets a specific occupation within an industry; (b) intervenes by becoming a valued actor in the industry that employed that occupation; (c) exists for the primary purpose of assisting low-income people to obtain decent employment; and (d) creates, over time, systemic change within that occupation's labor market" (Clark & Dawson, 1995). In this way, both place-based and sector-based workforce development strategies exist to address poverty by connecting low-income people to good jobs (Conway & Giloth, 2014).

Apprenticeship as a Training Model

Historically, workforce development models such as apprenticeship were either the destiny of poor, orphaned, or delinquent children or geared toward marginalized and minority groups (Newman & Winston, 2016). This history has attached a stigma of "lesser than" to

the value of apprenticeship that still exists today (Newman & Winston, 2016), and explains why some individuals have a problem with vocational education. In part, the notion has helped advance the *college for all* model that has our country indebted to student loans.

Though the success of apprenticeships as a proven model for economic development is well-documented (Hollenbeck, 2011; Lerman, 2013; Team CELNA, 2019), only 0.3% of the U.S. workforce comes from apprenticeship programs (Education & Labor Committee, 2021) despite the positive return on investment and bipartisan support. Seen as more effective than a pure school-based career and technical education program, the apprenticeship model is viewed as more effective (Eichhorst et al., 2015). Apprenticeship programs teach mastery of occupational and soft skills, including problem-solving, communication, and dealing with supervisors and a diverse set of coworkers (Lerman, 2010). Furthermore, apprenticeships have been instrumental to our economic success for generations but may be underutilized (Education & Labor Committee, 2021; Fuller & Sigelman, 2017). "People have a mental image of apprenticeship in trades, but do not think of it as being used for new and emerging industries like information technology" (U.S. Department of Labor, n.d.-a).

Moreover, the recruitment pool for apprentices has traditionally been youth. The work and learning experiences embedded in the career and technical education (CTE) curricula have traditionally been afforded to students through programs offered in high schools due, in large part, to the federal Smith-Hughes Act of 1917 (Hunt et al., 2010). Hunt et al. (2010) noted,

> The Smith-Hughes Act succeeded in dramatically expanding funding and enrollments in vocational subjects and encouraging states and localities to support vocational education. Subsequent federal laws extended and expanded aid for vocational

> education as national interest in manpower, economic development, and youth training intensified in the Great Depression, World War II, and beyond. (p. 836)

The Smith-Hughes Act effectively placed vocational education programs in public schools but lacked close ties to industry, which is needed to facilitate the transition of students to jobs (Gray & Herr, 1998).

Some believe that a lack of economic success directly results from poor workforce preparation (Herr & Gray, 1998) and that this preparation can only come from attending a four-year university. Others subscribe to social Darwinism as a law of nature (Spencer, 1864). In this survival of the fittest, the most educated are the most successful as education acts as a signal and is positively correlated with earnings (Spencer, 1864).

However, there is capital merit in completing apprenticeship programs. According to Hollenbeck (2011), the return on training from an apprenticeship is greater than for other types of education, such as postsecondary 2- and 4-year institutions. According to Lerman (2013), who examined Hollenbeck's (2008) study, "The present value for apprentices post-program increases in earnings, net of any earnings foregone during the training period, amounted to over $50,000.00 for the first 2.5 years after exiting the program" (p. 108). Lerman (2010) relayed that 6 years after starting a program, earnings of the average apprenticeship participant (after the average duration of an apprenticeship) stood at 1.4 times the earnings of nonparticipants with the same pre-apprenticeship history. Furthermore, those who complete an apprenticeship program will have an average annual salary of more than $50,000 and will earn an average of about $300,000 more than nonparticipants over a lifetime (Lerman, 2010).

As an illustration, the U.S. Department of Labor funded a study of the effectiveness and cost-benefit of registered apprenticeship in 10 states (Reed et al., 2012). The main findings were that participants in registered apprenticeships earned an average of $98,700 more over their careers than nonparticipants. Even more paramount for this study's context, apprenticeship completers earned an average of $240,000 more than nonparticipants, underscoring the value of completion of registered apprenticeship programs (U.S. Department of Labor, n.d.-a).

Despite the proven success of apprenticeship as a training model, any path of workforce education that does not lead to a credential from a 4-year university is stigmatized and seen as less meaningful despite the evidence that other paths are possible and feasible. In fact, some of these alternative pathways offer tremendous education benefits, which is the case for service in the nation's armed forces. The corresponding GI Bill benefit allows servicemembers to pursue higher education debt-free.

The GI Bill's Impact on Education

The GI Bill, also known as the Serviceman's Readjustment Act, is considered a pivotal instrument of national economic policy and one of the best investments the United States government has made (Kowalski, 2016). Higher education historians and sociologists have long credited the bill as the reason for the large influx of veterans into colleges after WWII, resulting in an enrollment boom for colleges and increased educational attainment across the population (Wilson et al., 2013). Consider this example from Harvard in 1946; enrollment almost doubled from 2,750 in February to 5,000 in September of that year (Kowalski, 2016). Furthermore, almost half of all college admissions in 1947 were veterans,

as the bill opened the door of higher education to the working class in a way never done before (Herbold, 1994).

Minority veterans, however, were not afforded the same opportunities. As Herbold (1994) shared, “though Congress granted all soldiers the same benefits theoretically, the segregationist principles of almost every institution of higher learning effectively disbarred a huge proportion of Black veterans from earning a college degree” (p. 3). Black veterans were limited to vocational training programs and trade schools. Those who did pursue enrolling at predominately Black institutions were met with long waiting lists and curriculum “defined by the Washingtonian ‘preach and teach’ philosophy of higher education” (p. 3).

Despite these challenges, this mass expansion of postsecondary access in the 1960s saw the emergence of a bachelor’s degree as the baseline qualification for most well-compensated white-collar occupations (Stevens, 2018). Now, however, this 4-year degree is a serious investment, leveraged with loans, and whose completion comes much less assurance of job security throughout adulthood. Stevens (2018) argued that bachelor’s degrees do not signal much in the way of specific skills, particularly given the inconsistencies in programs. The lack of a 4-year degree does not “necessarily mean a candidate for employment lacks particular attributes— college credentials are now a perniciously legitimate mechanism of employment discrimination, systematically favoring those privileged enough to have attained them, regardless of underlying aptitude or ability” (p. 50).

As Peter F. Drucker (1992) noted, “the GI Bill of Rights and the enthusiastic response to it on the part of America’s veterans signaled the shift to a knowledge society. In this society, knowledge is the primary resource for individuals and for the economy overall”

(para. 3–4). While some scholars have focused their research to explore the workforce development trends of veterans and transitioning soldiers, they often focus on the barriers transitioning soldiers face as they enter the civilian workforce.

Veteran Transition Research

A veteran's transition back to civilian life is not always a good one; many veterans must combat barriers such as discrimination and stereotypes about their lack of ability to translate their skills for a civilian workforce (Davis & Minnis, 2017). According to Minnis (2014), veterans can experience considerable difficulty demonstrating their skills acquired and developed through military service. Additionally, veterans are undeniably susceptible to posttraumatic stress disorder (PTSD), particularly after combat experience. This fact often leads to a perception that veterans only possess combat-related skills or are mentally unstable or incapable of meeting work demands (Minnis, 2014). Researchers (e.g., Figinski, 2017; Keeling et al., 2019) found that this thinking and the resulting discrimination can be a significant barrier to veterans' employment in a civilian workforce. Stereotypes about veterans lacking skill transferability (Stern, 2017) present as a bias, with veterans viewed as having poorer social skills than nonveterans (Stone et al., 2017). While veterans feel employers respect their military service, employers may not fully understand how to capitalize on veterans' talent (Gonzalez & Simpson, 2020) nor do they appreciate that military skills are relevant in the commercial world and translate to civilian life (Sharp, 2018).

Veterans as Talent

While some companies hire veterans out of a sense of patriotism, others have recognized that veterans are talented group and are good for business. According to Harrell and Berglass (2012), the top reasons companies hire veterans include:

- Veterans have leadership and teamwork skills
- Veterans' character makes them good employees
- Veterans are disciplined, follow processes well, and operate safely
- Veterans have expertise that companies seek
- Veterans adapt and perform well in dynamic environments
- Veterans are effective employees
- Hiring veterans is the "right thing to do"
- Other veterans in the organization have been successful
- Veterans are resilient
- Veterans are loyal to their organizations
- Hiring veterans carries public relations benefits

Additionally, veterans have demonstrated that they have higher than usual abstract reasoning abilities (PRWeb, 2018). Sharp (2018) reported, according to Barclay's Military Insight Tool veterans were assessed using a series of game-based psychometric tests that measured them against key performance traits in the workplace. The findings revealed that "veterans outperform their civilian peers, scoring in the top 30% for social influence, creativity, rational decision making, emotional resilience, and dealing with ambiguity (Sharp, 2018, "The Problem," para. 9). Twenty-one percent of veterans also scored at the top for creative

thinking, compared with 16% of civilians. Additionally, veterans proved to have twice as much potential as civilians in demonstrating board-level leadership (Notes and news, 2018).

The Military as Workforce Development

The uniqueness of military training is in its discipline. The just-in-case preparation of the collectives helps distinguish it from other forms of training (Fletcher & Chatelier, 2000). For some, it is seen as a matter of life and death; military training must often prepare individuals to enter in harm's way while performing mentally and physically demanding tasks, with proficiency (Fletcher & Chatelier, 2000), a clear delineation of the "what is in it for me" of andragogy. While this just-in-case-training is key to helping veterans develop critical thinking and leadership, it differs from standard civilian or corporate training. Most civilian training emphasizes just-enough and just-in-time training; training individuals to perform tasks that may never be required is not cost-effective (Fletcher & Chatelier, 2000).

Additionally, the ever-changing dynamics of technology have influenced the military's level and types of training. Gone are the days of fighting with a shield and sword; today's soldiers guide robotic vehicles, release weapons by pushing buttons, and locate enemies with increasingly advanced sensors. Soldiers contend with people they may never see or approach in person and use technology to do so. This "infusion of technology into nearly every aspect of military operations ... has increased the complexity of operations, the number of tasks individuals must perform, and the demand for knowledge and skill among military personnel" (Fletcher & Chatelier, 2000, II-2). In addition to the traditional skills taught, like discipline and teamwork, today's soldiers must also learn the soft skills of communication and problem-solving.

While the military and college are two different training paths, they share similarities, particularly with entrance requirements. The military requires applicants to take a placement test called the Armed Services Vocational Aptitude Battery, or ASVAB. “Currently, the U.S. Armed Forces does not recruit individuals who are illiterate, but they do enlist individuals who must improve their verbal and quantitative skills to work in specific occupations categories” (Fletcher & Chatelier, 2000, p. III-6). In that way, the armed forces are similar to community colleges by providing a pathway to employment regardless of preparation. They have admission requirements but use multiple measures to create pathways of progress.

The Military as an Apprenticeship/Pre-apprenticeship

Many service members enlist immediately after high school; thus, the military provides all the occupational training necessary for soldiers to perform their jobs effectively (Hanson & Lerman, 2016). This occupational training generally resembles apprenticeship training as service members prepare for their occupations by taking classes, learning by doing, and contributing to production while earning a wage (Hanson & Lerman, 2016). In that way, the military itself can be thought of as an apprenticeship.

The very nature and risk of military operations require the application of knowledge and exercises of skills that cannot be sufficiently learned in lecture halls (Fletcher & Chatelier, 2000). Thus, military training relies heavily on simulation; this would be the very definition of apprenticeship in a civilian world. Moreover, while simulation differs in definition and effectiveness from work-based learning, the criterion problem that often exists in military training explains why simulation is similar in this regard. In some instances, the military must train individuals and groups without using proper criterion testing. After all, staging wars to assess combat effectiveness is not only impractical but ethically questionable

(Miller, 1974). Since the transfer effectiveness of simulation—whether live, constructed, virtual, or networked— is tried and proven (Fletcher & Chatelier, 2000), it is reasonable to assert that the simulation involved in military training is similar to the work-based learning component of the apprenticeship model.

Furthermore, the military's model of training closely resembles a pre-apprenticeship framework. Jobs for the Future (JFF) developed a framework for high-quality pre-apprenticeship programs (Allen et al., 2019). The framework, which builds from the elements outlined by the U.S. Department of Labor, (2012; 2017) in its Training and Employment Notice (TEN 13-12) and Training and Employment Guidance Letter (TEGL 13-16), includes six elements:

1. **Transparent entry and success requirements:** The first element delineates that all entry and success requirements are clearly articulated concerning educational prerequisites, social and emotional skills, and physical capabilities. It also includes guidance that strategies should be implemented to aid participants in addressing gaps in requirements, including making programs accessible and free of barriers.
2. **Alignment with skills sought by local employers and high-quality apprenticeship programs:** The alignment with skills element details that programs should be widely accessible and aligned to workforce pathways. It also provides guidance that participants should be supported in obtaining the relevant employability skills and credentials needed for entry
3. **Culmination in one or more industry-recognized credentials:** Culmination in one or more industry-recognized credentials details that programs should embed

preparation for and help facilitate the earning of relevant, portable, in-demand labor-market credentials

4. **Development of skills through hands-on activities and work-based learning:** The fourth element explains that learning should be hands-on; participants should complete meaningful job-related tasks in an actual or simulated workplace setting.
5. **Offering of academic, career exploration, and wraparound supports:** Offering of academic, career exploration, and wraparound supports states that participants should be well-oriented to the industry and available opportunities, including the range of occupations, career pathways, and wage information. The element also details that programs should share postsecondary options, support participants in developing a career plan and path, and provide wraparound supports and resources to help them achieve their short- and long-term goals.
6. **Transition into a registered apprenticeship or other high-quality apprenticeship programs:** The final element states that programs work to determine section processes and help facilitate job placements of participants with relevant partners (Allen et al., 2019).

Similarly, the armed forces provide transparent entry and success requirements through ASVAB testing and promotion and rank frameworks. Job specializations within the military are based on need and supported with relevant hands-on skills training. The military provides appropriate wraparound supports and resources, including housing. Furthermore, it provides transitioning soldiers with resources to help facilitate job placement as a civilian.

As such, the military, like pre-apprenticeship programs, provides a bridge to career opportunities and effectively prepares underrepresented populations for high-quality

employment opportunities by increasing diversity and equity in the workforce systems (Allen et al., 2019). Since militaries represent a large, single employer, penetrating the military system can substantially expand apprenticeships (Hanson & Lerman, 2016).

Growing Investment and Expansion in Apprenticeships

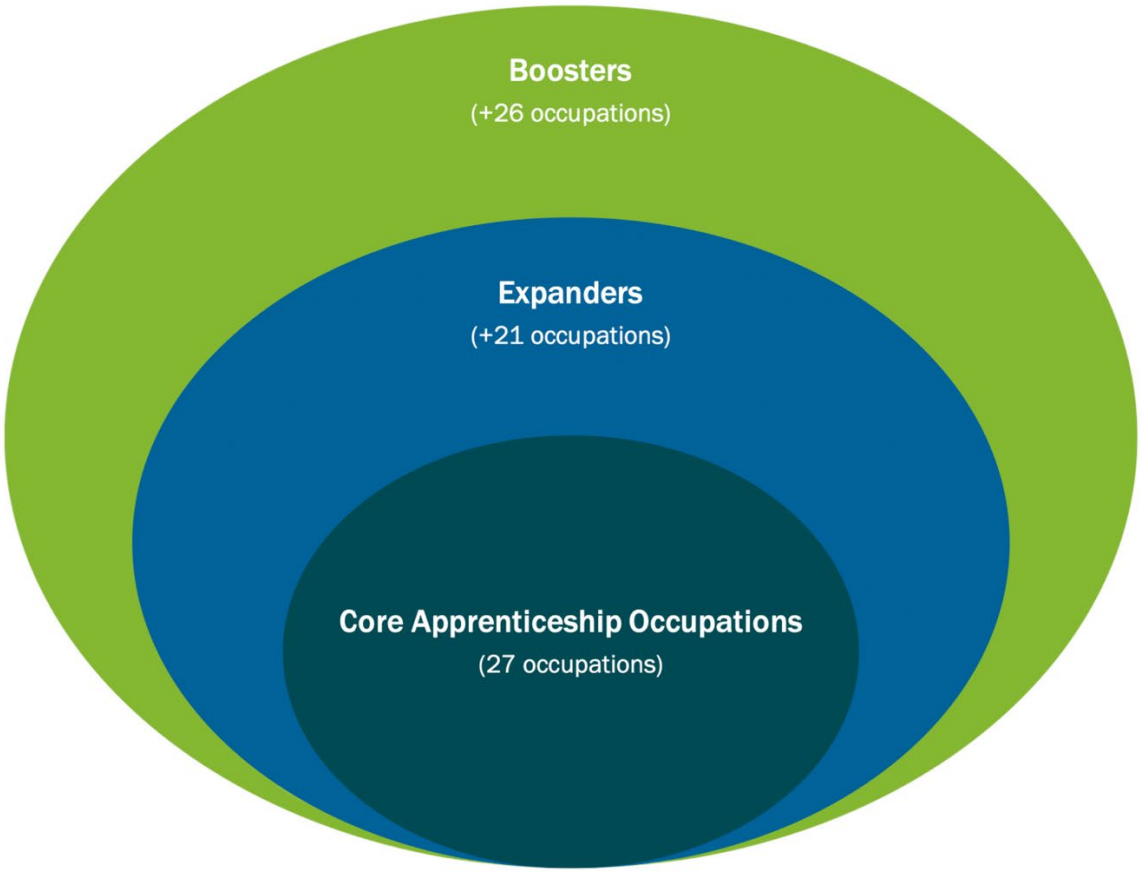
Current workforce development strategies across the United States have seen a rise in the number of registered and nonregistered apprenticeships (U.S. Department of Labor, n.d.-d). The increase is primarily due to strong fiscal support and favorable policy by previous and current administrations (Herr & Gray, 1998). In addition to the more than $130 million in grants issued in 2021 to support registered apprenticeship programs (U.S. Department of Labor, 2021), the Scaling Apprenticeship Through Sector-Based Strategies grants were also awarded to support the training of more than 85,000 apprentices in industries such as IT, including increasing opportunities for veterans (U.S. Department of Labor, n.d.-a). Similarly, the Expanding Community College Apprenticeship Initiative (EECA) is a $20 million partnership between the American Association of Community Colleges and the Department of Labor to create 16,000 new apprentices by the summer of 2022, with a push to expand opportunities in IT (U.S. Department of Labor, n.d.-a).

As such, many companies have adopted the Registered Apprenticeship (RA) model as a solution to address the shortage in the workforce pipeline, evolving it beyond its prior perception and image of trade-union jobs in construction, manufacturing, or transportation. Currently, there are registered apprenticeships in white-collar occupations such as insurance and IT (Gurchiek, 2019; McGregor, 2017).

Fuller and Sigelman (2017) identified a set of criteria to identify occupations with the potential for apprenticeship expansion. These criteria included the following

recommendations: (a) they are not heavily licensed; (b) they require a relatively narrow cluster of skills, (c) they do not require a bachelor's degree, (d) they tend to have above-average worker stability, and (e) they pay a living wage ($15 per hour or more). Fuller and Sigelman then divided this list into two groups of occupations—Expanders and Boosters, in which education is the dividing factor.

Figure 1. Fuller & Sigelman's Scope for Apprenticeship Expansion



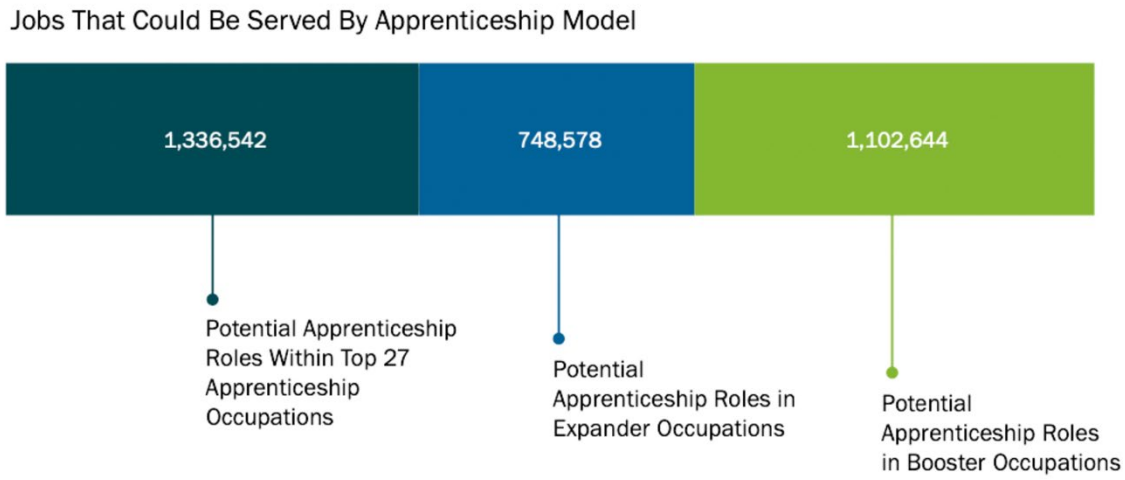
Note. From Fuller, J. B., & Sigelman, M. (2017, November). *Room to grow: Identifying new frontiers for apprenticeships*. Harvard Business School. https://www.hbs.edu/managing-the-future-of-work/Documents/room-to-grow.pdf

As shown in Figure 1, the Expanders group represents 21 occupations where some postsecondary education is required, but not necessarily a bachelor's degree, while those occupations in the Boosters category commonly require a bachelor's degree (Fuller & Sigelman, 2017). Fuller and Sigelman shared that computer user support specialists who staff IT help desks are a noteworthy example of Expanders and Boosters:

> While 60% of postings for those positions request a bachelor's degree, an analysis of job postings reveals little, if any, real difference in the skill sets required between postings that require a bachelor's degree and those that do not. However, employers report that they pay a wage premium of 11% to 30% to hire a recent college graduate to do the same job as a nondegree worker with experience. (p. 8)

Fuller and Sigelman (2017) highlighted that this fact certainly makes Booster occupations a compelling avenue for middle-class earnings without a degree and that apprenticeships offer a cost-effective alternative for students and employers; students do not incur the debt required of a bachelor's degree, and employers do not pay the premium for the higher educational attainment. As shown in Figure 2, millions of jobs could be served by apprenticeship expansion.

Figure 2. Fuller & Sigelman's Apprenticeship Expansion Model



Note. From Fuller, J. B., & Sigelman, M. (2017, November). *Room to grow: Identifying new frontiers for apprenticeships*. Harvard Business School. https://www.hbs.edu/managing-the-future-of-work/Documents/room-to-grow.pdf

Apprenticeships for Veterans

Military apprenticeships have existed for many decades; both the Army and the Navy have had apprenticeship programs since the 1970s (Hanson & Lerman, 2016). The United States Military Apprenticeship Program (USMAP) is an expanding segment of registered apprenticeships. USMAP trains service members in the Navy, Marine Corps, and Coast Guard while on active duty using the apprenticeship model to lead to an occupational credential. While USMAP apprentices are less likely to remain with their employer (the military), they are encouraged to use the skills learned and certifications earned for the civilian workforce. In this way, military apprenticeships attempt to bridge the gap between military experience and civilian job requirements. However, there are a few key differences between military and civilian apprenticeships:

- **Sequential Learning.** Standard military training is sequential. Classroom instruction is followed by work-based learning and experience.
- **Skills Development.** Civilian apprentices typically train for skills they would otherwise not develop, whereas military apprentices mainly document the skills they would have typically developed in their day-to-day activities.
- **Retention.** In civilian apprenticeships, there is no guarantee that apprentices will stay. However, the military has reenlistment for a while, while also expecting that the servicemember will eventually return to the civilian sector.
- **Barriers to Completion.** USMAP apprentices typically experience more barriers to completion due to deployment and reassignment.
- **Occupation Choices.** Civilian apprentices are constrained by the sector-based or place-based opportunities available. Service members are limited to occupation choices within their military occupational specialty (MOS; Hanson & Lerman 2016).

Additionally, there are many focused attempts to better advertise apprenticeship opportunities to veterans, particularly by the government. The Bringing Registered Apprenticeships to Veterans Education (BRAVE) Act of 2021 is a bill that would require that service members be provided with information about registered apprenticeship programs when they separate from military service. Additionally, the bill would require the U.S. Department of Veterans Affairs to create a user-friendly online system for veterans to access information on registered and certified apprenticeship programs (BRAVE Act, 2021). Similarly, the Veterans Apprenticeship and Labor Opportunity Reform (VALOR) Act (2018) provides increased access to apprenticeship opportunities for veterans by removing administrative hurdles in multistate apprenticeship programs.

According to Hanson and Lerman (2016), civilian apprentices face fewer barriers to completing apprenticeship programs than their USMAP counterparts. Deployments and reassignment to a different occupation can extend or alter completion timelines for military apprentices. USMAP reported that 18,000 apprentices completed apprenticeship programs in the 2013 and 2014 fiscal years. This equates to about 9,000 per year. By 2020, this number had grown to over 17,000 in a single year (Employment and Training Administration, 2020).

Theoretical Framework

The positive correlation of education and earnings is well-established. Researchers have long shared that individuals with higher levels of education will earn higher wages in the labor market (Schultz, 1961; Beker, 1964; Bedard, 2001). Causality of this relationship, however, is subject to many different theories as scholars debate whether the correlation is motivated intrinsically or extrinsically in nature (Schultz, 1961; Becker, 1964; Spence, 1973).

Human capital theory (Schultz, 1961) asserts that the pursuit of education and training are investments that produce capital in human beings in terms of knowledge and skills (Benjamin et al., 1998). These investments, in turn, influence productivity and thus allow individuals to earn more than those without similar investments (Bedard, 2001). Ultimately, education is treated as an extrinsic factor. Those who pursue higher education or increased training have a competitive advantage over those who forgo it; thus, they are more productive and earn higher wages.

Signaling theory (Spence, 1973), however, posits that education is simply a signal of inherent human capital and that it is the inherent human capital that determines a worker's wage (Kjelland, 2008). The very fact that one would pursue education signals they are

intrinsically motivated and thus, would perform better in the labor market than someone who did not possess the same signal. This research study used both human capital and signaling frameworks as lenses to approach the research questions posed and to ultimately determine the impact of veteran status on the completion and earnings of apprentices in registered IT apprenticeship programs.

Human Capital Theory

Defined as the stock of knowledge, skills and other personal characteristics embodied in people that helps them to be productive (OECD, n.d.), the original concept of human capital emerged with classical economics in 1776 (Kwon, 2009). However, it was not until the 1960s that the theory manifested, specifically, as a theory for education and in academics. Schultz (1961) was one of the first to recognize human capital as an important factor for national economic growth (Kwon, 2009). Schultz, along with Becker, are mostly credited with theorizing human capital in the traditional sense it is used in education.

In his 1961 work titled, *Investment in Human Capital*, Schulz described the value of investing in human resources as a form of workforce development and economic growth. Schultz (1961) concentrated his insights on five major categories:

> Health facilities and services, broadly conceived to include all expenditures that affect the life expectancy, strength and stamina, and the vigor and vitality of a people; on-the-job training, including old-style apprenticeship organized by firms; formally organized education at the elementary, secondary, and higher levels; study programs for adults that are not organized by firms, including extension programs notably in agriculture; and migration of individuals and families to adjust to changing job opportunities. (p. 9)

Although Schultz (1961) mentioned on-the-job training, he admittedly offered little to the discussion on apprenticeships, noting that "apprenticeships has all but disappeared, partly because it is now inefficient and partly because schools now perform many of its functions "(p. 10).

Becker (1964), in contrast, offered a robust discussion of on-the-job training "not because it is more important than the other kinds of investment in human capital—although its importance is often underrated—but because it clearly illustrates the effect of human capital on earnings, employment, and other economic variables" (p.8). According to Becker (1964), on-the-job training is how workers increase their productivity by learning new skills and perfecting old ones.

Furthermore, Becker (1964) offered some distinction between general and specific training. General on-the-job training not only increases the future marginal productivity of employees working for specific employers, but also similarly increases the workers' marginal productivity for other jobs as well. Specific on-the-job training works conversely by having a stronger benefit to the firm directly, and no effect on the productivity of employees that would be useful to other employers (Becker, 1964). Interestingly, the military is used as an illustration. Becker explained:

> The military offers some forms of training that are extremely useful in the civilian sector, as already noted, and others that are only of minor use to civilians, i.e., astronauts, fighter pilots, and missile men. Such training falls within the scope of specific training because productivity is raised in the military but not (much) elsewhere. (p.19)

Kwon (2009) stated that the terms human capital and knowledge can be treated interchangeably as knowledge can broadly include skills, experience, and competency, and thus "human capital and 'knowledge as broad meaning' is recognized as synonymous expression," (p. 2).

Signaling Theory

In the most basic terms, a *signal* is defined as an observable indicator of something with unobservable quality (Spence, 1974). Signals play a crucial role in education and the labor market. Attributed to Michael Spence (1973), signaling theory asserts that an individual worker's "innate productivity levels are identified by their years of schooling, rather than enhanced by them" (Page, 2010, p. 321). Signaling theory uses the following assumptions: individuals have different innate levels of productivity (which are not affected by their education); additional education incurs additional costs and are different for high- and low-productivity workers; there is asymmetric information with respect to workers' productivity: individual workers know their skill level, but potential employers do not; and education qualifications are used to predict productivity (Page, 2010).

Spence (1973) substantiated the theory by sharing that the cost of making certain adjustments, or signaling costs, play a key role in certain signaling situations. Education, for instance, is a prime example because one will typically only invest in education if there is sufficient return as defined by the offered wages. Therefore, individuals are assumed to select education as to maximize their earnings (Spence, 1973). The investment in level of education or the monetary cost of education is not the only consideration. Time, for example, would qualify as a signaling costs and therefore signaling costs should be interpreted broadly to include psychic costs, as well as direct monetary ones (Spence, 1973).

Weiss (1995) stressed that signaling and human capital theories are not necessarily mutually exclusive. Often, the terms signaling, screening, and sorting are used interchangeably to describe variants of the same basic model (Page, 2010). Education, for example, may simultaneously enhance an individual's productivity and act as a signal about their inherent abilities. Similarly, signaling provides an extension of human capital theory by acknowledging that some of the productivity differences are unobservable, but correlated with educational costs (Page, 2010).

Chapter Summary

Chapter 2 presented a review of literature for the themes that undergird this study: apprenticeships as workforce development, veterans as talent, and the expansion of IT apprenticeships. Beginning with an overview of workforce development and the importance of a skilled workforce, the training model of apprenticeship was discussed from a historical context. The chapter also discussed the impact of the GI Bill on education and specifically, in veterans' pursuit of higher education, that has allowed military servicemembers to augment their military training and skillset as they transition to the civilian workforce. Furthermore, military service and the training it offers was compared with a pre-apprenticeship framework, as the discussion on the growing investment in registered IT apprenticeships was shown. Chapter 3 presents propensity score matching as the quantitative research methodology used for this research study, which examined the effect of veteran status on completion and earnings of apprentices in registered IT apprenticeship programs.

Chapter 3: Methods

Introduction to Methodology

According to Fan and Nowell (2011), propensity score matching is a provisional technique used to make the groups in a comparison analysis statistically more equivalent, resulting in a stronger foundation for causal inferences. In observational studies, one must account for the differences in baseline characteristics of treatment groups, from those of control groups, through methods such as regression adjustment or propensity score. Interest in the latter has been growing due to its ability to reduce or eliminate the effects of confounding when using observational data (Austin, 2011). This research study used propensity score matching as its research methodology.

Defined by Rosenbaum and Rubin (1983) as the probability of treatment assignment conditional on observed baseline covariates, the propensity score represents a balancing score in which the distribution of measured baseline covariates is similar between the treated and untreated groups (Austin, 2011). Thus, in a set of groups who share the same propensity score, the distribution of observed baseline covariates will be the same between the treated and untreated subjects. While the propensity score in randomized experiments is known and defined by the study design, it is generally estimated in observational studies using logistic regression, bagging or boosting, recursive partitioning, tree-based methods, random forests, and neural networks. Though many methods exist, logistic regression is the most commonly used and requires that the treatment status is regressed on the observed baseline characteristics (Austin, 2011).

Removing the effects of confounding when estimating the treatment effects on the outcome can be achieved by a few different methods, including stratification or

subclassification, inverse probability of treatment weighting (IPTW), covariate adjustment, or propensity score matching (Austin, 2011). Matching allows researchers to separate the data into comparison groups with similar characteristics using pretests and other relevant criteria (Powell et al., 2019). This study's methodology was selected for its statistical reliability in determining the impact of veteran status on the completion and salary of IT apprenticeship programs.

Methodology Used for This Study

Using propensity score matching in this study entailed "forming matched sets of treated and untreated subjects who shared a similar value of the propensity score" (Austin, 2011, para. 16). Propensity score matching allowed the researcher to estimate the average treatment effect on the treated (ATT) or the overall effect of veteran status on the completion and salary of IT apprenticeship programs (Powell et al., 2019). In randomized control designs, the probability of group membership is determined by the randomization procedure and thus, is already known (Powell et al., 2019). However, for nonexperimental designs, participants do not enter into groups randomly, and therefore, the probability of getting the treatment is generally not known a priori. As such, differences in the outcome variable could be due to many different factors, making it difficult to pinpoint or measure the ATT (Powell et al., 2019). The use of propensity score matching allowed the researcher to estimate the likelihood of group membership from covariate values, controlling for the covariates while statistically accounting for preexisting differences that may influence any differences in the outcomes. According to Austin (2011), the treatment effect can be estimated by directly comparing outcomes between treated and untreated subjects in the matched sample once a matched sample has been formed.

It should be noted that propensity scores rarely produce identical covariate distributions in groups and do not allow for the degree of causal inference that comes from a randomized assignment. Though they cannot control for any unobserved covariates as randomization, their distributions are often close enough to mimic the effects of randomization and thus provide a meaningful research method for measuring causality, particularly in education and this research study (Powell et al., 2019).

Data Source

The data source for this study was the United States Department of Labor's Office of Apprenticeship. The United States Department of Labor and various State Apprenticeship Agencies are responsible for oversight of Registered Apprenticeship Programs. A Registered Apprenticeship Program (RAP) is a proven model of apprenticeship that has met specific criteria and is formally registered with the Office of Apprenticeship or an appropriate state agency (U.S. Department of Labor, n.d.-d). Administration of the Registered Apprenticeship Program can be somewhat fragmented; while there is no single repository of data from all the programs, a good majority of the data is collected and maintained in the RAPIDS system (U.S. Department of Labor, 2019; Workforce Data Quality Campaign, n.d.).

Data Set

According to the U.S. Department of Labor (2021), the RAPIDS dataset captures individual record data from 25 Office of Apprenticeship (OA) states. Additionally, it includes registered apprenticeship information from 18 of the 28 State Apprenticeship Agency (SAA) states/territories (U.S. Department of Labor, 2021). "For SAA states that manage their data outside of RAPIDS, information is provided in the aggregate to the U.S. Department of Labor on a quarterly basis" (U.S. Department of Labor, n.d.-a).

Data Construction

RAPIDS collects various data about the apprentices. This includes, but is not limited to, demographic information, education level, and current enrollment status in an apprenticeship program (U.S. Department of Labor, n.d.-a). The database also includes various program data, such as the duration of on-the-job instruction, the related instruction provider, and the apprentices' wage rates (U.S. Department of Labor, 2019).

According to the U.S. Department of Labor (2019), in FY 2018, more than 238,000 individuals nationwide entered the apprenticeship system, with 71,7000 participants having graduated. Additionally, over 47,000 veterans nationwide participated in a registered apprenticeship program (U.S. Department of Labor, 2019). The researcher studied a subset of the dataset that included apprentices in select IT career clusters based on the North American Industry Classification System (NAICS) and Occupational Information Network Standard Occupational Classification (O*NET-SOC) codes available. Two groups were identified and studied from the subset: apprentices who served in the U.S. Armed Forces (veterans) and apprentices who did not identify as veterans, to examine the completion rate and salary of veterans in IT apprenticeship programs versus nonveterans in similar programs. The groups were matched on the various demographic data, including their gender, race, age, ethnicity, and starting wage using available data from RAPIDS to determine if there was a difference in their demographics after matching and the effect of veteran status on completion and salary.

The researcher inquired to the Office of Apprenticeship in the United States Department of Labor's Education and Training Administration regarding access to the RAPIDS dataset. The U.S. Department of Labor confirmed the dataset is open source, public data. The researcher was provided a copy by the Office of Apprenticeship. Additionally, the

researcher was shown where this dataset is stored on the Office of Apprenticeship's website. This process was cleared through North Carolina State University's Institutional Review Board.

Participants

The research study's population included participants from the various Registered Apprenticeship Programs. Participation in this nationally recognized program requires entities to follow and maintain a set of structured standards of the "learn and earn" model of apprenticeship, including requirements for related (classroom) instruction and paid on-the-job learning experiences (U.S. Department of Labor, n.d.-a). This is accomplished with a formal agreement, or Program Registration and Apprenticeship Agreement, through the U.S. Department of Labor's Office of Apprenticeship that outlines the requirements and expectations of the program between the sponsors and apprentices (U.S. Department of Labor, n.d.-c). Additionally, these registered apprenticeships must allow participants to earn nationally recognized credentials and certificates of completion that certify an occupational proficiency (National Skills Coalition, n.d.).

Participants of the Registered Apprenticeship Programs reported in this dataset ranged in ages from 15–95, with cases from all 50 states and the District of Columbia reported to the aggregate RAPIDS dataset. The participants' race included American Indian or Alaska Native, Asian, Black or African American, Multi-Race, Native Hawaiian or Other Pacific Islander, White, or was not specified. Additionally, some of the participants indicated that they were disabled and shared the highest education they had received. The participants represent apprenticeship occupations ranging in trades such as carpentry and electrician to white-collar industries such as accounting and IT.

Research Questions and Data Analysis

Three research questions were used to guide this study exploring the effect of veteran status on the completion rate and salary of apprentices in registered IT programs. They are presented in this section, along with the steps of propensity score matching and relevant data analysis techniques used to determine the results of this study. Table 1 summarizes the research questions for the study, the independent and dependent variables, the analysis technique for each research question, and what results are reported.

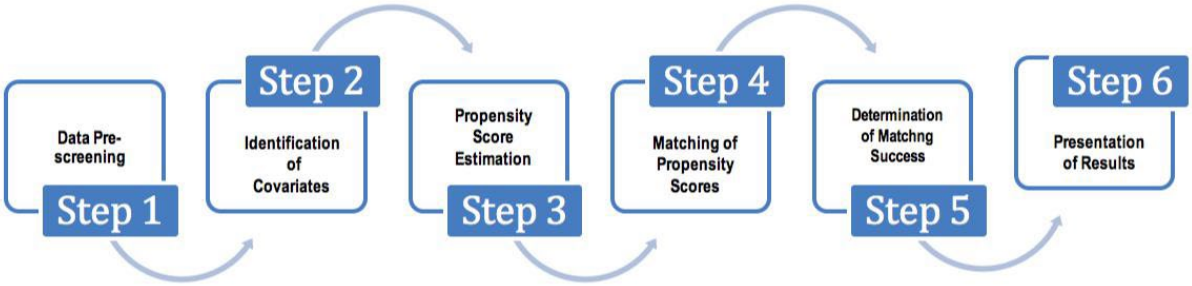
Table 1. *Research Questions and Data Analysis*

	Research Question	Independent Variable	Dependent Variable	Analysis Technique	Reported
RQ1.	What are the demographics of the two groups (veteran IT apprentices and nonveteran IT apprentices) prior to matching?	Veteran Status	Apprentice Demographics	Descriptive Analysis Frequencies Chi-Square	The descriptive statistics of the participants in this sample.
RQ2.	After propensity score matching, is there a difference in demographics of the two study groups?	Veteran Status	Apprentice Demographics	Propensity Score Matching Logistic Regression	The amount of variance in the demographics of the study groups.
RQ3.	Is there a difference in completion and ending salary of IT apprenticeships between veteran and nonveteran apprentices?	Veteran Status	Completion	Propensity Score Matching Logistic Regression	The amount of variance in the completion of veteran and nonveterans in selected apprenticeship programs.

Data Analysis Using Propensity Score Matching

According to Frye and Bartlett (2017), there are six essential steps to propensity score matching: data prescreening, covariate identification, propensity score estimation, matching of propensity scores, determination of matching success, and presentation of results. Figure 1 describes the six steps used in performing propensity score matching for this study.

Figure 3. *The Six Steps of Propensity Score Matching*



Data Prescreening

The first step of the data analysis procedure involves data prescreening. Data prescreening requires checking for missing values on study variables and running frequencies (Frye & Bartlett, 2017). Multivariate techniques, like propensity score matching, offer tremendous analytical power and value to the researcher, but not without a burden; researchers must ensure that the statistical and theoretical underpinning on which they are based are also supported (Hair et al., 1998). By prescreening the data before propensity score matching, the researcher gained critical insights into the characteristics of the data and could identify whether there was missing data. A small number of missing values is generally acceptable and expected. However, many missing data can be "detrimental not only through its potential "hidden" biases of the results but also in its practical impact on the sample size available for analysis (Hair et al., 1998, p. 47).

The RAPIDS dataset used for this research study contained over three million records (*n* = 3,043,287) and included information on registered apprentices from 2008 through the first quarter of 2022. The researcher began pre-analysis by identifying duplicate cases reported based on the apprentice ID number. There were 77 duplicated cases identified. These cases were filtered out to produce a new dataset containing unique cases (*n* = 3,043,210). Next, the researcher ran some preliminary demographic frequencies of the dataset. Table 2 shows the descriptive statistics of the RAPIDS Dataset.

Table 2. *Descriptive Statistics of RAPIDS Dataset (through Q1 2022)*

Variable	Level	n	%
Gender	Male	2,735,026	89.9
	Female	308,184	10.1
Race	American Indian or Alaska Native	72,422	2.4
	Asian	40,229	1.3
	Black or African American	340,861	11.2
	Do not wish to answer	170,344	5.6
	Multiple-Race Selected	181,654	6.0
	Native Hawaiian or Other Pacific Islander	33,735	1.1
	White	194,0212	63.8
	Missing	263,753	8.9
Ethnicity	Hispanic	488,517	16.1
	Non-Hispanic	1,622,616	53.3
	Not Provided	932,077	30.6
Veteran Status	No	2,549,007	83.8
	Yes	359,058	11.8
	Not Provided	135,145	4.4

The RAPIDS dataset indicated that 89.9% (n = 2,735,026) of apprentices were male, while 10.1% (n = 308,184) indicated female as their gender. A majority of apprentices (63.8%; n = 1,940,212) indicated White as their race. The average age of apprentices was 29.63, with a median age of 27. Only 11.8% of the apprentices indicated that they were veterans (n = 359,058).

After running these preliminary frequencies, the researcher reduced the complete RAPIDS dataset only to include IT apprentices from the reporting period of 2008 through the first quarter of 2022, the subset of data needed for this study's analysis. This reduction was accomplished with the following steps.

First, the researcher ran frequencies of the data by their standard occupation classification code (onetSocCode) to identify any missing data and inconsistencies. Since the study focused on specific IT occupations, the researcher closely examined the subset of data in this career cluster to identify any reporting irregularities. It was identified that all but one of the IT clusters was reporting correctly; one category of codes contained "15.1151.00" instead of "15-1151.00." This affected (n = 111) records. The researcher recoded this to match the others as 15-1151, which yielded a final number of 161 for this classification code. Next, the researcher filtered the dataset by the standard occupational classification codes to reflect the IT population included in the IT Career Clusters. This filtering of data included selecting cases while controlling for the specific standard occupation classification codes in the IT Career Cluster, according to the Occupational Information Network. See Appendix A for a detailed list of the IT codes. The selection of cases by IT classification codes yielded a sample size of (N = 17,136) of all apprentices registered in IT apprenticeships programs.

After narrowing the sample by career clusters, the researcher began by running frequencies. Tables 3 and 4 display the descriptive statistics and covariates for the IT RAPIDS dataset.

Table 3. *Descriptive Statistics of IT RAPIDS Dataset*

Variable	*n*	%
Gender		
Female	4,428	25.8
Male	12,708	74.2
Race		
American Indian or Alaska Native	434	2.5
Asian	1,045	6.1
Black or African American	3,144	18.3
Do not wish to answer	3,099	18.1
Multiple Race	681	4.0
Native Hawaiian or Other Pacific Islander	151	0.9
White	7,891	46.0
Not provided	691	4.0
Ethnicity		
Hispanic	1,478	8.6
Non-Hispanic	8,725	50.9
Not provided	6,933	40.5
Veteran Status		
No	10,777	62.9
Yes	4,975	29.0
Not provided	1,384	8.1

Note. *N*= 17,136

Table 4. *Apprentices' Starting Age*

Covariate	Median	*M*	*SD*
Age at Start	30.00	32.21	10.225

Although there were 17,136 records identified in the original sample size, the researcher identified that this sample size would be further reduced to omit a third group indicated by the variable of Veteran Status. The three valid values for Veteran Status were 1=No; 2= Yes; and 9=Not Provided. Even though the apprentices in the omitted group were registered for the identified IT apprenticeships (n = 1384), they did not indicate their veteran status and therefore could not be placed into the treatment or control group. The researcher filtered out this small group to create a control group (n = 10777) and treatment (n = 4975), yielding a final analytical sample size of 15752.

Further pre-analysis of frequencies indicated some outliers in the "Starting Wage" and "Age at Start" fields. According to the RAPIDS Data Dictionary (U.S. Department of Labor, 2019), apprentices' starting wages and exit wages can be reported as hourly, weekly, monthly, or annually; however, there is no variable in the dataset indicating the reporting frequency. Therefore, the data reported represented a wide range of numbers (0–162,000.00). All cases reporting as under the minimum wage value (7.25) or between the ranges of (431–15,000) were recoded as missing so that they would be excluded from the final model but retained in the dataset.

Additionally, the "Age at Start" category reported some missing data and irregularities; many cases were missing data (n = 617), and a small number of cases (n = 7) reported irregular data (-8, -1, and 0). The researcher recoded all missing data for the categorical mean and recoded the irregular cases (n = 7) as missing so they would not affect the results of the data analysis.

Next, multi-collinearity was addressed. Because some of the independent variables are highly correlated to each other, multi-collinearity can distort the prediction equation

when determining the importance of individual independent variables (Frye & Bartlett, 2017). As such, researchers are advised to exclude the least important variable and retain the most important one using a variance inflation factor (VIF) and tolerance statistic (Frye & Bartlett, 2017). According to Hair et al. (1998), the common threshold is a tolerance value of .10 or a VIF value above 10.

Identification of Covariates

After prescreening the data, the next step of the propensity score matching data analysis procedure advises researchers to identify, code, and derive independent variables that could bias the research study. The initial use of logistic regression permits the researcher to identify covariates by using multiple quantitative independent variables to predict the probability of the dependent variable (group membership; Frye, 2014). Though literature presents some debate as to the appropriate use of pretreatment covariates, researchers generally agree that appropriate independent variables explain differences in group membership that are constant over time (Rosenbaum & Rubin, 1983, 1984; Titus, 2007). In this research study, the researcher performed a logistic regression to examine the covariates and determine which best predicted the membership in the control or treatment groups and used this data to support the selection of identification variables.

Propensity Score Estimation

After covariates are identified, the next step of the data analysis requires estimating propensity scores. In this study, this was accomplished first by calculating the between-group differences on all the covariates using some measure of effect size to compare the group-membership effects before and after matching (Powell et al., 2019). The standardized

difference, D, the mean difference between the groups scaled to be on the standard deviation metric, is a commonly used effect size for continuous variables (Powell et al., 2019).

Next, a classification model was developed using group membership as the outcome variable and covariates as the predictor variables. As Powell et al. (2019) explained,

> It is important that the predictor variables not include any outcome variable so that any group differences on the outcomes do not influence the propensity score values" and that "the predictors should not be related to any reason for forming groups. (p. 4)

Typically, this classification model is logistic regression, though nonparametric methods are becoming accepted alternatives (Powell et al., 2019). After the classification model was determined, the propensity score was created by estimating each observation's predicted probability of group membership (Powell et al., 2019).

Matching of Propensity Scores

Once the propensity scores are estimated, they should be matched. Additionally, researchers should ensure that the covariates are assessed for balance, so there are minimal group differences in the covariates' distributions after accounting for the propensity scores using matching (Powell et al., 2019). The researcher aimed to find one or more participants in each of the groups who had similar values on all the pertinent covariates but recognized that since propensity scores are probabilities and, thus, continuous, matching might need to be done using an approximate method as recommended by Powell et al. (2019), or algorithm, such as greedy or nearest neighbor.

For this study, the data analyses procedure began with running logit analyses on specific independent variables in SPSS and estimating and testing propensity scores to be

used in the final model. Using the propensity score matching function in SPSS, Version 28, the logit analyses were executed and analyzed to determine if balance occurred.

The propensity scores ranged from 0.0 to 1.0. According to Frye (2014), these scores match groups from a large database to produce comparison groups based on significant covariates. “Propensity scores must be assessed to ensure that the distributions are similar across the two groups and that outliers are not present in the propensity score that could affect the analysis” (Frye, 2014, p. 104). These propensity scores were used to match apprentices from the control and treatment groups, nonveteran and veterans, respectively, to produce a comparison, or matched, group on the significant covariates. The researcher assessed propensity scores to verify that the distributions were similar across the matched groups and that any outliers were eliminated using a minima-maxima technique of common support. According to Caliendo and Kopeinig (2008), the basic criterion of minima and maxima comparison is to delete all observations whose propensity score is smaller than the minimum and larger than the maximum in the opposite group.

The researcher selected a tolerance level of 0.05 and the matching algorithm of nearest neighbor to “create sufficient overlap between the propensity scores in both groups” (Wilson, 2018, p. 51). SPSS created matched groups based on the estimated propensity scores for the final analysis.

Next, the researcher executed logistic regression analyses to determine the factors that explain membership in the two comparison groups. Significant predictors and covariates to retain in the model were identified by analyzing Nagelkerke R-square, chi-square, beta coefficients, and values; those independent variables with a value < .05 were retained, as they indicated significance. Logistic regression results indicated that six independent variables

should be retained—ethnicity, gender, race, age at start, starting wage, and standard occupational classification code—as they were connected with the dependent variable of veteran status (-2 Log Likelihood = 7812.306; chi-square = 2762.003, $p < .001$; Nagelkerke R Square = .382). The model correctly classified 81.8% of the cases and explained 38.2% of the variance in the dependent variable. Regression coefficients and Wald statistics also confirmed the model's predictive power and related variables.

Determination of Matching Success

After the groups are matched on the propensity scores, the data analysis procedure requires researchers to determine the success of the matching. In this study, the researcher continued to assess balance by comparing the average values of each covariate between the treatment and comparison groups for the matched sample using *t*-tests, multiple analysis of variance, or the effect size between the groups. "If propensity score matching has been successful, there should be no significant difference (5% threshold) between the groups on the initial covariates" (Wilson, 2018, p. 43).

Presentation of Results by Comparing Outcomes

The last step of the propensity score matching procedure requires researchers to assess the outcomes of the matched data sets and compare the treatment to nontreatment groups across the outcome variable(s). In this study, the researcher analyzed this data to determine which results and conclusions could be generalized about the effect of veteran status on the treatment group.

Summary

Chapter 3 presented propensity score matching as a quantitative research methodology and the researcher's rationale for its use to address the research questions examining the effect of veteran status on the completion and ending wage of IT apprenticeship programs. The researcher performed a propensity score match using data from the Registered Apprenticeship Partners Information Data System, which is one of the largest repositories of registered apprenticeship data. The results and findings of this study are presented in Chapter 4.

Chapter 4: Findings

Propensity score matching was used as a methodology to determine the impact of veteran status on the completion rate of IT apprentices in registered apprenticeship programs, according to data reported to The Registered Apprenticeship Partners Information Data System (RAPIDS). The researcher examined two groups: veteran IT apprentices and nonveteran IT apprentices and their completion rates and salary of registered apprenticeship programs in the IT Career Clusters to detect what, if any, the effect of veteran status had on the completion rate and salary.

The use of propensity score matching in this study necessitated using demographical information to form matched sets of treated and untreated subjects who shared a similar value of the propensity score, which permitted the researcher to estimate the overall effect of veteran status on the completion and salary of IT apprenticeship programs (Powell et al., 2019). This allowed the researcher to estimate the likelihood of group membership from covariate values and control for the covariates while statistically accounting for preexisting differences that may influence the outcomes. The results of this research study are reported by research question in Chapter 4.

Findings

The first research question in this study sought to describe the demographics of the IT apprentices by veteran status prior to the propensity score matching. Tables 5 and 6 provide an overview of the IT apprentices', veterans (n=4,975) and nonveterans (n=10,777), demographics. In this study, the treatment group consisted of IT apprentices that were veterans and the control group consisted of IT apprentices without veteran status. Table 5 reports the frequency and percent for categorical variables of gender, race, and ethnicity.

Table 6 reports the mean and standard deviation for the continuous variables of starting salary and age at start. The demographic variables in these tables serve as part of the covariates used for propensity score matching to create balanced groups to examine the impact of veteran status on completion and salary.

Table 5. *Descriptive Statistics of Treatment (Veteran) and Control (Nonveteran) Groups Prior to Propensity Score Matching*

	Treatment		Control	
Variable	n	%	n	%
Gender				
Female	952	19.1	3,051	28.3
Male	4,023	80.9	7,726	71.7
Race				
American Indian or Alaska Native	31	0.6	402	3.7
Asian	244	4.9	767	7.1
Black or African American	944	19.0	2,057	19.1
Do not wish to answer	1,348	27.1	782	7.3
Multiple Race	126	2.5	546	5.1
Native Hawaiian or Other Pacific Islander	31	0.6	118	1.1
White	2,204	44.3	5,471	50.8
Not provided	47	0.9	634	5.9
Ethnicity				
Hispanic	370	7.4	1,061	9.8
Non-Hispanic	1,287	25.9	7,171	66.5
Not provided	3,318	66.7	2,545	23.6

Note. Treatment: n = 4,975; Control: n = 10,777

Prior to propensity score matching, IT apprentices were primarily male (80.9 % (n=4,023) in the control group and 71.7% (n=7,726) in the treatment group) and indicated White as their race (44.3% (n=2,204) in the control group and 50.8% (n=5,471) in the treatment group). The nonveterans had an average age of 33.10 (SD=9.52), whereas veterans

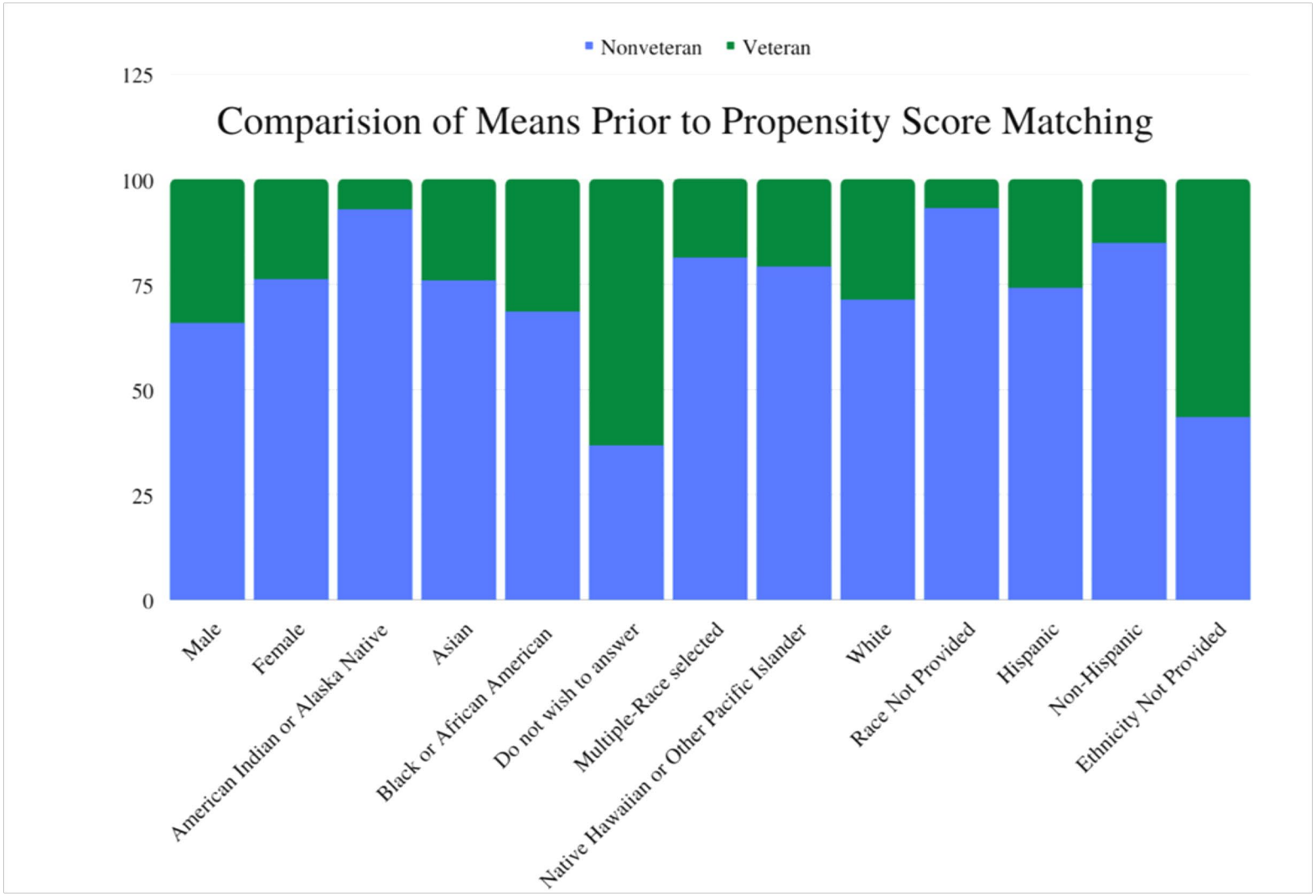
had an average age of 31.99 (SD=10.28). The nonveterans had an average starting wage of 40,804.55 (SD=20,159.19), whereas veterans had an average wage of 34,772.74 (SD=16137.25). Figure 2 illustrates a comparison of the means of each covariate prior to matching.

Table 6. *Apprentices' Age and Starting Wage, Prior to Propensity Score Matching*

Covariate	Treatment		Control	
	M	*SD*	*M*	*SD*
Age at Start	33.10	9.52	31.99	10.28
Starting Wage	40,804.55	20,145.19	34,772.74	16137.25

Note. Treatment: n = 4,975; Control: n = 10,777

Figure 4. *Comparison of Covariate Means Prior to Propensity Score Matching*



The second research question sought to examine the demographics after propensity score matching. Table 7 shows the output of the logistic regression that was used to match cases of veterans and nonveterans. All the demographic variables except for Asian and Native Hawaiian or Other Pacific Islander as an identified race, were significant in the logistic regression when predicting veteran and nonveteran status. Additionally, all standard occupation classification codes were significant, with the exception of 15-1122: Information Security Analyst, 15-1131: Computer Programmer, 15-1151 Computer User Support Specialist, 15-1199: Computer Occupation (All Other), 15-1231: Computer Network Support Specialist, 15-1254: Web Developer, and 15-1255: Web and Digital Interface Designer, 15-2041: Statistician, 15-2051: Business Intelligence Analyst.

Table 7. *Logistic Regression Results Predicting Membership in Treatment Group (Variables in the Equation*

Covariates	β	S.E.	Wald	*df*	Sig.	Exp(β)
Ethnicity Not Provided			134.846***	2	<.001	
Hispanic	-1.011	.104	95.176***	1	<.001	.364
Not Hispanic	-.717	.077	85.719***	1	<.001	.488
Female	-.773	.067	131.871***	1	<.001	.461
White			345.666***	7	<.001	
American Indian or Alaska Native	-1.890	.336	31.676***	1	<.001	.151
Asian	.197	.107	3.392	1	.066	1.218
Black or African American	.446	.080	31.353***	1	<.001	1.563
Do not wish to answer (Race)	1.347	.091	216.701***	1	<.001	3.845
Multiple Race	.672	.171	15.469***	1	<.001	1.959
Native Hawaiian or Other Pacific Islander	-.127	.229	.307	1	.579	.881
Race Not Provided	-2.144	.353	36.946***	1	<.001	.117
Age at Start	.046	.003	243.889***	1	<.001	1.047
Starting Wage	.000	.000	133.151***	1	<.001	1.000

Table 7. *(continued)*

15-2099			409.999***	20	<.001	
15-1122	4.707	1.121	17.644***	1	<.001	110.728
15-1131	-16.202	19962.155	.000	1	.999	.000
15-1133	-16.436	40192.970	.000	1	1.000	.000
15-1142	4.112	1.031	15.903***	1	<.001	61.090
15-1151	-16.416	5718.084	.000	1	.998	.000
15-1199	25.970	40192.969	.000	1	.999	1.899E+11
15-1211	4.968	1.020	23.698***	1	<.001	143.680
15-1212	4.831	1.017	22.569***	1	<.001	125.382
15-1231	-15.574	12586.934	.000	1	.999	.000
15-1232	4.309	1.016	17.995***	1	<.001	74.332
15-1241	2.401	1.058	5.150*	1	.023	11.032
15-1242	6.043	1.036	34.031***	1	<.001	420.976
15-1244	4.331	1.020	18.042***	1	<.001	76.028
15-1251	3.521	1.018	11.971***	1	<.001	33.810
15-1252	3.426	1.020	11.271***	1	<.001	30.738
15-1254	-15.801	28277.275	.000	1	1.000	.000
15-1255	-15.685	8373.600	.000	1	.999	.000
15-1299	4.602	1.017	20.485***	1	<.001	99.723
15-2041	2.585	1.447	3.190	1	.074	13.265
15-2051	-15.028	19857.933	.000	1	.999	.000
Constant	-6.206	1.023	36.798***	1	<.001	.002

Note. Chi-square = 2762.003, $p < .001$, -2 LL 7812.306, Nagelkerke R^2 .382, 81.8 % predicted correctly *** p <.001, ** p <.01, * p <.05

After performing propensity score matching, it is crucial to test the procedure's success. Table 8 shows the number of observations considered in the logistic regression (missing values removed), whereas Tables 9 and 10 show the demographics of each group after matching.

Table 8. *Logistic Regression Case Processing Summary for Propensity Score Matching*

Analysis	*n*	%
Included in Analysis	9057	57.5
Missing Cases	6695	42.5
Total	15752	15752
Unselected Cases	0	.0
Total	15752	100.0

Table 9. *Descriptive Statistics of Treatment (Veteran) and Control (Nonveteran) Groups After Propensity Score Matching*

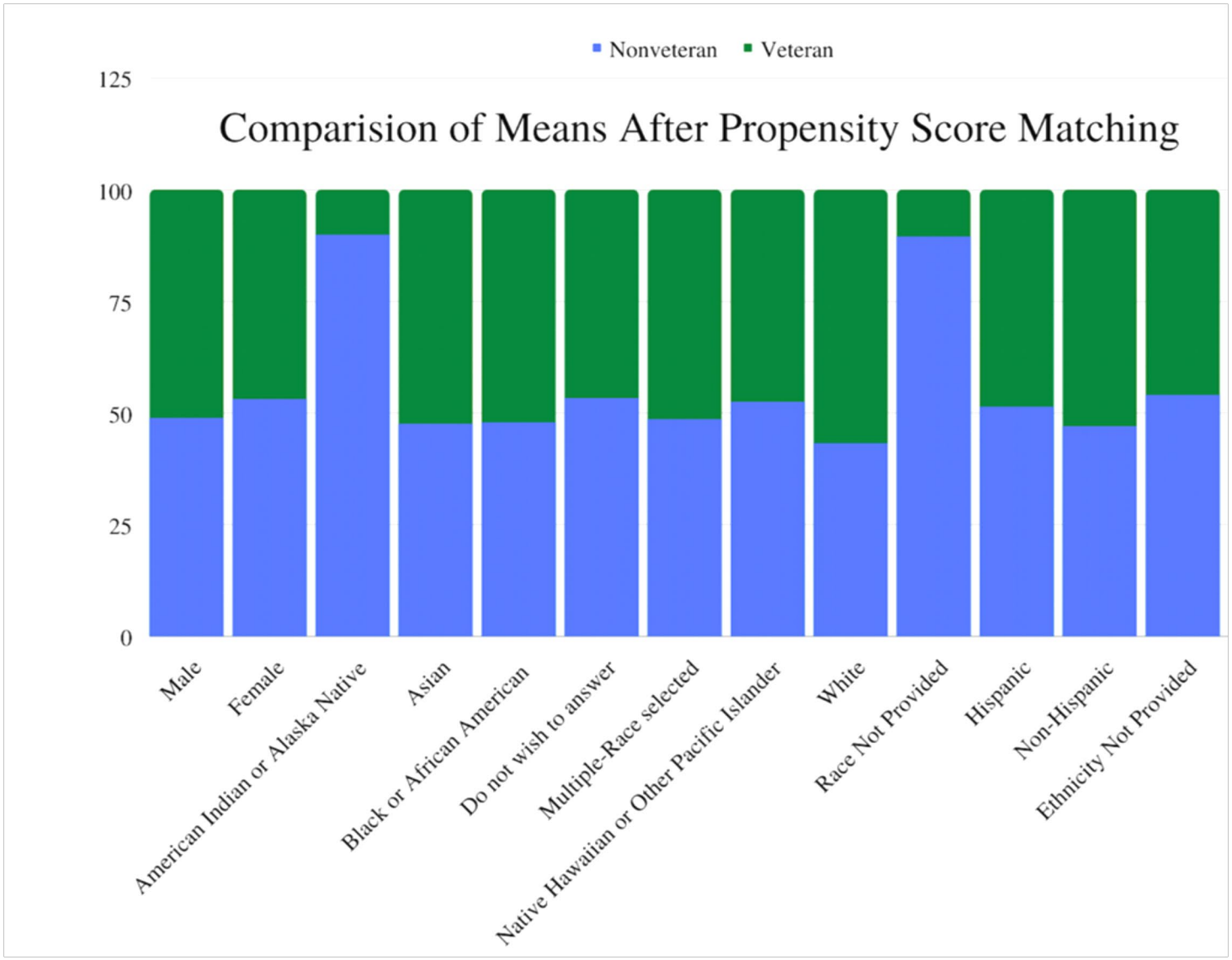
	Treatment		Control	
Variable	n	%	n	%
Gender				
Female	490	28.4	432	25.1
Male	1,234	71.6	1,292	74.9
Race				
American Indian or Alaska Native	89	5.2	10	0.6
Asian	139	8.1	153	8.9
Black or African American	331	19.2	360	20.9
Do not wish to answer	463	26.9	406	23.5
Multiple Race	89	5.2	94	5.5
Native Hawaiian or Other Pacific Islander	32	1.9	29	1.7
White	504	29.2	663	38.5
Not provided	77	4.5	9	0.5
Ethnicity				
Hispanic	203	11.8	192	11.1
Non-Hispanic	857	49.7	967	56.1
Not provided	664	38.5	565	32.8

Table 10. *Apprentices' Age and Starting Wage, Post-Propensity Score Matching*

Covariate	Treatment		Control	
	M	*SD*	*M*	*SD*
Age at Start	33.078	11.0159	33.295	8.7172
Starting Wage	47055.206	22463.0203	37609.6347	16771.872

Figure 3 illustrates the success of the propensity score match by comparing the means of each variable after matching. As shown, the groups became are more balanced on the co-variates after matching on gender (male and female); race (Asian, Black or African American, race not indicated (do not wish to answer), multiple-race selected, Native Hawaiian or Other Pacific Islander, White); and ethnicity (Hispanic, Non-Hispanic, and Ethnicity Not Provided).

Figure 5. Comparison of Covariate Means After Propensity Score Matching



The researcher further explored the differences in categorical variables of the two groups, veteran and nonveteran IT apprentices, by conducting a series of chi-square tests to determine goodness of fit and t-tests to examine the differences. Chi-square was explored on the following variables: gender, ethnicity, and race to determine any significant differences pre- and post-matching. While cell sizes were small and contained zeros in the standard occupational classifications codes, Chi-Square were conducted but interpretation is cautioned. Inspecting the descriptive data for standard occupation classification code was used to examine balanced grouping for post-matching compared to pre-matching. *T*-tests were also employed to examine the continuous variables of Age at Start and Starting Wage, prior to and Post-Propensity score matching. Tables 11 through 22 report these results.

Since sample size in chi-square impacts significant differences, there were statistically significant differences in the variable of gender occurred before and after matching, as indicated by $p = <.001$ and $p = <.001$, respectively (see Tables 11 and 12). The decrease in the phi, a measure of effective size, from .098 in pre-matching to .038 in post-matching indicates evidence that the matching technique provided balancing of the groups.

Table 11. *Chi-Square Analysis of Gender Pre-Propensity Score Matching*

	Treatment		Control	
Variable	*n*	%	*n*	%
Gender				
Female	952	19.1	3,051	28.3
Male	4,023	80.9	7,726	71.7
Total	10,777		4,975	

Note. Chi-square = 151.153, $df = 1$, $p = <.001$, phi = 0.098, $p = <.001$

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

Table 12. *Chi-Square Analysis of Gender Post-Propensity Score Matching*

Variable	Treatment		Control	
	n	%	*n*	%
Gender				
Female	432	25.1	490	28.4
Male	1,292	74.9	1,234	71.6
Total	1,724		1,724	

Note. Chi-Square = 4.980, *df* = 1, *p* = <.001, phi = 0.38, *p* = <.001

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

Similarly, an analysis of ethnicity revealed that there were significant differences before and after matching, as indicated by *p* = <.001 and *p* = <.001 (see Tables 13 and 14). The decrease in the phi, a measure of effective size, from .419 in pre-matching to .066 in post-matching indicates matching evidence the matching technique provide balancing of the groups.

Table 13. *Chi-Square Analysis of Ethnicity Pre-Propensity Score Matching*

Variable	Treatment		Control	
	n	%	*n*	%
Ethnicity				
Hispanic	370	7.4	1,061	9.8
Non-Hispanic	1,287	25.9	7,171	66.5
Not provided	3,318	66.7	2,545	23.6
Total	4,975		10,777	

Note. Chi-Square = 2767.286, *df* = 1, *p* = <.001, phi = 0.419 *p* = <.001

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

Table 14. *Chi-Square Analysis of Ethnicity Post-Propensity Score Matching*

Variable	Treatment		Control	
	n	%	*n*	%
Ethnicity				
Hispanic	192	11.1	203	11.8
Non-Hispanic	967	56.1	857	49.7
Not provided	565	32.8	664	38.5
Total	1,724		1,724	

Note. Chi-Square = 14.915, *df* = 1, *p* = <.001, phi = 0.066 *p* = <.001

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

The chi-square tests of race indicated that there were significant differences before and after matching as shown through Tables 15 and 16. Prior to matching, *p* = <.001 (Table 15); post matching, *p* = <.001 (Table 16). The decrease in the phi, a measure of effective size, from .300 in pre-matching to .205 in post-matching indicates matching evidence the matching technique provide balancing of the groups.

Table 15. *Chi-Square Analysis of Race Pre-Propensity Score Matching*

Variable	Treatment		Control	
	n	%	n	%
Race				
American Indian or Alaska Native	31	0.6	402	3.7
Asian	244	4.9	767	7.1
Black or African American	944	19.0	2,057	19.1
Do not wish to answer	1,348	27.1	782	7.3
Multiple Race	126	2.5	546	5.1
Native Hawaiian or Other Pacific Islander	31	0.6	118	1.1
White	2,204	44.3	5,471	50.8
Not provided	47	0.9	634	5.9
Total	4,975		10,777	

Note. Chi-Square = 1416.673, *df* = 7, *p* = <.001, phi = 0.300 *p* = <.001

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

Table 16. *Chi-Square Analysis of Race Post-Propensity Score Matching*

Variable	Treatment		Control	
	n	%	n	%
Race				
American Indian or Alaska Native	10	0.6	89	5.2
Asian	153	8.9	139	8.1
Black or African American	360	20.9	331	19.2
Do not wish to answer	406	23.5	463	26.9
Multiple Race	94	5.5	89	5.2
Native Hawaiian or Other Pacific Islander	29	1.7	32	1.9
White	663	38.5	504	29.2
Not provided	9	0.5	77	4.5
Total	1,724		1,724	

Note. Chi-Square = 144.382, *df* = 7, *p* = <.001, phi = 0.205 *p* = <.001

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

Further examination of the chi-square tests of standard occupation classification code revealed that there were significant differences before and after matching as shown through p <.001 in Tables 17 and 18. Prior to matching, p = .000 as indicated in Table 17; post matching, p = <.001 (Table 18). The phi, a measure of effective size, from .379 in pre-matching to .456 in post-matching indicates matching on this variable did not add to balancing.

Table 17. *Chi-Square Analysis of Standard Occupation Classification Code Pre-Propensity Score Matching*

	Treatment		Control	
O*Net Standard Occupational Classification	n	%	n	%
15-1121.00: Computer Systems Analyst	190	3.8	2	0.0
15-1122: Information Security Analyst	7	0.1	17	0.2
15-1131: Computer Programmer	0	0	24	0.2
15-1133: Software Developer, Systems Software	0	0	1	0.0
15-1142: Network and Computer Systems Administrator	132	2.7	82	0.8
15-1151: Computer User Support Specialist	0	0	161	1.5
15-1199: Computer Occupation, All Other	1	0	17	0.2
15-1199.09: IT Project Manager	0	0	2	0.0
15-1211: Computer Systems Analyst	287	5.8	210	1.9
15-1212: Information Security Analyst	589	11.8	527	4.9
15-1231: Computer Network Support Specialist	0	0	10	0.1
15-1232: Computer User Support Specialist	397	8.0	1,124	10.4
15-1241: Computer Network Architect	15	0.3	370	3.4
15-1242: Database Administrator	90	1.8	52	0.5
15-1244: Network and Computer Systems Administrator	150	3.0	541	5.0

Table 17. *(continued)*

15-1251: Computer Programmer	346	7.0	2,709	25.1
15-1252: Software Developer	112	2.3	664	6.2
15-1254: Web Developer	0	0	2	0.0
15-1255: Web and Digital Interface Designer	0	0	20	0.2
15-1299: Computer Occupation, All Other	2,613	52.5	3,849	35.7
15-1299.08: Computer Systems Engineers/Architect	0	0	1	0.0
15-1299.09: IT Project Manager	44	0.9	241	2.2
15-2031.00: Operations Research Analyst	0	0	1	0.0
15-2041: Statistician	1	0	19	0.2
15-2051: Business Intelligence Analyst	0	0	5	0.0
15-2099: Mathematical Science Occupation, All Other	1	0	126	1.2
Total	4,975		10,777	

Note. Chi-Square = 2265.243, *df* = 25, *p* = <.000, phi = 0.379 *p* = <.000

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

Table 18. *Chi-Square Analysis of Standard Occupation Classification Code Post-Propensity Score Matching*

O*Net Standard Occupational Classification	Treatment		Control	
	n	%	n	%
15-1121.00: Computer Systems Analyst	0	0	0	0
15-1122: Information Security Analyst	7	0.4	0	0
15-1131: Computer Programmer	0	0	0	0
15-1133: Software Developer, Systems Software	0	0	0	0
15-1142: Network and Computer Systems Administrator	29	1.7	0	0
15-1151: Computer User Support Specialist	0	0	1	0.1
15-1199: Computer Occupation, All Other	0	0	0	0
15-1199.09: IT Project Manager	0	0	0	0
15-1211: Computer Systems Analyst	106	6.1	45	2.6
15-1212: Information Security Analyst	286	16.6	155	9.0
15-1231: Computer Network Support Specialist	0	0	0	0
15-1232: Computer User Support Specialist	389	22.6	124	7.2
15-1241: Computer Network Architect	12	0.7	0	0
15-1242: Database Administrator	47	2.7	34	2.0
15-1244: Network and Computer Systems Administrator	144	8.4	88	5.1

Table 18. *(continued)*

15-1251: Computer Programmer	222	12.9	83	4.8
15-1252: Software Developer	112	6.5	145	8.4
15-1254: Web Developer	0	0	0	0
15-1255: Web and Digital Interface Designer	0	0	0	0
15-1299: Computer Occupation, All Other	336	19.5	711	41.2
15-1299.08: Computer Systems Engineers/Architect	0	0	0	0
15-1299.09: IT Project Manager	32	9.7	240	13.9
15-2031.00: Operations Research Analyst	0	0	0	0
15-2041: Statistician	1	0.1	19	1.1
15-2051: Business Intelligence Analyst	0	0	0	0
15-2099: Mathematical Science Occupation, All Other	1	0.1	79	4.6
Total	1724		1724	

Note. Chi-Square = 718.257, *df* = 14, *p* = <.001, phi = 0.456 *p* = <.001

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

The researcher performed t-tests analysis on the continuous variable of Age at Start to determine whether the means of the two groups were statistically different from each other prior to and after propensity score matching. Results indicated that there was not a statistical difference; *p* < .001 before matching and p < .001 after matching. Tables 19 and 20 indicate these results. Cohen's *d*, a measure of effective size, from .302 in pre-matching to -.018 in post-matching indicates matching evidence the matching technique provide balancing of the groups.

Table 19. *Results of t-test Analysis of Age at Start, Pre-Propensity Score Matching*

	Treatment		Control				
df	*M*	*SD*	*M*	*SD*	*t*	*p*	*d*
10389.927	31.985	10.2841	33.104	9.5147	-6.683	<.001	-.111

Note. Cohen's *d* uses the pooled standard deviation.

Equal variances not assumed.

Table 20. *Results of t-test Analysis of Age at Start, Post-Propensity score matching*

	Treatment		Control				
df	*M*	*SD*	*M*	*SD*	*T*	*p*	*d*
3446	33.078	11.0159	33.295	8.7172	-.642	<.001	-.022

Note. Cohen's *d* uses the pooled standard deviation

T-test analysis on the continuous variable of Starting Wage indicated that there was a statistical difference before and after matching. Results showed that prior to matching p < .001 and after matching $p = .125$. Tables 21 and 22 indicate these results. The decrease in the Cohen's *d*, a measure of effective size, from .302 in pre-matching to -.018 in post-matching indicates matching evidence the matching technique provide balancing of the groups.

Table 21. *Results of t-test Analysis of Starting Wage, Pre-Propensity Score Matching*

	Treatment		Control				
df	*M*	*SD*	*M*	*SD*	*t*	*p*	*d*
5424.784	12412.0861	23316.0312	5730.5246	18680.1269	14.095	<.001	.302

Note. Cohen's *d* uses the pooled standard deviation.
Equal variances not assumed.

Table 22. *Results of t-test Analysis of Starting Wage Post-Propensity Score Matching*

	Treatment		Control				
df	*M*	*SD*	*M*	*SD*	*t*	*p*	*d*
3446	7418.6114	19151.0406	7784.5240	21441.7617	-.528	.125	-.018

Note. Cohen's *d* uses the pooled standard deviation.

Equal variances not assumed.

The researcher performed *t*-test analysis on the propensity scores before and after matching to determine the match's success. If the propensity scores are balanced between groups and there are no significant statistical differences between the propensity scores after the match, then the propensity score matching was successful. The results in Tables 23 and 24 indicated that the propensity score match was successful. The decrease in the Cohen's *d*, a measure of effective size, from -1.509 in pre-matching to -.126 in post-matching indicates matching evidence the matching technique provide balancing of the groups.

Table 23. *Results of t-test Analysis of Propensity Score, Pre-Propensity Score Matching*

	Treatment		Control				
df	*M*	*SD*	*M*	*SD*	*t*	*p*	*d*
3189.583	.1884079	.16896792	.4919138	.26954503	-52.069	.000	-1.509

Note. Cohen's *d* uses the pooled standard deviation.

Equal variances not assumed.

Table 24. *Results of T-Test Analysis of Propensity Score, Post-Propensity Score Matching*

	Treatment		Control				
df	*M*	*SD*	*M*	*SD*	*T*	*p*	*d*
3446	.3374698	.21525135	.3645519	.21349663	-3.709	.947	-.126

Note. Cohen's d uses the pooled standard deviation.

Equal variances not assumed.

The researcher used chi-square analysis to determine the completion rate of veterans and nonveterans in IT apprenticeship programs. The analysis revealed a statistical difference for the two group before and after matching as indicated in Tables 25 and 26. Of the 1,724 veterans, 58.6% (n=1011) complete while only 31.9% (n=550) of the 1,724 nonveterans completed.

Table 25. *Chi-Square Analyses of Completion Pre-Propensity Score Matching*

	Treatment		Control	
Completion	*n*	%	*n*	%
Not Completed	2,728	54.8	5,608	52.0
Completed	2,247	45.2	5,169	48.0
Total	4,975		10,777	

Note. Chi-Square =10.691, *df* = 1, *p* = .001, phi = -.026, *p* = .001

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

Table 26. *Chi-Square Analyses of Completion Post-Propensity Score Matching*

Completion	Treatment		Control	
	n	%	*n*	%
Not Completed	713	41.4	1,174	68.1
Completed	1,011	58.6	550	31.9
Total	1,724		1,724	

Note. Chi-Square = 248.768, *df* = 1, *p* = <.001, phi = .269, *p* = <.001

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

T-tests were also conducted on the outcome variable of salary. Tables 27 and 28 show the results of the analysis, pre- and post-matching. In both cases, there was a significant difference in the exit salary. On average veterans made over $13,000 more than non-veterans.

Table 27. *Apprentice Exiting Salary, Pre-Propensity Score Matching*

	Treatment		Control				
df	*M*	*SD*	*M*	*SD*	*t*	*p*	*d*
4297	56,516.21	21419.50	46,705.81	24206.98	-15.943	<.001	-.420

Note. Cohen's *d* uses the pooled standard deviation

Equal variances not assumed

Table 28. *Apprentice Exiting Salary, Post-Propensity Score Matching*

	Treatment		Control				
df	*M*	*SD*	*M*	*SD*	*t*	*p*	*d*
1618	59,711.57	2446.12	46,529.39	31737.42	-10.471	<.001	-.476

Note. Cohen's *d* uses the pooled standard deviation.

Equal variances not assumed

Summary

Chapter 4 presented the research study's results using propensity score matching to determine the impact of veteran status on the completion rate and salary of IT apprentices in registered apprenticeship programs. The study utilized data reported to The Registered Apprenticeship Partners Information Data System (RAPIDS). By examining two groups, veteran IT apprentices and nonveteran IT apprentices, and their completion rates of registered apprenticeship programs in the IT Career Clusters and resulting salaries, the researcher was able to detect what, if any, was the effect of veteran status on the completion rate and salary. The logistic regression model provided a good fit in determining that the variables of ethnicity, gender, race, age at start, starting wage, and standard occupation classification code were statistically reliable in predicting membership in veteran status (dependent variable). With the exception of standard occupational classification code, each of the covariates. were good variables to base matching on. Because it can be challenging to determine if group differences are based on preexisting differences in group characteristics or based on the treatment (Frye, 2016), propensity score matching allowed the researcher to control for selection bias and to estimate the effect of veteran status on the completion and salary of IT apprenticeship programs. Discussion of these findings is presented in Chapter 5.

Chapter 5: Discussion of Findings

Summary of Findings

This research study examined the impact of veteran status on the completion and earnings of apprentices in registered IT apprenticeships. The researcher explored if veterans were more successful than nonveterans in IT apprenticeships. The goal of the findings was to allow the investigation into what and why, if anything, makes veterans more successful than nonveterans in IT apprenticeships to begin. Ultimately, the results from this study will better inform the literature on the factors that contribute to the successful completion of registered IT apprenticeship programs and serve as a crucial first step in understanding the impact of veteran status, if any, on apprentices in IT occupations.

The U.S. Department of Labor (2019) provided aggregate data and evidence to suggest that veterans who participate in registered apprenticeship programs are also successful in completing these programs. This evidence similarly correlates to the success experienced by all individuals who participate in registered apprenticeship programs (Lerman, 2010). However, there was little current research that explored veterans' completion in registered apprenticeship programs, and specifically IT apprenticeships, versus nonveterans in similar programs, to examine the effect of veteran status on completion and ending salary.

Chapter five presents this research study's findings from examining the effect of veteran status on the completion and earnings of IT apprentices. The primary purpose of this study was to examine the completion rate and salary of veterans in registered IT apprenticeship programs versus nonveterans in similar programs using propensity score matching. According to Caliendo and Kopeinig (2008), propensity score matching addresses

the problem of selection bias. For this study, the researcher desired to know the outcomes of apprentices with veteran status compared to a control group of apprentices who were not veterans by implementing the balancing technique of propensity score matching. The researcher used the following covariates to match veterans and nonveterans: gender, ethnicity, race, age at start, starting wage, and standard occupational classification code. Once matched, an artificial control group of nonveterans was created. This process of matching apprentices who were veterans (treatment group) with apprentices who were not apprentices (control group) helped control for selection bias. The artificial control group allowed for IT apprentices with similar characteristics to be compared using these matches. For this study, the participants were IT apprentices from registered apprenticeship programs, with or without veteran status and the matching variables were part of the existing data from the RAPIDS (U.S. Department of Labor, 2019) system.

Three research questions guided this study:

RQ1. What are the demographics of the two groups (veteran IT apprentices and nonveteran IT apprentices) prior to matching?

RQ2. After propensity score matching, is there a difference in demographics of the two study groups?

RQ3. Is there a difference in the completion and ending salary of IT apprenticeships between veteran and nonveteran apprentices?

Using two theoretical frameworks: signaling theory (Spence, 1973) and human capital theory (Schultz, 1961), the researcher sought to identify whether military training could be considered a pathway with comparable outcomes in terms of completion of apprenticeship programs and salary for veterans. This study explored one specific

postsecondary training model to understand if veterans who participate in apprenticeship programs yield a similar return on investment in terms of completion and earnings success indicators as nonveterans. This study aimed to provide a deeper understanding of veterans' participation in apprenticeships and provide knowledge that will inform those stakeholders in veteran transition programs, organizational leaders in desperate need of a workforce in IT industries, and those industries that utilize IT occupations.

The use of propensity score matching proved to be an effective quantitative methodology. It allowed the researcher to control for selection bias across several demographic covariates so that only the treatment results were evident (Powell et al., 2019). According to Austin (2008), "Propensity-score methods are increasingly being used to reduce the impact of treatment-selection bias in the estimation of causal treatment effects using observational data" (Austin, 2008, p. 2038).

In the context of this study, propensity score methods allowed the researcher to match two groups on demographic data so that the veteran status could be isolated between the groups. After prescreening for missing data and reporting irregularities, the researcher executed logistic regression analyses to determine the factors that explained membership in the two comparison groups. Analyzing the Nagelkerke R^2, chi-square, beta coefficients, and p values helped identify the significant predictors and covariates to retain in the model. Ultimately, the six independent variables: ethnicity, gender, race, age at start, starting wage, and standard occupational classification code were retained as they were connected with the dependent variable of veteran status (-2 Log Likelihood = 7812.306; chi-square = 2762.003, $p < .001$; Nagelkerke $R^2 = .382$). The model correctly classified 81.8% of the cases and explained 38.2% of the variance in the dependent variable. This chapter provides a summary,

interpretation, and discussion based on each of the study's research questions, delineating conclusions and recommendations for policy and practice.

Research Question 1

Research Question 1 asked, "*What are the demographics of those that participated in IT apprenticeships from the RAPIDS database and what are the demographics of the participants when disaggregating by veteran and nonveteran status (Veteran IT apprentices and nonveteran IT apprentices demographics)?"*

Examination of the demographics prior to matching revealed that IT apprentices were overwhelmingly male in both the control and treatment groups. Of the 10,777 apprentices included in the analytical sample, 80.9% of the treatment group (n = 4,023) and 71.7% of the control group (n = 7,726) were males. Additionally, both groups indicated White as their highest race category (n = 2204; [44.3%] for the treatment group; n = 5,471; [50.8%] for the control group), followed by Black or African American, in which both categories for the treatment and control groups were similar in percentages (veterans, 19.0%; nonveterans 19.1%). Nonveterans were 3.7 times more likely to indicate that they did not wish to answer information about their race, whereas the control group was 6.5 times more likely to leave the response blank.

Similarly, 66.7% of veteran apprentices did not provide their ethnicity, whereas 66.5% of nonveteran apprentices indicated that they were non-Hispanic. Both groups reported similar results for Hispanic ethnicity; 7.4% (n = 370) of veterans identified as Hispanic and 9.8% (n = 1061) of nonveterans were Hispanic. Both groups reported an average age between 32–33; (veterans, M=33.104; nonveterans, M=31.985) respectively.

Research Question 2

Research Question 2 asked, **"***After propensity score matching, is there a difference in demographics of the two study groups?"* Results of the propensity score matching analysis revealed that although the treatment and control groups of IT apprentices were matched successfully, the following observations were made concerning their demographics post-matching:

Overall, IT apprentices were more likely to be male than female (71.6% and 74.9%, veteran and nonveteran, respectively). However, data indicated more female veteran IT apprentices (n = 490) than nonveterans (n = 432).

- Overall, IT apprentices were more likely to be male than female (veterans, 71.6%; nonveterans, 74.9%). However, data indicated more female veteran IT apprentices (n = 490) than nonveterans (n = 432).
- There were more American Indian or Alaska Native veteran IT apprentices (n = 89) than nonveteran (n = 10).
- Similar numbers of apprentices listed their race as Native Hawaiian or Other Pacific Islander (veterans, n = 32; nonveterans, n = 29) or identified as multiple-race (veterans, n = 89; nonveterans, n = 94) between the treatment and control groups.
- The average age of IT apprentices was 33 for veterans (M = 33.078) and nonveterans (M = 33.294).
- After post-matching, apprentices were more likely to be non-Hispanic (veterans, 49.7%; nonveterans, 56.1%).

- Veterans (22.6%) indicated they worked as computer user support specialists in their apprenticeship program; 7.2% of nonveterans indicated the same.
- Veterans were 2.6875 times more likely to work as computer programmers in their registered apprenticeship programs vs. nonveterans and 2.35 times more likely to be computer systems analysts.
- Veterans were less likely to be IT project managers

Research Question 3

Research Question 3 asked, **"***Is there a difference in completion and ending salary of IT apprenticeships between veteran and nonveteran apprentices?"* Examination of IT apprentices' completion revealed that veterans were less likely to complete the registered apprenticeship programs prior to propensity score matching. However, post-matching results indicated that veterans were much more likely to complete their registered IT apprenticeship programs than nonveterans when matched on the identified covariates of ethnicity, gender, race, age at start, starting wage, and standard occupational classification code.

Prior to matching, only 45.2% of veterans reported completing their registered IT apprenticeship program, whereas 48% of nonveterans completed. However, after matching, 58.6% of veterans in IT apprenticeships completed, as opposed to 31.9% of nonveterans. In addition to completing the IT apprenticeships at higher rates, the veterans reported higher exit wages and salaries than nonveterans.

Implications for Theory

Two theoretical frameworks were used to guide this study: human capital theory (Schultz, 1961; Becker, 1964) and signaling theory (Spence, 1973). Findings from this study align with the positive correlation between wages and education, indicating that military

training and education can be used as a signal to theorize success and increased wages in the workforce.

Becker (1964) discussed that on-the-job training is how workers increase their productivity, learn new skills, and perfect old ones. Additionally, Becker (1964) offered distinction between general and specific training, explaining that the productivity and skills gained in general training allows for skill transferability when workers move from one place of employment to the next. Specific on-the-job training, on the other hand, has a stronger benefit to a company directly.

In using the military as an illustration, Becker (1964) explained that veterans experience and benefit from both types of training as the military offers some skills that are very useful in the civilian sector and some that are specific to military service. Furthermore, Page (2010) explained that terms signaling, screening, and sorting are often used interchangeably to describe variants of the same basic model.

In this case, military service simultaneously enhanced veterans' productivity and acted as a signal about their ability to complete registered IT apprenticeships. The results also showed that veterans also earn higher wages than nonveterans in these registered apprenticeship programs, signifying the value of military training as a means of human capital. Furthermore, the results supported the following findings.

Finding 1: Veteran Status as a Signal and Success Metric for IT Apprenticeship

Signal theory (Spence, 1973) states that "in most job markets the employer is not sure of the productive capabilities of an individual at the time he hires them" (p. 356). Employers can, however, observe certain characteristics and attributes of the individual that ultimately determine their assessment of the investment. These "observable, personal attributes that

collectively constitute the image the job applicant presents" include both fixed and alterable characteristics (Spence, 1973, p. 357). Race and sex, for example, would be fixed, while education would be alterable. Observable characteristics that are alterable are referred to as signals, with these signals regarded as parameters in shifting conditional probability distributions that define an employer's beliefs (p. 358).

Spence (1973) assumed that signaling costs are negatively correlated with productivity and "most appropriately viewed as a prerequisite for an observable, alterable characteristic to be a persistently informative signal in the market" (p. 359). What this infers is that a characteristic may be a signal with respect to some jobs, but not with others. This study found that veteran status in IT apprenticeship programs could be associated with higher completion and resulting wages. This finding aligns with signaling theory (Spence, 1973) by indicating that veteran status could be a signal and success metric for IT apprenticeships.

Finding 2: Military Training and Higher Earnings in IT Apprenticeships

Human capital theory (Schultz, 1961) has been the dominant theory used in research seeking to understand the value of education and training by stressing that each are investments with positive future returns (Benjamin et al., 1998). As a result, individuals typically decide to acquire learning and training with the expectation that they will experience increased future earning potential (Schultz, 1961). This learning, however, is not limited to formal education, as Schultz (1961) concentrated his insights on major categories, including, but not limited to, "old-style apprenticeship organized by firms, formally organized education at the elementary, secondary, and higher levels, study programs for adults that are not organized by firms" (p. 9).

Furthermore, apprenticeship, as a training model, has been instrumental to workforce development by teaching mastery of many kinds of occupational and work-related skills (Lerman, 2010). Though some have viewed apprenticeship as pathway into blue-collar industries, researchers assert that it can be used for white-collar professions such as information technology (Fuller and Sigelman, 2017), particularly as the United States leverages innovation and challenges its traditional view of talent to fill the skills gap (Meritosis, 2015).

Along those same lines, the continued creation and support of high-quality pre-apprenticeship programs, which are designed to create seamless paths and pipelines to registered apprenticeships, has allowed for individuals to enter and succeed in Registered Apprenticeship Programs. This in turn, has allowed participants to learn, work, and earn in order to compete and thrive in a middle-class workforce. Thus, pre-apprenticeship programs serve as an important precursor to registered apprenticeships.

Furthermore, there is guidance to determine the nature of a high-quality pre-apprenticeship. Jobs for the Future's framework for pre-apprenticeship outlines that high-quality pre-apprenticeship programs have six elements: transparent entry and success requirements; alignment with in-demand skills; culminate in industry-recognized credentials; teach skill development through work-based learning; offer academic, career, and other supports; and facilitate the successful transition into registered apprenticeship programs (Allen et al., 2019).

The military, by nature of its structure, innately possesses many of these elements. Entry and success requirements are made clear by way of ASVAB testing and the promotion and rank frameworks. Servicemembers are assigned place-based or sector-based job

specializations based on need and supported with the relevant skills training. Career-placement, housing, and other wrap-around supports are also provided, as well as opportunities for soldiers to transition into registered apprenticeship programs.

This study found that veteran status in IT apprenticeships, and thus, military training, is associated with higher earnings. This finding suggests merit not only in the just-in-time training model of the armed forces, but also support for the notion that military training operates with similar strengths to high-quality pre-apprenticeships.

Implications for Human Capital Theory

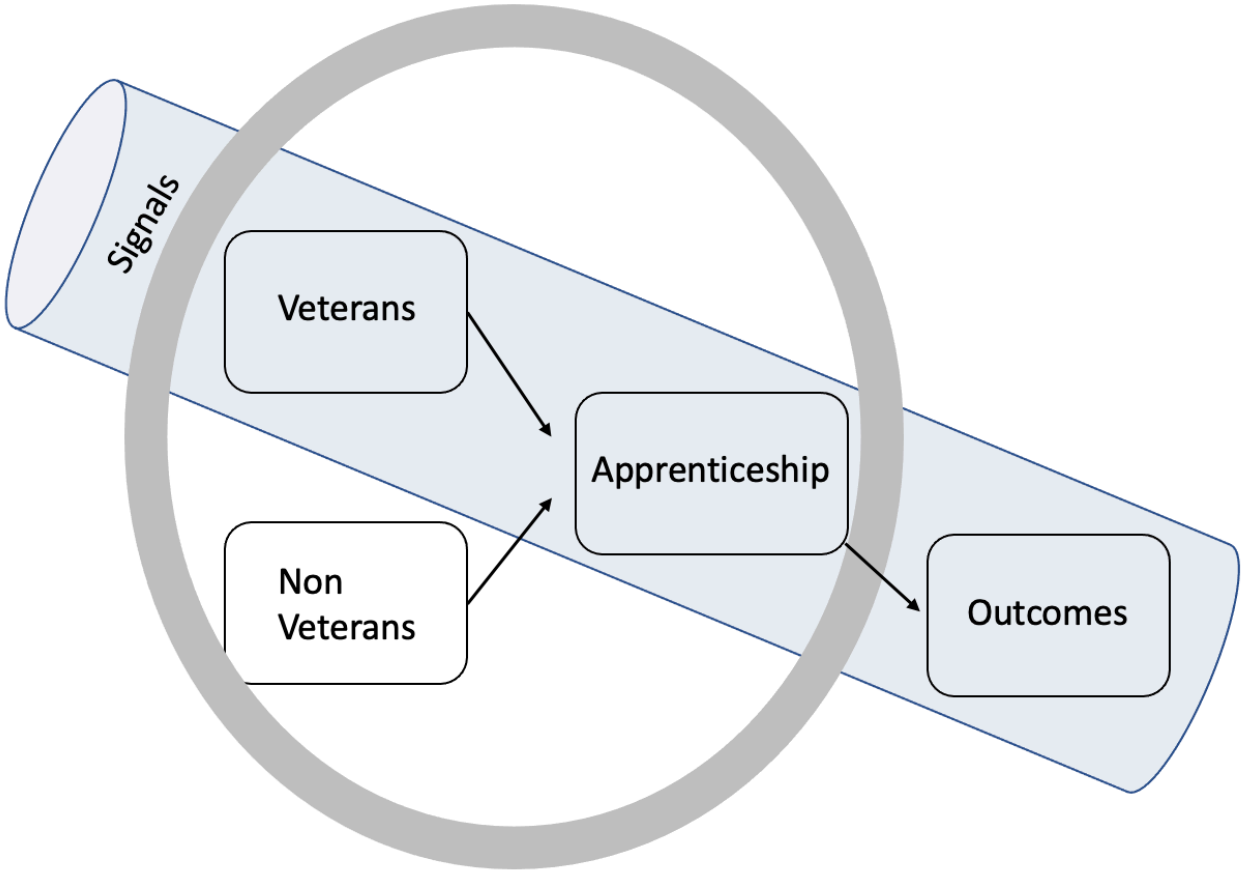
The findings of this study support human capital theory and the notion that there is a positive correlation between training and earnings. Veterans, by nature of their designation and the training that results from serving in the armed forces, completed registered IT apprenticeship programs at much higher rates than nonveterans, when matched on demographic covariates so that the effect of veteran status, as a treatment, could be statistically isolated. This was proven, despite the fact that during pre-matching the opposite occurred. That is, prior to matching, results revealed that the groups experienced similar levels of success, with the control group of nonveterans completing registered IT apprenticeship at a slightly higher rate than veterans.

Implications for Signaling Theory

The findings of this study support signaling theory (Spence, 1973) by indicating that there is merit in veteran status as a signal for the traits, competencies, and skillset needed for the in-demand jobs of the future in IT. Whereas some of the literature concerning veterans' employment focuses on their uniqueness from a deficit-model–veterans present with issues that make it difficult for them to transition into the civilian workforce (Figinski, 2017;

Keeling et al., 2019)—other research proves the opposite (Sharp (2018). Veterans are a talented group and possess the leadership, critical thinking, and soft-skills needed for the in-demand IT jobs. Figure 6 displays this concept in relation to this study.

Figure 6. Human Capital and Signaling of Veteran Status in Registered IT Apprenticeship



This study limited the examination of veteran status as human capital and a form of signaling to registered IT apprenticeships, specifically. Success in these registered IT apprenticeships was determined by the apprentices' completion and ending salary outcomes.

Military training, as a form of human capital and workforce development (Scultz, 1961) attracts and shapes certain traits in individuals that are carried beyond service and into civilian life. When veterans transition out of the military to education and workforce settings, they bring with them a strong requisite skill set that includes leadership, teamwork, character, discipline, and resiliency Constantine (2018),

Implications for Practice

The findings and results of this study revealed a few things that have implications for stakeholders in veteran transition programs, organizational leaders in desperate need of a workforce in IT industries, and those industries that utilize IT occupations.

Implication for Practice 1: Development of Veteran to Apprenticeship Pipeline

Given the results of this study that indicate the success of veterans in IT apprenticeship programs, stakeholders should continue to support the development of a veteran to apprenticeship pipeline. In this study, veteran status served as a positive signal for IT apprenticeship and could potentially be used to inform veterans' success in other apprenticeable occupations. As such, continued investment in registered apprenticeships and specifically those who identify veterans as a target recruiting group could be beneficial for the talent pipeline.

Implication for Practice 2: Veteran Preference in Apprenticeship Programs

Veteran status could not only serve as a signal for investment in the veteran to apprenticeship pipeline, but also as a signal that veteran status might be a preference to consider when recruiting for other registered apprenticeship programs. As Fuller and Sigelman (2017) have proven, there is opportunity to expand registered apprenticeships to other Booster and Expander occupations. Results from this study indicate that veterans are a

skilled and talented group and supports the business case for not only hiring veterans, but recruiting them specifically.

Recommendations for Future Research

The findings of this research study examining the effect of veteran status on apprentices' completion and salary in registered IT apprenticeship revealed that veteran status could be considered a signal and success metric for the completion and earnings in IT apprenticeships. The study also found that military training is correlated with higher earnings in IT apprenticeships. Based on the study's results and these findings, the researcher recommends the following potential projects for future research.

Recommendation 1: Replicate with Other Apprenticeship Occupations

This study focused on registered IT apprenticeships based on the standard occupation codes used to classify industries and jobs. However, IT is only one of many industries and occupational classifications available for exploration. Furthermore, Fuller and Sigelman (2017) identified several industries for apprenticeship expansion, including, but not limited to: tax preparers, customer service representatives, claims adjusters, insurance underwriters, graphic designers and human resource specialists.

The researcher suggests exploring veterans vs. nonveterans' success in other registered apprenticeship programs based on other career clusters to determine if similar results are found. Partnering with local organizations, such as the National Fund or ApprenticeshipNC may be beneficial in locating programs to investigate. Apprenticeships have expanded to various fields and are no longer confined to low-wage trades. Expanding future research outside of the existing context and dataset used for this study will provide a variety of lenses to look at the impacts of veteran apprentices.

Recommendation 2: Propensity Score Match on Demographic Data

This study used propensity score matching as a methodology to compare two groups: veterans vs. nonveterans in registered apprenticeship programs. By matching on the demographic data of gender, race, ethnicity, and other variables that included the apprentices' age at start, beginning wage, and standard occupation code, the researcher was able to control for selection bias and isolate the treatment effect of veteran status. This proved to be successful in understanding the effect of veteran status on the completion and ending salary of apprentices in registered IT apprenticeship programs, but is only one approach to understanding the potential effects of other pairings. The researcher recommends exploring other groupings: gender; race; ethnicity, and education level, for example, to explore their effect on further completion and ending wages in registered apprenticeship programs. Studies that examine matching on race can help further understand the potential impacts, positive or negative, of apprenticeships and equity. Examining the connection between other characteristics and apprenticeships as a future research project will help highlight positive impacts and brings attention to areas that need to be challenged and improved.

Recommendation 3: Longitudinal Qualitative Study

In order to further understand the lived experiences with the components of prior military participation, a longitudinal qualitative study could be conducted to track military experiences. This type of study would be helpful to further examine how those lived experiences translate into the apprenticeship and beyond. Understanding there is a difference between veterans and nonveterans in apprenticeship programs is only the beginning. As researchers dig deeper into the why and how we can use those findings to expand the success

rates for apprenticeship programs in nonveteran populations by creating purposeful experiences for them that will mirror the results from our veteran groups.

Recommendation 4: Military Experience Alignment with Pre-apprenticeship Experience

Given that many service members enlist immediately after high school, the military can be credited with providing the occupational training necessary for soldiers to perform their jobs effectively (Hanson & Lerman, 2016), especially considering that service members prepare for their occupations by taking classes, learning by doing, and contributing to production while earning a wage (Hanson & Lerman, 2016).

The military's model of training closely resembles a pre-apprenticeship framework by including elements similar to those mentioned above. Through ASVAB testing and promotion and rank frameworks, the military has provided transparent entry requirements. Job specializations are based on soldiers' MOS codes and are assigned based on need; furthermore, soldiers are supported with relevant hands-on skills training. The military also provides appropriate wraparound supports and resources, including housing, uniforms, and other services. Therefore, the military, like pre-apprenticeship programs, provides a bridge to career opportunities and effectively prepares underrepresented populations for high-quality employment opportunities by increasing diversity and equity in the workforce systems (Allen et al., 2019). More research could be conducted to help develop and provide resources for the military's pre-apprenticeship framework.

Conclusion

Long before higher education and postsecondary pathways existed, apprenticeship was a proven training model to support workforce development. This training was used in myriad disciplines and industries, from manufacturing to law. However, changes in

traditional career and technical education offered at the secondary level, along with the emergence of the postsecondary pathways that lead to bachelor's and higher degrees moved this training model to the background. Recent issues in higher education, including dissatisfactory student success data and the student loan debt crisis, have allowed this apprenticeship training model to re-enter the forefront as the government recognizes the value of apprenticeships by investing millions of dollars in grants for registered apprenticeship programs.

Additionally, stakeholders are recognizing that the apprenticeship framework can be used to train for the IT jobs of the future quickly and reliably as a way to mitigate the skills gap. Furthermore, the value of veterans as a talent pool is being considered and leveraged for many of these apprenticeships. It was not until the GI Bill that soldiers were even recognized for their talent or afforded the opportunity to become educated. However, even this realization leaves a gap because it does not explore the idea that perhaps veterans were already educated and highly trained in the armed forces. Conceivably their military training and education contribute to veterans' success in the civilian workforce and in apprenticeships programs. This study exploring veterans' success in these registered apprenticeship programs allowed for a closer examination of the value and benefits of military training in terms of human capital, signaling, or both, that can be used to inform decisions for other apprenticeship programs.

Chapter Summary

Chapter Five presented a discussion of the results, findings, and implications for this study by examining the completion rate and salary of veterans in registered IT apprenticeship programs compared to nonveterans in similar programs using propensity score matching. The

matching of two equivalent groups of apprentices from these apprenticeship programs, with or without veteran status, using existing data from RAPIDS revealed that veterans experience greater levels of completion of registered IT apprenticeship programs, and earn higher wages when they complete.

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APPENDICES

Appendix A: Information Technology Career Clusters and O*Net SOC Code Frequencies Identified in RAPIDS Dataset

O*Net Standard Occupation Classification Code	Occupation	*n*
15-1121.00*	Computer Systems Analyst	196
15-1122.00*	Information Security Analyst	24
15-1131.00*	Computer Programmer	24
15-1133.00*	Software Developer, Systems Software	1
15-1142.00*	Network and Computer Systems Administrator	214
15-1511.00*	Computer User Support Specialist	161
15-1199.00*	Computer Occupation, All Other	18
15-1199.09*	Information Technology Project Manager	2
15-1211.00	Computer Systems Analyst	523
15.1211.01	Health Informatics Specialist	0
15.1212.00	Information Security Analyst	1,186
15-1231.00	Computer Network Support Specialist	10
15-1232.00	Computer User Support Specialist	1,712
15-1241.00	Computer Network Architects	458
15-1241.01	Telecommunications Engineering Specialist	0
15-1242.00	Database Administrator	172
15-1243.00	Database Architect	0
15-1243.01	Data Warehousing Specialist	0
15-1244.00	Network and Computer Systems Administrator	880
15-1251.00	Computer Programmer	3,243
15-1252.00	Software Developer	1,264
15-1253.00	Software Quality Assurance Analyst and Tester	0
15-1254.00	Web Developer	3
15-1255.00	Web and Digital Interface Designer	23
15-1255.01	Video Game Designer	0
15-1299.00	Computer Occupation, All Other	6,542
15-1299.01	Web Administrator	0
15-1299.02	Geographic Information Systems Technologists and Technician	0
15-1299.03	Document Management Specialist	0
15-1299.08	Computer Systems Engineers/Architect	1
15-1299.09	Information Technology Project Manager	297
15-2031.00	Operations Research Analyst	1
15-2041.00	Statistician	20
15-2051.01	Business Intelligence Analyst	34
15-2099.00	Mathematical Science Occupation, All Other	127

Note. $N = 17{,}136$

Appendix B: Program Registration and Apprenticeship Agreement (ETA 671)

Program Registration and Apprenticeship Agreement
Office of Apprenticeship

U.S. Department of Labor
Employment and Training Administration

APPRENTICE REGISTRATION – SECTION II OMB No. 1205-0223 Expiration Date: 03/31/2023

This agreement does not constitute a certification under Title 29 Code of Federal Regulations (CFR) Part 5 for the employment of the apprentice on Federally financed or assisted construction projects. Current certifications must be obtained from the Office of Apprenticeship (OA) or the recognized State Apprenticeship Agency.

The program sponsor and apprentice agree to the terms of the Apprenticeship Standards incorporated as part of this agreement and in accordance with Title 29 CFR Parts 29 and 30. The sponsor's Apprenticeship Standards are attached and hereby incorporated into this agreement as they exist on the date of the agreement. These Standards may be amended during the period of this agreement with the consent of the parties to the agreement. This agreement may be terminated by either of the parties, citing cause(s), with notification to the registration agency, in compliance with Title 29 CFR Part 29.

PART A: TO BE COMPLETED BY APPRENTICE. NOTE TO SPONSOR: PART A SHOULD ONLY BE FILLED OUT BY APPRENTICE.

1. Name (Last, First, Middle) and Address *Social Security Number
– –
(No., Street, City, State, Zip Code, Telephone Number)

2. Date of Birth (Mo., Day, Yr.)

3. Sex (Mark one) ☐ Male ☐ Female

Answer Both A and B (Voluntary) (Definitions on reverse)

4. a. Ethnic Group (Mark one)
☐ Hispanic or Latino
☐ Not Hispanic or Latino

b. Race (Mark one or more)
☐ American Indian or Alaska native
☐ Asian
☐ Black or African American
☐ Native Hawaiian or other Pacific Islander
☐ White

5. Veteran Status (Mark one)
☐ Non-Veteran
☐ Veteran

6. Education Level (Mark one)
☐ Less than 9th grade
☐ 9th to 12th grade, no diploma
☐ High School graduate or GED
☐ Some College or Associate's degree
☐ Bachelor's degree
☐ Master's degree
☐ Doctorate or Prof. degree

7a. Employment Status (Mark one) ☐ New Employee ☐ Existing Employee

7b. Career Connection (Mark one) (Instructions on reverse) ☐ None ☐ Pre-Apprenticeship ☐ Technical Training School ☐ Military Veterans
☐ Job Corps ☐ YouthBuild ☐ HUD/STEP-UP ☐ Career Center Referral ☐ School-to-Registered Apprenticeship

8. Signature of Apprentice Date

9. Signature of Parent/Guardian (if minor) Date

PART B: SPONSOR: EXCEPT FOR ITEMS 6, 7, 8, 10a. - 10c, REMAINDER OF ITEMS REPOPULATED FROM PROGRAM REGISTRATION.

1. Sponsor Program No.
Sponsor Name and Address (No. Street, City, County, State, Zip Code)

2a Occupation (The work processes listed in the standards are part of this agreement).

2b Occupation Code:

2b.1. Interim Credentials Only applicable to Part B, 3.b. and 3.c. (Mark one) ☐ Yes ☐ No

3. Occupation Training Approach (Mark one)
3a. ☐ Time-Based
3b. ☐ Competency-Based
3c. ☐ Hybrid

4. Term (Hrs., Mos., Yrs.)

5. Probationary Period (Hrs., Mos., Yrs.)

6. Credit for Previous Experience (Hrs., Mos., Yrs.)

7. Term Remaining (Hrs., Mos., Yrs.)

8. Date Apprenticeship Begins

9a. Related Instruction (Number of Hours Per Year)

9b. Apprentice Wages for Related Instruction ☐ Will Be Paid ☐ Will Not Be Paid

9c. Related Training Instruction Source

10. Wages: (Instructions on reverse)

10a. Prior Hourly Wage $ 10b. Apprentice's Entry Hourly Wage $ 10c. Journeyworker's Hourly Wage $

Check Box	Period 1	2	3	4	5	6	7	8	9	10
10d. Term ☐ Hrs., ☐ Mos., or ☐ Yrs.										
10e. Wage Rate (Mark one) % ☐ or $ ☐										

11. Signature of Sponsor's Representative(s) Date Signed

12. Signature of Sponsor's Representative(s) Date Signed

13. Name and Address of Sponsor Designee to Receive Complaints

PART C: TO BE COMPLETED BY REGISTRATION AGENCY

1. Registration Agency and Address

2. Signature (Registration Agency)

3. Date Registered

4. Apprentice Identification Number (Definition on reverse):

Appendix C: NCSU IRB Application Submission

NORTH CAROLINA STATE UNIVERSITY
INSTITUTIONAL REVIEW BOARD FOR THE USE OF HUMAN SUBJECTS IN RESEARCH
SUBMISSION FOR NEW STUDIES

Protocol Number 23737

Project Title

Exploring the Impact of Veteran Status on Completion of White Collar Apprenticeships: A Propensity Score Match

IRB File Number:

Original Approval Date:

Approval Period

- 01/01/2100

Source of funding (provide name of funder not account number):

NCSU Faculty point of contact for this protocol:NB: only this person has authority to submit the protocol

Bartlett, Michelle E: Educational Leadership, Policy, and Human Development (ELPHD)

Does any investigator associated with this project have a significant financial interest in, or other conflict of interest involving, the sponsor of this project? (Answer No if this project is not sponsored)

No

Is this conflict managed with a written management plan, and is the management plan being properly followed?

No

Preliminary Review Determination

Category:

In lay language, briefly describe the purpose of the proposed research and why it is important. Provide a brief synopsis of the study including who is targeted to participate and the data collection methods employed (limit text to 1500 characters)

The purpose of this study will be to examine the completion rate of veterans in white-collar apprenticeship programs versus non-veterans in similar programs using propensity score matching. The researcher will match two equivalent groups of apprentices on the propensity of completion of these apprenticeship programs, with or without veteran status, using existing data from The Registered Apprenticeship Partners Information Management Data Systems (RAPIDS).

If any investigator on the project (or the spouse, domestic partner or any members of the investigator's immediate family who reside in the same household) has a financial or other type of conflict of interest that could potentially affect the design, conduct, or reporting of this research project, please describe the conflict of interest here or indicate that it has been fully disclosed in the investigator's most recent COI disclosure filed with NC State. If your team does not have any

conflicts of interest,

please respond with N/A. If you are uncertain how to respond or have questions, please contact coi-noi-compliance@ncsu.edu.

N/A

My research qualifies for Exemption. Exempt research is minimal risk and must fit into the categories d.1 - d.8 found here: http://www.hhs.gov/ohrp/humansubjects/guidance/45cfr46.html

1

Is this research being conducted by a student?

Yes

Is this research for a thesis/dissertation/capstone?

Yes

Is this research for a dissertation?

No

Is this independent research?

No

Is this research for a course?

No

Do you currently intend to use the data for any purpose beyond the fulfillment of the class assignment?

No

Please explain

If so, please explain

If you anticipate additional NCSU-affiliated investigators (other than those listed on the Title tab) may be involved in this research, list them here indicating their name and department.

N/A

Will the investigators be collaborating with researchers at any institutions or organizations outside of NC State?

No

List collaborating institutions and describe the nature of the collaboration. If researchers from both institutions are doing any of the following activities: recruitment, consent process, data collection or handling of identifiable information/specimens a reliance agreement may be appropriate. For more information, please contact irb-coordinator-admin@ncsu.edu

What is NCSU's role in this research?

Describe funding flow, if any (e.g. subcontractors)

Is this international research?

No

Identify the countries involved in this research

An IRB equivalent review for local and cultural context may be necessary for this study. Can you recommend consultants with cultural expertise who may be willing to provide this review? Consultants may not be a part of the research team or have a stake in the research project. Provide email contact information for consultant(s). A local context review may lengthen the time it takes for your approval.

Adults 18 - 64 in the general population?

Yes

NCSU students, faculty or staff?

No

Adults age 65 and older?

No

Minors (under age 18--be sure to include provision for parental consent and/or child assent). If minors are included in your research, please read through the NC State University Regulation for your additional responsibilities. Following this regulation is a requirement of your affiliation with NC State.?

No

List ages or age range:

Could any of the children be "Wards of the State" (a child whose welfare is the responsibility of the state or other agency, institution, or entity)?

No

Please explain:

Prisoners (any individual involuntarily confined or detained in a penal institution -- can be detained pending arraignment, trial or sentencing)?

No

Pregnant women?

No

Are pregnant women the primary population or focus for this research?

No

Provide rationale for why they are the focus population and describe the risks associated with their involvment as participants

Fetuses?

No

Students?

Yes

Does the research involve normal educational practices?

No

Is the research being conducted in an accepted educational setting?

No

Are participants in a class taught by the principal investigator?

No

Are the research activities part of the required course requirements?

No

Will course credit be offered to participants?

No

Amount of credit?

No

If class credit will be given, list the amount and alternative ways to earn the same amount of credit.Note: the time it takes to gain the same amount of credit by the alternate means should be commensurate with the study task(s)

How will permission to conduct research be obtained from the school or district? IRB approval is not permission to conduct the research. You need to access a gatekeeper. If you are implementing a survey with NC State populations, please make sure you follow the NC State survey regulation.

N/A

Will you utilize private academic records?

No

Explain the procedures and document permission for accessing these records.

Employees?

No

Describe where (in the workplace, out of the workplace) activities will be conducted.

From whom and how will permission to conduct research on the employees be obtained?

How will potential participants be approached and informed about the research so as to reduce any perceived coercion to participate?

Is the employer involved in the research activities in any way?

No

Please explain:

Will the employer receive any results from the research activities (i.e. reports, recommendations, etc.)?

No

Please explain. How will employee identities be protected in reports provided to employers?

Impaired decision making capacity/Legally incompetent?

No

How will competency be assessed and from whom will you obtain consent?

Mental/emotional/developmental/psychiatric challenges?

No

Identify the challenge and explain the unique risks for this population.

Describe any special provisions necessary for consent and other study activities (e.g., legal guardian for those unable to consent).

People with physical challenges?

No

Identify the challenge and explain the unique risks for this population.

Describe any special provisions necessary for working with this population (e.g., witnesses for the visually impaired).

Economically or educationally disadvantaged?

No

Racial, ethnic, religious and/or other minorities?

No

Non-English speakers?

No

Describe the procedures used to overcome any language barrier.

Will a translator be used?

No

Provide information about the translator (who they are, relation to the community, why you have selected them for use, confidentiality measures being utilized).

Explain the necessity for the use of the vulnerable populations listed.

The Registered Apprenticeship Partners Information Database System collects records from participants in registered apprenticeship programs. In some instances, these programs are operated by a community college partner, in which the apprentice is also a student.

State how, where, when, and by whom consent will be obtained from each participant group. Identify the type of consent (e.g., written, verbal, electronic, etc.). Label and submit all consent forms. Consent Form Template for NC State Research – Adults Parental Permission and Minor Assent

Information comes from a public database created by the Office of Apprenticeship at the US Department of Labor.

If any participants are minors, describe the process for obtaining parental consent and minor's assent (minor's agreement to participate).

N/A

Are you applying for a waiver of the requirement for consent (no consent information of any kind provided to participants) for any participant group(s) in your study?

Yes

For each participant group that you are requesting a waiver of consent for, please state what method this waiver is needed for, why it is needed and address each of the above 5 criteria to justify why your study qualifies for a waiver of consent.

The proposed study will complete secondary analysis of existing public data; therefore a waiver of consent is requested.

Are you applying for an alteration (exclusion of one or more of the specific required elements) of consent for any participant group(s) in your study?

No

Identify which required elements of consent you are altering, describe the participant group(s) for which this waiver will apply, and justify why this waiver is needed.

Are you applying for a waiver of signed consent (consent information is provided, but participant signatures are not collected)? A waiver of signed consent may be granted only if: The research involves no more than minimal riskThe research involves no procedures for which consent is normally required outside of the research context.

No

Would a signed consent document be the only document or record linking the participant to the research?

No

Is there any deception of the human subjects involved in this study?

No

Describe why deception is necessary and describe the debriefing procedures.Does the deception require a waiver or alteration of informed consent information?Describe debriefing and/or disclosure procedures and submit materials for review.Are participants given the option to destroy their data if they do not want to be a part the study after disclosure?

For each participant group please indicate how many individuals from that group will be involved in the research. Estimates or ranges of the numbers of participants are acceptable. Please be aware that participant numbers may affect study risk. If your participation totals differ by 10% from what was originally approved, notify the IRB.

Registered apprentices in the US included in database: ~238,000

Veterans in registered apprenticeship programs: ~47,000

How will potential participants be be found and selected for inclusion in the study?

This information is available via a public dataset on file with the Department of Labor; therefore there is no recruitment required.

For each participant group, how will potential participants be approached about the research and invited to participate? Please upload necessary scripts, templates, talking points, flyers, blurbs, and announcements.

This information is available via a public dataset on file with the Department of Labor; therefore there is no recruitment required.

Describe any inclusion and exclusion criteria for your participants and describe why those criteria are necessary (If your study concentrates on a particular population, you do not need to repeat your description of that population here.) Inclusion and exclusion criteria should be reflected in all of your recruitment materials and consent forms.

I will be looking for only participants in the existing dataset that are veterans and that were in an apprenticeship.

Is there any relationship between researcher and participants - such as teacher/student; employer/employee?

No

What is the justification for using this participant group instead of an unrelated participant group? Please outline the steps taken to migitate risks to participants from the pre-existing relationship, including power dynamics of this relationship and/or perceived coercion.

Describe any risks associated with conducting your research with a related participant group.

Describe how this relationship will be managed to reduce risk during the research.

How will risks to confidentiality be managed?

Address any concerns regarding data quality (e.g. non-candid responses) that could result from this relationship.

In the following questions describe in lay terms all study procedures that will be experienced by each group of participants in this study.For each group of participants in your study, provide a step-by-step description of what they will experience from beginning to end of the study activities.

N/A

Are you requesting the use of secondary information to be used as data for this research project? The secondary information can either currently exist or be generated in the future. Discuss the following: permission to access the information, the act of accessing the information, the transfer, storage, destruction of the data, and the identifiable/re-identifiable nature of the data. Discuss if the data requires a Data Use Agreement and if data are subject to FERPA or HIPAA.

Yes; database will be accessed via transfer from the Department of Labor. No identifiable information is included and data is not subject to FERPA or HIPAA

Social/Reputational?

No

Psychological/Emotional?

No

Financial/Employability?

No

Legal?

No

Physical?

No

Academic (affect grades, graduation)?

No

Employment (affect job)?

No

Financial (affect financial welfare)?

No

Medical (harm to treatment)?

No

Insurability (harm to eligibility)?

No

Legal (reveals unlawful behavior)?

No

Private behavior (harm to relationships/reputation)?

No

Religious Issues/Beliefs?

No

Describe the nature and degree of risk that this study poses. Describe the steps taken to minimize these risks. You CANNOT leave this blank, say 'N/A', none' or 'no risks'. You can say "There is minimal risk associated with this research." For each 'Yes' selected above, describe the probability of the risk occuring and the magnitude of harm should the risk occur. Discuss how you are mitigating those risks through participant selection, study design, and data security.

There is minimal risk associated with this research.

If you are accessing private records, describe how you are gaining access to these records, what information you need from the records, and how you will receive/record data. Private records may include: educational, medical, financial, employment. Some of these private records may be subject to laws such as FERPA and HIPAA. Your content here should match what you've discussed on the procedures tab.

N/A

Are you asking participants to disclose information about other individuals (e.g., friends, family, co-workers, etc.)?

No

You have indicated that you will ask participants to disclose information about other individuals (see Populations tab). Describe the data you will collect and discuss how you will protect confidentiality and the privacy of these third-party individuals.

If you are collecting information that participants might consider personal or sensitive or that if revealed might cause embarrassment, harm to reputation or could reasonably place the subjects at risk of criminal or civil liability, what measures will you take to protect participants from those risks?

N/A

If any of the study procedures could be considered risky in and of themselves (e.g. study procedures involving upsetting questions, stressful situations, physical risks, etc.) what measures will you take to protect participants from those risks?

N/A

Describe the anticipated direct benefits to be gained by each group of participants in this study (compensation is not a direct benefit).

No direct benefits are expected.

If no direct benefit is expected for participants describe any indirect benefits that may be expected, such as to the scientific community or to society.

This research is an important first step in understanding the impact of veteran status, if any, on apprentices in white collar occupations, to better inform workforce development, specifically with regard to veterans and white collar occupations.

Will you be receiving already existing data without identifiers for this study?

Yes

Will you be receiving already existing data which includes identifiers for this study?

No

Describe how the benefits balance out the risks of this study.

Will data be collected in a way that would not allow you to link any identifying information to a participant?

Yes

Will any identifying information be recorded with the data (ex: name, phone number, IDs, e-mails, etc.)?

No

Will you use a master list, crosswalk, or other means of linking a participant's identity to the data?

No

Will it be possible to identify a participant indirectly from the data collected (i.e. indirect identification from demographic information)?

No

Audio recordings?

No

Video recordings?

No

Images?

No

Digital/electronic files?

Yes

Paper documents (including notes and journals)?

No

Physiological Responses?

No

Online survey?

No

Restricted Access (who, what, when, where)?

No

Password Protection (files, folders, drives, workstations)?

No

Suggestion of anonymous browsing?

No

Locks (office, desks, cabinets, briefcases)?

No

VPN (transfer, upload, download, access)?

No

Encryption (files, folders, drives)?

No

Describe all participant identifiers that will be collected from each data collection method (surveys, interviews, focus groups, existing data, background data collected via host site or software). Discuss why it is necessary to record identifiers at all and describe the deidentifying process

N/A

If recording identifiable information about participants, discuss any links between the data and the participants and why you need to retain them. Discuss destruction of links or removal of identifers.

N/A

Discuss if you'll be working with your departmental IT to create a data management plan and if you're using NC State managed devices, NC State Google Drive or other NC State non-networked device. If using a personal device, discuss data protection.

Data will be stored on NC State Google Drive.

Describe any ways that participants themselves or third parties discussed by participants could be identified indirectly from the data collected, and describe measures taken to protect identities. (Data can be reidentified by researcher access, technology employed, researcher expertise, and triangulation of data or other information. Discuss the probability of reidentification and the magnitude of harm to participants should the data be reidentified. Discuss the probability of reidentification occuring and the magnitude of harm should it occur).

N/A

For all recordings of any type:Describe the type of recording(s) to be made Describe the safe storage of recordings Who will have access to the recordings? Will recordings be used in publications or data reporting? Will images be altered to de-identify?Will recordings be transcribed and by whom?

No recordings will be made

Describe how data will be reported (aggregate, individual responses, use of direct quotes) and describe how identities will be protected in study reports. Reporting data may sometimes reidentify your participants. If needed, you can adjust how you report your data to protect the identities of your participants. Discuss.

Data will be reported in aggregate, as well as disaggregated per study requirements. Data does not include any identifiable information.

Will anyone besides the PI or the research team have access to the data (including completed surveys) from the moment they are collected until they are destroyed? This includes sharing data with sponsors, journals, or using the data for future research endeavors. If you are sharing the data, this should be in your consent form.

Because data is collected via the US Department of Labor, others have access to it.

Describe any compensation that participants will be eligible to receive, including what the compensation is, any eligibility requirements for that compensation, and how that compensation will be delivered. Examples of compensation include: monetary compensation, research credits, raffle/drawing, novel items. Make sure to check with your department regarding issues of tracking payments as your department accounting office may have requirements that affect your human subjects privacy (such as the mandatory tracking of anyone who receives compensation). This tracking may influence the confidentiality/anonymity of your research and must be addressed in this application.

No compensation is provided. Data is already collected.

Explain compensation provisions if the participant withdraws prior to completion of the study.

No compensation will be offered nor withdrawn. Dataset is existing so participants have already participated.

Appendix D: NCSU IRB Protocol Reviewed Documentation

NC STATE

Kamisha Kirby <kkirby@ncsu.edu>

Bartlett - 23737 - IRB Protocol reviewed, does not qualify as human subjects research

1 message

IRB Administrative Office <pins_notifications@ncsu.edu> Wed, Jan 27, 2021 at 9:40 AM
Reply-To: ncsuirboffice@ncsu.edu
To: kkirby@ncsu.edu

Dear Kamisha Kirby:

IRB Protocol 23737

Title: Exploring the Impact of Veteran Status on Completion of White Collar Apprenticeships: A Propensity Score Match

PI: Bartlett, Michelle E

Thank you for providing this information. Based on what you have submitted, you are not conducting research with human subjects as defined by the regulations that govern the use of human subjects. You do not need IRB approval for this activity.

Please let us know if you have any questions or if you would like to talk about this more.

********** **********

NCSU IRB Office

Please contact ncsuirboffice@ncsu.edu if an official PDF approval letter with signature is required by your funding source.