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Use of Human–Computer Interaction Devices and Web 3.0 Skills Among Engineers

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Walden University
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Abstract

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by

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MBA, Florida Institute of Technology, 2011

BS, South Carolina State University, 2008

Dissertation Submitted in Partial Fulfillment

of the Requirements for the Degree of

Doctor of Philosophy

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Abstract

Despite massive company investments in human–computer interaction devices and software, such as Web 3.0 technologies, engineers are not demonstrating measurable performance and productivity increases. There is a lack of knowledge and understanding related to the motivation of engineers to use Web 3.0 technologies including the semantic web and cloud applications for increased performance. The purpose of this quantitative correlational study was to investigate whether the use of human–computer interaction devices predict Web 3.0 skills among engineers. Solow's information technology productivity paradox was the theoretical foundation for this study. Convenience sampling was used for a sample of 214 participants from metropolitan areas of Georgia. Multiple linear regression was used to develop a predictive model and evaluate the influence on Web 3.0 skills of 10 independent variables measuring self-reported reliance on and competence with five human–computer interaction devices, two aggregate indices of reliance and competence, and two-factor interactions. Results indicated a significant linear relationship between several predictors (laptop reliance, tablet reliance, desktop competence, wearable competence, and five interactions) and the dependent variable (Web 3.0 skills). The results may enable engineering managers to make more informed, strategic decisions regarding the types of technology to invest in to improve engineer skills and productivity. The results of this study have potential implications for positive social change by helping engineering organizations overcome the information technology productivity paradox to reap the benefits from engineers who are more motivated and skilled.

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Dedication

Of highest significance is my thankfulness to God, who gave me continued strength during this program of study and reminded me to have patience and keep the belief that all things happen for a reason and to trust his divine timing.

This dissertation is dedicated to my parents, Dr. Earlene Walker-Kelly, Robert Walker, and James Kelly, who always loved me unconditionally and taught me to work smart for goals I aspire to achieve.

This work is also dedicated to my sister, Dr. Roblena E. Walker, who is a constant source of support and encouragement during graduate school and life. I am genuinely thankful for having her in my life.

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I will always be thankful for my family's continued support and encouragement that filled my heart and soul, especially during challenging moments to continue. This accomplishment is as much as the family's success as it is mine.

Finally, I appreciate the love and support from my brothers, aunts, uncles, cousins, friends, and exceptional colleagues who have helped me reach this point in my academic career.

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Chapter 1: Introduction to the Study

Since the 1990s, digital technology has transformed the economy and society (Gamble & Calverley, 2015). Web 1.0 and Web 2.0 technologies have dominated the World Wide Web (henceforth referred to as *the web*), and Web 3.0 opportunities are now driving digital technologies forward. The web is the fastest-growing publication medium of all time (Rudman & Bruwer, 2016). A large body of literature is available on the antecedent events of web technologies, from the beginning of Web 1.0 evolving to significant web technological advances on the Internet of Things (IoT) or Web 3.0 technologies (Gamble & Calverley, 2015; James, 2015; Rudman & Bruwer, 2016).

Measured growth in the labor productivity and total factor productivity of engineers is not yielding gains despite considerable investments in emerging information and communications technology (ICT) and information technology (IT) tools designed for increased usability and productivity for Web 3.0 (Tarute & Gatautis, 2014). IT includes the entire information domain of hardware, software, peripherals, and networking and serves as the umbrella to ICT, a branch that deals explicitly with digital devices used to communicate with digital information. The third phase in the evolution of the web, or Web 3.0, describes the human interaction and usage in the network of digital communications through different paths of the web defining advanced communication, demand-orientated information, transactions via the net economy, and transformation of the network in a database (Tarute & Gatautis, 2014).

Procedures to increase productivity using Web 3.0 technologies remain challenging to find (Rudman & Bruwer, 2016). Research is needed to identify strategies that will enable engineers to become more productive while using advanced technologies and devices. Addressing this management-related, real-world issue is of significant concern in various engineering and technology fields because research may enable organizations to be more efficient and effective in the global economy and provide them the knowledge to make sound investments in technology.

Background of the Study

Gamble and Calverley (2015) defined Web 1.0 as data and information, with minimal user interaction for leaving comments and creating website content. The concept of human–computer interaction (HCI) refers to the interface between humans and computing devices and computer technology. Gamble and Calverley identified five HCI devices that I considered in my study: desktop (e.g., stationary workstation); laptop (e.g., portable computer); tablet (e.g., touchscreen); smartphone (e.g., handheld computer); and wearable (e.g., virtual reality [VR] headset). These devices can access Web 3.0 technologies. HCI has evolved since Web 1.0 technologies, providing a better user experience with more interactive, powerful, and appealing software applications (Gamble & Calverley, 2015).

In 2018, Web 1.0 technologies and methods displayed content such as laws and manuals (Rudman & Bruwer, 2016). Web 1.0 presented static informative characteristics that progressed to a more interactive experience, advancing to Web 2.0 (James, 2015). Dale Dougherty coined the term *Web 2.0* in 2004 (James, 2015).

In less than 18 months, the term Web 2.0 had received more than 9.5 million citations on Google (James, 2015). Web 2.0 technologies, such as web-conferencing, e-surveys, and YouTube videos, have rapidly evolved into Web 3.0 technologies. In the 2010s, the new phase of evolution in Web 3.0 technologies, the driving force behind the semantic web, much like that of Apple's Siri, impacted how organizations viewed the internet and intranet (Rudman & Bruwer, 2016).

Web 3.0 has matured to become competitive with new technological trends, rapidly advancing to Web 4.0 (Rudman & Bruwer, 2016; Serin & Yalçıner, 2021). The amount of data and information presented based on Web 3.0 technologies—that is, machine-to-machine communication on the Internet, cloud computing, and software applications—presented a significant challenge in extracting relevant information to use for productive day-to-day activities (Gamble & Calverley, 2015). By 2017, the web provided more knowledge and action capacity for users, resulting in considerable changes in several aspects of daily life. The next wave of web evolution, Web 4.0 technologies, refers to controlling the power of human and machine intelligence on a universal web, where both humans and computers interact, reason, and assist each other in more innovative ways (James, 2015).

Adopting the most advanced IT for the engineering industry is essential to the economy's success in the 21st century (Priem et al., 2012). Productivity growth is critical for sustainability and elevation of the standard of living for U.S. workers (Gamble & Calverley, 2015). The most prominent factors behind successful productivity growth in organizations are a technological edge and an inspired pace of technological change (Gamble & Calverley, 2015).

The number of personal computers in the workplace and the web has made new Web 3.0 technologies easily accessible to employees in the workplace. Increasing technological capacity and untapped potential of engineers is needed to propel the new economy forward (Gamble & Calverley, 2015). Engineers must figure out new ways of creating and sharing information resources by fully utilizing technology, especially Web 3.0 technologies (Priem et al., 2012).

Productivity has risen in many economies worldwide, especially in the United States, in recent years due to advancements in IT and other improvements in technical efficiency. However, productivity among engineers is not growing despite considerable investments in Web 3.0 technologies (Tarute & Gatautis, 2014). The reasons for this lack of productivity growth have not been thoroughly researched and documented in the scholarly literature. There is a lack of research into the factors that motivate engineers to embrace and fully utilize the capabilities offered by Web 3.0 technologies.

Based on this summary of research, expanded in the literature review in Chapter 2, there is a gap related to why engineers are not demonstrating measurable performance increases despite investments in technology and which technologies are associated with higher engineer performance and productivity. Specifically, current research fails to cover the motivation of engineers to learn Web 3.0 skills, one indicator of skill level, motivation, and productivity. Further research is needed to investigate the influence of various factors on motivation and productivity that may lead to practical solutions for the lack of productivity growth. Knowledge is needed on how to enhance the use of HCI devices through well-conceived investments in technology and the impact on engineers' motivation to learn new skills. This research has the potential to enable organizations to make better investment decisions and, as a result, yield higher productivity levels for engineers.

Problem Statement

The social problem in this study was that despite massive company investments in new HCI devices and software such as Web 3.0 technologies (Gamble & Calverley, 2015), engineers are not demonstrating measurable performance increases. Stakeholder pressure on senior executives and engineers has heightened the need for engineers to become more productive considering significant investments in emerging ICT and IT projects (Shambaugh et al., 2018). According to the Office of Occupational Statistics and Employment Projections (2021), the employment of engineers is projected to grow 9% from 2019 to 2029. Prospective employees are hired based on their capabilities using the latest skills and knowledge of trends in technology.

While current research covers Web 3.0, it fails to cover the motivation among engineers to learn and use new technology such as Web 3.0, which led to my research problem: a lack of knowledge and understanding of the influences on engineers' willingness to learn and adopt new technological tools, specifically Web 3.0 tools. The lack of motivation among engineers results in inadequate proficiency, which leads to an overall lack of performance. Engineers' ability and willingness to develop new skills is an ongoing motivational challenge as technology advances.

One challenge is measuring the extent to which engineers have mastered advanced Web 3.0 technological tools, or the semantic web, and cloud applications for increased performance. My research is needed because technology impacts the workplace, yet there seems to be a lack of motivation among engineers to use new technology tools despite the enormous investment organizations have made.

Purpose of the Study

The purpose of this quantitative correlational study was to investigate whether the use of HCI devices predicts Web 3.0 skills among engineers—in other words, whether the use of HCI devices influences, facilitates, or indicates the willingness or motivation to learn new skills, increasing performance, and enhancing productivity. Use of HCI devices has two components: reliance on and competence with HCI devices.

There were five independent variables representing reliance on each of the five devices: (a) desktop reliance (DTR), (b) laptop reliance (LTR), (c) tablet reliance (TTR), (d) smartphone reliance (SPR), and (e) wearable reliance (WBR). There were five independent variables representing competence with the devices: (a) desktop competence (DTC), (b) laptop competence (LTC), (c) tablet competence (TTC), (d) smartphone competence (SPC), and (e) wearable competence (WBC). In addition, I evaluated two aggregate indices: reliance on HCI devices (RHCID) and competence with HCI devices (CHCID). I also evaluated two-factor interactions (2FIs) between independent variables.

I chose Web 3.0 skills to represent leading edge capabilities, an indication of an engineer's increase in capabilities and productivity. The dependent variable was a measure of Web 3.0 skills. All independent variables and the dependent variable are listed in Table 1.

Table 1

Study Variables

Variable	Variable abbreviation	Variable type
Desktop reliance	DTR	Independent
Desktop competence	DTC	Independent
Laptop reliance	LTR	Independent
Laptop competence	LTC	Independent
Smartphone reliance	SPR	Independent
Smartphone competence	SPC	Independent
Tablet reliance	TTR	Independent
Tablet competence	TTC	Independent
Wearable reliance	WBR	Independent
Wearable competence	WBC	Independent
Reliance on HCI devices	RHCID	Independent
Competence with HCI devices	CHCID	Independent
Web 3.0 skills	WS	Dependent

By understanding the relationship between HCI device use and Web 3.0 skills, my research was intended to help close a gap in the research, knowledge, and understanding of what influences and motivates engineers to embrace and utilize new technologies such as Web 3.0. This research was aimed at providing insights into which kinds of HCI devices (e.g., desktop, laptop, tablet, smartphone, and wearable devices) influence engineers to obtain advanced skills and apply those new skills in small and medium enterprises, which is research that has not been conducted before.

Research Question and Hypotheses

The overarching research question in this study was: What is the relationship between the use of HCI devices and Web 3.0 skills? This question was designed to explore the motivations for engineers to use Web 3.0 technologies to enhance their overall skills and performance based on which HCI devices they relied on or were competent with. Because there were two measures related to the use of HCI devices (reliance and competence on each of five specific devices, and aggregate indices of reliance and competence), there were two pairs of hypotheses (a null and alternate hypothesis for each) to address the research question:

> $H_0$1: There is no significant relationship between any of the predictors (10 independent variables and 2FIs) and Web 3.0 skills (dependent variable).
>
> H_A1: There is a significant relationship between at least one of the predictors and the dependent variable.
>
> $H_0$2: There is no significant relationship between reliance on or competence with the five HCI devices, in the aggregate, and their 2FI; and Web 3.0 skills.
>
> H_A2: There is a significant relationship between either reliance on and competence with the five HCI devices, or both reliance and competence, in the aggregate; or their 2FI; and Web 3.0 skills.

Theoretical Foundation

The theoretical foundation for this study was the Solow IT productivity paradox. Solow (1957) was one of the pioneers in growth theory, who sparked an ongoing debate about the technological factors that can increase the growth of national income and social wealth. The Solow IT productivity paradox occurs when, as more investments are made in IT, engineer productivity or performance potentially goes down instead of up.

Both researchers and industry professionals remain perplexed as to why investment in new technology has not yielded significant increases in productivity for organizations that have adopted and continue to purchase advanced systems. In Chapter

2, I describe the IT productivity paradox in greater detail and explain the rationale and theoretical underpinning for this research.

The Solow IT productivity paradox theory aligned with my study, providing the theoretical explanation of why investments in technology do not consistently result in increases in skills and productivity. My research was intended to discover which technological devices are associated with higher skill levels, where organizations might be able to make investments that pay off, and what factors they ought to consider when contemplating technology investments.

Nature of the Study

In this correlational study, I investigated if and to what extent there is a relationship between the independent variables (reliance on and competence with five HCI devices, individually and in the aggregate) and the dependent variable (a self-reported survey measurement of Web 3.0 skills). Several different methods based on standards for human performance have been employed to study the relationships among fundamental HCIs, tasks with a computer, and overall skill level, such as those proposed by Biagi (2013), Chua and Chua (2017), and Gamble and Calverley (2015). I chose a quantitative method using a correlational design to explore the relationship between the use of HCI devices and motivation to embrace and use Web 3.0 technologies. The objective was to explore some of the critical human behaviors of engineers (their use of HCI devices) and their Web 3.0 skills. The data collection instrument was a self-designed questionnaire, the Web 3.0 technological skill survey (see Appendix A), refined with a pilot test using subject matter experts who provided feedback. In this correlational study, I employed the quantitative questionnaire to inform the independent variables.

I also used the questionnaire to inform the dependent variable, Web 3.0 skills. The engineers rated their knowledge level for eight different Web 3.0 technologies: web technologies, developer tools, relational database technology, software design, blockchain technology, operating systems and server technologies, server software, and virtualization. The dependent variable, Web 3.0 skills, was an aggregate of the eight questions or knowledge of technologies (KOT) subscale.

I used multiple linear regression (MLR) to build a predictive model of skill level as a function of the use of each of five HCI devices. I used MLR to test the research hypotheses and to assess the influence or predictability of the independent variables (the use of HCI devices) on the dependent variable (Web 3.0 skills). The target population was engineers employed by small and medium enterprises in metropolitan areas of Georgia. In the United States, the definition of small and medium enterprise is based on the industry size, revenue, and the number of employees—which may be up to 1,500 employees, but the cap is typically 500 employees (Goerzig & Bauernhansl, 2018). Small and medium enterprises are innovative and considered the backbone of America's economy, contributing to the most significant number of employers (Goerzig & Bauernhansl, 2018).

In this research, I addressed the spectrum of desktops, laptops, tablets, smartphones, and wearable devices and its association with engineers' competence with Web 3.0 technologies. The rationale for including these devices was that they represent the kinds of devices procured by small and medium enterprises as an investment in their engineers to improve their productivity, specifically related to the use of Web 3.0 technologies. HCI devices excluded in this research were devices that engineers do not use for working or for developmental purposes (e.g., gaming consoles, television remote controllers, and standard calculators). Desktops, laptops, tablets, smartphones, and wearable devices were the most appropriate for understanding where small and medium enterprises ought to prioritize their investment in technology for their engineers.

Definitions

The following are definitions for the special terms and concepts used in this study. Some of these I defined for the purpose of my research, and citations are provided for the others. The definitions are intended to provide consistency throughout the manuscript:

Adjusted R^2: The coefficient of determination; the portion of the variation in the dependent variable that is attributed to the variation of the model (Frost, 2020).

Competence with HCI devices (CHCID): The extent to which engineers are competent, in the aggregate, with the five HCI devices.

Computer technology: Ability to input, process, store, and transmit data or information in various output file formats electronically (Heaggans, 2012).

Counterproductive work behaviors: Intentional behaviors of an employee that are viewed by an organization to be contrary to its legitimate interests (Glassman et al., 2015).

Cyberloafing: Employees engaging in counterproductive work (Glassman et al., 2015).

Desktop competence (*DTC)*: The extent to which engineers are competent with a stationary workstation.

Desktop reliance (*DTR)*: The extent to which engineers rely on a stationary workstation.

Human–computer interaction (*HCI*): The interaction between human user and computer, relating specifically to the interface design and usage of computer technology (Gamble & Calverley, 2015).

Human–computer interaction (*HCI*) *device*: A device based on state-of-the-art hardware and software developments that have led to the evolution from command-line to more advanced human-like or natural user interfaces for virtual environments, gesture design, and recognition (Bachmann et al., 2018). HCI devices related to this study include desktop (e.g., stationary workstation), laptop (e.g., portable computer), tablet (e.g., touchscreen), smartphone (e.g., handheld computer), and wearable (e.g., VR headset) devices.

Information and communications technology (*ICT*): All applications and systems, networking components, and all devices combined to allow people and organizations to interact and engage in the digital world (Tarute & Gatautis, 2013).

Input–output price ratio: The ratio of the aggregate price of capital services and labor hours relative to the price of the output (Byrne & Corrado, 2017).

Input price: The cost to produce goods and services (Byrne & Corrado, 2017).

Laptop competence (*LTC)*: The extent to which engineers are competent with a portable computer.

Laptop reliance (*LTR)*: The extent to which engineers rely on a portable computer.

Ontology: The transporter of interpreted meanings of information that is integrated information collected from various sources (Rudman & Bruwer, 2016).

Organization for Economic Cooperation and Development (*OECD*): An organization that provides a platform for governments to share common experiences and work toward common solutions driving change in developmental sectors that include the economic, social, and environment sectors (OECD, 2012).

Productivity: The ratio of inputs to outputs and its effect on a country's economy and its competitiveness (Schuh et al., 2014).

Reliance on HCI devices (RHCID): The extent to which engineers rely on the five HCI devices in the aggregate.

Robot: A machine programmable by a computer that can transmit complex instructions into a series of actions automatically. Often a series of actions resemble humans, as the image of robots are mechanical with human-like movement and expression (Gamble & Calverley, 2015).

Smartphone: A portable and handheld computer considered smarter than a cellphone (for just making phone calls) that uses many applications (Web browsers, games, maps, emails, and image editors) and is wireless with a specialized operating system (Wang et al., 2016). A device that includes a virtual keyboard, voice action, multisensory touchscreen, and has network connectivity (e.g., Apple iPhone, Google Pixel, and the Samsung Galaxy; Wiberg & Wiberg, 2018).

Smartphone competence (*SPC)*: The extent to which engineers are competent with a handheld computer.

Smartphone reliance (*SPR)*: The extent to which engineers rely on a handheld computer.

Tablet competence (*TTC)*: The extent to which engineers are competent with a touchscreen.

Tablet reliance (*TTR)*: The extent to which engineers rely on a touchscreen.

Use of HCI devices: An engineers' reliance on and competence with each of five HCI devices.

Value-added output: Compensation of employees, taxes on production and imports, contributions, and gross operating surplus. Value added does not incorporate intermediate inputs (Ekuobse & Olutayo, 2016).

Wearable competence (*WBC)*: The extent to which engineers are competent with a VR headset.

Wearable reliance (*WBR)*: The extent to which engineers rely on a VR headset.

Web-based application: An online communication service that users can access and interact with directly on their computer or handheld devices with network support from the internet or intranet (Kreps & Kimppa, 2015).

Web 1.0: The read-only Web, or a platform in which information is published in a static form, portrayed in an environment with text and images that are well designed. The data are displayed with no interaction (static) between the information and the consumer, having minimal content creators (Rudman & Bruwer, 2016).

Web 2.0: Introduced in October 2004, an extension of Web 1.0 technologies with enhanced principles and underlying infrastructure. Website presenting user-generated content is known as the main feature (Kreps & Kimppa, 2015).

Web 3.0: An application using crowd-sourced data, IoT, cloud computing, and semantic web (Kreps & Kimppa, 2015).

Web 3.0 skills: A self-reported measure of composite knowledge and skills related to eight components of Web 3.0 technologies: web technologies, developer tools, relational database technology, software design, blockchain technology, operating systems and server technologies, server software, and virtualization. Web 3.0 skills is the dependent variable in this study.

Assumptions

Assumptions are out of a researcher's control and cannot be proven or demonstrated but are essential for conducting research (Field, 2013; Frost, 2020). My first assumption was that all engineers would respond to the survey truthfully. I assumed that convenience sampling of participants who completed the questionnaire would be sufficient to answer the research question.

I assumed that self-reported Web 3.0 skill levels indicated engineers' performance. The assumption was that an engineer's motivation to learn new skills impacts skill level, which in turn, impacts performance and productivity. I assumed that Web 3.0 skills are an indicator of leading-edge engineering skills that are assumed to correlate to whether engineers can succeed, receive better job offers, and work on better projects because those are the macro concerns of the engineering community. If an engineer has Web 3.0 skills, that indicates motivation; possession of Web 3.0 skills is associated with productivity, and engineers with Web 3.0 skills are more competent, motivated, and productive.

I assumed that the five HCI devices are representative of the technologies that companies might choose to invest in to increase the capabilities of their engineers and that an investment in these technologies might be motivation for engineers to develop skills and become more productive. Engineers who understand skills with new Web 3.0 platforms help small and medium enterprises become innovative in building new applications that enhance users' interactions with devices adequately and productively.

Scope and Delimitations

This research was focused on understanding the organized flow of information relating to HCI devices using web technologies, the more advanced forms of digital technology used in engineering. The study was limited in scope by time and geographic location. My research intended to assess the level of skill and interactions with technologies available and advanced technologies for building a smarter world, much like that of Web 3.0 technologies or IoT, cloud computing, and artificial intelligence (AI). The research covered the technologies that engineers use based on innovation and competitive advantage for organizations and their skill levels with advanced technologies such as Web 3.0.

Delimitations are factors that limit the scope of a study and define the limits of a study (Bryman, 2012). This research was limited to engineers employed by small and medium enterprises. This study was limited by time, whereby the study was conducted over a brief interval serving as a snapshot of the technological conditions existing in the past 5 years. The small and medium enterprises of interest were chosen based on the size—fewer than 500 employees, defined by OECD (2012) in the United States.

This study includes engineering professionals who live and work in metropolitan areas of Georgia. According to the *Atlanta Journal-Constitution*, Atlanta is among the top 25 cities for evolving technology and is home to the fourth-largest technology hub in the United States, known as Atlanta Tech Village. Atlanta ranks behind giants in the tech regions such as Silicon Valley (San Jose, California); San Francisco, California; and Washington, D.C., known as the top three tech-centric markets. According to the *Atlanta Journal-Constitution* (Pirani, 2017), previous research considered several factors to determine which cities would make up the Tech 25, including Atlanta's institutions of higher learning, investment funding, well-qualified workforce, entrepreneurship, and more.

Limitations

Limitations are potential weaknesses in the research design or methods out of a researcher's control affecting conclusions. Because correlation does not prove causation, the results of this study might not prove if the use of HCI devices causes a change in Web 3.0 skill levels. Convenience sampling does not provide the same level of random investigation, which theoretically might introduce bias and impact generalization. However, with sufficient sample size and careful explanation of results, bias was minimized, and generalization was within the appropriate scope.

Significance of the Study

Engineers must figure out new ways of creating and sharing information by fully using technology (Priem et al., 2012). My research fills a gap in understanding the motivation to learn and adopt Web 3.0 technologies that equip engineers to perform well. My research also fills a gap in describing the relationship between HCI devices and Web 3.0 skills for engineers' requirement to be motivated to perform well, especially when those enterprises are making significant investments in the technology. Despite the growing awareness of HCI, its overall impacts on using new technologies remain unknown, and views differ regarding its effects on human welfare and social change (Tisdell, 2014).

This study is unique because it addressed an ongoing yet understudied challenge for small and medium enterprises (Benner & Tushman, 2013); Web 3.0 was implemented in 2006 but has yet to reap the expected benefits in terms of performance. In this chapter, the definition of productivity incorporates efficiency, which means economical use of resources, production of excellent products or services, and quality or technical specifications and outcomes related to customer engagement. This study provides much-needed insights into the processes for increasing the motivation of engineers' performance in the beginning phases of launching new projects while adopting new technologies throughout a project.

Significance to Theory

In this research, I examined the significance of HCI devices and their impact on Web 3.0 skills. As a basis for understanding digital technologies and computer literacy, I explained the IT productivity paradox and its effect on engineering managers' decision making. My research was focused on addressing the practical challenges that arise in the engineering workplace explained by the theory.

This study contributes to the IT and engineering literature by expanding on the IT productivity paradox. The IT productivity paradox signifies an unresolved relationship between investment in IT and performance that is evident in previous studies and continues to puzzle managers, software developers, and engineers (Xu & Zhang, 2016). Enhancement of engineers' productivity and engagement of digital technologies is a major priority, especially for small and medium enterprises (Gamble & Calverley, 2015). Yet, if investments do not pay off, as predicted, and explained in the IT productivity paradox, they are wasted. This study contributes to the theoretical understanding by investigating HCI and Web 3.0 skills as indicators of engineers' performance. This research fills a gap in understanding how the adoption of specific Web 3.0-related technologies, in various combinations, can enhance performance levels among engineers and avoid the paradox captured in the theory.

Significance to Practice

My research is relevant to the practice of engineering management and technology management in various fields, including accounting, finance, economics, engineering, human resources management, IT, organizational behavior, operations management, and project management. This study addressed administrative and operational challenges related to managing technological advancements and innovation in which ICT, HCI, and Web 3.0 are common management issues. The results of this study may provide much-needed insights into the processes related to technology investments for increasing the performance of engineers in the beginning phases of new projects. This research may lead to an increased understanding of the factors influencing engineers' motivation and to the more effective adoption of Web 3.0, greater skills, and more productivity in the workplace. Understanding more clearly why investments are or are not paying off may lead to new motivation, training, and learning approaches. These approaches may benefit organizations in both effectiveness and efficiency using new technologies. Training and implementing rapid advancements in technology may help engineering management ultimately decide best practices for the adoption of groundbreaking technologies and tools for optimizing better performance in an organization's operations and for its employees. This research may benefit engineering management, emphasizing the need for a strategic focus and planning capabilities while seeking improvements in operational performance on complex engineering tasks in small and medium enterprises.

Significance to Social Change

Historically, ICT innovations have significantly influenced economic growth and social change. The digital age, much like past industrial revolutions, resulted in a significant change in society (Schuh et al., 2014). Increased productivity can ultimately improve living standards and conditions for society. Enhanced skills and productivity benefit the engineering workforce and small and medium enterprises; society benefits from increased effectiveness and efficiency. This research may lead to positive change for engineering organizations, management, engineers, and society. Engineering management benefits from wise decision-making strategies regarding investment in the right kinds and combinations of HCI devices and technologies used in small and medium enterprises. If the technologies provided to engineers are the right combinations of HCI devices, engineers may become more comfortable with and motivated to use new technologies enabled by Web 3.0 tools, making their daily tasks easier to complete. Thus, engineers equipped with the right kinds and combinations of HCI devices may be likely to increase their skills and productivity. Engineering organizations may then be more effective and efficient and, therefore, more successful. Society benefits because the engineering workforce may be better equipped and more productive, the quality of engineering products and services may increase while their costs may decrease due to efficiency.

Summary and Transition

ICT, IT, and Web 3.0 technologies have drastically advanced communication by increasing the productivity of engineers and revolutionized how information is analyzed and used to profit organizations (Kreps & Kimppa, 2015; Tarute & Gatautis, 2013). Web 3.0 technologies were projected to increase the performance of professionals and improve knowledge and communication. The overall objective of this quantitative study was to improve the understanding of components of HCI and Web 3.0 skills and their impact on performance for engineers.

Current research suggests that scholar–practitioners and industry professionals believe that economic productivity will not be achieved until the full power of technology evolves. Therefore, the productivity paradox remains in question and invites explanation.

In the next chapter, I analyze current literature and present findings that support the need for this study and a review of various methods used in relevant studies.

Chapter 2: Literature Review

The social problem in this study was that despite massive company investments in new HCI devices and software such as Web 3.0 technologies (Gamble & Calverley, 2015), engineers are not demonstrating measurable performance increases. Measured growth in the labor productivity and total factor productivity of engineers is not yielding gains despite considerable investments in emerging ICT and IT tools designed for increased usability and productivity for Web 3.0 (Tarute & Gatautis, 2014). The research problem was a lack of knowledge and understanding of the motivation of engineers to learn and use Web 3.0 technologies. The purpose of this quantitative correlational study was to investigate whether the use of HCI devices predicts Web 3.0 skills among engineers.

In this chapter, I document the evaluation of approximately 150 scholarly articles related to the social problem. The intent of this literature review was to present and critically assess research into the opportunities and challenges related to HCI and web technologies for rendering better performance by engineers. First, I describe my research strategy, then explain the theoretical foundation for my research. These topics lead to a critical assessment and comparison of research into the prominent opportunities and challenges relating to HCI and Web technologies for rendering better performance by engineers. The objective of this review was to demonstrate what has been researched and where a gap exists in the scholarly research.

Literature Search Strategy

I employed an initial literature search strategy to find peer-reviewed articles about HCI and web technologies, but available articles on these topics were limited. Instead, many articles were related to IT and ICT. Primary keywords and key phrases used to conduct the literature search were *cloud computing*, *computer literacy*, *engineers*, *HCI*, *ICT*, *IT*, *productivity*, *performance*, *semantic web*, *technology*, *web*, *web technologies*, *Web 3.0*, and *Web 3.0 skills*. I searched Emerald Management Journals, ProQuest Central, SAGE, Google Scholar, and dissertations and theses in the Walden University library. Regarding the theoretical foundation, I conducted searches for *Solow IT productivity paradox* and seminal articles related to the origin and historical background of these theories. I located Solow's original work from 1957 and current literature that referenced Solow.

Theoretical Foundation

The theoretical foundation for this study was the computer paradox (or IT productivity paradox) proposed by Solow in 1957. Solow was a pioneer in growth theory and sparked an ongoing debate about the technological factors that can increase the growth of national income and social wealth.

The Solow IT productivity paradox was the best choice of theory for my study in my efforts to build on existing theory and for creating a conceptual productivity model that highlights a complex system of interrelated variables (e.g., technological skills and behavior). In the United States, the IT productivity paradox means a slowdown in productivity growth despite investments made in advanced technology. Performance outcomes may or may not be positively associated with the productivity of engineers in small and medium enterprises and start-up organizations.

IT Productivity Paradox

The Solow growth model is a neoclassical model of economic growth (Solow, 1957). Solow's (1957) growth model has been applied to the economic growth of the 21st century, considering three essential points for GDP: (a) labor, (b) capital, and (c) skill. Solow's (1957) growth model considers the ICT effect on long-run growth, which is calculated as total ICT effect on GDP growth = ICT use effect + ICT output effect. This equation measures the economic growth of production of goods and services. For consumers, this means ICT directly impacts the creation of value-added goods and services for the economy.

The Solow growth model assumes that the growth rates of skills and labor are constant. The number of investments allotted for production are also assumed to be constant and exogenous. The growth model suggests that output directly impacts the growth of capital in the economy, as technical changes occur over time (Solow, 1957)

The Solow growth model is based on endogenous technological progress or change and worldwide capital growth (Solow, 1957). Mathematically the Solow productivity growth model is represented as

$$Q = A(t)f(K, L) \tag{1}$$

where,

Q = output

A = skill

t = time

f = technical change

K = capital

L = labor

$A(t)$ = combined impact of technical changes over time

This equation means that technical change occurs from adding new education or skills, which increase or decrease output, and the multiplicative factor $A(t)$ represents the combined impact of technical changes over time.

Solow Residual

The Solow residual measures productivity increase in an economy per year. In the digital era of ICT, new models of connection, computing, information sharing, and knowledge management impact local, global, virtual, and multicultural growth (James, 2015). Biagi (2013) assessed that the Solow residual has several ICT mechanisms that could contribute to improved organizational efficiency and productivity of skilled labor or enterprise software, more efficient dissemination of information or cell phones and texting, and reduced transaction costs and more efficient market transactions or online banking.

Research Involving the IT Productivity Paradox

Byrne et al. (2016) claimed that the United States is experiencing a slowdown in measured labor productivity growth. Byrne et al. (2016) compared data for the periods 1947–1973, 1973–1995, 1995–2003, 2003–2007, 2007–2010, and 2010–2015. Compared to the 2.8% average annual growth sustained throughout 1995–2004, there has been a decline in labor productivity growth (Syverson, 2016). From 2005 to 2015, labor productivity growth averaged only 1.3% per year (Syverson, 2016). According to the Bureau of Labor Statistics (2021), in the first quarter of 2021, labor productivity decreased 1.7%, output increased 1.4%, and hours worked increased 3.1%; these annual rates provide more evidence that productivity has decreased over time.

The IT productivity paradox has been firmly supported by empirical evidence from the 1970s to the early 1990s (see, for example, Byrne et al., 2016; Syverson, 2016). Researchers have explained the IT productivity paradox in four components: (a) mismeasurement of outputs and inputs, (b) lags caused by learning and time adjustment, (c) redistribution or a waste of profits, and (d) mismanagement of IT (Byrne et al., 2016; Solow, 1957; Syverson, 2016).

Xu and Zhang (2016) emphasized that the difficulty of measuring the return of IT investments is due, in part, to time lag and the learning curve. Specifically, Xu and Zhang (2016) argued that the reason for the IT productivity paradox is empirical measurement challenges. For example, Xu and Zhang proclaimed that the empirical measurement issue was the most noted and accepted explanation among IT researchers, which describes a positive relationship between IT investments and organization performance yet highlights the challenges in measuring IT investment payoff due to lags caused by learning and time adjustment.

Relevant research (see, for example, Syverson, 2016; Xu & Zhang, 2016) has illustrated the strategic use of IT and ICT and the existence of the Solow IT productivity paradox, which serves as the theoretical foundation for this study. Other research studies that include the Solow IT productivity paradox have helped researchers further understand the positive effect of the four components of the IT productivity paradox.

Until the late 1990s, the first generation of case studies of the Solow IT productivity paradox involved mixed empirical results that assumed the paradox would resolve by observing productivity. Consequently, in the second generation of case studies, researchers (see, for example, Acemoglu et al., 2014; Biagi, 2013) focused more on quantitative performance measures in various sectors that used IT and ICT and found that organizations were adopting quantitative performance measures in IT for better performance of the national economy. In contrast, historical research methods of the Solow (1957) computer paradox examined in the literature depicted only measurements of variables of interest (e.g., investments and labor) without the need to control extraneous (irrelevant) variables and assessment of the relationship between the variables.

Literature Review

In this chapter, I review the literature related to digital technologies with a thorough examination of ICT, HCI, Web 3.0, and digital literacy. This review covers the existing research from studies conducted from 2012 to the present about the breakthroughs and barriers of digital technology adoption and the usage and application in the next generation of web technologies or Web 3.0. I examine approaches to understanding the relationship between technical ability and productivity related to the usage of Web 3.0 technologies for engineers to enhance performance in the United

States. I examine methodologies that impact engineers' technological capability to make innovative decisions and strategic planning for propelling firms to the next level.

This review focuses on historical research on the topics of ICT, HCI, and Web 3.0 and its impact in technology, construction, healthcare, and other sectors that have integrated technological adoption for increased performance. The challenges of advanced tools and digital literacy are also examined.

Historical Research: ICT

ICT has drastically changed society in the 21st century (Stanley et al., 2018). There is growing research in ICT. The strategic asset for organizations has been sustainable competitive advantage and innovation (Ekuobse & Olutayo, 2016). ICT serves as a solid foundation in transforming business practices and is considered a competitive advantage factor for many organizations that attain and sustain technological advancement (Mihalič et al., 2015). ICT-based innovation is at the root of growth in performance improvement, but competitiveness is extreme and critical to the success of any organization (Ekuobse & Olutayo, 2016).

Organizations face multiple challenges, including increased government regulations, stricter budgets, and rapidly changing technologies. Amid these challenges, organizations can still thrive on innovation and improve productivity or performance. Gamble and Calverley (2015) proposed that an opportunity exists for smaller businesses, start-ups, and conglomerate companies in emerging countries that often have less access to capital. With productivity analysis, a competitive strategy may decide which processes or products should be expanded and eliminate projects that should be phased out (Mashal, 2017).

Positive Effect of ICT on Productivity

ICT is a branch of IT that deals explicitly with digital devices used to communicate using digital information. Researchers have documented the positive effect of ICT on productivity. Mihalič et al. (2015) examined ICT for competitiveness, evolving resource theory, and the competitive advantage factor from 2000 to 2010. Additional researchers have suggested that ICT has a significant positive effect on the financial management system. For example, Cardona et al. (2013) provided empirical evidence that ICT severely impacted the beginning of the digital economy two decades ago, organizational performance, and proficiency of products and services.

Gamble and Calverely (2015) explained that ICT advanced other technologies, such as IoT, enhanced computer control systems, cloud usage, and various computer simulation methods. ICT and advances in other areas, such as new energy sources, genomics, and nanotechnology, are transforming many industries, including energy, materials, agriculture, and healthcare (Gamble & Calverley, 2015). Harkushenko and Kniaziev (2019) expressed the need for ICT for economic development, stating that the scientific community, commercial manufacturing sector, and even the government are on board with financial and mathematical models of ICT for better impact on output and productivity.

Borras-Gene et al. (2016) proclaimed that ICT impacted engineering education by innovation methods supporting learners' technologies. Both theoretical and empirical research suggested that ICT permits further innovation and adoption of advanced technologies (Cardona et al., 2013).

Total Factor Productivity

Total factor productivity is a measure of the increase in outputs holding capital and labor inputs constant and helps explain the effect of ICT on economic growth (Stanley et al., 2018). Biagi (2013) proposed that productivity growth is measured in labor productivity, at both the macroeconomic and the sector levels. Gamble and Calverley (2015) proposed that labor productivity growth impacts changes in productivity per hour and includes total factor productivity gains due to higher technical skills and more machines.

Two basic methods, growth in gross domestic product (GDP) and labor productivity, have been used to estimate the contribution of ICT. Theoretically, researchers (see, for example, Stanley et al., 2018) have argued that ICT should be an effective and essential stimulant of economic and productivity growth.

The use of ICT leads to efficient management of processes of budget accounting. Wambui and Njuguna (2016) examined critical factors that influence the effectiveness of financial management systems of health-oriented, civil society organizations in Kenya. Organizations that invest in a management information system experience lower administrative cost (Wambui & Njuguna, 2016).

Wambui and Njuguna (2016) researched the financial management processes of non-governmental organizations due to resource scarcity and lack of social developmental activity funding. The extent of ICT’s impact on financial management system effectiveness, improper management of project budgets, and strategic decision making was Wambui and Njuguna's focus. Their findings suggested that 87% of donors do, in fact, support organizations in accomplishing their mission by using ICT (Wambui & Njuguna, 2016). Wambui and Njuguna recommended that ICT be further developed so that ICT is maximized to improve performance, efficiency, and better financial management investments for Web 3.0 technologies.

ICT in the construction sector has also influenced small and medium enterprises' decisions to adopt new technology (Sawhney et al., 2014). Gamble and Calverley (2015) studied the impact of significant investments in new ICT equipment and web technology software. Kusumaningtyas and Suwarto (2014) examined the extent of demographic factor differences of age, gender, education level in ICT, Internet and computer adoption, skill level, and usage related to 196 managers working in small and medium enterprises. Kusumaningtyas and Suwarto found that gender was not associated with differences in ICT adoption. Instead, the level of education, technological skill capacity, and age impact ICT adoption.

The ICT maturity model proposed by Ekuobse and Olutayo (2016) adds another layer regarding the importance of ICT adoption. Ekuobse and Olutayo found that the service industry is affluent in using web-based ICT. However, their ICT maturity model suggests that the correlation between ICT maturity and ICT value in the Nigeria service industry is weak and negative. Gamble and Calverley (2015) asserted that ICT has changed how production is organized and managed; and suggested that new laws, regulations, and infrastructures are needed to support the nature of work and leisure from the usage of ICT.

Human–Computer Interactions and Engineers

In this section, I investigate ways engineers can purpose their devices or machines in their work and everyday life for society. Historically, innovations in HCI have had significant influences on economic growth and social change. Dawson's (2016) research on HCI added to understanding the proper usage of 21st century ICT tools and advanced technologies like Web 3.0 for engineers. Gamble and Calverley (2015) asserted that HCI changed how production is organized and managed; described the types of goods produced; identified where it is made; and suggested that new laws, regulations, and infrastructures are needed to support the nature of work and leisure from the use of HCI devices.

According to Bryne et al. (2016) and Decker et al. (2017), transformative innovation in advanced HCI devices yields higher productivity growth and supports the notion that startups and small and medium enterprises' technological innovations provide economic dynamism. Hampton and Shalin (2017) investigated ergonomics in society through a measure of urgency in social media. In their review of the literature, Hampton and Shalin (2017) found that HCI research generally aims to determine which features users benefit the most from, find more straightforward to use, and which computing devices and technologies are favorable among engineers.

Despite that, previous literature has not resolved the question: What motivates engineers to interact with their devices, allowing for a fulfilling experience while solving complex problems with ease or intensity? Other questions are raised considering how and why engineers opt to use one software or new technology. At what cost will Web 3.0 technologies impact an engineer's work-life balance, social interactions, and well-being?

Businesses continue to invest billions in semantic technology. New and increased knowledge in the related fields of ICT for development and HCI for development (HCI4D) have resulted in leaps in technologies with special ergonomic attention and care to the social environment in business and sociocultural contexts (Sambasivan et al., 2017). For example, engineers can walk in virtual worlds using VR, and voice user interface (VUI) is now considered a must-have feature on digital devices like smartphones to aid in faster human productivity and capability in IoT and intelligent spaces.

VUI is an input method that allows voice input from humans to control computers and devices (Corbett & Weber, 2016). In the 2000s, the only capability of VUI was known as *human speech over the telephone* (Corbett & Weber, 2016; Sambasivan et al., 2017). The popularity of utilizing voice as a control modality in mobile HCI or smartphones was introduced in 2011 by Apple's iPhone 4S, which included a beta version of Siri on the operating system iOS 4.

Voice experiences are innovative since this tool offers ease of use, is faster, and populates search results quicker (Amazon, 2018). For example, Amazon's voice service-developed VUIs known as Alexa and Amazon Echo, are capable of learning user speech patterns, and have evolved even smarter-building vocabulary for users to speak various commands (Corbett & Weber, 2016). Industry professionals predict that more people will interact with their devices using voice commands and project 50% of all searches using their voice instead of text (Shneiderman et al., 2016).

Innovative concepts like VUI have propelled the digital technology era especially with enhanced accessibility and integration via mobile devices. The intent of VUIs was for completely being hands-free, for users who have a variety of motor impairments, limiting their hand dexterity (Corbett & Weber, 2016). The advancement of smartphones coupled with voice recognition has given independence to many users, especially while driving, and provides convenience when integrated into both office and home environments (Corbett & Weber, 2016).

Research in HCI has provided minimal evidence of ergonomic usage per HCI device since Web 1.0 displayed read-only information and content (Gamble & Calverley, 2015). In 2004, O'Reilly and Dougherty popularized Web 2.0, an evolution into a social web and participatory culture (James, 2015). The evolution of Web 3.0 means even more interactivity, hence emphasizing how humans interact with computers or their HCI devices.

Evolution of Web 3.0

The research in this section consists of whitepapers and reports with few peer-reviewed articles due to limited research of Web 3.0 conducted in the past 5 years. Minimal research has been conducted or published concerning the effects that Web 3.0 skills and tools will offer organizations (Bruwer, 2014). Research that establishes a detailed framework to reduce potential risks in Web 3.0 has not been conducted. To understand Web 3.0, I compare, contrast, and synthesize existing research and literature regarding the social problem and evolution of Web 3.0.

Web 1.0

The advancement of the web occurred in stages, as the first generation of the Internet, Web 1.0, was developed for content that provided users with information (Bruwer, 2014; Farah, 2012). Web 1.0 was considered traditional and document centric (Thirunarayan & Sheth, 2013). Simply put, Web 1.0 allowed employees to input data into spreadsheets or documents, like the software program Excel.

The primary benefit intended in Web 1.0 was for databases, where users input more data into a relational database instead of documents, which reduced inconsistencies, permitted data to be searched, and avoided duplicates in information. For example, this was a skill set intended for software developers or engineers familiar with relational database tools. Limited HCI with web content posed challenges of active engagement, which led to the second generation, Web 2.0.

Web 2.0

Web 2.0, introduced in 2004, is known for interactivity, where HCI is enhanced according to how the user interacts with other users on social networking websites, such as Facebook (Horzum & Aydemir, 2014). Web 2.0 was also considered *user-generated* and *content-focused* (Thirunarayan & Sheth, 2013). Other popular social networking websites such as Snapchat, Instagram, Tumblr, and YouTube increased the amount of time users spend on their smartphones, tablets, and laptop computers. Web 2.0 has permitted users to render search results from intelligent keyword-based search tools found in Google Search, for example.

User personalization in Web 2.0 also became a challenge in assessing human factors for those who opted to use their smartphones for searching that was aligned with the user's need for information based on their lifestyle. James (2015) proposed a new model for adopting and using Web 2.0 technologies, known as the *user benefits model*, which was developed to assist professionals in an organizational setting.

In 2015, Internet content became more semantic and diverse, with the volume of data increasing, measuring engineers' usage, and managing data became more critical (Kreps & Kimppa, 2015). Internet and survey research using Web 2.0 technologies (blogs, wikis, 2D, social media, and podcasts) have provided a vast amount of information and resources (Roback, 2012; Sivarajah et al., 2015).

Web 3.0

Web 3.0 refers to software applications that collaborate based on previous user interactions, cloud computing, and web-based customer relation management (CRM) systems (James, 2015). Rudman and Bruwer (2016) confirmed that Web 3.0 computer programs and devices evolved from Web 1.0 to generate and process information semantically for humans. In Web 3.0, information is presented in a meaningful way with semantically linked data. Rudman and Bruwer (2016) urged organizations to accept the paradigm shift of the Web 3.0 evolution so that organizations can better understand big data and make better decisions.

In 2017, the term Web 3.0 was used occasionally, but an overview of the literature suggests that there is still no agreed-upon definition. The future prediction of Web 3.0 is yet to be determined, and no one knows how much it will impact society (Farah, 2012).

Despite its many successes and general acceptance throughout the world, the Western system of Web 3.0 has not led to greater productivity, replaced workers, or decreased the workload required to remain competitive in a global economy (Atabekova et al., 2015; Gomes & Cardoso, 2020). Bruwer (2014), Byrne et al. (2016), Horzum and Aydemir (2014), James (2015), Kreps and Kimppa (2015), Mashal (2017), Roback (2012), Rudman and Bruwer (2016), and Thirunarayan and Sheth (2013) used industry or firm data to validate the positive effects of Web 3.0.

Web Ontology Language

In 2004, web ontology language (OWL), or the beginning of the semantic web, was birthed (Pew Research Center, 2014; Pew Research 2016). The semantic web, smartphones, tablets, software, cloud applications, social media, three-dimensional (3D) portals are propelling faster towards a more dynamic environment, where the democratization of the capacity of knowledge and action helps businesses in almost all sectors, ranging from retail, applied for molecular medicine, micro-businesses to conglomerate corporations (James, 2015; Kreps & Kimppa, 2015).

OWL is an ontology language that enables a device or machine to universally process informative content from the web (Bruwer, 2014). According to Bruwer (2014), web ontology emerged from the need to extract descriptions of web information and comprehend the relationships between pieces of web information.

OWL is a Web 3.0 tool that can allow engineers to optimize their performance (James, 2015). Globally engineers can develop ontologies based on their native language and need. One objective of any engineering organization, including small and medium enterprises, is to equip engineers to align work behavior with organizational goals. Therefore, it is the responsibility of management to develop performance measures that will prompt organizationally desirable behaviors.

Earlier adoption of ontology languages was user-specific or designed solely for user communities, particularly science and organization-specific e-commerce applications (Bruwer, 2014). Ontology languages were not compatible with the web's architecture, especially not Web 3.0. However, with the creation of OWL2, HCI devices and machines without HCI can read and comprehend information on the web and are equipped with a more powerful syntax and more extensive vocabulary (Bruwer, 2014).

Web 3.0 Technologies

As the semantic web evolves and better gauge the projected direction of Web 3.0 technologies (i.e., AI, IoT, AR), measuring the impact on small and medium enterprises will provide more insight into productivity usage expectations. Web 3.0 technologies may foster research and technological skills far exceeding what is possible today (Roback, 2012).

Web 3.0 technologies drastically advance communication, increase engineers' IT productivity, and revolutionize how information is analyzed and used to benefit organizations (Farah, 2012; Santos, 2015). Thirunarayan and Sheth (2013) proclaimed that data and services associated with small and medium enterprises that adopt cloud computing, social networks, sensors, smartphones, tablets, and other devices that comprise IoT help define these advanced web resources and applications of Web 3.0. Web 3.0 technologies facilitate a worldwide data warehouse consisting of any data format that can be understood and shared by any device and over any network (Rudman & Bruwer, 2016).

Web 3.0 technologies describe machine-to-machine communication on the Internet, using the semantic web to provide personalized information (James, 2015). Web 3.0 technologies provide an integrated web experience where machines can understand and index data like humans (Rudman & Bruwer, 2016). Thirunarayan and Sheth (2013) proclaimed that Web 3.0 technologies might increase productivity and improve knowledge and communication.

Chua and Chua (2017) assumed that a significant causal relationship between conscientiousness personality traits and attitude toward social networking sites (SNS) like Facebook would occur. Therefore, one could infer that social media is a gateway for computer-mediated communication (CMC), skill, motivation, and advanced learning of other Web 3.0 technologies (Chua & Chua, 2017).

Ensuring adequate skills in engineers leads to a society that thrives in a well-developed communications network that supports the free flow of communication across borders with the ability to make decisions promptly (Cebr, 2016). Technological skills of Web 3.0 are specifically known as the third generation of Internet-based services that collectively comprised of an intelligent web (semantic web), machine learning, data mining, artificial intelligence, and natural language technologies (Kreps & Kimppa, 2015). Web 3.0 technologies have made it possible for content relevance to be heightened by location and time (including Web 3D developments evolving from spatial and simulative technology (Kreps & Kimppa, 2015).

The development of Web 3.0 technologies in making code-to-code and machine-to-machine more intuitive connect people in real-time and across different locations worldwide (Gamble & Calverley, 2015). Engineers collaborating across borders must interact across virtual networks, utilizing CMC for significant projects to be sought after. For example, in the 20th century constructing the Sydney Opera House in Australia was built by an engineer from London. The Sydney Opera House's original cost was approximated at $7 million, and scheduling was aimed for completion in 1957. However, the Sydney Opera House was completed 10 years late and went well over budget due to many challenges.

Conversely, advanced Web 3.0 technologies made it possible to construct the world's largest building in Dubai, the Burj Khalifa, in only 1,325 days. Since excavation work began in 2004, the tallest free-standing structure in the world was completed in 2010 as the official launch ceremony was conducted for the Burj Khalifa.

The potential problem found in current research is the rapid growth in Web 3.0 technologies with little training and implementation of new technologies (Biagi, 2013; Benner & Tushman, 2013). Biagi (2013) revealed that not using new technology properly caused an economic slowdown. Syverson (2016) proclaimed that the slowdown in measured labor productivity is statistically and economically significant.

Academia has also experienced similar problems in analyzing the influential contributions that stemmed from new technology and usage. Still, the interpretation has been viewed as a negative signal of IT value. Management information systems managers find difficulty in justifying total investments in IT and Web 3.0 technologies. Management is tasked with a significant responsibility to provide incentives that guarantee worker-performance that is productive, especially since monitoring information about performance is costly (Glassman et al., 2015).

Engineers are tasked to convert productivity from considerable investments in HCI devices and Web 3.0 applications (Tarute & Gatautis, 2014). Roback (2012) proposed a framework and future direction for utilizing productive web applications, social media, and other Web 3.0 technologies, asserting that there is still a need to develop solutions for practical usage in yielding substantial performance results for engineers. Engineers must know why their organization exists and become equipped with new technological skills that fulfill their organizational objectives.

Digital technologies play a vital role in monitoring analytics and traction and equip engineers with insight into better performance trends that adjust machines to proper conditions. Gomes and Cardoso proposed a fourth industrial revolution (Industry 4.0) framework and future direction for utilizing productive Web 3.0 applications and technologies. Web 3.0 technologies may yield new research and technological skills far exceeding Industry 4.0 projections (Gomes & Cardoso, 2020).

Further advances in Web 3.0 technologies present both risk and rewards. Improving Web 3.0 in AI robot production risks replacing cheaper labor in emerging markets in other countries (Gamble & Calverley, 2015). A recurring theme in the ongoing debate sparked by engineering and IT experts further questions which types of jobs will become automated by robots in the future (Michie et al., 2017). For example, the possibilities ranged from surgical robots to massive assembly lines to family-friendly Wall-e science fiction or Star Wars-type images of robots (Gamble & Calverley, 2015). The options for robots are limitless since IoT and AI are accessible as open source.

Xu and Chen (2018) proposed utilizing an IoT-based framework to equip industrial environments with just-in-time manufacturing. Quality assurance processes impacted by the emergence of Web 3.0 technologies and Industry 4.0 may alter industry standards and benefit operational efficiency (Gomes & Cardoso, 2020). Serin and Yalçıner (2021) examined engineers' perspectives of innovation and the new Industry 4.0 to gauge the potential direction of Web 4.0 in which is still being defined.

Technologically Savvy Engineers

The Digital Age, much like past industrial revolutions, resulted in a substantial change in how we interact with others making a more virtual society (Schuh et al., 2014). The Digital Age has birthed new learning theories that include the heutagogy theory (self-determined learning); the paragogy model for establishing peer-to-peer learning; rhizomatic theory of negotiating knowledge and explanation; the connectivism theory for connecting through distributed learning (Corbett & Spinello, 2020); and the cybergogy theory for creating learner-centered, and collaborative virtual learning environment autonomously (Wang & Kang, 2006).

Older theories like Vygotsky's zone of proximal development and Bruner's scaffolding models are becoming less effective in explaining the digital literacy and computer literacy phenomenon. Since the 1980s, academic research has accepted the five-factors model proposed by Tupes and Christal in 1961, whereby there is a valid and reliable assessment scale for measuring five factors of personality (Tupes & Christal, 1992). The five-factors model is based on the theory of personality associated with words, but not neuropsychological experiments, suggesting five broad dimensions commonly associated with a person's character and psyche are known as (a) openness to experience (or intellect), (b) conscientiousness, (c) extraversion, (d) agreeableness, and (e) neuroticism (or emotional stability) (Tupes & Christal, 1992). Current literature about factors that directly interface with the IT productivity paradox problem references the digital age and its importance to teaching engineers, professionals, and older adults that are not digital natives' best practices for using technology (James, 2015; Malek, 2017).

Employers seek out advanced digital natives or technologically savvy engineers who can help with mobile application development and forward-thinking initiatives (Jayarama et al., 2015). Computers and technology impact humanity worldwide; therefore, knowing new technology and being computer literate means understanding the usage of software, hardware, and other known applications of a computer.

James (2015) proposed that digital natives, who have interacted with digital technology from an early age, use web technologies as second nature. The perspective regarding the education on computers should begin at an early age; however, older adults were not susceptible to computer education at an early age before the Digital Age since it did not exist. Therefore, deficiencies in prior research do not address these factors pre-dating the Digital Age other than the fact that web technologies were not accessible to older adults as it is to the younger generations today.

Through more discovery and consideration of the potential factors that might lead to the IT productivity paradox, other research has indicated that the digital literacy in non-millennials, or older engineers not born between 1981 and 1996 (millennials ages 22-37 in 2018) as the potential root to the complex IT productivity paradox (see, for example, Litchfield & Javernick-Will, 2015; Sharma et al., 2016). In 2015, one-fifth of the nations' workforce was classified in the demographic of age 50 and older. A significant issue in society is that many working professionals who are 50 and older tend to struggle with proper computer use (Tishman et al., 2012). Conversely, for digital immigrants, age 50 and older, it involves an often long and challenging learning curve (James, 2015). Biagi (2013) and James (2015) further conveyed the technology and productivity interrelationship by pointing out that technological inability factors impacted organizational productivity due to age stereotypes of older adults.

McKenna et al. (2014) proclaimed that these three significant challenges relate to the engineering field: (a) the demand for digitally inclined engineers, (b) scarcity of trained engineers, and (c) the absence of ethnic and gender diversity. Computer literacy, also referred to as digital literacy, is at the heart of the research problem for my study. Sharma et al. (2016) and Gamble and Calverley (2015) argued that various combinations of variables, such as age, race, skill, and others, provide evidence of the digital divide that causes issues with digital literacy.

Engineers provide technical solutions and translate knowledge for users who are not as tech-savvy (Gamble & Calverley, 2015). An engineer can either be an asset or a liability as technology evolves (Tishman et al., 2012). For that reason, employers require proficient, computer literate, and technologically savvy engineers—who are critical to the success of small and medium enterprises.

The Hanover Research Industry Trend Report (2017) proclaimed that becoming equipped with 21st-century skills, coupled with having technological expertise, would prepare future engineers to meet the demands and challenges of today's world. To ensure engineering students are adept in advanced technology, Hanover Research (2017) declared that the United States must cultivate economic, political, and social progression at a younger age in four critical areas: (a) creativity and imagination; (b) critical thinking; (c) problem solving; (d) collaboration and teamwork.

Measuring productivity for engineers and data management has evolved in the last decade. In a fast-paced digital society, the growing international movement is focused on achieving skills that engineering students must master, which is critical to the quality of life and social change (Borras-Gene et al., 2016). Technologically savvy engineers are expected to have robust simulation, modeling, 3D computer-aided design (CAD), computer coding, and problem-solving skills (Priem et al., 2012).

Edwards and Jensen (2014) proposed that senior management implement critical performance indicators (KPIs) tailored to assess engineering skills and productivity. Also, updated performance management systems should factor in redesigning technology and production that consider human characteristics for engineers who operate those systems (Edwards & Jensen, 2014).

According to Mashal (2017), the productivity of engineers is measured by five primary functions: (a) define productivity and direct behavior that communicates to the engineers or employees, the common expectation from the task(s); (b) monitor performance and provide feedback from an implemented measurement system that can check progress toward an objective; (c) diagnose problems or conduct productivity analysis and examination of trends that identify challenges prior to escalating authorized corrective action and early adjustment as needed; (d) facilitate planning and control so that productivity measurement allocates information on costs, time, output rate, and resource usage in order to foster better decision-making regarding pricing, purchasing, production scheduling, delivery scheduling, contracting and many other activities in the industrial cycle; and (e) support innovation of cost data coupled with productivity analysis which supports re-evaluation of proposed changes to current processes and products, allowing new products to pitch. General technological skills of technologically savvy engineers include the following: (a) managing complicated projects with varying milestones and deadlines; (b) managing budgets; (c) peers' needs in other departments; and (d) communicating effectively (virtually and in person).

Diversity in Engineering

Expanding the discussion on McKenna et al.'s (2014) assertion regarding the absence of ethnic and gender diversity, a factor that potentially induces the IT productivity paradox, this section explores diversity in the engineering field. Examining reports and data from the Centre for Economics and Business Research (Cebr), Google, and OECD databases highlights the global economic impact of women and minorities in engineering. A report conducted by Cebr (2016) for the Royal Academy of Engineering highlighted the engineering index, which included a robust dataset of engineering students and graduates' measured strength in engineering and considered engineering as the driver in economic development. The engineering index considers engineering data and compares countries based on engineering wages, gender balance in engineering, employment and benefits, type of organization, exports, and quality of infrastructure.

Historically, women have been under-represented in the field of engineering. A low proportion of women and students pursue engineering programs in many developed countries like the United States and the United Kingdom (Cebr, 2016). Slight improvement in diversity occurred between 2008 and 2012 in the United States and most OECD countries as the number of women in engineering graduates increased (Cebr, 2016). However, data from organizational databases (see, for example, Cebr and OECD, 2012) still indicate a significant deficiency in hiring diversity, a lack of high diversity enrollment rates in college admissions for STEM majors, and an overall lack of diversity in prominent engineering educational institutions.

Google's diversity report data collected in 2017 indicated that the workforce was composed of 69% male and 56% white. Only 31% were women, and barely 2% of engineers at Google were black (Corbett & Weber, 2016; Google, 2018). An initiative aimed at inviting more engineers from historically black colleges and universities

(HBCUs) to apply for jobs at Google, known as Google in Residence, has helped equip engineering students with computer science skills and teaches future engineers how to position themselves for engineering careers in the 21st century (Corbett & Weber, 2016; Google, 2018). This initiative addressed the lack of ethnic representation at Google and provided better talent engagement and community outreach efforts (Google, 2018).

Summary and Conclusions

In practice, researchers and industry professionals have struggled to understand why investment in new technology has not consistently provided a return on investment in terms of skills and productivity. However, the reasons for this lack of productivity have not been thoroughly researched and documented in the scholarly literature, particularly related to the factors that motivate engineers to embrace and fully utilize new capabilities, such as those offered by Web 3.0 technologies. My research was intended to fill the gap in understanding how to enhance the use of HCI devices through well-conceived investments in technology, which may enable organizations to make better investment decisions, and as a result, to yield higher productivity levels for engineers.

Specifically, my research was intended to determine which IT-related devices are most associated with engineer productivity, as measured by their skills with the latest technology (Web 3.0). Web 3.0 involves crowd-sourced data, IoT, cloud computing, and the semantic web. The objective was to identify where engineering organizations and managers might make the most effective and efficient investments, to increase productivity; rather than making large-scale investments across a wide spectrum of technology, which has been both theorized and proven practically to decrease skills and productivity.

This chapter included an exploration of the prominent literature in ICT, HCI, and Web 3.0 technologies. The literature provides definitions of advanced technologies, innovation in adopting web technologies, and limitations. The technology timeline provides a snapshot of how rapidly digital technologies have advanced and projects how digital life in 2025 in the United States would impact both people in society and small and medium enterprises for better or worse (Pew Research Center, 2014).

The major themes in the literature review explained ICT, HCI, Web 3.0, digital literacy. But the existing research exhibits a gap in identifying how engineers interact with advanced devices and how engineers obtained Web 3.0 skills based on reliance and competence of HCI devices. My research was intended to close this gap in research.

The literature review supports the need to examine the relationship between the use of HCI devices and Web 3.0 skills. In summary, the contribution of Web 3.0 skills to output and performance is documented in several studies, although the return on technology investment based on output growth, high profits, and market value is still to be determined (Decker et al., 2014; Kreps & Kimppa, 2015). Several researchers have attested to a need for future studies to expand on technological shifts by organization, industry, and other organizational characteristics for innovation and adoption of advanced technologies like Web 3.0 (Acemoglu et al., 2014; Bruwer, 2014; Byrne et al., 2016; Chua and Chua, 2017; Decker et al., 2014; Gamble & Calverley, 2015; Gomes &

Cardoso, 2020; Roback, 2012; Rudman & Bruwer, 2016; Shambaugh et al., 2018; Stanley et al., 2018).

In Chapter 3, I concentrate on the numerical analysis of quantitative data. There is a shift in thinking from a focus on personality characteristics that typically were viewed as natural and generally accepted, to an emphasis on Web 3.0 skills and abilities that can be learned and developed. Although other factors such as personality attributes may play an integral role in engineering productivity and management decision-making, focusing on Web 3.0 skills obtained by engineers in my research was intended to suggest their abilities, knowledge, and types of devices used, which could be leveraged for effective management.

Chapter 3: Research Method

The purpose of this quantitative correlational study was to investigate whether the use of HCI devices predicts Web 3.0 skills among engineers. In this chapter, I document the methodology for my nonexperimental descriptive survey research study. Significant sections of this chapter include the research design and rationale, research methodology, sampling procedures, population, and survey design.

Research Design and Rationale

In this quantitative correlational study, I investigated whether the use of HCI devices (reliance on and competence with HCI devices) correlates with Web 3.0 skills among engineers. In this correlational study, I employed a quantitative questionnaire to measure the reliance on and competence with five specific HCI devices among engineers (10 primary plus two aggregate independent variables). The questionnaire was also used to inform the dependent variable (Web 3.0 skills). The objective of using the quantitative research method was to evaluate the relationship between variables by collecting numerical data from a sample of a target population and analyzing data statistically (Yilmaz, 2013). This research design is intended to generalize the findings from a sample of the population. I chose the quantitative correlational methodology to determine if the use of various HCI devices is correlated with or predicts the skill of engineers with Web 3.0 technologies. A qualitative methodology might lead to more insights among a few participants, but it would not determine a correlation between HCI device use and Web 3.0 skills. Therefore, I chose the quantitative design.

Variables

The quantitative questionnaire measured the dependent variable (Web 3.0 skills) and the 12 independent variables (reliance on and competence with five HCI devices, individually and in the aggregate). The dependent variable, Web 3.0 skills, was operationally defined by computing the mean response from Questions 1 through 8 of the questionnaire with responses from a 5-point Likert scale as follows:

1. No prior experience or training with the technology;
2. Minimal training received; minimal experience with the technology, below average level of expertise;
3. Medium level of experience and expertise (able to competently use key functionality);
4. Significant experience with the technology; above average level of knowledge, skill, and confidence, but not yet in senior, trainer, or mentor role; and
5. Experienced, confident, and skilled; able to train or mentor others, considered expert in field on this technology.

The independent variables measured two components of the use of five specific HCI devices: reliance on an HCI device and competence with each device. There was one variable for reliance on each device: desktop (DTR), laptop (LTR), tablet (TTR), smartphone (SPR), and wearable (WBR) devices. There was one variable for competence on each: desktop (DTC), laptop (LTC), tablet (TTC), smartphone (SPC), and wearable (WBC).

The independent variables were informed by the response for each device from Questions 9 and 10. The value of each independent variable for each participant was a discrete ordinal numerical value (no composite score) derived from the response for each device, using two 5-point Likert scales. For reliance on HCI device, as follows:

1. Device not used;
2. Minimal use of the device;
3. Moderate use of the device;
4. Significant use of and reliance on the device; and
5. Heavily reliant on the device most of the time, cannot be apart from the device.

For competence with an HCI device:

1. No competence with any functions,
2. Competence and confidence with some functions,
3. Competence and confidence with many functions,
4. Competence and confidence with most functions, and
5. Expert on all functions.

In addition, there were two aggregated variables, RHCID and CHCID. RHCID was calculated by computing the mean response from Question 9. CHCID was calculated by computing the mean response from Question 10. RHCID and CHCID were continuous random variables.

Research Question and Hypotheses

The primary research question was, What is the relationship between the use of HCI devices and Web 3.0 skills? This question was designed to explore the use of Web

3.0 technologies to enhance productivity in the United States. My findings focused on the outcomes of a test of these hypotheses:

$H_0$1: There is no significant relationship between any of the predictors (10 independent variables and 2FIs) and Web 3.0 skills (dependent variable).

H_A1: There is a significant relationship between at least one of the predictors and the dependent variable.

$H_0$2: There is no significant relationship between reliance on or competence with the five HCI devices, in the aggregate, and their 2FI; and Web 3.0 skills.

H_A2: There is a significant relationship between either reliance on and competence with the five HCI devices, or both reliance and competence, in the aggregate; or their 2FI; and Web 3.0 skills.

I used MLR to construct a predictive model of the dependent variable and to determine the relationship between the independent variables (reliance on and competence with HCI devices) and their 2FIs and the dependent variable (Web 3.0 skills). SPSS was the statistical package I used for descriptive statistics and MLR.

Methodology

The methodological approach relied on a quantitative questionnaire and data analysis involving MLR to develop a predictive, multivariable model and to test the hypotheses. In this quantitative correlational study, I investigated whether and to what extent there is a relationship between the independent variables, reliance on and competence with HCI devices, and the dependent variable, a Web 3.0 skill level measure.

Population

The target population of this study consisted of full-time engineers working in multinational small and medium enterprises in metropolitan areas of Georgia. I chose multinational engineering organizations for my research because multinational engineering organizations have common business problems that need investigation and explanation (Baturay & Toker, 2015; Contreras et al., 2012). Engineering disciplines include aerospace, agricultural, biomedical, chemical, civil, computer, computer hardware, electrical, electronics, environmental, health and safety, industrial, materials, mechanical, mining, and geological, network, nuclear, petroleum, software, system, marine, and naval architects. The population is appropriate for this study because (a) engineers in Georgia are finding innovative solutions for gaining the competitive advantage from technology, and (b) Web 3.0 skills and tools will soon drive innovative technology and smart cities, once established with internet access available for all engineers.

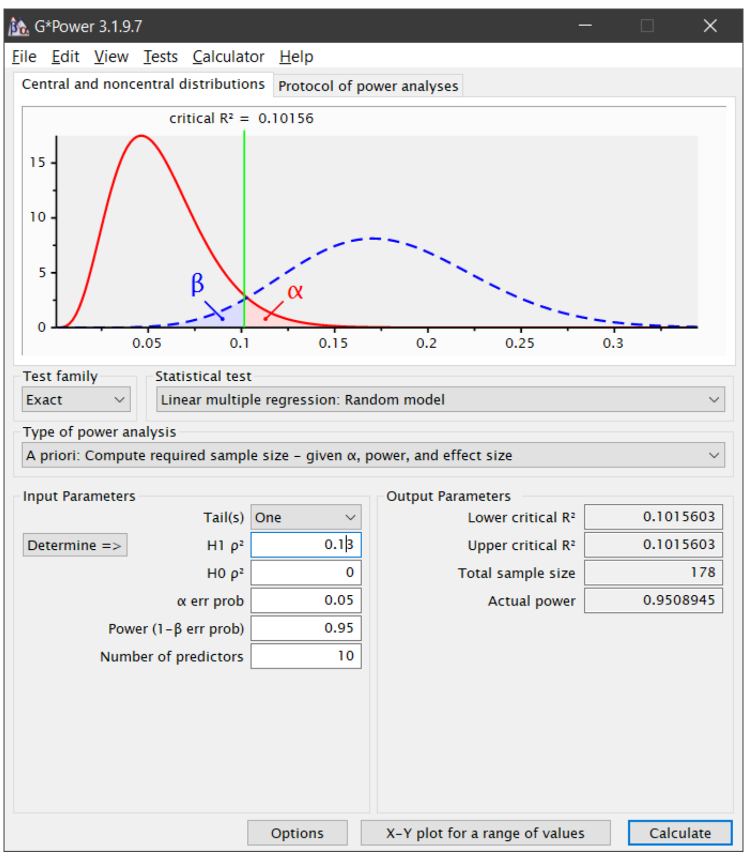
Sampling and Sampling Procedures

I used the G*Power software Version 3.1.9.2 (Faul et al., 2009) to calculate the sample size after identifying the level of significance, power, and the effect size. Power ($1 - \beta$) is the likelihood of rejecting the null hypothesis when it should be rejected. Power is directly related to the probability of a Type II error (β)—a false negative, or the likelihood of failing to reject the null hypothesis when it should be rejected. Power, then, is the likelihood of finding a significant outcome when one exists. The level of significance (α) is the probability of a Type I error—a false positive, or the likelihood of rejecting the null hypothesis when it should not be rejected. Confidence (1 – α) is the likelihood of not concluding that an effect exists when it does not.

Considering my self-designed instrument, I planned to test for a medium effect size (Cohen, 1988), based on the population squared correlation coefficient, $\rho^2 = 0.13$ (see also Cohen, 1992); with $\alpha = 0.05$ and power = 0.95. I used G*Power (Faul et al., 2009) to compute the minimum sample size using the a priori analysis, given α, power, effect size, exact test, and the linear multiple regression statistical test, random model. The minimum sample size was 178. Figure 1 shows the G*Power calculations.

Figure 1

Calculating Minimum Sample Size



Procedures for Recruitment and Participation

The process for selecting engineering participants at small and medium enterprises (or businesses with up to 1,500 employees) in Georgia was planned to be handled through the combination of SurveyMonkey's audience selection feature and a backup plan of convenience sampling of my network list of potential engineers contacted via email or LinkedIn. The minimum a priori sample size was calculated to be 178. I requested SurveyMonkey to provide 215 completed questionnaires to account for the possibility that some questionnaires might be invalid. In the event SurveyMonkey could not obtain a sample size of 215 participants, I planned to use convenience sampling to recruit more participants to complete the questionnaire via LinkedIn. I relied on SurveyMonkey to select participants and to provide 215 valid and complete responses to the survey according to my criteria. Informed consent was provided to all participants via SurveyMonkey on the first page of the questionnaire (or by email with a link to access the questionnaire). Participants who were unable to complete the informed consent form were not included in the research.

Instrumentation and Operationalization of Constructs

The most used research instrument in quantitative research is either a survey or an experiment (Rahi, 2017). I used a survey to reduce time and so that respondents could provide a snapshot to rate their current skills and experience using Web 3.0 technologies. Using surveys as a data collection tool in my study was the most beneficial in cost effectiveness and the survey's potential to facilitate generalizability (Schmitz, 2012).

I considered other questionnaires for my survey. I searched for instruments from scholarly research into the variables of interest but did not find an existing questionnaire that assessed HCI and Web 3.0 skills suitable for my study. For example, I reviewed Hoboubi et al.'s (2016) uses of the Osipow occupational stress questionnaire, a questionnaire to examine the level of job stress; Smith et al.'s (1969) uses of the Job Descriptive Index for job satisfaction; and the employee productivity questionnaire by Hersey and Goldsmith (1980). James (2015) proposed a new model for adopting and using Web 2.0 technologies, known as the user benefits model, which was developed to assist professionals in an organizational setting.

Bock et al. (2016) revised and validated the psychometric properties of the mobile phone affinity scale (MPAS) used to measure health behavior change for young adults and adolescents who used their cell phones often. Bock et al. assessed the construct validity of MPAS by relating the measuring instrument to a general theoretical framework. The researchers reviewed the items to determine face validity. Items that were confusing or ambiguous were edited, and duplicates were deleted. Before disseminating to the larger sample, the authors administered a pilot study to eight adults to confirm item clarity and comprehension. MPAS was designed to measure the use of technology, both negative (including excessive phone use and Internet addiction) and positive (productivity and efficiency) construct associated with cell phone usage (Bock et al., 2016).

Bock et al. (2016) stated that there were no existing instruments that measured and assessed mobile phone and technology usage, including items of these positive elements. Though no existing instruments were suitable for my research, some did provide insights into creating an appropriate instrument. Both of Bock's constructs were included to assess MPAS subscales. Finally, to test for the concurrent validity of the final measure, I examined the association between MPAS subscales and measures of motivation.

Bock et al.'s (2016) scale involved 57 statements that assessed mobile phone usage. Bock et al.'s productivity factor provided participants with only four generic statements related to mobile phone usage for being organized at work and school.

My self-designed questionnaire, the Web 3.0 technological skill survey, provided in Appendix A, provided a value for eight different Web 3.0 technologies: web technologies, developer tools, relational database technology, software design, blockchain technology, operating systems and server technologies, server software, and virtualization. The dependent variable, Web 3.0 skills, was the mean of the responses to questions 1 through 8, related to engineers' knowledge of technologies. This was a self-reported assessment of skills, meaning that the 214 engineers responded to the questionnaire based on their assessment of their own skills. No managers at any small and medium enterprise were contacted to report how the 214 engineers performed or gave feedback of their Web 3.0 skill level.

The values of the independent variables representing reliance on the five specific HCI devices (DTR, LTR, TTR, SPR, and WBR) were determined from question 9 of the questionnaire. The values of the independent variables representing competence with the five specific HCI devices (DTC, LTC, TTC, SPC, and WBC) were determined from question 10 of the questionnaire. The Web 3.0 technological skill survey asked participants to self-evaluate reliance and competence with the five HCI devices, and their Web 3.0 skills. The aggregate indices (RHCID and CHCID) were assessed separately and calculated as the mean of the respective independent variables related to reliance and competence.

Engineers rated statements according to their skill level and productivity using the semantic web, IoT, and cloud computing. Results for Web 3.0 skills were intended to be distributed normally, such that an engineer's score to the right of the peak of the curve (the mean) is good, and to the left is poor. Once items were aggregated, every item that was skill-scored provided insight into how proficient an engineer claimed to be with Web 3.0 technologies.

In addition to the skills assessment portion of the Web 3.0 technological skill survey, I included a short section on participant demographics. The self-designed questionnaire includes participants' demographics by identifying the participant number (ID). The demographic information was used to compare the sample to the population. Table 1 specifies the complete demographic information for the sample. The length of the questionnaire was under three pages, and its duration was about 15 minutes.

Pilot Study

The objective of the pilot study was to calculate Cronbach's reliability coefficient (α) on the scales provided from the Web 3.0 technological skill survey. The pilot study benefited the research design before conducting a full-scale study. The pilot study ensured that the questions in the questionnaire were valid. For the pilot study, I selected five engineers to take the questionnaire to help refine the questions and to improve item clarity and comprehension.

Data Collection

I used SurveyMonkey to generate the link to the questionnaire. Instructions about survey participation, deadlines for participation, and a list of frequently asked questions were included in the invitation to the survey. The duration for each questionnaire was up to 15 minutes, and participants were asked to return within 48 hours upon receiving an invitation unless they had further questions to address before taking the survey.

Data Analysis Plan

All questionnaires returned by SurveyMonkey were expected to be complete questionnaires, with no data missing. I did not anticipate outliers occurring in this survey since a Likert scale bounded the choices. I input data directly into SPSS by typing in Data View.

I used MLR to construct a predictive model of the relationship between predictors (independent variables: reliance on and competence with HCI devices, individually and in the aggregate; and 2FIs) and the dependent variable (Web 3.0 skills); and to test the hypotheses. Using SPSS, I created scatterplots and for graphical analysis of variables, descriptive statistics for the participants' demographics, and descriptive statistics of the responses to items in the questionnaire related to the research question.

Multiple Linear Regression

The regression model is the following:

$$Y = \beta_0 + \beta_1 X_1 + \ldots + \beta_k X_k + \varepsilon. \quad (2)$$

where (X_1 to X_k) are predictors of Y

Y = the dependent variable

β_0 = the Y intercept, or the value of Y if the value of all Xs = 0

β_j = the coefficient for predictor, X_j; the slope of the regression line; or the amount that Y will change per one unit change of X_j

X_j = the jth predictor

ε = random error in Y.

Two-Factor Interactions

The influence on the dependent variable of 2FIs between independent variables is evaluated as an essential part of MLR analysis. 2FIs are created as the cross-product of the independent variables and tested in the MLR analysis.

Hypotheses

Null hypothesis. The null hypothesis for the overall multiple regression model (the hypothesis regarding the influence of the Xs on Y) is that there is no significant relationship between (independent variables and 2FIs) and the dependent variable, depicted mathematically as follows:

$$H_0: \beta_1 = \beta_2 = \ldots = \beta_k = 0. \tag{3}$$

Alternative hypothesis. There is a linear relationship between the dependent variable and at least one predictor, depicted mathematically as follows:

$$H_a: \text{at least one } \beta_j \neq 0. \tag{4}$$

Hypotheses are tested regarding the overall model (testing if there is a significant relationship between the dependent variable and the entire set of predictors) using the F

test (and its associated p value). The *F* test and its associated *p* value assess whether the set of independent variables and 2FIs predict the dependent variable. Adjusted R^2, the coefficient of determination, indicates goodness-of-fit of the regression model—the proportion of variation in the dependent variable that is attributed to the model of predictors. The *t* test and its associated *p* value are used to assess the significance of each predictor.

Assumptions of MLR

MLR assumes the following: (a) numerical variables; (b) linearity: a straight-line relationship between the independent variables and the dependent variable, (c) independence: the values of the residuals are independent; no autocorrelation; (d) homoscedasticity: the variation of the residuals (error terms) is constant for all values of the independent variables; (e) absence of multicollinearity: no relationship among independent variables; (f) normally distributed residuals; and (g) no influential cases: no significant outliers. Both the independent and dependent variables must be numerical; categorical independent variables must be converted to numerical using dummy variables. A scatterplot assesses linearity, independence, and homoscedasticity. A Durbin-Watson test is also used to test for independence.

Variance inflation factors (VIFs) are used to assess the absence of multicollinearity. The absence of multicollinearity indicates no relationship among independent variables (Dunteman, 1984). VIF values greater than five suggests the presence of multicollinearity. When multicollinearity is present, independent variables are eliminated, sequentially, starting with the variable with the highest VIF.

A normal probability plot of residuals is used to assess their normality. Cook's distance test is used to assess for outliers in regression. Cook's distance is a combined measurement of both observations (graphic and visual) and residual values, where the assumption of an outlier means that an observation has a Cook's distance of more than three times the mean, μ (Barnett & Lewis, 1985).

Model-Building: Stepwise Regression

Two forms of the stepwise regression approach to model-building are used to evaluate possible regression models, considering the influence of individual predictors, including the 2FIs, and their contribution to the strength of the overall regression model. The two-regression model-building approaches are statistical regression (both *backward elimination* and *forward selection* in SPSS) and sequential regression (using the SPSS *enter* method). Non-significant variables and interaction terms are sequentially eliminated (based on the inclusion criterion and improvement in adjusted R^2) to produce the best predictive model—considering adjusted R^2, which accounts for the number of predictors in the model.

Predictive Regression Model

The predictive regression model includes significant independent variables and interaction terms. For significant predictors, the dependent variable increases or decreases by the coefficients (b_j) associated with each predictor. The predictive regression model is expressed in the following form:

$$\hat{Y} = b_0 + b_1X_1 + \ldots + b_kX_k \qquad (5)$$

where

$\hat{Y}$ = “Y-hat”, the dependent variable

b_0 = Y intercept for the population

b_j = slope (coefficient) for the population for predictor, X_j

X_j = jth predictor (independent variable or interaction term)

There is no error term in the predictive model. The difference between the predicted value of Y (for any set of values for the independent variables) and the actual, measured value of Y for that set of values for the independent variables is the error in the model, called a residual.

Threats to Validity

Surveys are valid, reliable, and widely used in descriptive studies (Borg & Gall, 1983; Rahi, 2017). The questionnaire in this research was self-designed. The advantages of this self-designed questionnaire include the following: (a) provided the ability to reach many engineers easily; (b) was economical; (c) provided quantifiable responses; (d) was easy to analyze; and (e) took less time than conducting observations or interviews (Bailey, 1982).

I conducted a pilot study to ensure that the questionnaire was comprehensible and phrased adequately. The validity of the questionnaire determined by feedback from the pilot test included expert reviews of content. The methodology used to validate the instrument was based on the experts’ review, after which items were updated or removed to better focus on the research target of this study.

External Validity

To declare external validity via SurveyMonkey, I disabled IP address tracking to make the questionnaire anonymous and ensure secure transmission of answers. Participants were able to change their answers on any page of the questionnaire until they completed the questionnaire. The design of my questionnaire in SurveyMonkey targeted participants who met the criteria of occupation/income or engineer, age, gender, and country.

SurveyMonkey utilized nonprobability sampling from an audience sample of subject matter experts in the engineering field, including both males and females, from the target population of Atlanta—this also improved external validity in this study. In the event I needed additional responses, I used multiple target audience collectors feature in SurveyMonkey where I then sent the questionnaire web link or email invitation to my LinkedIn network. Use of convenience sampling by identifying only subject matter experts familiar with Web 3.0 technologies on LinkedIn, eliminated sample bias and increased external validity.

This study offers both population and ecological validity. Establishing population validity ensured that this study could be generalized to a broader population of engineers and management professionals. Replication of this study aimed at other technical professionals (based on their peculiar characteristics like socioeconomic background, gender, and country) that utilize Web 3.0 technologies and devices would establish higher population validity. The findings of this study can be generalized to real-world scenarios that refer to ecological validity.

Survey Reliability

Reliability refers to the stability of measurement, and its absence can be a significant threat to the validity of a study (Frankfort-Nachmias et al., 2015). I computed Cronbach's α to assess reliability. Many factors may interfere with survey reliability; among them are timing, changes in participants, the environment, or the clarity of the questionnaire. To increase reliability, I utilized multiple-item scales and indexes to enhance the reliability and precision of measurements. The number of test items, item-interrelatedness, and dimensionality affects the value of Cronbach's α. The most critical of the three assumptions is unidimensionality. Unidimensionality is a fundamental determinant of Cronbach's α since it assumes the questions only measure one latent variable or dimension (Field, 2013).

In science and technology studies, perceived ease of use and performance is measured using 5-point Likert scales more frequently than 7-point Likert scales (Joshi et al., 2015). For example, Bock et al. (2016) used a 5-point Likert scale (1 = not true to 5 = extremely true), and the instrument contained 57 items measuring seven constructs, with six to nine items per construct. Since I was interested in how new technology (Web 3.0) and devices like smartphones, tablets, personal computers, and wearables increased performance, I adapted part of Bock et al.'s 5-point Likert scale in my instrument.

Internal Validity

Achieving internal validity meant that my research measured what I intended it to measure. I designed a questionnaire relevant to the independent variables (use of HCI devices) and dependent variable (Web 3.0 skills) for responding to the research question.

The independent variables (use of HCI devices) cannot be manipulated in this research design. Validity of the responses were achieved by using the 5-point Likert scales.

I computed Cronbach's α to assess how well the items in the scaling method correlate. Across the 5-point Likert scales, the numerical values have meaning and distinction (Bonett & Wright, 2015). A value of .80 or higher indicates good internal consistency. To compute Cronbach's α, I asked a few subject matter experts to complete the Web 3.0 technological skill survey for pilot testing. In addition, I used a scatterplot to illustrate split-half correlation (even items vs. odd-numbered items).

Internal validity in non-experimental studies is generally lower than in quasi-experimental and experimental studies (Frankfort-Nachmias et al., 2015). Non-experimental research lacks manipulating the independent variable(s) or treatments, random assignments of participants to conditions, or both (Frankfort-Nachmias et al., 2015).

Summary

In this chapter, I identified the research plan strategy and explained how I intend to conduct the research. Included in this chapter is the purpose of the study, a description of my role as a researcher, sampling process, the type of participants, selection of instruments, data collection technique, data analysis, reliability, validity, and the research method and design. Reasons for sampling involved better: speed of data collection, accuracy in results, and cost-effectiveness. The selection of the sampling method depended on the nature of this research and included statistical, theoretical, and practical matters. ICT, IT, and Web 3.0 technologies drastically advance communication by increasing engineers' productivity and revolutionizing how information is analyzed and used to profit organizations. Web 3.0 technologies are projected to increase the productivity of engineering professionals and improve knowledge and communication.

Chapter 4: Results

The purpose of this quantitative correlational study was to investigate whether the use of HCI devices predicts Web 3.0 skills among engineers—in other words, whether the use of HCI devices influences, facilitates, or indicates the willingness or motivation to learn new skills, increasing performance and enhancing productivity. Use of HCI devices has two components: reliance on and competence with HCI devices. I tested reliance on each of the five HCI devices that I hypothesized influence the dependent variable: desktop (DTR), laptop (LTR), tablet (TTR), smartphone (SPR), and wearable (WBR) devices. I also tested the competence with each of the five HCI devices (DTC, LTC, TTC, SPC, and WBC) that I hypothesized influence the dependent variable. In addition, I tested two independent variables that were aggregate measures of reliance and competence (RHCID and CHCID).

$H_0 1$: There is no significant relationship between any of the predictors (10 independent variables and 2FIs) and Web 3.0 skills (dependent variable).

$H_A 1$: There is a significant relationship between at least one of the predictors and the dependent variable.

$H_0 2$: There is no significant relationship between reliance on or competence with the five HCI devices, in the aggregate, and their 2FI; and Web 3.0 skills.

$H_A 2$: There is a significant relationship between either reliance on and competence with the five HCI devices, or both reliance and competence, in the aggregate; or their 2FI; and Web 3.0 skills.

In this chapter, I address the pilot study, explain data collection, and provide descriptive statistics for the questionnaire's demographic portion. Data collection and conversion of data, missing data, and an overview of the sampling selection are discussed. Tests of MLR assumptions are provided. MLR analyses, regression model building, and the results of the hypotheses tests and answers to the research question are provided.

Pilot Study

Upon approval by the Walden University's IRB to conduct my study (approval number 06-25-19-0392340), the recruitment of participants for the pilot study consisted of a convenience sample of 100 experts via LinkedIn from the population of full-time engineers working in Georgia. Five experts responded and participated in the pilot study. The pilot study was intended to ensure that the questions from the Web 3.0 technological skill survey were valid and understandable.

Data Collection for Pilot Study

Table 2 identifies the participant number of each participant. Gender was coded as 1 = male, and 2 = female. Race was coded as B = African American, W = Caucasian, O = other. Age identifies the participant's age in years.

Table 2

Demographics of Experts in Pilot Study

ID	Gender	Race	Occupation	Age
001	Female	African American	System engineer	32
002	Male	African American	Network engineer	26
003	Male	Caucasian	Software engineer	34
004	Female	Caucasian	Mechanical engineer	45
005	Male	Other	Industrial engineer	27

Cronbach's α: Scale Reliability

Cronbach's α measures reliability, or internal consistency, of the psychometric instrument (Frankfort-Nachmias et al., 2015). Field (2013) proclaimed that reliability analysis is used to measure the consistency of a measure. Frankfort-Nachmias et al. (2015) proposed that Cronbach's α demonstrates the overall reliability of a questionnaire, with recommended values described as the following: $\alpha \geq 0.9$, excellent; $0.7 \leq \alpha < 0.9$, good; $0.6 \leq \alpha < 0.7$, acceptable; $0.5 \leq \alpha < 0.6$, poor; and $\alpha < 0.5$, unacceptable. The validity and reliability of the questionnaire's three subscales were assessed with Cronbach's α. The subscales were constructed as follows:

- Subscale 1—Knowledge of technologies (KOT): web technologies (WT), developer tools (DT), relational database technology (RD), software design (SD), blockchain technology (BT), operating systems and server technologies (OS), server software (SS), and virtualization (VZ)
- Subscale 2—Reliance on HCI devices (Reliance): desktop (DTR), laptop (LTR), tablet (TTR), smartphone (SPR), and wearable (WBR)
- Subscale 3—Competence with HCI devices (Competence): desktop (DTC), laptop (LTC), tablet (TTC), smartphone (SPC), and wearable (WBC)

Pilot Study Results

The pilot study participants provided consent and answered the 10 questions of the main study questionnaire. Participants in the pilot study provided no feedback that required any changes to the questionnaire items. Based on Cronbach's α, the Web 3.0 technological skill survey was found to be highly reliable (18 items; Cronbach's $\alpha = .97$).

Subscale 1 (KOT) consisted of eight items (Cronbach's α = .961) and had excellent internal consistency. Subscale 2 (reliance) consisted of five items (Cronbach's α =.966) and is an excellent measure of the internal consistency of the test or instrument. No items were rejected using Subscale 2 (reliance). Subscale 3 (competence) consisted of five items (Cronbach's α = .916) and is an excellent measure of the internal consistency of the test or instrument.

Internal consistency was achieved, indicating interrelatedness of the items within the test for Subscale 1, KOT. Subtracting from 1.00 produced the index of measurement error. For the KOT subscale, the test has a reliability of 0.96, there was 0.08 error variance (random error) in the scores ($0.96 \times 0.96 = 0.92$; $1.00 - 0.92 = 0.08$). Table 3 indicates the item-total statistics of KOT. In the column, labeled corrected item-total correlation; the total score from the questionnaire should correlate with values at or above .08. Any values less than .08 would be rejected. Therefore, no items needed to be rejected in the KOT subscale.

Table 3

Item-Total Statistics of KOT

	Scale mean if item deleted	Scale variance if item deleted	Corrected item–total correlation	Cronbach's α if item deleted
Web technologies	28.0	26.5	.929	.951
Developer tools	28.4	26.8	.889	.953
Relational database technology	27.8	27.7	.712	.965
Software design	28.2	27.7	.940	.952
Blockchain technology	28.0	26.5	.929	.951
Operating systems and server technologies	28.4	26.8	.889	.953
Server software	28.0	26.5	.929	.951
Virtualization	28.6	28.3	.641	.969

Table 4 displays the item-total statistics of Subscale 2, reliance. In the column, labeled corrected item–total correlation, the total score from the questionnaire correlated with values at or above .08. Any values less than .08 were rejected. In the column Cronbach's α, if item deleted, the overall values for Cronbach's α are shown. Any items that were greater than .966 would be deleted to increase Cronbach's α and to improve reliability. In this case, no items were deleted.

Table 4

Item-Total Statistics of Reliance

	Scale mean if item deleted	Scale variance if item deleted	Corrected item–total correlation	Cronbach's α if item deleted
DTR	16.0	10.0	.894	.960
LTR	15.8	9.2	.906	.957
TTR	16.2	9.2	.906	.957
SPR	15.8	9.2	.906	.957
WBR	16.2	9.2	.906	.957

Internal consistency is expressed as a number between 0 and 1 and described the extent to which all the items in Subscale 3 (competence) are the same concept or construct by indicating interrelatedness of the items within the test. Subtracting from 1.00 produced the index of measurement error. The results of Subscale 3 demonstrated that the test has a reliability of 0.92, and there is 0.18 error variance (random error) in the scores ($0.92 \times 0.92 = 0.85$; $1.00 - 0.82 = 0.18$). Table 5 displays results for the item–total statistics of competence. In the column labeled corrected item–total correlation, the total score from the questionnaire correlated with values at or above 0.18. Any values less than 0.18 were rejected. No items were rejected in Subscale 3. In the column Cronbach's α if item deleted, the overall values for Cronbach's α are shown. In this case, item SPC (.960) was greater than .916, and if deleted, would highly increase Cronbach's α and improve reliability. The column labeled squared multiple correlation (not shown) returned missing values because the determinant of the covariance matrix was zero or approximately zero (.08).

Table 5

Item–Total Statistics of Competence

	Scale mean if item deleted	Scale variance if item deleted	Corrected item–total correlation	Cronbach's α if item deleted
DTC	16.2	9.2	.907	.870
LTC	16.2	11.2	.845	.893
TTC	16.2	9.2	.907	.870
SPC	16.0	12.5	.423	.960
WBC	16.2	9.2	.907	.870

Impact on Main Study

Cronbach's α computations suggested that the questionnaire was reliable. Therefore, no changes were made. Achieving internal validity meant that my questionnaire measured what I intended. The reliability of the questionnaire, including three subscales (KOT, reliance, and competence) I created, were suitable for this research. As confirmed by the pilot study, the Web 3.0 technological skill survey is reliable and valid.

Data Collection

Sample

Once I obtained informed consent consistent with IRB ethical standards, much like that of the pilot study, eligible participants were provided with an explanation of this research study and instructed to complete the Web 3.0 technological skill survey found on the first page of the questionnaire (or by clicking on the SurveyMonkey link sent via LinkedIn direct message). Potential participants received the Web 3.0 technological survey from June 25, 2019, to July 11, 2019. To achieve an initial desired sample size of 215, I used SurveyMonkey's sample calculator, set the confidence level to 95%, the population size of 500, and 5% margin of error, which would return 218 responses.

In SurveyMonkey, I set a response limit to 215 to meet my required minimum sample size of 178 of complete and valid questionnaires and handle missing or corrupt data issues and to ensure sufficient valid samples to achieve the desired power and confidence given the effect size of this research study. Throughout this timeframe, I notified participants about my research study by contacting engineering colleagues working in small and medium enterprises in metropolitan areas of Georgia, via direct messaging from my LinkedIn network of over 2,000 connections. If not contacted already by SurveyMonkey, potential participants could access the questionnaire using the SurveyMonkey link I provided via LinkedIn. SurveyMonkey's nonprobability sampling returned the requested sample size of 215. There were no significant discrepancies in data collection from the plan or any adverse events affecting the success of recruitment and response rates for the main study.

Missing Data

The participants were required to answer all questions on the Web 3.0 technological skill survey via SurveyMonkey before submitting their questionnaire to be considered valid. Participants were able to change their responses before submitting the questionnaire. One questionnaire was incomplete. The final sample size, of valid questionnaires was 214. Because the a priori minimum sample size was 178, the additional questionnaires yielded a post hoc statistical power of 98.2%, given a level of significance of 5%, a medium effect size of $\rho^2 = .13$, and 10 predictors. Or, given a sample size of 214, level of significance of 5%, power of 95%, and 10 predictors, the detectible effect size was $\rho^2 = .11$, somewhat more precise than the planned medium effect size of .13.

Validity of the Instrument

Once the data were collected, I input the responses from the SurveyMonkey dataset into SPSS and computed Cronbach's α testing for internal consistency once again, but with 214 responses, to measure internal consistency and reliability. According to

Frankfort-Nachmias et al. (2015), Cronbach's α recommended values are $\alpha \geq 0.9$, excellent; $0.7 \leq \alpha < 0.9$, good; $0.6 \leq \alpha < 0.7$, acceptable; $0.5 \leq \alpha < 0.6$, poor; and $\alpha < 0.5$, unacceptable. The evaluation of reliability met a *good* threshold of internal consistency (Cronbach's $\alpha = .787$). I concluded that the questionnaire was acceptably valid and reliable for this research.

Data Analysis

Demographics of the Sample

The sample included various engineers from small and medium enterprises in Atlanta based on LinkedIn profile information of each targeted participant. The following define the demographic attributes of the sampling frame:

- Race—Three levels: African American (*B*), Caucasian (*W*), Other (*O*)
- Gender—Two levels for Male (one), Female (two)
- Occupation—String type for various titles of engineers (e.g., mechanical engineer)
- Age—A discrete numerical variable in years

The sample involved participants who identified themselves as 87 (40.05%) African American, 76 (35.03%) Caucasian, and 52 (24.04%) Other. The average age of participants was 35.3 years ($SD = 9.68$). The age of participants ranged from 21 to 64 years. Age was non-normally distributed, with skewness of .735 ($SE = .166$) and kurtosis of .031 ($SE = .330$). There were 109 men and 106 women participants (men's age: $M = 34.8$, $SD = 9.44$; women's age: $M = 35.7$, $SD = 9.95$).

The target population consisted of full-time engineers working in multinational small and medium enterprises in Atlanta. I compared the demographics of the sample of 215 participants to the demographics of the target population in race, age, gender, and occupation—to which the results of this study can be generalized.

According to the U.S. Bureau of Labor Statistics (2021) and Data USA: Engineering (2019), the average age of male engineers working in Atlanta is 43.1 years, and the most common age of female engineers is 36.6. The most common race/ethnicity for engineers is Caucasian or White (Non-Hispanic) (Data USA, 2019). Though there are differences, the sample used in this study represents the population of engineers employed in metropolitan areas of Georgia. Differences should be considered when generalizing the results.

Variables

The independent variables measured two components of the use of HCI devices: reliance on an HCI device and competence with each device. There was an independent variable for reliance on each of the five HCI devices: desktop (DTR; e.g., stationary workstation), laptop (LTR; e.g., portable computer), tablet (TTR; e.g., touchscreen), smartphone (SPR; e.g., hand-held computer), and wearable (WBR; e.g., VR headset). The value for each of these five independent variables was determined from question 9 of the questionnaire. There was an independent variable for competence on each of the five HCI devices: DTC, LTC, TTC, SPC, and WBC. The value for each of these five independent variables was determined from question 10 of the questionnaire.

The dependent variable, Web 3.0 skills (WS), was a measure of skills with various related technologies encompassed of eight components of the Knowledge of Technologies (KOT) subscale: web technologies, developer tools, relational database technology, software design, blockchain technology, operating systems and server technologies, server software, and virtualization. WS was computed in SPSS as the mean response to questions 1 through 8 on the questionnaire.

The 10 independent variables (DTR, LTR, TTR, SPR, WBR, DTC, LTC, TTC, SPC, and WBC) and 2FIs were postulated to predict the dependent variable, WS. In addition, two composite variables were calculated from the 10 independent variables. The five variables used to measure reliance (DTR, LTR, TTR, SPR, WBR) were averaged to compute a composite variable, RHCID. The five variables measuring competence using HCI devices (DTC, LTC, TTC, SPC, and WBC) were averaged to compute the composite variable, CHCID.

RHCID, CHCID, and their 2FI (RH*CH) were computed to support an additional MLR analysis. RHCID measured overall reliance on HCI devices, and CHCID measured overall competence using HCI devices.

Descriptive Statistics

Independent Variables

Table 6 shows the means and standard deviations for the 10 independent variables; and two composite indices (there is one variable for reliance on each of the five HCI devices; and one variable for competence with each of the five HCI devices) used in a separate analysis. The data were examined for outliers falling three or more standard deviations from the mean. No outliers were found among the 10 independent variables and two indices. No outliers were found among the eight components of the dependent variable (WT, DT, RD, SD, BT, OS, SS, and VZ).

Table 6

Means and Standard Deviations for Independent Variables

	Mean	*SD*
DTR	3.73	1.140
LTR	3.68	1.120
TTR	3.81	1.070
SPR	3.77	1.080
WBR	3.75	1.100
DTC	3.67	1.080
LTC	3.63	1.090
TTC	3.63	1.090
SPC	3.67	1.160
WBC	3.68	1.200
RHCID	3.75	0.694
CHCID	3.66	0.758

Figure 2 illustrates the reliance on HCI devices. The number of engineers who rated each category (WBR, SPR, TTR, LTR, and DTR) is on the y-axis and bar graph. The legend of both color and number corresponds to how the engineers rated, indicating significant use of and reliance on all devices *(WBR, SPR, TTR, LTR, and DTR*). Figure 3 shows the summary of competence on HCI devices.

Figure 2

Reliance on HCI Devices

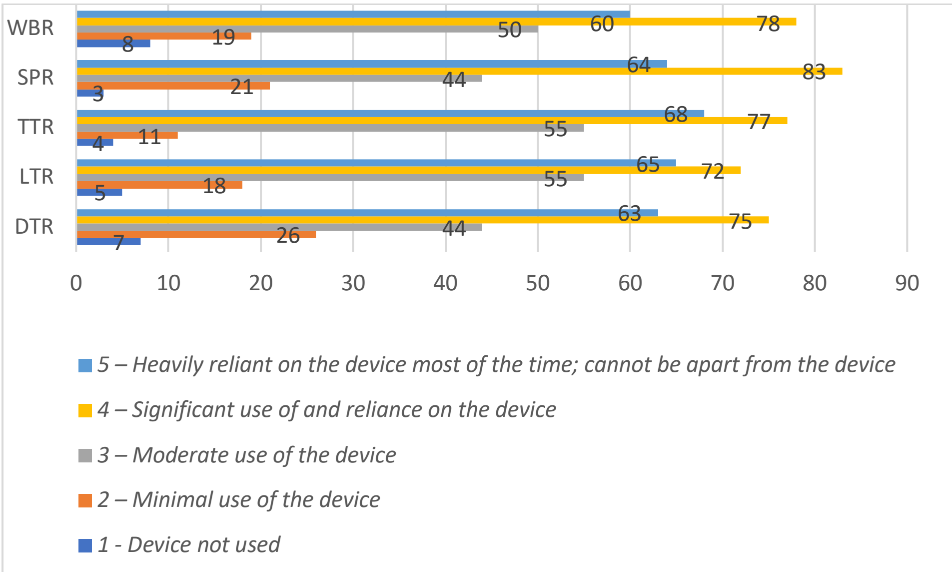
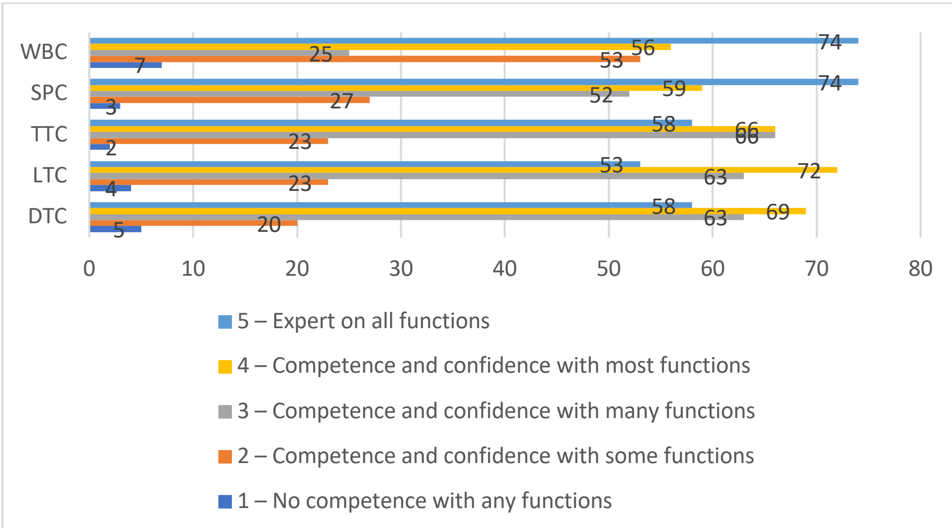


Figure 3

Summary of Competence on HCI Devices



Note. The number of engineers who rated each category (WBC, SPC, TTC, LTC, and DTC) is on the y-axis and bar graph. The legend of both color and number corresponds to how the engineers rated, indicating expertise, and competence and confidence with most functions on all (WBC, SPC, TTC, LTC, and DTC) devices.

Dependent Variable

Table 7 shows the means and standard deviations for the eight components of the dependent variable (WS).

Table 7

Means and Standard Deviations for Components of Dependent Variable

	Mean	*SD*
Web technologies	3.76	1.080
Developer tools	3.53	1.140
Relational database technology	3.52	1.140
Software design	3.35	1.100
Blockchain technology	2.70	1.340
Operating systems and server technologies	3.62	1.070
Server software	3.18	1.300
Virtualization	3.20	1.270
Web 3.0 skills	3.36	0.641

Results

Assumptions of MLR

MLR assumes the following:

- numerical variables
- linearity: a straight-line relationship between the independent variables and the dependent variable
- independence: the values of the residuals are independent; no autocorrelation
- homoscedasticity: the variation of the residuals (error terms) is constant for all values of the independent variables
- absence of multicollinearity: no relationship among independent variables
- normally distributed residuals
- no influential cases: no significant outliers

The MLR assumptions were checked in SPSS by running an initial MLR analysis (SPSS run 0) with all 10 independent variables: DTR, LTR, TTR, SPR, WBR, DTC, LTC, TTC, SPC, and WBC; and the dependent variable, WS. A separate MLR assumptions check was conducted in SPSS for the RHCID and CHCID indices.

Numerical Variables

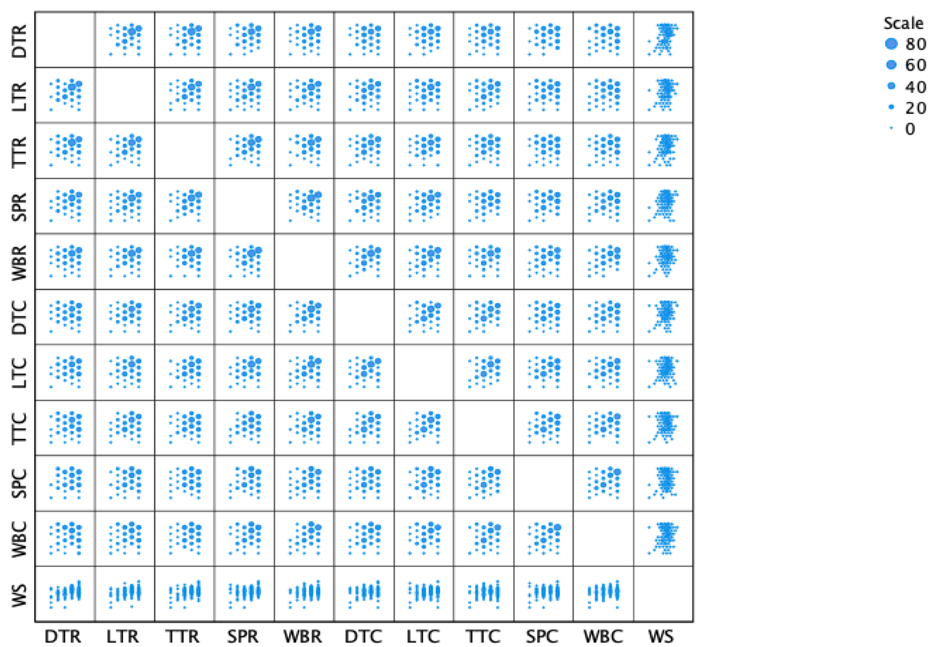
All study variables were discrete or continuous, numerical variables.

Linearity

I checked the linearity assumption using scatterplots to assess the relationship of the dependent variable, *WS*, to the independent variables (Figure 4). There are no noticeable nonlinear patterns in the scatterplots. The outcome variable is linear in relation to the *HCI devices*.

Figure 4

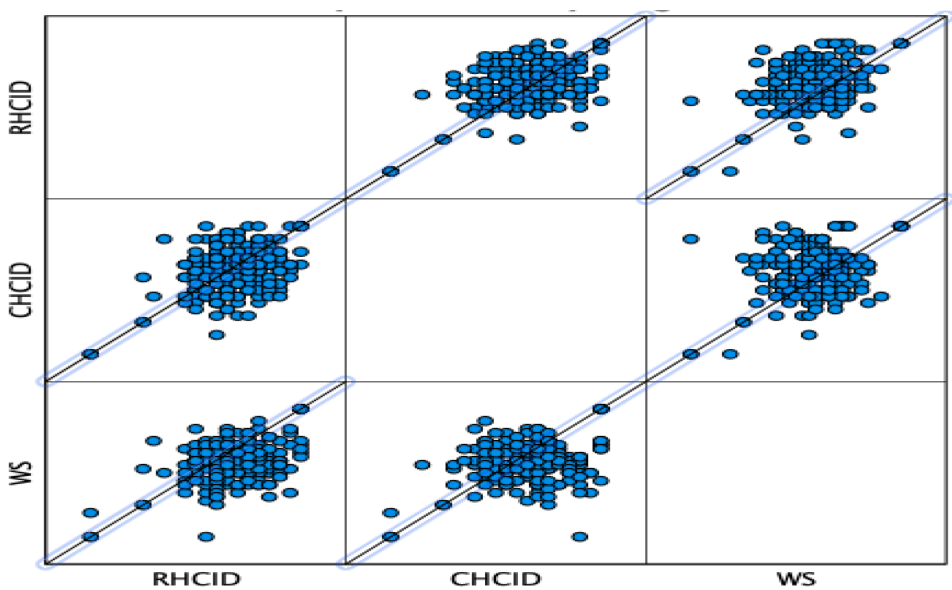
Matrix Graph of Linearity Diagnostics of HCI Devices



Next, I checked the linearity assumption using scatterplots to assess the relationship of the dependent variable, WS, to the indices, RHCID and CHCID. Figure 5 shows the matrix graph of linearity diagnostics of RHCID and CHCID. There are no noticeable nonlinear patterns in the scatterplots. The outcome variable is linear in relation to the RHCID and CHCID indices.

Figure 5

Matrix Graph of Linearity Diagnostics of RHCID and CHCID



Independence of Residuals—No Autocorrelation

Using the Durbin–Watson statistic, I tested the assumption of independence of residuals of HCI devices. Table 8 shows the Durbin-Watson statistic for the 10 independent variables (DTR, LTR, TTR, SPR, WBR, DTC, LTC, TTC, SPC, and WBC), and the dependent variable (WS), which was 1.67. A value near 2.0 means that there is no autocorrelation detected in the sample and residuals are independent among the 10 independent variables.

Table 8

Model Summary for HCI devices

R	R^2	Adjusted R^2	Std. error of the estimate	R^2 change	F change	df1	df2	Sig. F change	Durbin-Watson
.489	.239	.202	.573	.239	6.42	10	204	< .001	1.67

The same steps were repeated in assessing independence of errors for the RHCID and CHCID indices (Table 9). The Durbin-Watson test statistic = 1.63. There was no autocorrelation detected in the sample and residuals were independent of each other within each index.

Table 9

Model Summary for RHCID and CHCID

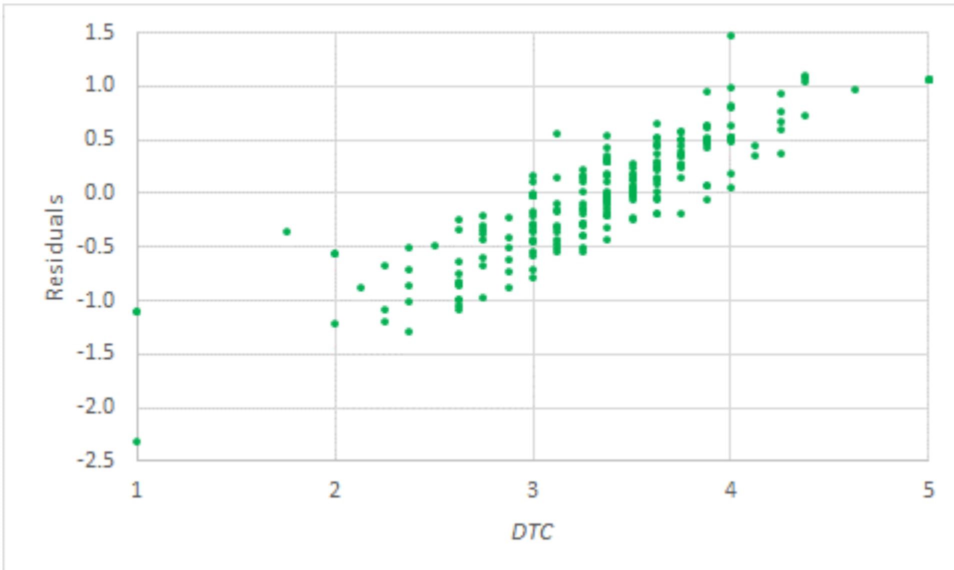
R	R^2	Adjusted R^2	Std. error of the estimate	R^2 change	F change	df1	df2	Sig. F change	Durbin-Watson
.458	.210	.202	.573	.210	28.15	2	212	< .001	1.63

Homoscedasticity

Testing the assumption for homoscedasticity required analysis of a scatterplot of residuals across the values for each HCI device (10 independent variables), and for the RHCID and CHCID indices. Figure 6 illustrates the test for the homoscedasticity assumption for the independent variable, DTC. The scatterplot indicates no change in the variation of residuals over the range of values for DTC. This was typical for all independent variables and demonstrated no violation of the homoscedasticity assumption.

Figure 6

Homoscedasticity Test: Scatterplot of Residuals Versus DTC



Absence of Multicollinearity

The assumption of absence of multicollinearity was analyzed using VIFs. VIFs less than five suggest the absence of multicollinearity. VIFs were calculated by performing an initial, standard regression analysis using the SPSS enter method (Table 10). No independent variables had a VIF greater than 1.42 for HCI devices, and no multicollinearity was present.

The assumption of absence of multicollinearity was analyzed for the indices of CHCID and RHCID in Table 11. No index had a VIF greater than 1.36. There was no presence of multicollinearity.

Table 10

Coefficients and Collinearity Statistics for 10 Independent Variables

	Unstandardized B	Coefficients std. error	Standardized coefficient Beta	t	Sig.	Collinearity statistics Tolerance	VIF
(Constant)	1.650	.027		6.950	< .001		
DTR	.148	.038	.262	3.920	< .001	.831	1.20
LTR	.057	.039	.099	1.460	.146	.806	1.24
TTR	.087	.040	.145	2.170	.032	.828	1.21
SPR	.037	.041	.062	.891	.374	.769	1.30
WBR	.020	.042	.034	.467	.641	.712	1.41
DTC	.056	.042	.095	1.340	.182	.742	1.35
LTC	.044	.043	.074	1.020	.308	.707	1.41
TTC	-.026	.041	-.044	-.626	.532	.744	1.34
SPC	-.009	.039	-.017	-.235	.815	.747	1.34
WBC	.045	.039	.085	1.170	.243	.707	1.42

Table 11

Collinearity Statistics for CHCID and RHCID

Model		Tolerance	VIF
1	CHCID	.737	1.36
	RHCID	.737	1.36

Normality—Normally distributed residuals

Figure 7 depicts the normal probability plot of standardized regression residuals and reveals a normal distribution for the regression model of the 10 independent variables (DTR, LTR, TTR, SPR, WBR, DTC, LTC, TTC, SPC, and WBC). Figure 8 depicts the normal probability plot of standardized regression residuals and reveals a normal distribution of residuals for the model of the CHCID and RHCID indices.

Figure 7

Test of Normality of Residuals (HCI Devices)

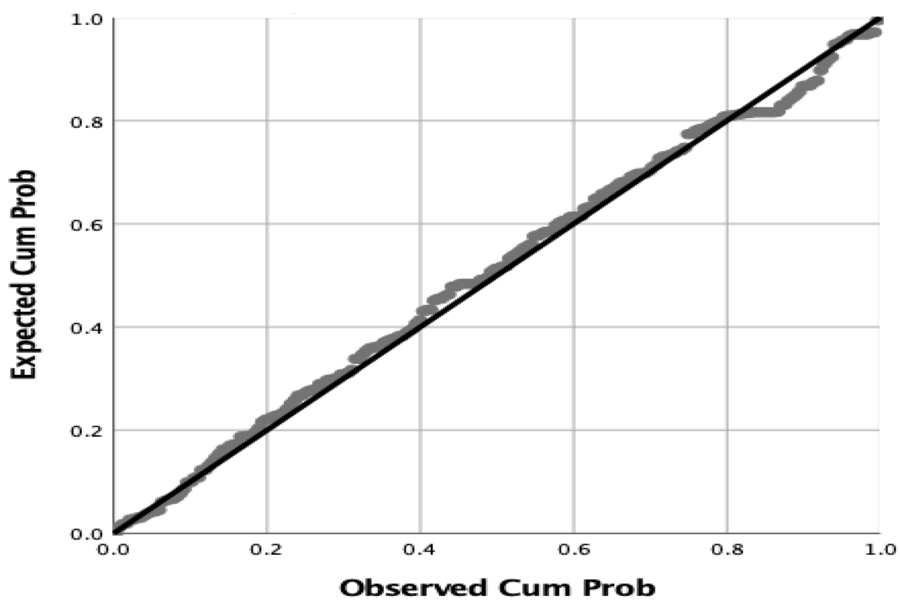
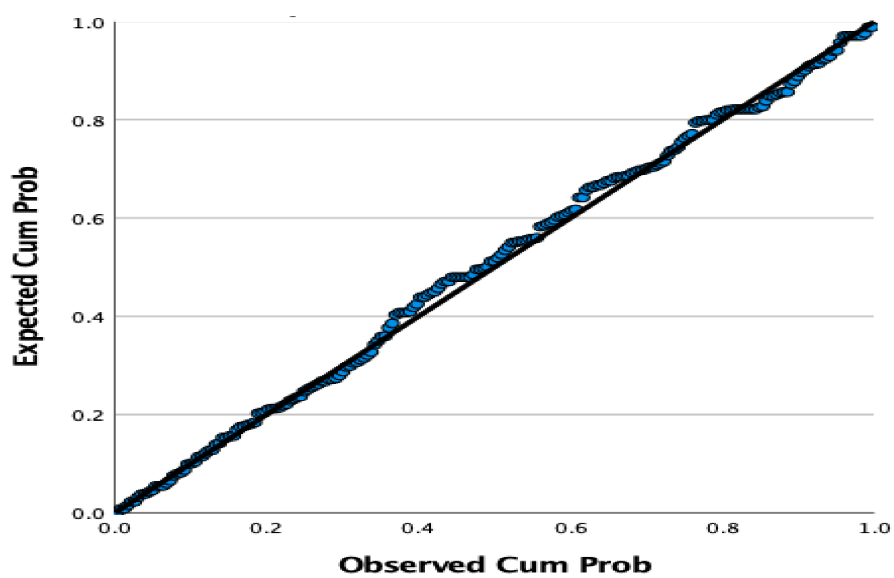


Figure 8

Test of Normality of Residuals (CHCID and RHCID)



A check of normality of error terms using a histogram, Figure 9, indicates a normal distribution of residuals for the regression model of the 10 independent variables. Figure 10 shows the histogram of residuals with normal curve for CHCID and RHCID.

Figure 9

Histogram of Residuals with Normal Curve for HCI Devices

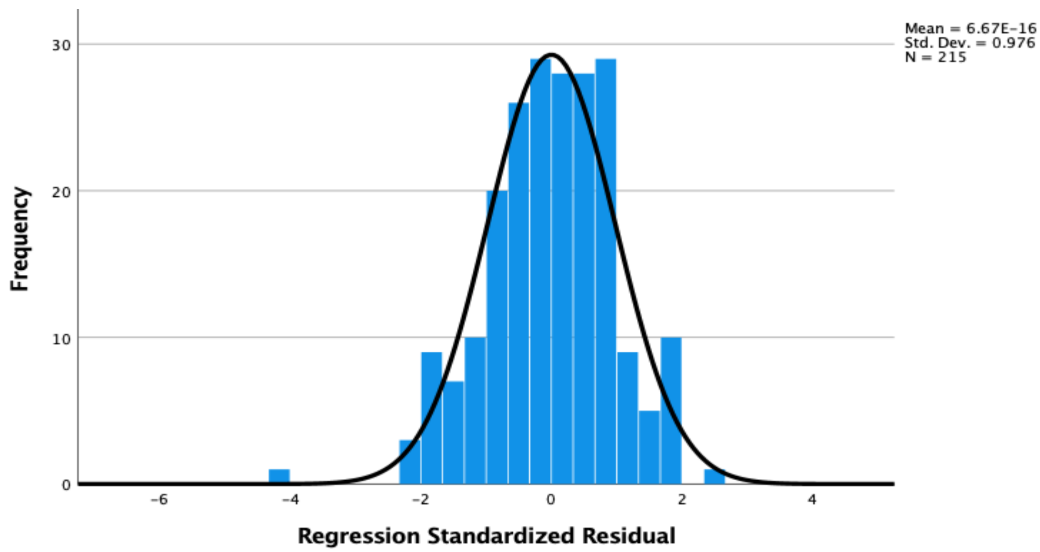
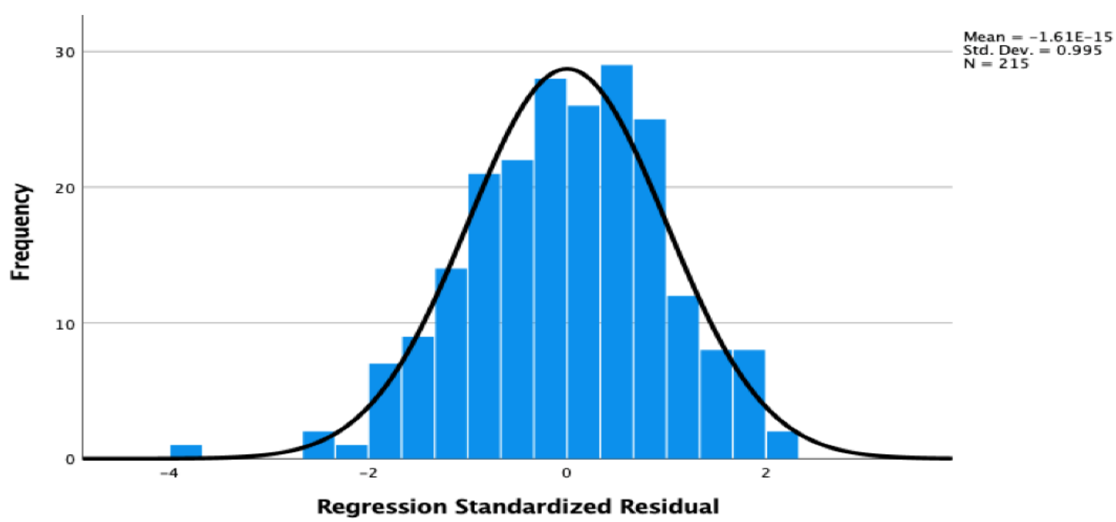


Figure 10

Histogram of Residuals with Normal Curve for CHCID and RHCID

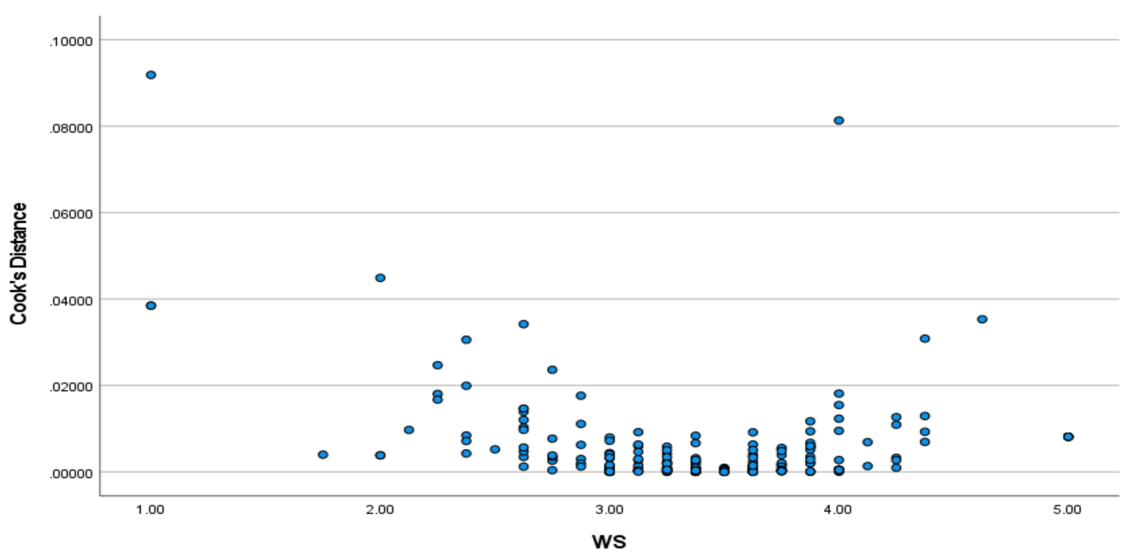


No Influential Cases

Cook's Distance is a measure of how much influence a predictor variable has on the predicted value of the outcome variable, testing to ensure there are no significant outliers or overly influential cases biasing the model. A value greater than 4 ÷ n (in this study, 4 ÷ 214 = .02) indicates the possibility of an outlier. Figure 11 depicts Cook's distance for *WS*, there were some exceptions that may be overly influential to the analysis. Upon further investigation, I found only three of these were more than three standard deviations from the mean. Since the data were obtained from a Likert scale questionnaire, and there were only three cases for which WS was more than three standard deviations from the mean, out of 214 observations, I concluded that outliers were not an issue with data analysis.

Figure 11

Scatterplot of Cook's Distance by Predicted Value



Multiple Linear Regression

For MLR, the objective was to create the best predictive model of the dependent variable (WS) as a function of the 10 independent variables (DTR, LTR, TTR, SPR, WBR, DTC, LTC, TTC, SPC, WBC); and a predictive model of the composite predictors, RHCID and CHCID. I conducted the MLR analysis on 214 responses using two stepwise approaches in which predictive variables were eliminated or selected sequentially based on their significance and their contribution to the model's goodness-of-fit: *statistical regression*, which uses automated routines in SPSS such as *backward elimination* and *forward selection*; and *sequential regression* which is a manual approach to model-building that employs the SPSS *enter* routine. Using an *F* test and its associated *p* value, I tested the significance of each predictive model using $\alpha = .05$. I used .20 as the inclusion criterion for individual predictors, independent variables and 2FIs.

Model Building for the 10 Independent Variables

The first regression model-building analyses were performed on the 10 independent variables. The primary purpose of this analysis phase was to screen for independent variables that were highly unlikely to be included in a model that was a significant predictor of WS. The inclusion criterion of .20 was used. In this phase, during the sequential regression analysis, scrutiny was paid to the *p* value for each independent variable after each run. The intent was to eliminate from consideration any independent variables with a relatively high *p* value, indicating their contribution to model significance was unlikely. Independent variables with *p* values near the inclusion criterion would not necessarily be eliminated in the next phase, especially if their inclusion improved model goodness-of-fit (adjusted R^2).

Statistical Regression Using Backward Elimination

All 10 independent variables (DTR, LTR, TTR, SPR, WBR, DTC, LTC, TTC, SPC, WBC) were entered to start the *backward elimination* analysis (SPSS run 1). Using the *backward elimination method* (criterion: the probability of F-to-remove > .201), the following independent variables were removed because their p value exceeded the removal criterion (.201): SPC, WBR, TTC, SPR, and LTC after SPSS ran six models (see Table 12). Model 6 (see Table 13) consisted of DTR, LTR, TTR, DTC, and WBC; with an adjusted R^2 = .210. For the model, F = 12.308 and p < .001.

Table 12

Backward Method Model Summary

					Change statistics				
Model	R	R^2	Adjusted R^2	Std. error of the estimate	R^2 change	F change	df1	df2	Sig. F change
1	.489	.239	.202	.574	.239	6.390	10	203	< .001
2	.489	.239	.206	.573	< .001	.059	1	203	.808
3	.488	.238	.209	.572	-.001	.206	1	204	.650
4	.487	.237	.211	.571	-.002	.471	1	205	.493
5	.484	.234	.212	.570	-.002	.627	1	206	.429
6	.478	.228	.210	.571	-.006	1.640	1	207	.202

Table 13 shows results from the last run using the *backward method*—model 6 coefficients. The following variables are included in model 6: DTR, LTR, TTR, DTC and WBC.

Table 13

Backward Method—Model 6 Coefficients

Model		Unstandardized B	Coefficient std. error	Standardized coefficients beta	t	Sig.
6	(Constant)	1.720	.220		7.80	< .001
	DTR	.161	.036	.285	4.42	< .001
	LTR	.062	.038	.108	1.62	.107
	TTR	.093	.040	.155	2.32	.021
	DTC	.068	.040	.114	1.70	.091
	WBC	.057	.034	.107	1.67	.096

Statistical Regression Using Forward Selection

The *forward selection* regression technique (SPSS run 2) began with no independent variables in the model. Independent variables were entered sequentially (criterion: the probability-of-*F*-to-enter < .200). The independent variables were entered in this order: DTR, TTR, DTC, WBC, and LTR. Table 14 shows the model summary generated from using the *forward selection* and provides the adjusted R^2 for each model.

Table 14

Forward Selection—Model Summary

					Change statistics				
Model	R	R^2	Adjusted R^2	Std. error of the estimate	R^2 change	F change	df1	df2	Sig. F change
1	.366	.134	.130	.600	.134	32.88	1	212	< .001
2	.425	.181	.173	.585	.047	12.00	1	211	< .001
3	.454	.206	.195	.577	.026	6.78	1	210	.010
4	.468	.219	.204	.573	.012	3.25	1	209	.073
5	.478	.228	.210	.572	.010	2.62	1	208	.107

Table 15 shows model 5 coefficients. The independent variables remaining in both the *backward method* and *forward selection* processes resulted in the same predictive model, with an adjusted $R^2 = .210$. For the model, $F = 12.308$ and $p < .001$.

Table 15

Forward Selection—Model 5 Coefficients

Model		Unstandardized B	Coefficients std. error	Standardized coefficients Beta	t	Sig.
5	(Constant)	1.720	.220		7.80	< .001
	DTR	.161	.036	.285	4.42	< .001
	TTR	.093	.040	.155	2.33	.021
	DTC	.068	.040	.114	1.70	.091
	WBC	.057	.034	.107	1.67	.096
	LTR	.062	.038	.108	1.62	.107

Note. Dependent Variable: WS

Sequential Regression Using the Enter Method

I then employed sequential regression, which is a manual approach to model-building that employs the SPSS *enter* routine, testing individual models (combinations of the independent variables). The manual process of the sequential regression method reduces errors inherent in the statistical methods (automated backward and forward process) since the analyst can use subject matter expert judgment and an iterative approach, choosing to add or eliminate variables based on both *p* value (compared to the inclusion criterion) and goodness-of-fit (adjusted R^2).

For the sequential regression method, I started with all 10 independent variables (DTR, LTR, TTR, SPR, WBR, DTC, LTC, TTC, SPC, and WBC), which was run 0 originally performed to check the regression assumptions. I then sequentially eliminated independent variables based on their *p*-values (using an inclusion criterion of .20) and the change in adjusted R^2 after each run. Table 16 displays the model summary generated from SPSS run 0 using the *enter method* for all 10 independent variables in the initial model, adjusted R^2 = .202. The coefficient table was previously presented in Table 10.

Table 16

Enter Method—Run 0 Model Summary

					Change statistics				
Run	R	R^2	Adjusted R^2	Std. error of the estimate	R^2 change	F change	df1	df2	Sig. F change
0	.489	.239	.202	.574	.239	6.39	10	203	< .001

Note. Predictors: (Constant), WBC, DTR, LTR, TTR, LTC, TTC, SPR, DTC, SPC, WBR

In run 3 (runs 1 and 2 were statistical regression runs), I eliminated *SPC*. The resulting model had an adjusted R^2 = .206, which was an improvement. The coefficients and p values are shown in Table 17.

Table 17

Enter Method—Run 3 Model Summary

Run		Unstandardized B	Coefficients std. error	Standardized coefficients Beta	t	Sig.
3	(Constant)	1.639	.233		7.02	<.001
	DTR	.148	.038	.262	3.92	<.001
	LTR	.057	.039	.099	1.46	.147
	TTR	.087	.040	.145	2.17	.031
	SPR	.036	.041	.061	.877	.381
	WBR	.019	.042	.032	.449	.654
	DTC	.057	.042	.096	1.37	.173
	LTC	.042	.042	.071	.999	.319
	TTC	-.028	.040	-.048	-.688	.493
	WBC	.043	.038	.081	1.15	.251

For run 4, I eliminated WBR because it had the largest p value. This model resulted in F = 8.06 and p < .001. The adjusted R^2 = .209; again, an improvement and corroboration that eliminating WBR enhanced model goodness-of-fit. The coefficients and *p* values are shown in Table 18.

Table 18

Enter Method—Run 4 Model Summary

Run		Unstandardized B	Coefficients std. error	Standardized coefficients Beta	t	Sig.
4	(Constant)	1.653	.231		7.15	<.001
	DTR	.150	.037	.266	4.01	<.001
	LTR	.058	.039	.100	1.48	.140
	TTR	.088	.040	.147	2.21	.028
	SPR	.035	.041	.060	.864	.389
	DTC	.060	.041	.101	1.46	.146
	LTC	.046	.041	.079	1.14	.255
	TTC	-.027	.040	-.046	-.671	.503
	WBC	.047	.036	.089	1.30	.196

For run 5, I eliminated TTC. The resulting model had an adjusted $R^2 = .211$, $F = 9.17$, and $p < .001$, which was an improvement. The coefficients and *p* values are shown in Table 19.

Table 19

Enter Method—Run 5 Model Summary

Run		Unstandardized B	Coefficients std. error	Standardized coefficients Beta	t	Sig.
5	(Constant)	1.630	.228		7.15	<.001
	DTR	.149	.037	.264	3.99	<.001
	LTR	.054	.038	.094	1.41	.161
	TTR	.088	.040	.146	2.20	.029
	SPR	.033	.041	.056	.815	.416
	DTC	.055	.041	.093	1.37	.173
	LTC	.044	.040	.075	1.09	.278
	WBC	.042	.035	.079	1.18	.240

In run 6, I eliminated SPR. The resulting model had an adjusted $R^2 = .212$, $F = 10.60$, and $p < .001$, which was an improvement. The coefficients and p values are shown in Table 20.

Table 20

Enter Method—Run 6 Model Summary (Without 2FIs)

Run		Unstandardized B	Coefficients std. error	Standardized coefficients Beta	t	Sig.
6	(Constant)	1.660	.224		7.40	< .001
	DTR	.155	.037	.274	4.22	< .001
	LTR	.058	.038	.101	1.52	.131
	TTR	.091	.040	.152	2.31	.022
	DTC	.057	.040	.097	1.42	.156
	LTC	.050	.040	.085	1.26	.208
	WBC	.046	.035	.086	1.31	.193

I reached run 6, with an adjusted $R^2 = .212$, but with LTC p value = .208. Therefore, in run 7, I eliminated LTC. But, then the adjusted $R^2 = .210$, which was a decrease. So, my decision was to re-admit LTC (reverting to the model in run 6, as depicted in Table 20), because adjusted R^2 (.212) was higher for run6, and LTC's p value was close to the inclusion criterion. Since I had planned next to add the 2FIs, it was prudent to keep LTC and see how the significance of the six remaining independent variables was impacted by an analysis involving the 2FIs.

In summary, after conducting sequential regression using the enter method in SPSS, the best model based on adjusted R^2 (.212), consisted of the six variables: WBC, DTR, LTR, TTR, LTC, and DTC as shown in Table 20. Eliminating LTC decreased adjusted R^2. While the p value was .208, I decided to retain LTC pending further analysis of the model with 2FIs included.

To summarize the results of the backward elimination, forward selection, and sequential regression (enter) analyses of the 10 original IVs—if I had concluded sequential regression with only the five independent variables strictly meeting the inclusion criterion, then all three models would have included the same five variables: DTR, LTR, TTR, DTC, and WBC (with an adjusted $R^2 = .210$, $F = 12.308$, and $p < .001$). However, I elected to retain LTC using adjusted R^2, along with judgment and the knowledge that I would be continuing the analysis with the 2FIs. The model in run 6 (Table 20) resulted in adjusted $R^2 = .212$, $F = 10.60$, and $p < .001$. This concluded my screening analysis of the 10 IVs, using both statistical and sequential regression, to determine likely influential predictors to carry forward when I introduced the 2FIs.

2FIs for HCI Devices

2FIs—Statistical Regression

The next step in the analysis was to add in the 2FIs to the model, which included all 15 pairs of the six independent variables from run 6. Using the statistical *backward elimination* method (criterion: the probability of F-to-remove > .201), the following independent variables and 2FIs were removed in SPSS run 8 because their p value exceeded the removal criterion: LTR*TTR, WBC, TTR, LTC*WBC, DTR*LTR, LTR*WBC, LTR*DTC, DTR, DTR*LTC, TTR*DTC, LTR, DTR*WBC, DTR*DTC, and DTC*WBC. Table 21 shows the *backward elimination* method model summary resulting in model 15. The coefficients and p values for model 15 are shown in Table 22; adjusted $R^2 = .235$, $F = 10.41$, and $p < .001$.

Table 21

Backward Method Model Summary

Model	R	R^2	Adjusted R^2	Std. error of the estimate
1	.532	.283	.205	.572
2	.532	.283	.209	.570
3	.532	.283	.213	.569
4	.532	.283	.217	.566
5	.532	.283	.221	.566
6	.531	.282	.225	.565
7	.531	.282	.227	.564
8	.530	.281	.230	.563
9	.528	.279	.232	.562
10	.527	.277	.234	.561
11	.524	.275	.235	.561
12	.520	.271	.235	.561
13	.517	.267	.235	.561
14	.514	.265	.236	.561
15	.510	.260	.235	.561

Table 22

Backward Method—Coefficients

Model		Unstandardized B	Coefficients std. error	Standardized coefficients Beta	t	Sig.
15	(Constant)	1.342	.354		3.79	< .001
	DTC	.288	.098	.485	2.92	.004
	LTC	.369	.117	.627	3.14	.002
	DTR*TTR	.040	.009	.404	4.63	< .001
	LTR*LTC	.016	.010	.148	1.49	.137
	TTR*WBC	.014	.009	.135	1.55	.123
	TTR*LTC	-.032	.016	-.304	-1.94	.053
	DTC*LTC	-.068	.026	-.670	-2.57	.011

Statistical regression using *forward selection* (run 9) produced a model that included the same two IVs as with *backward elimination* (DTC and LTC), four 2FIs, adjusted $R^2 = .233$, $F = 11.84$, and $p < .001$. However, in comparison to the *backward elimination* method, the *forward selection* method resulted in a different set of 2FIs: adding DTR*WBC, but not selecting TTR*WBC and TTR*LTC. Table 23 shows the *forward selection* model summary. The coefficients and *p* values for model 6 are shown in Table 24.

Table 23

Forward Selection Model Summary

Model	R	R^2	Adjusted R^2	Std. error of the estimate
1	.398	.158	.154	.590
2	.447	.200	.192	.576
3	.462	.214	.202	.573
4	.472	.223	.208	.571
5	.480	.231	.212	.569
6	.504	.255	.233	.562

Table 24

Forward Selection—Coefficients

Model		Unstandardized B	Coefficients std. error	Standardized coefficients Beta	t	Sig.
6	(Constant)	1.432	.350		4.09	<.001
	DTR*TTR	.026	.007	.259	3.61	<.001
	LTR*LTC	.016	.010	.152	1.54	.126
	DTC	.327	.096	.551	3.42	.001
	DTR*WBC	.012	.008	.114	1.55	.122
	DTC*LTC	-.077	.026	-.762	-2.97	.003
	LTC	.282	.110	.479	2.57	.011

2FIs—Sequential Regression

In this analysis, I began with run 10, with the six IVs and 15 2FIs. I added and eliminated terms (independent variables and 2FIs) based on an inclusion criterion of .20 and run-to-run change in adjusted R^2. The model summary and coefficient tables for runs 10 through 23 (except run 22) are provided in Appendix D.

Adjusted R^2 increased with each run up to run 22. After run 23, I concluded that run 22 was the best model, consisting of LTR, TTR, DTC, WBC, DTR*TTR, LTR*LTC, TTR*DTC, DTC*WBC, and DTC*LTC. Adjusted $R^2 = .239$, $F = 8.452$, p value $< .001$. I selected run 22 because, in run 23, DTC*WBC was removed; but that decreased adjusted R^2. So, DTC*WBC was re-inserted, reverting to run 22.

Statistical and Sequential Regression: Model Comparison

Compared to statistical regression, sequential regression led to a model that included a different and larger set of terms (IVs and 2FIs), all of which met the inclusion criterion of .20, with a higher adjusted $R^2 = .239$, $F = 8.45$, $p < .001$. The best model produced by *backward elimination* (Table 21) yielded adjusted $R^2 = .235$; from *forward selection*, adjusted $R^2 = .233$. Therefore, a model with better goodness-of-fit was produced by sequential regression. LTC and DTR were found not to be significant individually (based on the inclusion criterion) but were moderators of other independent variables (and part of 2FIs).

The entire set of analyses, from runs 1 through 23, revealed some important insights about the process of model selection and the various techniques. First, LTC was brought forward to the analysis that included 2FIs, because as shown in runs 6 and 7, its presence increased model adjusted R^2, even though its p value exceeded, slightly, the inclusion criterion. However, while LTC was included in models produced by the two statistical regression techniques, in runs 8 and 9 (additional justification for carrying it forward after screening, to the full analysis with 2FIs), sequential regression demonstrated that LTC's influence was as a moderator of other independent variables, and not as a significant predictor by itself. Likewise, DTR was included in models produced by the statistical regression techniques but found in sequential regression to be only a moderator, not a significant predictor by itself.

Also, models produced by sequential regression enables manual additions and eliminations of predictors based partly on their individual significance, but also on the impact on model goodness-of-fit, as measured by adjusted R^2. As a result, sequential regression was able to uncover subtle nuances in the regression models that resulted in the identification of LTC and DTR as moderators (instead of predictors), as well as three independent variables which were significant when included in a larger model of predictors *(*LTR, TTR, and WBC) plus two 2FIs—predictors not selected by statistical regression, but that contributed to model goodness-of-fit.

Final Model

Table 25 shows the model summary from run 22. Table 26 shows the coefficients and p values. The final predictive regression model was the following:

$$\begin{aligned}\hat{Y}\text{ (WS)} = &-.190(\text{LTR}) + .179(\text{TTR}) + .631(\text{DTC}) + .187(\text{WBC})\\ &+ .036(\text{DTR*TTR}) + .068(\text{LTR*LTC}) - .059(\text{TTR*DTC})\\ &- .037(\text{DTC*WBC}) - .059(\text{DTC*LTC}) + .108 \qquad (10)\end{aligned}$$

Table 25

Sequential Model Summary—Run 22

Run	R	R^2	Adjusted R^2	Std. error of the estimate	F
22	.520	.271	.239	.560	8.452

Note. Predictors: (Constant), DTC*LTC, DTR*TTR, LTR, WBC, TTR, DTC, LTR*LTC, DTC*WBC, TTR*DTC.

Table 26

Sequential Regression—Coefficients

Run		Unstandardized B	Coefficients std. error	Standardized coefficients Beta	t	Sig.
22	(Constant)	1.080	.454		2.39	.018
	LTR	-.190	.107	-.331	-1.78	.077
	TTR	.179	.112	.298	1.59	.113
	DTC	.631	.161	1.060	3.93	< .001
	WBC	.187	.100	.351	1.87	.063
	DTR*TTR	.036	.009	.359	3.83	< .001
	LTR*LTC	.068	.028	.646	2.46	.015
	TTR*DTC	-.059	.029	-.581	-2.07	.040
	DTC*WBC	-.037	.027	-.378	-1.38	.170
	DTC*LTC	-.059	.028	-.578	-2.10	.037

Adjusted R^2 = .239 (Table 25) explained approximately 24% of WS variation. Based on the F test (F = 8.452), its associated p value < .001, and α = .05, I rejected the null hypothesis and concluded there was sufficient evidence that at least one coefficient was not equal to zero. The final regression model was a significant predictor of WS.

2FI Explanation for the Final Model

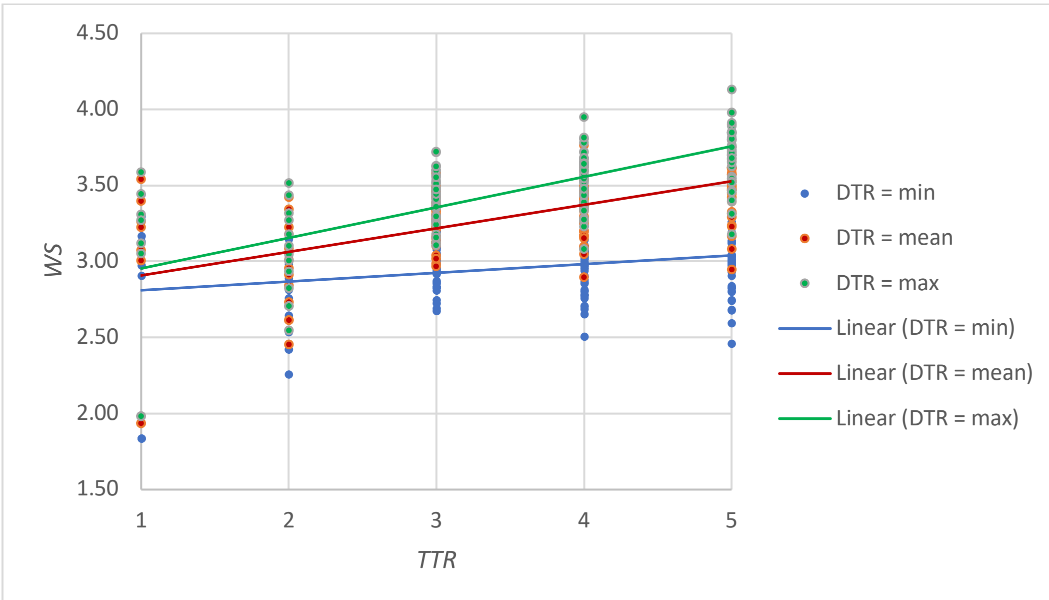
Based on the sequential regression analysis of the independent variables and 2FIs, there were four independent variables and five 2FIs that exerted a significant influence on

WS. In the 2FI figures to follow, there are two views of the interactions in which the independent variables are both, individually, significant predictors of WS. However, since there is no relationship between DTR and LTC, individually, and WS, there is only one depiction of the 2FIs involving DTR and LTC. There is no significance to the colors in the figures, as they are provided merely to show the differences in linear functions for various values of the moderating variable in each 2FI.

The first significant 2FI was between DTR and TTR, depicted in Figure 12, which illustrates that the relationship between WS and TTR changes depending on the value of DTR. The influence of TTR on WS (slope) is very slightly positive (almost flat, or nonexistent) at the minimum value of DTR, but that influence (scope) is greater as DTR increases in value, such that the influence of TTR on WS is positive and highest at the maximum value of DTR. DTR is, by itself, not a significant predictor, but it does moderate the influence of TTR on WS.

Figure 12

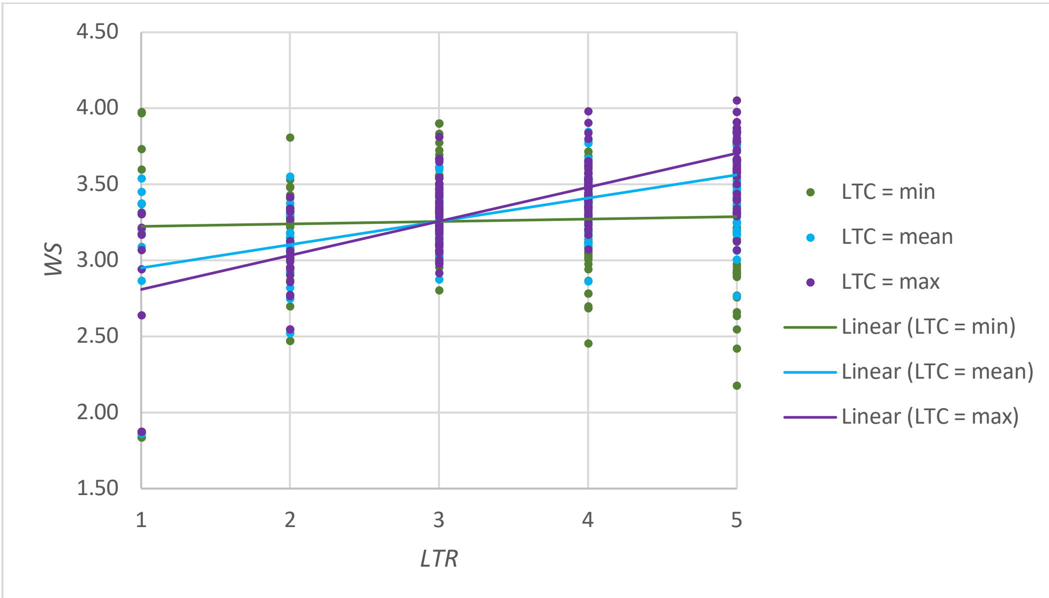
2FI: DTR and TTR



The second 2FI was between LTR and LTC. This 2FI is depicted in Figure 13, which demonstrates that the relationship between WS and LTR changes depending on the value of LTC. The influence of LTR on WS (slope) is virtually non-existent (flat) at the minimum value of LTC, but that influence (slope) grows as LTC increases in value, such that the influence of LTR on WS is positive and at its highest at the maximum value of LTC. While LTC is, by itself, not a significant predictor, it does moderate the influence of LTR on WS.

Figure 13

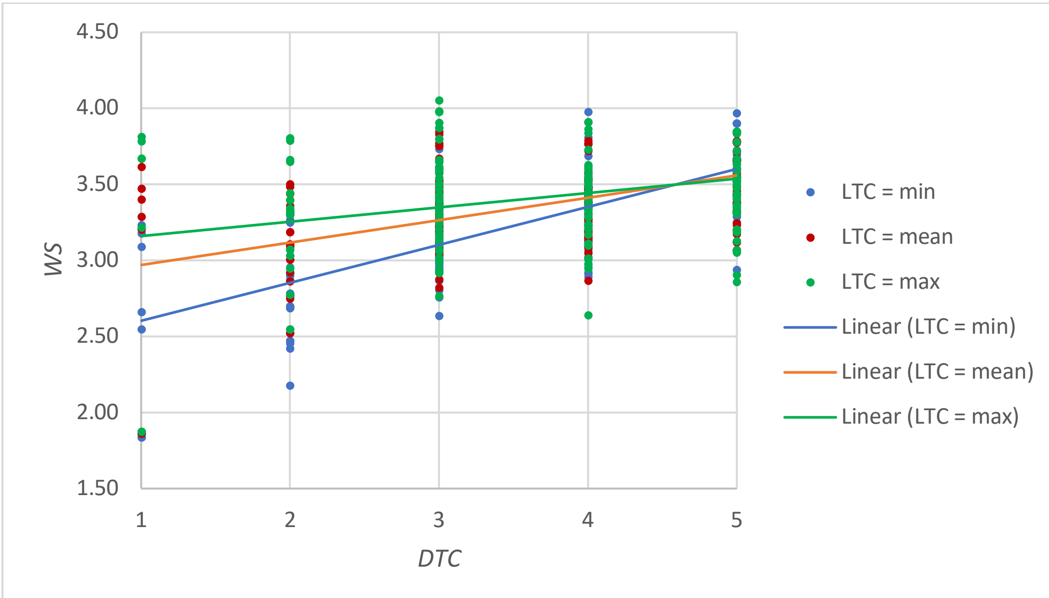
2FI: LTR and LTC



Another significant 2FI was between DTC and LTC. This 2FI is depicted in Figure 14 which shows that the relationship between WS and DTC changes depending on the value of LTC. The influence of DTC on WS (slope) is positive at all values of LTC, but that influence (slope) diminishes as LTC increases in value from minimum to maximum. Again, LTC is, by itself, not a significant predictor, but it moderates the influence of DTC on WS.

Figure 14

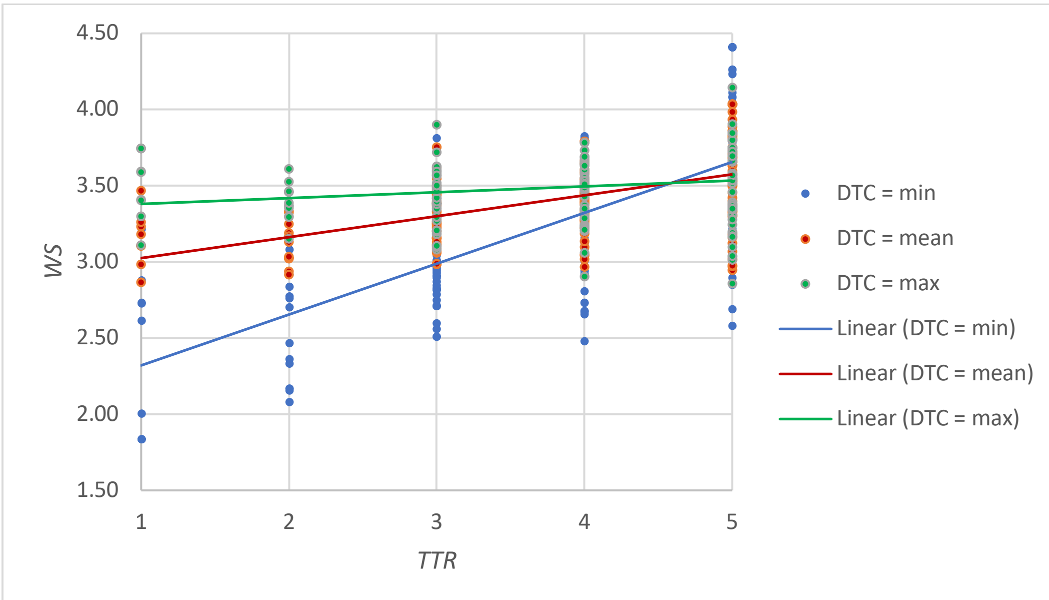
2FI: DTC and LTC



The next significant 2FI was between TTR and DTC, both of which were significant predictors of WS. This 2FI is illustrated in Figure 15 which shows that the relationship between WS and TTR changes depending on the value of DTC. The influence of TTR on WS (slope) is positive at all values of DTC, but that influence (slope) decreases as DTC increases in value, such that at the maximum value of DTC, there is almost no influence by TTR on WS (a flat or zero slope, or linear relationship).

Figure 15

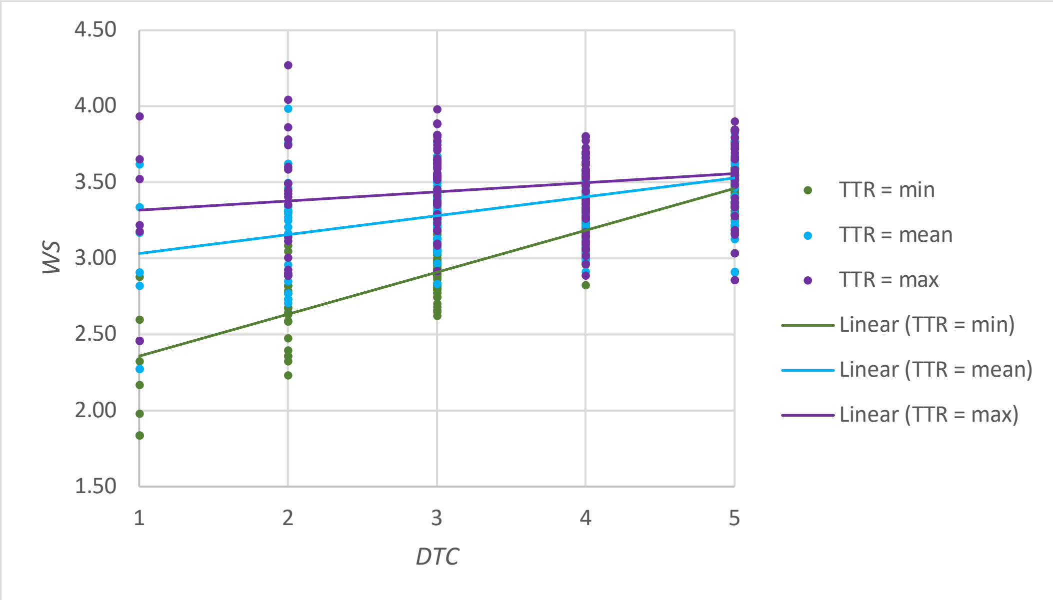
2FI: TTR and DTC (First View)



The same 2FI can be depicted in another way in Figure 16. The relationship between WS and DTC changes depending on the value of TTR. The influence of DTC on WS (slope) is positive at all values of TTR, but that influence (slope) decreases as TTR increases in value, such that at the maximum value of TTR, there is almost no influence by DTC on WS (a flat or zero slope, or linear relationship).

Figure 16

2FI: TTR and DTC (Second View)



The final significant 2FI was between DTC and WBC, both of which were significant predictors of WS. This 2FI is illustrated in Figure 17 which shows that the relationship between WS and WBC changes depending on the value of DTC. The influence of WBC on WS (slope) is positive at the minimum value of DTC, but that influence (slope) decreases as DTC increases in value, such that at the maximum value of DTC, there is virtually no influence, or perhaps a slightly negative influence by WBC on WS (a flat or slightly negative slope or linear relationship).

Figure 17

2FI: DTC and WBC (First View)

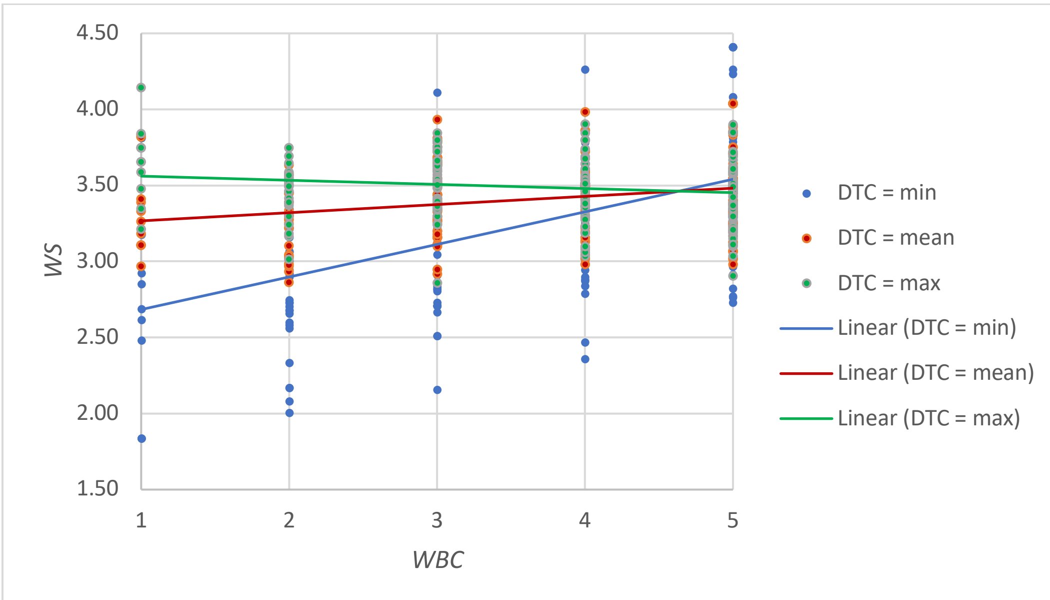
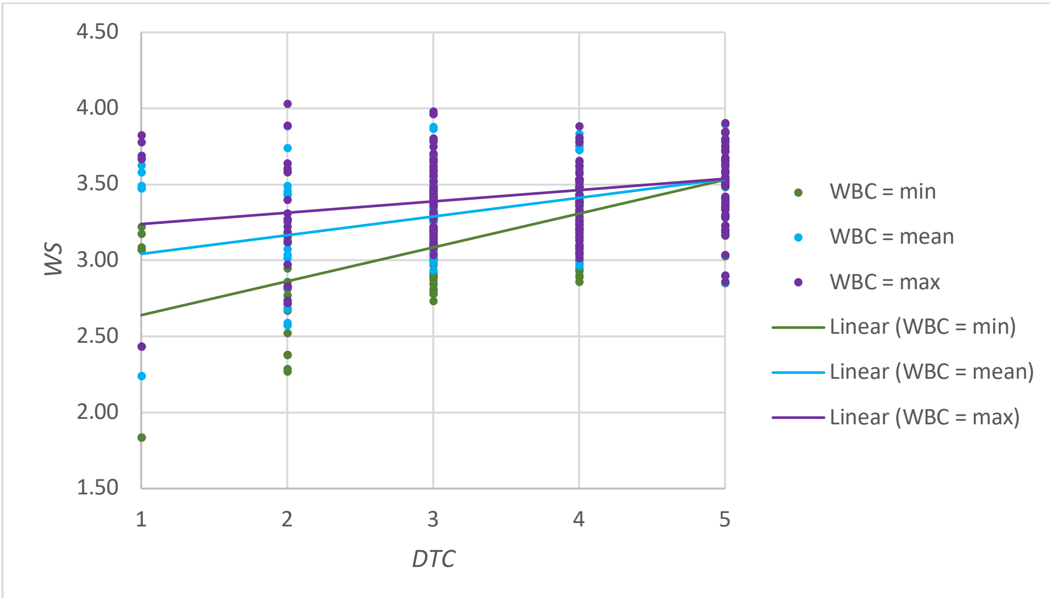


Figure 18 shows this 2FI in another way. The relationship between WS and DTC changes depending on the value of WBC. The influence of DTC on WS (slope) is positive at all values of WBC, but that influence (slope) decreases as WBC increases in value from minimum to maximum.

Figure 18

2FI: DTC and WBC (Second View)



Model-Building for RHCID and CHCID

Statistical Regression Using Backward Elimination

Next, I performed MLR model-building to assess if and to what extent two aggregate indices, RHCID and CHCID, plus their 2FI, RH*CH, predicted WS. In SPSS run 24, using *statistical regression* (*backward elimination* method, criterion: probability-of-F-to-remove < .201), all variables were entered to start. No variables were eliminated using the backward elimination technique, and Table 27 provides a model summary (adjusted R^2 =.206, F = 19.56, and p < .001). The coefficients and p values are depicted in Table 28.

Table 27

Backward Method—Model Summary

Run	R	R^2	Adjusted R^2	Std. error of the estimate
24	.466	.218	.206	.572

Table 28

Backward Method—Coefficients

Run		Unstandardized B	Coefficients std. error	Standardized coefficients Beta	t	Sig.
24	(Constant)	1.010	.535		1.88	.062
	RHCID	.601	.158	.648	3.81	< .001
	CHCID	.269	.164	.317	1.64	.102
	RH*CH	-.063	.044	-.428	-1.44	.151

Statistical Regression Using Forward Selection

Using the *forward selection* regression process in run 25, no variables were included at the start, and only RHCID was entered by the automated routine (Criterion: probability-of-F-to-entry < .200). Table 29 shows the model summary generated from *forward selection* process and the adjusted R^2 = .204, F = 55.72, and p < .001.

Table 29

Forward Selection—Model Summary

Run	R	R^2	Adjusted R^2	Std. error of the estimate
25	.455	.207	.204	.572

Table 30 shows regression coefficients for the model. The adjusted R^2 = .204, F = 55.72, and p < .001.

Table 30

Forward Selection Coefficients

Run		Unstandardized B	Coefficients of std. error	Standardized coefficients Beta	t	Sig.
25	(Constant)	1.760	.215		8.24	<.001
	RHCID	.422	.057	.455	7.46	<.001

Note. Predictors: (Constant), RHCID

Sequential Regression using the Enter Method

I next employed *sequential regression* (using the SPSS *enter* method) starting with RHCID, CHCID, and RH*CH, with the intent to sequentially omit variables that contributed the least to the model goodness-of-fit based on their p values and the change in adjusted R^2 after each run. No variables were eliminated in run 27 (run 26 was another check of assumptions). This result was consistent with statistical regression using *backward elimination* in run 24. Table 31 displays the model summary generated from sequential regression, the adjusted $R^2 = .206$, $F = 19.56$, $p < .001$. Table 32 provides the coefficients for the model. This model is superior to the model developed by the *forward selection* method, based on a higher adjusted R^2, and all terms met the inclusion criterion of .20

Table 31

*Enter Method— RHCID, CHCID, and RH*CH Model Summary*

Run	R	R^2	Adjusted R^2	Std. error of the estimate	F
27	.466	.218	.206	.572	19.56

Note. Predictors: (Constant), RH*CH, RHCID, CHCID

Table 32

*Enter Method— RHCID, CHCID, and RH*CH Coefficients*

Model		Unstandardized B	Coefficients std. error	Standardized coefficients Beta	t	Sig.
1	(Constant)	1.010	.535		1.88	.062
	RHCID	.601	.158	.648	3.81	< .001
	CHCID	.269	.164	.317	1.64	.102
	RH*CH	-.063	.044	-.428	-1.44	.151

Note. Predictors: (Constant), RHCID, CHCID, RH*CH

The final predictive regression equation for the two indices and their 2FI was the following:

$$\hat{Y}\text{ (WS)} = .601(\text{RHCID}) + .269(\text{CHCID}) - .063(\text{RH*CH}) + .101 \qquad (11)$$

In the final model, adjusted $R^2 = .206$ indicated that the model explained approximately 21% of WS variation. $F = 19.56$, and its associated p value < .001. Therefore, based on $\alpha = .05$, I rejected the null hypotheses, and concluded there was sufficient evidence of a significant relationship between both reliance and competence, in the aggregate; and Web 3.0 skills. The regression model composed of the two indices and their 2FI was significant in predicting WS.

In the analysis of the two indices, RHCID and CHCID, the 2FI was evaluated and found to be significant in the model predicting WS (inclusion criterion of .20; $p < .001$). Illustrations of the 2FI are provided in Figures 19 and 20. Figure 19 shows that the relationship between WS and RHCID changes depending on the value of CHCID. The influence (slope) of RCHID on WS is positive for all values of CHCID but increases as CHCID decreases in value.

Figure 19

2FI: CHCID and RHCID (First View)

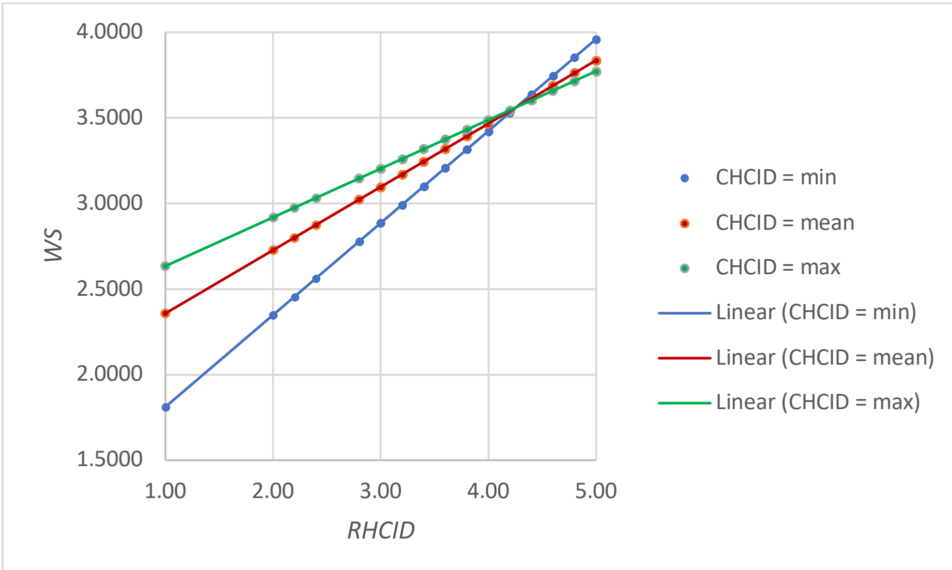
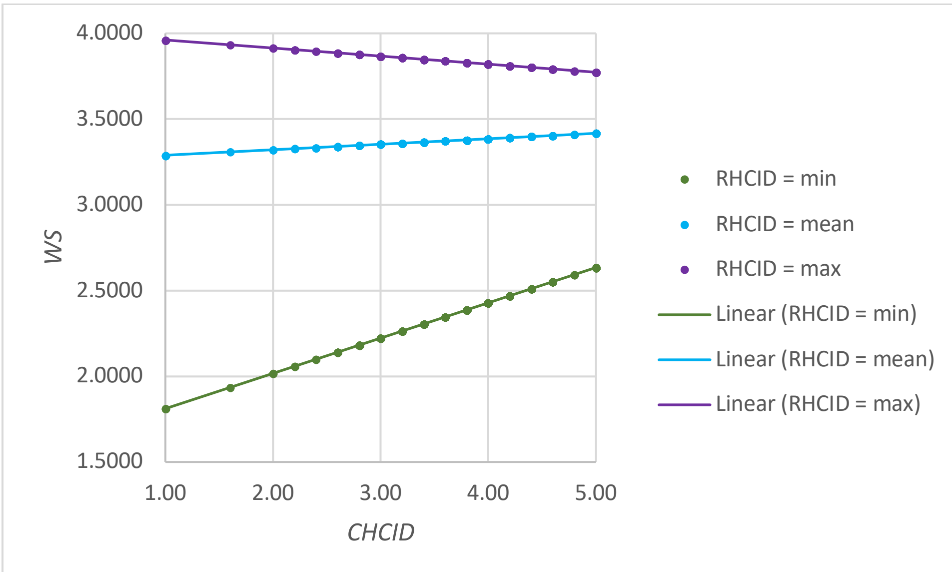


Figure 20 shows, likewise, that the relationship between WS and CHCID changes depending on the value of RHCID. The influence (slope) of CHCID on WS is positive at the minimum value of RHCID, but that influence decreases as RHCID increases in value, such that the influence of CHCID on WS is negative at the maximum value of RHCID.

Figure 20

2FI: CHCID and RHCID (Second View)



Summary

In Chapter 4, I provided a description of the pilot study and data collection. Reliability analysis was completed to confirm the internal validity and consistency of the questionnaire items used to inform each variable. I calculated Cronbach's alpha for the statements belonging to each construct in the research model and found that each subscale was valid. A sample of 214 responses was analyzed. I performed statistical analysis to address the research question.

The research question was, What is the relationship between the use of HCI devices and Web 3.0 skills? This question was designed to explore the motivations for engineers to use Web 3.0 technologies to enhance their skills and performance. Do the independent variables (use of HCI devices—reliance and competence) predict the dependent variable (Web 3.0 skills of engineers)? I postulated that reliance on and competence with five HCI devices could predict the self-reported level of Web 3.0 skills for engineers.

Initially, I considered the 10 independent variables—reliance on and competence with five HCI devices: desktop (DTR/DTC), laptop (LTR/LTC), tablet (TTR/TTC), smartphone (SPR/SPC), and wearable (WBR/WBC) devices. I added a second analysis in which I aggregated the original 10 independent variables to one variable for reliance on all five HCI devices (RHCID); and one variable for competence on all five HCI devices (CHCID). The dependent variable, Web 3.0 skills (WS) was a composite value of means or an index aggregated from eight components of the KOT subscale: web technologies, developer tools, relational database technology, blockchain technology, operating systems and server technologies, server software, and virtualization.

I performed descriptive statistics and graphical analysis to characterize the sample and evaluated statistical assumptions. For both analyses (of the 10 independent variables and the two aggregate indices), I performed three different regression techniques: statistical regression with *backward elimination*, statistical regression with *forward selection*, and sequential regression with iteration. This strategy was intended to generate collaborative evidence for selecting the predictors in a model of WS and to avoid the pitfalls with automated stepwise regression techniques.

I performed the regression model-building task involving the 10 independent variables in two stages. The first was a screening exercise involving only the independent variables, to identify those which were unlikely to be included in a predictive model of WS and those to carry into a full analysis that also included 2FIs. The second stage was intended to develop the best predictive model of WS, including all predictors (independent variables and 2FIs) meeting the inclusion criterion of .20 and contributing to model goodness-of-fit (adjusted R^2).

In the first stage of the analysis of the 10 independent variables, the model developed in run 6 (Table 20) consisted of six independent variables: DTR, TTR, DTC, WBC, LTR, and LTC. All except LTC met the inclusion criterion. However, LTC was only slightly over the inclusion criterion. Therefore, I decided not to exclude it knowing that the next stage of analysis would provide further analysis of its significance. These six independent variables were carried into the second stage of the analysis.

Stage 2 resulted in a final predictive regression model with an adjusted R^2 of .239 included four independent variables (TTR, DTC, WBC, and LTR) and five 2FIs (DTR*TTR, DTC*LTC, TTR*DTC, LTR*LTC, and DTC*WBC. For this final model, F = 8.452, its associated p value < .001. Based on standardized coefficients depicted in Table 26, DTC was the most influential predictor. However, its influence on WS was moderated by TTR as illustrated by the significant 2FI, TTR*DTC.

Analysis of the aggregate indices, RHCID and CHCID, was performed in only one stage since the analysis was relatively simple. All three regression techniques were applied, and the final model consisted of both indices and their 2FI, depicted in Tables 35 and 36. For this model, $F = 19.56$ and its associated p value < .001. RHCID was the more influential predictor based on standardized coefficients, but its influence was moderated by CHCID.

In response to the research question, both null hypotheses were rejected based on the *F* test and a *p* value < α = .05. The analysis revealed that a subset of the original 10 independent variables and 2FIs (see Tables 25 and 26) comprised a significant predictive model of WS. Similarly, a model consisting of the two aggregate indices for reliance and competence, and their 2FI, also significantly predicted WS (see Tables 35 and 36).

I conclude with the following six key findings from my analysis (a) A model of aggregate indices of reliance on and competence with HCI devices and their 2FI was a significant predictor of WS based on an *F* test ($F = 8.452$), its associated *p* value <.001, and α = .05. (b) Within a significant final predictive, regression model, the independent variables LTR, TTR, DTC, and WBC were predictors of WS based their *p* value < the inclusion criterion of .20. (c) The effects of the four independent variables in the final predictive model were moderated by other variables and captured in the form of five 2FIs. (d) Two of the original independent variables (DTR, LTC) were not individually significant based on the inclusion criterion of .20 but were moderating variables (part of significant 2FIs). (e) Both of the aggregate indices of reliance and competence were predictors in a model that was a significant predictor of WS. (f) Four of the original independent variables were not part of a significant predictive model of WS (SPR, WBR, TTC, and SPC) and therefore not considered predictors of WS.

In Chapter 5, I interpret the results related to these six key findings. I also address recommendations for future research. Additionally, I explain the real-world, practical, and operational significance of these results and the potential impact for positive social change.

Chapter 5: Discussion, Conclusions, and Recommendations

The purpose of this quantitative correlational study was to investigate whether the use of HCI devices predicts Web 3.0 skills among engineers. The analysis revealed six key findings. First, a model of reliance on and competence with HCI devices was a significant predictor of Web 3.0 skills. Second, four independent variables were included in a model which was a significant predictor of Web 3.0 skills: two related to competence with devices (desktops and wearables) and two related to reliance on devices (laptops and tablets). Next, five 2FIs indicated that the effects of the four significant independent variables were moderated by other independent variables. The fourth key finding was that two independent variables (competence with laptops and reliance on desktops), while not significant predictors individually, were moderators of the influence of the significant predictors. A fifth key finding was that both aggregate indices of reliance and competence were predictors of Web 3.0 skills. Engineers' usage of HCI devices—their competence with and reliance on HCI devices—predicts Web 3.0 skills among engineers. And, lastly, four of the original independent variables were not part of a significant predictive model. In this chapter, I interpret the findings within the context of previous research and professional practice. I provide recommendations for further research and discuss limitations that impacted my study. I also provide implications for engineering management and explain how my research may lead to positive social change.

Interpretations of the Findings

The theoretical foundation for this research was the Solow IT productivity paradox. The theory maintains that as more investments are made in IT, engineer productivity or performance may go down instead of up. In engineering organizations, management is responsible for motivating its engineers to become more skilled and, therefore, more productive. But they are faced with the challenge of knowing what technologies to invest in that will motivate their engineers to improve their skills. Measuring engineering skills is a vast and complex task, and for this research, I chose one among many measures of skills and focused on Web 3.0.

In this research, I assessed the relationship between reliance on and competence with five specific HCI devices and Web 3.0 skills. To perform this analysis, test the hypotheses, and answer the research question, I performed model building with several types of regression analysis: statistical regression in two forms, backward elimination and forward selection; and sequential regression using the enter method. These techniques were used collaboratively to generate evidence to select the best predictive model of Web 3.0 skills. The evidence generated from these different statistical techniques was used in the aggregate to test the hypotheses and answer the RQs. There were six findings that resulted from this analysis. The following is an interpretation of those findings in terms of previous research and professional practice.

Statistically Significant Predictive Model

I had one RQ and two sets of hypotheses to guide this research. The analysis generated two predictive models documented in Chapter 4. One model was developed using the original 10 independent variables, with a final model that was a statistically significant predictor of Web 3.0 skills and included independent variables and 2FIs meeting my inclusion criterion. The second model was also a statistically significant predictor of Web 3.0 skills and was based on two aggregated measures of reliance and competence.

Research has not been conducted to examine if and to what extent engineer reliance on and competence with specific technology and devices are associated with or can predict advanced skills, such as Web 3.0. Consequently, engineering managers may make uninformed decisions regarding investment in technology, which may not result in increased skills or productivity. My research, as captured in this key finding, showed that it is possible to predict Web 3.0 skills using a regression model consisting of measures of reliance on and competence with various devices.

Predictors of Skills

Four independent variables were included in a model, which was a significant predictor of Web 3.0 skills: two related to competence with devices (desktops and wearables) and two related to reliance on devices (laptops and tablets). Because Web 3.0 is still evolving, current research has not identified the significant predictors of Web 3.0 skills. Previous research addresses Web 2.0 skills but does not identify engineer reliance on and competence with specific technology and devices. Furthermore, as a result, managers cannot make informed decisions about their investments in technology. The IT productivity paradox is well documented in the literature and supported by my research. My research showed that engineers exhibit varying degrees of reliance on and competence with laptops, tablets, desktops, and wearable devices to be productive. Self-reported Web 3.0 skills were predicted by competence with desktops and wearables, and by reliance on laptops and tablets, insights not previously identified by scholarly research.

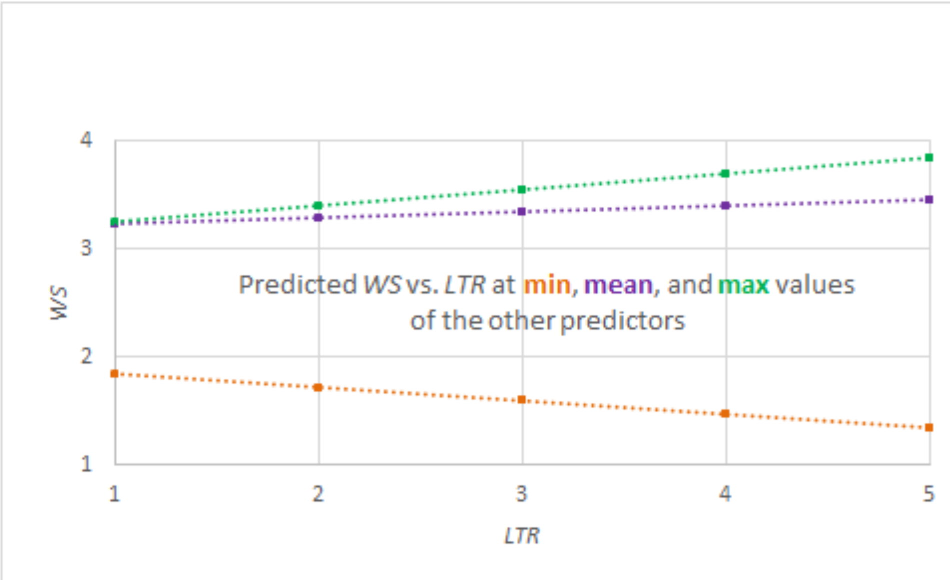
Laptop Reliance

Engineers' reliance on laptops was a negative predictor of skills with advanced technologies (Web 3.0). Within the predictive model of multiple predictors and interactions, an increase in laptop reliance predicts a decrease in Web 3.0 skills. This outcome must be qualified, however, by the interaction between laptop reliance and laptop competence, which was depicted in Figure 13. More broadly, the influence of laptop reliance depends on the values of the other significant predictors as shown in Figure 21. Figure 21 shows that when the other predictors are their minimum values (low reliance or competence), skills decline as laptop reliance increases. But, as the values of the other predictors increase, the influence of laptop reliance on Web 3.0 skills becomes increasingly more positive. So, while overall the influence of laptop reliance is negative, that influence is moderated by the other predictors.

Under those circumstances, engineers' reliance on laptops may decrease their willingness to become motivated to learn Web 3.0 skills on their own. As an example, laptops with the latest operating systems perform tasks that allow engineering users to complete tasks using speech recognition, often without typing text on the keyboard. As a result, there may not be an incentive to develop Web 3.0 skills further.

Figure 21

2FI: Predicted WS and LTR



Engineers can now work on automated and stored projects in the cloud, where information is understood and experienced spatially. Laptops are powerful devices that can process the primary capabilities of Web 3.0 technologies—the semantic web, decentralized technology, 3D interactive technology (i.e., AR/VR, and the spatial web), and the social web.

Laptops that utilize biometric tools (e.g., Apple's facial recognition algorithms and fingerprint sensors) can access content stored on laptops. Engineers who use Apple devices can customize, prioritize tasks via a tool known as mission control, allowing for multiple desktop-like interfaces on their laptops. The capabilities of a laptop are many and beneficial for engineers, often eliminating the need for engineers to learn Web 3.0 manually, learning instead how to use and rely on their laptop device (Rudman & Bruwer, 2016).

Engineers explore data and interact with their laptop devices, but this does not translate into increased Web 3.0 skills. In the workplace, engineers are often focused on solving problems and providing solutions. My research provided evidence that, overall, engineers' Web 3.0 skills tend to be higher with less reliance on laptops. But, to reiterate, my research also showed that the relationship between laptop reliance and skills is complex and depends on engineer's reliance on and competence with other HCI devices.

Tablet Reliance

An increase in engineers' reliance on tablets predicts an increase in Web 3.0 skills. This may be explained by understanding that Web 3.0 technologies interface better on tablet devices. Tablet devices are convenient, portable, best suited for applications, and allow engineers to interact with data better than they can on other kinds of devices.

The third generation of the Internet, or Web 3.0, can equip engineers with websites and applications to process information in an intelligent, human-like fashion using machine learning and big data (Ilchenko & Kramar, 2020). Today, the semantic web has evolved into applications that equip engineers with many options for being productive (i.e., business suites, developer tools, and open-source repositories) on tablet devices. Tablet devices, (e.g., Apple iPads) can display decentralized applications and applications built on Ethereum blockchain—which are disrupting old business models and creating new business practices by using backend code known as smart contracts that operate by a decentralized network instead of a centralized server.

My research highlights that engineers' reliance on tablets provides them access to many applications and widgets leading to higher Web 3.0 skills. Tablet devices are unique since engineers can touch the tablet's screen with their fingers to rotate, scroll, pan, or zoom content. Accessibility features on tablets allow engineers to customize gestures allowing for a high level of interactivity for greater accuracy.

Adapting tablet devices (e.g., Apple iPads, Microsoft Surface, or Samsung tablets) in the workplace can empower engineers to communicate effectively, on the go, and boost employee productivity. Tablet reliance was the highest among the five HCI devices. Based on previous research and in my experience operationally, tablets are worth the investment since their use is associated with higher Web 3.0 skills.

Desktop Competence

Desktop competence was the most influential predictor of Web 3.0 skills (based on standardized coefficients), indicating that engineers tend to have higher Web 3.0 skills while using desktops. Within the predictive model of multiple predictors and interactions, an increase in desktop competence predicts an increase in Web 3.0 skills.

Engineers are competent using desktop devices but as a result may be confined to a specific stationary area for working. Obtaining Web 3.0 skills while working on a desktop equips engineers with readily available tools to develop and manage their workloads. The development of Web 3.0 skills occurs while using a desktop device since this type of device's screen size can range from the size of a laptop, 13 inches, to 55 inches—the size of a TV monitor. Desktops are highly suited for using Web 3.0 technologies and processing data on dashboards.

Interaction with desktops allows engineers to work on multiple projects simultaneously and productively. Output and productivity increase as more projects are completed. Sambasivan et al. (2017) highlighted insights about knowledge of technologies in related fields of ICT for development and HCI for development (HCI4D), which have evolved in technological design with special ergonomic attention and care to desktops in the social-work environment in manufactures, business, and sociocultural contexts. My study provides evidence that engineers' competence in Web 3.0 skills is associated with their competence with desktops in the office environment.

Wearable Competence

Wearable competence was a predictor of Web 3.0 skills, indicating that wearable competence is associated with increased Web 3.0 skills for engineers. Consistent with the research from Farah (2012) and Santos (2015), my findings indicate competence with wearable devices or smartwatches that are unique in size (38 mm or 42 mm) is associated with increased Web 3.0 skills and productivity for engineers.

Comparable to Corbett and Weber (2016), my study indicated that wearable, digital devices with voice user interface functions allow engineers to control their devices for more productivity. Wearables revolutionize how information is displayed and analyzed.

My results indicated that immersion in wearables like VR headsets is beneficial for displaying 3D data and large computer aid design models. Engineers' competence with VR and virtual collaboration with peers while working on projects is associated with higher skills and productivity. For example, previous experience allowed me to interact with engineering colleagues remotely while accessing real-time 3D data with the ability to seek help from other experts via their wearable devices.

Two-Factor Interactions

There were four primary independent variables as predictors in the final regression model, but their influence was moderated by other predictors (see Table 25 and Table 26). This moderating effect was captured in my analysis of five 2FIs. One of these was an interaction between two of the predictor variables: desktop competence and tablet reliance. Another was also the interaction between the two predictor variables, desktop competence and wearable competence. The remaining three 2FIs in the model involved a moderating independent variable that was not included in the MLR equation with an independent variable that was included in the MLR equation: DTR*TTR, LTR*LTC, DTC*LTC.

2FI Between Desktop Competence and Wearable Competence

My research revealed a 2FI between desktop competence and wearable competence, illustrated in Figures 17 and 18. In Figure 17, the influence of wearable competence on Web 3.0 skills was positive at low values of desktop competence; however, the influence of wearable competence on Web 3.0 skills decreased with increases in wearable competence as desktop competence increased in value. At the highest value of desktop competence, wearable competence was not influential, or perhaps negatively influential, on Web 3.0 skills.

The second view of the 2FI between desktop competence and wearable competence (Figure 18) revealed that the relationship between Web 3.0 skills and desktop competence changed depending on the value of wearable competence. The influence of desktop competence on Web 3.0 skills was positive at all values of wearable competence. However, the influence of desktop competence on Web 3.0 skills decreased as wearable competence increased in value.

Consistent with Rudman and Bruwer (2016), my research suggested that Web 3.0 technologies provide an integrated web experience for engineers across HCI devices, where machines can compute, understand, and index data like humans. Regarding *WS*, this 2FI indicates that engineers' Web 3.0 skills are decreasingly associated with the competence of either device, when engineers are competent with the other device; that is, when they opt to be mobile (using their wearable for remote monitoring) or stationary (using their desktop). This finding also highlights the difference in human computer interaction and engineers' Web 3.0 skill level based on the type of device—wearable technology versus desktop technology and its associated level of competence required to be efficient for usage.

2FI Between Tablet Reliance and Desktop Competence

My research revealed a 2FI between competence of desktops and reliance on tablets. The influence of tablet reliance on engineers' skills and tablet reliance was positive for all values of desktop competence but diminished as the level of desktop competence increased. Likewise, the influence of desktop competence on engineers' skills was positive for all values of desktop competence but lessened as tablet reliance increased. Figures 15 and 16 illustrate this 2FI.

Regarding the impact on WS, this 2FI indicates that as desktop competence increases, the impact on WS of increasing tablet reliance is reduced. In other words, as engineers' competence with desktops increases, their skills tend to associate less with their reliance on tablets. Similarly, as engineers' reliance on tablets increases, their skills are associated less with desktop competence.

Moderating Variables

Analysis of the 2FIs revealed that there were two independent variables that exhibited a moderating effect on the significant predictors, even though they were not, by themselves, significant predictors. These were reliance on desktops and competence with laptops.

Desktop Reliance

The moderating effect of desktop reliance is explained by its interaction with reliance on tablets, a 2FI which contributes to the goodness of fit of the model and the predictability of Web 3.0 skills. This 2FI is illustrated in Figure 12.

The relationship between tablet reliance and Web 3.0 skills changes according to the value of desktop reliance. Based on Figure 12, for those engineers who heavily rely on their desktops, their Web 3.0 skills increase as their reliance on tablets increases.

There is an interesting phenomenon apparent in two of the 2FIs involving the influence of tablet reliance on Web 3.0 skills. Whereas the influence of tablet reliance on Web 3.0 skills appears to decrease with higher competence on desktops (Figure 15), that influence appears to increase with higher reliance on desktops (Figure 12). In other words, at lower desktop competence and higher desktop reliance levels, Web 3.0 skills increases as tablet reliance increases. Engineers who are competent with but not reliant on desktops have skill levels not associated with their reliance on tablets.

Operationally, this means that engineering managers should invest in new desktop devices and tablets that can handle extensive workloads with speed or plan to hire a team of independent contractors and IT service technicians to update desktops periodically.

Laptop Competence

The 2FIs included in the model indicated that laptop competence was a moderating variable—not significant by itself but moderating the influence of laptop reliance and desktop competence. This moderating effect is explained in the following two 2FIs.

2FI Between Laptop Reliance and Laptop Competence. My analysis of Figure 13 revealed that, as laptop competence increases, the influence of laptop reliance on Web 3.0 skills increases. This is a logical and self-evident outcome. Engineers who are competent with laptops have skill levels that are associated with their reliance on laptops. Engineering management's investment in the right kinds of laptops can motivate engineers to develop their Web 3.0 skills.

2FI Between Desktop Competence and Laptop Competence. The relationship between Web 3.0 skills and desktop competence changed depending on the value of engineers' competence with laptops (2FI illustrated in Figure 14). The greater the competence with laptops, the less influence that desktop competence has on Web 3.0 skills. This is an intuitive outcome. It might be expected that engineers are more competent with one platform than another, and their Web 3.0 skills would be more influenced by the device with which they are more competent.

The 2FI provides some insights that can be inferred from the interaction and raises the question of how and why engineers' Web 3.0 skills change; and perhaps implies some insights about how they opt to use different devices. Web 3.0 skills are highest for engineers who are competent with both laptops and desktops. And skills are lowest when their competence with both devices is lowest. But their increase in skills based on desktop competence steepens when they are least competent with laptops.

Reliance and Competence Composite Indices

I explored the predictability of two composite indices of the independent variables. A key finding indicated that engineers' reliance and competence of HCI devices, plus their 2FI, were predictors of Web 3.0 skills.

Predictability of Competence and Reliability Indices

In the predictive model, an increase in a general reliance on and competence with HCI devices predicts an increase in Web 3.0 skills. This finding does not refute any previous research, but it does substantiate the notion that engineers' knowledge of and skills with various technologies can improve the productivity of businesses in almost all sectors, ranging from small and medium enterprises to conglomerate corporations.

My research revealed a 2FI between the composite indices of reliance on HCI devices and competence with functions of HCI devices. The influence of reliance on HCI devices on Web 3.0 skills decreased somewhat as competence of HCI devices increased (see Figure 19). Irrespective of the level of competence, there was a positive increase in Web 3.0 skills with increased reliance on HCI devices. However, engineers' Web 3.0 skills tend to be more associated with their reliance on devices when they have low overall competence. Figure 19 shows that when competence is low, WS increases the fastest as reliance increases. When competence is high, WS does not increase as fast as reliance increases. Thus, the engineers' inclination to learn skills increases with reliance on devices, and more so when their competence is low.

What is more interesting is that Figure 20 shows that when engineers are reliant upon HCI devices, moderately or more, their Web 3.0 skills are not greatly influenced by how competent they are with those devices; and those skills may even decline a bit as competence increases. That indicates that engineers' Web 3.0 skills are predicted by their reliance on HCI devices, generally, regardless of if they consider themselves competent with those devices. Reliance is the dominant predictor, not competence.

Variables Not Found to Be Predictors

Four of the original independent variables were not part of a significant predictive model, either as predictors or as moderators of other predictors: smartphone reliance, smartphone competence, wearable reliance, and tablet competence. This finding does not refute any previous research. The finding may indicate that since smartphone use is so prevalent and routine, competence and reliance are not associated with the level of Web 3.0 skills. As for the other two (wearable reliance and tablet competence), the finding suggests that engineers' Web 3.0 skills simply are not associated with reliance on wearables—perhaps because developing those skills does not frequently depend on wearable devices; and not associated with competence with tables because tablets are such a routinely used device in the workplace.

Limitations of the Study

A general limitation of my research was measuring reliance and competency, but not assessing the efficiency of production outputs among engineers. When engineering managers make decisions about investments in technology, they would be wise to consider efficiency as well as reliance and competence. There were a few specific limitations in this research:

- The measurement of reliance and competence was self-reported, which may reflect interest in Web 3.0 skills as opposed to possessing Web 3.0 skills. This may have led to some subjectivity, variability, and potential bias.
- Although operational definitions were provided for the responses based on a 5-point Likert scale, there was some potential bias and variability among respondents who were interpreting the meanings of each Likert response.
- Measuring skill level with technology was challenging.

The dependent variable, Web 3.0 skills, was an aggregated index of eight components: Web Technologies, Developer Tools, Relational Database Technology, Software Design, Blockchain Technology [based on Bitcoin], Operating Systems and Server Technologies, Server Software, and Virtualization. Research did not provide a Web 3.0 technological skill survey. Therefore, I created a questionnaire based upon the existing technologies, buzz words, and hot topics regarding the definition and evolution of Web 3.0. Because Web 3.0 is an emerging, current, and relevant set of technologies, using it to measure engineers' skills, and by inference their motivation, was an appropriate decision for this research. However, this is only one measure of skill and motivation, and a limitation of the research.

Engineers' use of advanced technologies differs according to their preferences, and ergonomic design of HCI devices, as this forms the basis for further investigation of whether HCI devices correlate with Web 3.0 skills among small and medium enterprise engineers. Convenience sampling might introduce bias and impact generalization. However, with a sufficient sample size of 214 and careful explanation of results, bias was minimized. The study results may be generalizable to other states and metropolitan locations, among small and medium enterprises that employ and rely on Web 3.0 technologies and across various industries.

Recommendations

Statistical data that have been collected in prior studies and provided by national databases, government departments, various agencies, or journals (e.g., *International Journal of Production Research* and *National Productivity Review*) sparked research for this study. Statistical data collected from my Web 3.0 technological skill survey might be assessed in greater depth and in future studies by researchers interested in discovering advances to Web technologies like Web 4.0. Future research might also include a qualitative analysis of the associations between HCI devices and Web 3.0 skills of engineers in small and medium enterprises.

Interviewing engineers could provide an in-depth understanding of their motivation and expectations of engineers to perform concerning their occupation and further advances in technology. As technology advances, this research could serve as the foundation for assessing future Web 4.0 technology and applications and its' to be determined impact on small and medium enterprises and the U.S. economy. Emerging technology like blockchain and cryptocurrency is expected to disrupt our economy, providing new investors and open-source technology opportunities to emerge further.

This study could provide insights leading to further research by current and new organizations to expand and produce new products. The future of autonomous vehicles, drones, and vehicle systems will emerge; therefore, developers and engineers must adopt strong technical skills to support economic endeavors in sustaining futuristic concepts and offerings. Researchers could assess and analyze if new advances in robotics aided in workforce labor.

Immersing in VR and investing in other wearables could potentially impact how consumers shop, how engineers work and offer an outlet to K-16 students for learning and gaming. Lastly, the rise of AI could spark an ongoing debate and future study in assessing the relationship between machine-to-machine interactions.

Cebr's (2016) report revealed that natural resources are scarce due to excessive use by humans; therefore, urging engineers to provide sustainable solutions. Based on the new wave of innovation in AI, researchers must discover new findings, and engineers develop efficient technology. ICT has been a part of the secondary level education curriculum since 1982 in both U.S. and developed countries worldwide (Sharma et al., 2016); therefore, newly developed educational courses and training methods could educate engineers and provide societal best practices for using technology productively and efficiently in the digital age and beyond.

Big data may motivate data engineers to adopt new Web 3.0 and Web 4.0 skills to inform society through better decision-making. Data engineers tasked to build machine learning models that organizations can use to become more productive involve creating these new tools to analyze data, pipelines, ingesting data, processing data, and updating dashboards. The quantitative approach to this study did not use theoretical data and provided non-empirical evidence to develop further the training of Web 3.0 technology (e.g., IoT, cloud computing, and AI) in small and medium enterprises. Operationally, emphasis on maximizing training programs for engineers can increase Web 3.0 skills and productivity.

Further research is recommended regarding the counterintuitive result that increased laptop reliance predicts a decrease in Web 3.0 skills when measured in a model of several predictors and factor interactions. This may be an illustration of the IT productivity paradox. But research is called for because engineering leaders who understand how Web 3.0 and other emerging technologies can transform business and create new value will perform better economically.

Further research for understanding what the next era of Web 3.0 entails (i.e., spatial web) is also recommended for engineering management. Further research should explore the association of HCI device competence and reliance with other measures of skill level and motivation.

I was unable to delve deeply into the degree of differences in the demographics among engineers (e.g., each category of age, occupation, and length of employment) or if their years of self-taught experience impacted their understandings of Web 3.0 skills.

Future research might perform more comprehensive analysis to understand the different degrees among these categories. I did not consider whether engineers who work in small and medium enterprises that use a pay-for-performance model might have different experiences with technology and skill levels. I did not obtain performance evaluation reports of engineers before this study, which means a combination of measurable inputs (e.g., goal setting, compensation, promotions, and incentives) could have been used to motive engineers to learn advanced concepts and tools per their job description. Justification based on an engineer's level or role within small and medium enterprise either equipped engineers to perform as expected or not within their organization and may or may not justify their Web 3.0 skill level.

Implications

Positive Social Change Implication

My study supports Berners-Lee's vision of an invention of the web (as reported by Ilchenko & Kramar, 2020)—that prudent investment in technology can benefit small and medium enterprises and become a powerful force in social change, social engineering, and individual creativity. As a result of my research, the impact and evolution of Web 3.0 technologies may transform the U.S. economy and our society by employing well-conceived types and combinations of HCI devices that will function in various areas, particularly engineering, finance, healthcare, and education sectors. The right decisions by engineering managers may improve skills and productivity, making their organizations more effective and efficient, giving people satisfaction and employment while benefitting consumers and all of society with improved products that are helpful and cost-effective. My research may lead to social change for engineers, consumers, and users who opt to invest, thoughtfully, in Web 3.0 technologies to make their daily tasks easier to complete.

The key findings of my study may help managers, engineers, consumers, and users make better investment decisions regarding the five types of HCI devices commonly employed in their daily tasks and pursuits. Web 3.0 technologies, like cloud services, now allow machine-to-machine interaction; therefore, the use of IoT devices will rise, causing smart cities to emerge. Advanced tools used in autonomous vehicles will ultimately transform how drivers operate their vehicles, potentially leading civil engineers to construct new routes for safety concerns.

Implication for Practice

The importance of my research is its potential positive impact on small and medium enterprises through best management practices. This study addressed organizational and operational challenges related to managing technological advancements and innovation in which ICT, HCI, and Web 3.0 were common management issues. Engineering management and the management of advanced technology impact the engineering sector and accounting, finance, economics, human resources management, IT, organizational behavior, operations management, project management, and many more non-technical-intensive fields that use Web 3.0.

Engineering managers and chief technology officers who utilize their training to coach and motivate other engineers to develop critical thinking skills for innovating new solutions to real-world issues may ultimately lead to better design and implementation of web technologies and product offerings and services. I found that competence and reliance on HCI devices were, generally, associated with increased Web 3.0 skills. More specifically, I found that specific devices and certain combinations are associated with increased Web 3.0 skills; therefore, I recommend engineering management make thoughtful decisions and investments based on my research findings.

Specifically, engineering managers should consider the effects of thoughtful combinations of the five HCI devices, rather than thinking about the devices in isolation. Consider both reliance upon and competence with devices. Furthermore, consider the engineer's perspectives, needs, and productivity with various devices and combinations of devices, when making significant investments in technology.

Theoretical Implication

The theoretical foundation of my research, the Solow (1957) IT productivity paradox, started a debate about the technological factors that can increase national income and social wealth. Solow's theory declares that as investments in technology increase, it is not certain that skills and productivity increase as well. My research was based on the IT productivity paradox and was intended to understand why significant investments can be spent on new technology without higher product margins. I investigated engineers' reliance on and competence with HCI devices and their predictability of Web 3.0 skills. Statistical results of my research confirm the theoretical foundation, where a complex system of interrelated variables (competence and reliance on technology among engineers) influences engineers' skills and productivity and levels of productivity in small and medium enterprises.

My research corroborated the theory by showing that reliance upon and competence with various HCI devices (and by extension, investment in them) is not always associated with increases in skills and, therefore, productivity. And my research showed that investigating the benefits of individual devices is too simplistic—that their influence on skills and productivity depends on a complex set of factors and interactions among factors, on various combinations of devices.

Acemoglu et al. (2014) may have declared the decline of the Solow IT productivity paradox prematurely. What has happened is that over time, the programming a software engineer needs to know has decreased and simplified. Programming for a statistician or data engineer is near effortless due to libraries that automatically compute the load and level of programs. Before, engineers knew many mathematical concepts for manual procedures that can now be computed and programmed using libraries and packages. Tech-savvy engineers continue to learn new skills that will drive the productivity revolution in building data pipelines, applications, and sustainable products for the U.S. economy.

My research supported Harkushenko and Kniaziev's (2019) concern of the need for ICT for economic development by creating financial and mathematical models of ICT for a greater impact on output and productivity-which ultimately affects the commercial manufacturing sector and government. Overall, my findings indicate that as engineers use advanced HCI devices and web technologies, their productivity and Web 3.0 skill level may increase or decrease depending on their level of reliance and competence on a combination of devices. However, the influence of some devices on skills and productivity is moderated by reliance on and competence with other devices.

Methodological Implications

There are known issues with relying on automated, statistical regression routines such as backward elimination and forward selection. These techniques can be helpful as pieces of evidence, especially when screening many potential predictors. However, the more effective and accurate process, demonstrated in my research, is to use a form of sequential regression, which allows some iteration among models of different combinations of predictors, while striving to find the model with the best-goodness-of-fit. In my analysis, that model (set of predictors) using sequential regression was different from the model developed with the automated statistical regression routines and produced a superior goodness-of-fit.

Sequential regression was able to identify more clearly the contributions of predictors (independent variables and 2FIs) to model quality, that were overlooked by the statistical methods, and that may have been eliminated based on the known pitfall that automated stepwise regression’s selection or elimination of predictors is heavily dependent upon the order they are examined. Sequential regression, with analyst judgment, can explore different combinations of predictors, resulting in a higher likelihood of including all significant predictors, and producing the highest quality model from the data set provided. The result in my research was a final model from sequential regression with the best goodness-of-fit, and potentially the avoidance of missed variable bias.

Conclusions

In this study, I investigated the relationship between reliance on and competence with various HCI devices and Web 3.0 skills. The insight gained from this research helps to explain the use of HCI devices of engineers in small and medium enterprises and the relationship with Web 3.0 skills that engineers obtain that can be associated with the amount of interaction spent with their devices. Adopting more than one type of device improved the engineers' Web 3.0 skills, in certain combinations.

The intention was to understand from a practical perspective the theoretical productivity paradox that plagues engineering managers; and help them to find a solution to remedy their struggle to know what kinds of investments to make in IT that will yield increases in engineering skills, motivation, and productivity. In the past, engineering managers made worthy efforts to make good decisions about investing in IT. But there has been little research into the somewhat complex dynamics that drive productivity and how much of it is influenced by investments in technology. I have provided insights into those workplace dynamics that need to be considered when engineering managers make important decisions that can make or break small and medium enterprises; and, if not the specific investments, at least the kinds of considerations that engineering managers should undertake which will lead logically to sound decisions. Perhaps engineering management can apply these insights and follow logical processes to better performance and ROI. In that case, they would be far more likely to make good decisions and investments and increase rather than decrease their engineering staff's skills, motivations, and productivity. Therefore, everyone in society potentially benefits from this.

In the examination of Web 3.0 skills, in particular social media trends among engineers (e.g., Facebook, Instagram, and Twitter), it is generally understood which technologies are more popular or considered favored technologies, and which devices aid in the success of how new technology or devices take form and shape. Reliance on the smartphone device is still prevalent since this device is easily accessible and used for emails, customer relationship management applications, and social media in small and medium enterprises. The life and success of technologies rely on how well users or engineers adapt their form and function. Reliance and competence in using HCI devices, like wearables with augmented reality, leads to productivity without an engineer physically being present. Small and medium enterprises' goals in obtaining and maintaining the competitive advantage over others can motivate strategic decisions to adopt web technologies. Understanding the various factors in the workplace, especially effective and efficient combinations of HCI devices, can be a strategic advantage for these businesses.

References

Acemoglu, D., Autor, D., Dorn, D., Hanson, G. H., & Price, B. (2014). Return of the Solow paradox? IT, productivity, and employment in US manufacturing. *American Economic Review*, *104*(5), 394–399. https://doi.org/10.1257/aer.104.5.394

Aghion, P. (2017). Entrepreneurship and growth: Lessons from an intellectual journey. *Small Business Economics*, *48*(1), 9–24. https://doi.org/10.1007/s11187-016-9812-z

Amazon Alexa. (2018). What is a voice user interface (VUI)? https://developer.amazon.com/en-US/alexa/alexa-skills-kit/vui

Atabekova, A., Belousov, A., & Shoustikova, T. (2015). Web 3.0-based non-formal learning to meet the third millennium education requirements: University students' perceptions. *Procedia—Social and Behavioral Sciences*, *214*, 511–519. https://doi.org/10.1016/j.sbspro.2015.11.754

Bachmann, D., Weichert, F., & Rinkenauer, G. (2018). Review of three-dimensional human-computer interaction with focus on the leap motion controller. *Sensors*, *18*(7), 1–39. https://doi.org/10.3390/s18072194

Badiger, K. G., Prabhu, S. M., & Badiger, M. (2018). Application of Web 2.0 and Web 3.0: An overview. *International Journal of Information Movement*, *2*(11), 119–125. http://www.ijim.in/wp-content/uploads/2018/03/Vol-2-Issue-XI-119-125-paper-1935-Kalikadevi-G-Badiger.pdf

Bailey, K. D. (1982). *Methods of social research* (2nd ed.). Collier Macmillan Publishers.

Bandaya, M. T., Musavir, A., & Tariq R. J. (2014). Applications of e-learning in engineering education: A case study, *Procedia—Social and Behavioral Sciences*, *123,* 406–413. https://doi.org/10.1016/j.sbspro.2014.01.1439

Barnett, V. & Lewis, T. (1985). *Outliers in statistical data* (2nd ed.). John Wiley & Sons.

Baturay, M. H., & Toker, S. (2015). An investigation of the impact of demographics on cyberloafing from an educational setting angle. *Computers in Human Behavior*, *50*, 358–366. https://doi.org/10.1016/j.chb.2015.03.081

Benner, M. J., & Tushman, M. L. (2013). Reflections on the 2013-decade award—“exploitation, exploration, and process management: The productivity dilemma revisited” ten years later. *Academy of Management Review*, *40(*4*)*, 497–514. https://doi.org/10.5465/amr.2015.0042

Biagi, F. (2013). *ICT and productivity: A review of the literature*. Joint Research Centre, Institute for Prospective Technological Studies, Publications Office. https://data.europa.eu/doi/10.2788/32940

Bock, B. C., Lantini, R., Thind, H., Walaska, K., Rosen, R. K., Fava, J. L., Barnett, N. P., & Scott-Sheldon, L. A. (2016). The mobile phone affinity scale: Enhancement and refinement. *JMIR Mhealth Uhealth*, *4*(4), 1–10. https://doi.org/10.2196/mhealth.6705

Bonett, D. G., & Wright, T. A. (2015). Cronbach’s α reliability: Interval estimation, hypothesis testing, and sample size planning. *Journal of Organizational Behavior, 36*(1), 3–15. https://doi.org/10.1002/job.1960

Borg, W. R., & Gall, M. D. (1983). *Educational research: An introduction* (4th ed.). Longman.

Borras-Gene, O., Martinez-Nunez, M., & Fidalgo-Blanco, A. (2016). New challenges for the motivation and learning in engineering education using gamification in MOOC. *International Journal of Engineering Education*, *32*(1), 501–512. https://repositorio.grial.eu/bitstream/grial/560/1/19_ijee3155ns.pdf

Bozeman, B., Rimes, H., & Youtie, J. (2013). The evolving state-of-the-art in technology transfer research: Revisiting the contingent effectiveness model. *Research Policy*, *44*(1), 34–49. http://doi.org/10.1016/j.respol.2014.06.008

Bruwer, H. J. (2014). An investigation of development in Web 3.0: Opportunities, risk, safeguards, and governance. *SUN Scholar*.

Bryman, A. (2012). *Social research methods.* Oxford University Press.

Byrne, D. M. & Corrado, C. A. (2017). ICT prices and ICT services: What do they tell us about productivity and technology? *Finance and Economics Discussion Series*. https://doi.org/10.17016/FEDS.2017.015

Capgemini Research Institute. (2018). Immersive technology has arrived: AR and VR set to become mainstream in business operations in the next 3 years. https://www.capgemini.com/news/ar-and-vr-in-operations/

Cardona, M., Kretschmer, T., & Strobel, T. (2013). ICT and productivity: Conclusions from the empirical literature. *Information Economics and Policy*, *25*(3), 109–125. https://doi.org/10.1016/j.infoecopol.2012.12.002

Centre for Economics and Business Research. (2016). Engineering and economic growth: A global view. *Royal Academy of Engineering,* 1–76. https://www.raeng.org.uk/publications/reports/engineering-and-economic-growth-a-global-view

Chua, Y. P., & Chua, Y. P. (2017). Do computer-mediated communication skill, knowledge and motivation mediate the relationships between personality traits and attitude toward Facebook? *Computers in Human Behavior*, *70*, 51–59. https://doi.org/10.1016/j.chb.2016.12.034

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Lawrence Earlbaum Associates.

Cohen, J. (1992). A power primer. *Psychological Bulletin*, *112*, 155-159. http://psycnet.apa.org

Contreras, F. K., de Oliveira, F. B., & Muller, E. S. M. (2012). Internet: Monitored freedom. *Journal of Information Systems and Technology Management*, *9*, 459-472. http://dx.doi.org/10.4301/S1807-17752012000300002

Corbett, E. & Weber, A. (2016). What can I say? Addressing user experience challenges of a mobile voice user interface for accessibility. http://dx.doi.org/10.1145/2935334.2935386

Corbett, F., & Spinello, E. (2020). Connectivism and leadership: harnessing a learning theory for the digital age to redefine leadership in the twenty-first century. *Heliyon*, *6*(1), 1-9. https://doi.org/10.1016/j.heliyon.2020.e03250

DATA USA. (2019). DATA USA: Engineering demographics. https://datausa.io/profile/cip/engineering#demographics

Decker, R.A., Haltiwanger, J., Jarmin, R.S., & Miranda. J. (2017). Declining dynamism, allocative efficiency, and the productivity slowdown. *American Economic Review, 107*(5), 322-326. https://dx.doi.org/10.1257/aer.p20171020

Dunteman, G.H. (1984). *Introduction to multivariate analysis.* Sage Publications.

Edwards, K., & Jensen, P.L. (2014). Design of systems for productivity and well-being. *Applied Ergonomics*, *45*, 26-32. http://dx.doi.org/10.1016/j.apergo.2013.03.022

Ekuobse, G.O., Olutayo, V.A. (2016). Study of Information and Communication Technology (ICT) maturity and value: The relationship. *Egyptian Informatics Journal*, *17*, 239–249. http://dx.doi.org/10.1016/j.eij.2015.12.001

Erdfelder, E., Faul, F., & Buchner, A. (1996). G*power: A general power analysis program. *Behavior Research Methods, Instruments, & Computer*, *28,* 1-11. https://doi.org/10.3758/BF03203630

Farah, J. (2012). Predicting the intelligence of Web 3.0 search engines. *International Journal of Computer Theory and Engineering*, *4*(3), 443-445. http://www.ijcte.org/papers/503-G1326.pdf

Faul, F., Erdfelder, E., Buchner, A., & Lang, A.G. (2009). Statistical power analyses using G*Power 3.1: Tests for correlation and regression analyses. *Behavior Research Methods*, *41*, 1149-1160. https://doi.org/10.3758/BRM.41.4.1149

Field, A. (2013). *Discovering statistics using IBM SPSS Statistics* (4th ed.). Sage.

Frankfort-Nachmias, C., Nachmias, D., & Deeward, J. (2015). Research methods in the social sciences (8th ed.). New York: Worth.

Frost. J. (2020). *Regression analysis: an intuitive guide for using and interpreting linear models*. https://statisticsbyjim.com/regression/regression-analysis-intuitive-guide/

Heinze, G. & Dunkler, D. (2017). Five myths about variable selection. *Transplant International*, *30*, 6-10. https://doi.org/10.1111/tri.12895

Gamble, S. & Calverley, J. (2015). Technology: Reshaping the global economy. *Standard Chartered*, 1-112. https://www.sc.com/en/media/press-release/technology-reshaping-the-global-economy/

Glassman, J., Prosch, M., & Shao, B.M. (2015). To monitor or not to monitor: Effectiveness of a cyberloafing countermeasure. *Information & Management*, *52* (2), 170–182. https://dx.doi.org/10.1016/j.im.2014.08.001

Goerzig, D. & Bauernhansl, T. (2018). Enterprise architectures for the digital transformation in small and medium-sized enterprises. *Procedia CIRP*, *67*, 540-545. https://dx.doi.org/10.1016/j.procir.2017.12.257

Gomes, R.F.S., & Cardoso, I.G. (2020). Emerging technology applied to quality engineering: Current scenario and perspectives. *Proceedings on Engineering Sciences, 2*(3), 295-304. https://dx.doi.org/10.24874/PES02.03.008

Google. (2018). Building a Google that works for everyone. https://diversity.google

Green, S. B. & Salkind, N. J. (2014). *Using SPSS for Windows and Macintosh: Analyzing and understanding data*. Pearson.

Haltiwanger, J., Jarmin, R., Kulick, R., & Miranda. J. (2017). High growth young firms: Contribution to job growth, revenue growth and productivity. In Haltiwanger, J., Hurst, E., Miranda, J. and Schoar, A. (eds.). *Measuring Entrepreneurial Businesses: Current Knowledge and Challenges. Forthcoming,* NBER Book Series Studies in Income and Wealth, University of Chicago Press.

Hampton, A.J. & Shalin, V.L. (2017). Sentinels of breach: Lexical choice as a measure of urgency in social media. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *59*(4), 505-519. https://dx.doi.org/10.1177/0018720817691612

Hanover Research. (2017). Hanover research 2017 industry trend report. http://www.hanoverresearch.com/2017-higher-education-trends-report/

Harkushenko, O.M., & Kniaziev, S.I. (2019). Analysis of economic and mathematical models of Information and Communication Technology (ICT) effect on the production output: Does the Solow paradox exist? *Science Innovation. 15*(4), 05—17. https://doi.org/10.15407/scine15.04.005

Heaggans, R.C. (2012). The 60’s are the new 20’s: Teaching older adults technology. *SRATE Journal*, *21*(2), 1-8. http://www.sratejournal.org

Hersey, P., & Goldsmith, M. (1980). A situational approach to performance planning. *Training & Development Journal*, *34*, 38-44. https://ijol.cikd.ca/pdf_60205_a42f02b2242998e2fdcc0e927d8c01b6.html

Hoboubi, N., Choobineh, A., Ghanavati, F.K., Keshavarzi, S., & Hosseini, A.A. (2016). The impact of job stress and job satisfaction on workforce productivity in an iranian petrochemical industry. *Safety and Health at Work*, 1-5. http://dx.doi.org/10.1016/j.shaw.2016.07.002

Horzum, M.B. & Aydemir, Z. (2014). Web 2.0 tools and educational usage self-efficacy: A scale development study. *Procedia—Social and Behavioral Sciences*, *116*(1), 453 – 458. https://dx.doi.org/10.1016/j.sbspro.2014.01.239

IBM Corp. (2017). IBM SPSS Statistics for Macintosh, Version 25.0. IBM Corp.

Ilchenko, O.M., &. Kramar, N.A. (2020). "Vague but exciting" —The narrative behind the history of Timothy Berners-Lee's invention of the Web. *Information and Telecommunication Sciences*, *11*(2), 92—99. https://ela.kpi.ua/bitstream/123456789/40637/1/ITS2020_11-2_p92-99.pdf

Issa, T., & Isaias, P. (2015). Usability and Human Computer Interaction (HCI). *Sustainable Design*, 19-36. https://doi.org/10.1007/978-1-4471-6753-2_2

James, D.J. (2015). Adoption and use of Web 2.0 technologies: A comparison of four adoption models as a case study of a state government eExtension project. https://eprints.usq.edu.au/27440/

Jayarama, D., Manraib, A.K., & Manraib, L.A. (2015). Effective use of marketing technology in Eastern Europe: Web analytics, social media, customer analytics, digital campaigns, and mobile applications. *Journal of Economics, Finance and Administrative Science*, *20*, 118-132. http://dx.d0i.0rg/l 0.1016/j.jefas,2015.07.001

Joshi, A., Kale, S., Chandel, S., & Pal, D. K. (2015). Likert scale: Explored and explained. *British Journal of Applied Science & Technology*, *7*(4), 396-403. https://dx.doi.org/10.9734/BJAST/2015/14975

Khusainova, R., Jong, A., Lee, N., Marshall, G.W., & Rudd, J.M. (2018). (Re) defining salesperson motivation: Status, main challenges, and research directions. *Journal of Personal Selling & Sales Management*, *38*(1), 2–29, https://doi.org/10.1080/08853134.2017.1415761

Kreps, D. & Kimppa, K. (2015). Theorising Web 3.0: ICTs in a changing society. *Information Technology & People*, *28*(4), 726-741. https://doi.org/10.1108/ITP-09-2015-0223

Kusumaningtyas, N. & Suwarto, D. H. (2014). ICT adoption, skill and use differences among small and medium enterprises managers based on demographic factors. *Procedia - Social and Behavioral Sciences*, *169*, 296-302. https://dx.doi.org/10.1016/j.sbspro.2015.01.313

Litchfield, K., & Javernick-Will, A. (2015). I am an engineer and: A mixed methods study of socially engaged engineers. *Journal of Engineering Education*, *104*(4), 393–416. https://dx.doi.org/10.1002/jee.20102

Malek, J. A. (2017). The impact of heutagogy education through telecentre in Smart Village (SV). *Journal of Social Sciences and Humanities*, *12*(2), 112-125. http://ejournals.ukm.my/ebangi/article/view/20399

Mashal, H. M. (2017). *Uncontrolled Workplace Breaks and Productivity (Doctoral dissertation)*. Retrieved from ProQuest Dissertations & Theses Full Text database (UMI No. 10255961)

McKenna, A. F., Froyd, J., & Litzinger, T. (2014). The complexities of transforming engineering higher education: Preparing for next steps. *Journal of Engineering Education*, *103*(2), 188–192. https://dx.doi.org/10.1002/jee.20039

Michie et al. (2017). The human behavior-change project: Harnessing the power of artificial intelligence and machine learning for evidence synthesis and interpretation. *Implementation Science*, *12*(121), 1-12. https://dx.doi.org/10.1186/s13012-017-0641-5

Mihalič, T., Praničević, D. G. & Arnerić, J. (2015). The changing role of ICT competitiveness: the case of the Slovenian hotel sector. *Economic Research*, *1*, *367-383*. http://dx.doi.org/10.1080/1331677X.2015.1043779

Ndiege, J. R. A., & Wamuyu, P. K. (2019). Knowledge management practices and systems in county governments in developing countries: Perspectives from selected counties in Kenya. *VINE: The Journal of Information & Knowledge Management Systems*, *49*(3), 420–439. https://doi-org.ezp.waldenulibrary.org/10.1108/VJIKMS-01-2019-0014

Office of Occupational Statistics and Employment Projections. (2021, May 14). *Architecture and Engineering Occupations.* U.S. Bureau of Labor Statistics. https://www.bls.gov/ooh/architecture-and-engineering/home.htm

Olaniyi, F. O. (2015). The relevance of learning theories in adult and non-formal education. *Journal of Educational and Social Research*, *5*(1), 261-264. https://doi:10.5901/jesr.2015.v5n1p261

Organization for Economic Cooperation and Development. (2012). *OECD Week 2012: Secretary-General's report to ministers 2012* [White paper]. http://www.oecd.org/

Pew Research Center. (2014). Digital Life in 2025. http://www.pewinternet.org/2014/03/11/digital-life-in-2025/

Pew Research Center. (2016). Internet surveys. http://www.people-press.org/methodology/collecting-survey-data/internet-surveys/

Pirani, F. (2017, October 19). Atlanta named one of America's 'Tech 25' — the nation's top 25 cities in tech. Atlanta Journal Constitution (AJC). pp. 1

Priem, R. L., Li, S., & Carr, J. C. (2012). Insights and new directions from demand-side approaches to technology innovation, entrepreneurship, and strategic management research. *Journal of Management*, *38*, 346-374. https://dx.doi.org/10.1177/0149206311429614

Rahi, S. (2017) Research design and methods: A systematic review of research paradigms, sampling issues, and instruments development. *International Journal of Economics and Management Sciences*, *6*(403), 1-5. https://dx.doi.org/10.4172/2162-6359.1000403

Roback, A. (2012). A framework and future direction for studying productive applications of social media/social networking sites. *17th ACM International Conference on Supporting Group Work,* 295-296. https://dx.doi.org/10.1145/2389176.2389226

Rudman, R., & Bruwer, R. (2016). Defining Web 3.0: opportunities and challenges, *The Electronic Library*, *34*, 132-154. https://doi.org/10.1108/EL-08-2014-0140

Sambasivan, N., Jain, N., Checkley, G., Baki, A., Herr, T. (2017). A framework for technology design for emerging markets. *Association for Computing Machinery, 24*(3), 70-73. https://dx.doi.org/10.1145/3058496

Sawhney, A., Mukherjee, K. K., Rahimian, F. P., & Goulding, J. S. (2014). Scenario thinking approach for leveraging ICT to support SMEs in the Indian construction industry. *Procedia Engineering*, *85,* 446–453. https://dx.doi.org/10.1016/j.proeng.2014.10.571

Schmitz, A. (2012). *Sociological inquiry principles: Qualitative and quantitative methods v.1.0*. https://2012books.lardbucket.org/books/sociological-inquiry-principles-qualitative-and-quantitative-methods/

Schuh, G., Potente, T., Wesch-Potente, C., Weber, A. R., & Prote, J. P. (2014). Collaboration mechanisms to increase productivity in the context of industrie 4.0. *Procedia CIRP*, *19*, 51-56. http://dx.doi.org/10.1016/j.procir.2014.05.016

Serin, D. A., & Yalçıner, A. Y. (2021). A survey to examine engineers' perspectives on innovation and industry 4.0. Proceedings, 74(16), 1-10. https://doi.org/10.3390/proceedings2021074016

Shambaugh, J., Nunn, R., Breitwieser, A., & Liu, P. (2018). The state of competition and dynamism: Facts about concentration, start-ups, and related policies. The Brookings Institution. https://www.brookings.edu/research/the-state-of-competition-and-dynamism-facts-about-concentration-start-ups-and-related-policies/

Sharma, R., Fantin, A., Prabhu, N., Guan, C., & Dattakumar, A. (2016). Digital literacy and knowledge societies: A grounded theory investigation of sustainable development. *Telecommunications Policy*, *40*, 628–643. http://dx.doi.org/10.1016/j.telpol.2016.05.003

Shneiderman, B., Plaisant, C., Cohen, M., Jacobs, S., Elmgvist, N., & Diakopoulos, N. (2016). *Designing the User Interface: Strategies for Effective Human-Computer Interaction,* (6th ed.). Pearson.

Sivarajah, U., Irani, Z., & Weerakkody, V. (2015). Evaluating the use and impact of Web 2.0 technologies in local government. *Government Information Quarterly*, *32*, 473-487. http://dx.doi.org/10.1016/j.giq.2015.06.004

Solow, R. M. (1957). Technical change and the aggregate production function. *Review of Economics and Statistics*, *39*, 312-320. http://www.jstor.org/stable/1926047

Stanley, T., Doucouliagos, H., & Steel, P. (2018). Does ICT generate economic growth? A meta-regression analysis: Does ICT generate economic growth? *Journal of Economic Surveys, 32,* 705–726. https://dx.doi.org/10.1111/joes.12211

SurveyMonkey. (2019). Sample size calculator. https://www.surveymonkey.com/mp/samplesizecalculator/?ut_source=help_center

Syverson, C. (2016). Challenges to mismeasurement explanations for the U.S. productivity slowdown. *National Bureau of Economic* Research *(NBER) Working Paper No. 21974.* https://dx.doi.org/10.3386/w21974

Tarute, A., & Gatautis, R. (2013). ICT impact on small and medium enterprises performance. *Procedia—Social and Behavioral Sciences*, *110*, 1218–1225. https://dx.doi.org/10.1016/j.sbspro.2013.12.968

Thirunarayan, K., & Sheth, A. P. (2013). Semantics-empowered big data processing with applications. *AI Magazine*, *35*(3), 68-75. http://corescholar.libraries.wright.edu/knoesis/1026

Tisdell, C. (2014). Information technology's impacts on productivity, welfare, and social change: Second version. *Economic Theory, Applications, and Issues*, 1-41. https://dx.doi.org/10.22004/ag.econ.195701

Tishman, F. M., Van Looy, S. & Bruyère, S. M. (2012). Employer strategies for responding to an aging workforce. *The NTAR Leadership Center*. https://www.ntarcenter.org/

Tupes, E. C, & Christal, R. E. (1992). Recurrent personality factors based on trait ratings. Journal of Personality, 60, 225–251. https://onlinelibrary.wiley.com/journal/14676494

U.S. Bureau of Labor Statistics. (2021). *Metropolitan and Nonmetropolitan Area Occupational Employment and Wage Estimates: Atlanta-Sandy Springs-Roswell, GA*. Division of Occupational Employment and Wage Statistics. https://www.bls.gov/oes/current/oes_12060.htm

U.S. Bureau of Labor Statistics. (2021). *Productivity and Costs*. U.S. Bureau of Labor Statistics. https://www.bls.gov/news.release/pdf/prod2.pdf

Wambui, C., & Njuguna, A. (2016). The effect of information and communication technology on financial management system effectiveness in health-oriented civil society organizations. *American Journal of Health, Medicine and Nursing Practice*, *1*, 16 - 33. https://ajpojournals.org/journals/index.php/AJHMN

Wiberg, M., & Wiberg, C. (2018). Digital integration in the 3rd wave of mobile HCI: A key challenge for overcoming the inverted digital divide. *International Journal of Mobile Human Computer Interaction, 10*(2), 57-64. https://doi.org/10.4018/IJMHCI.2018040103

Wiseman, I.M. (1984): Creating competitive weapons from information systems. *Journal of Business Strategy*, *5*, 42-49. https://doi.org/10.1108/eb039057

Xu, X., & Zhang, W. (2016). Revisiting the IT productivity paradox: A Technology Life Cycle Perspective. *Association for Information Systems*, *6*, 535-545. http://aisel.aisnet.org/whiceb2016/6

Xu, Y., & Chen, M. (2018). An internet of things-based framework to enhance just-in-time manufacturing. *Proceedings of the Institution of Mechanical Engineers, Part B, Journal of Engineering Manufacture, 232*(13), 2353-2363. https://doi.org/10.1177/0954405417731467

Yilmaz, K. (2013). Comparison of quantitative and qualitative research traditions: epistemological, theoretical, and methodological differences. *European Journal of Education*, *48*(2), 311-323. https://doi.org/10.1111/ejed.12014

Appendix A: Web 3.0 Technological Skill Survey

Respondent Information

Title (Occupation): ____

Age (in years): ____

Gender: ____

Race: ____

Rate your knowledge level for the following technologies using this scale:

1 – No prior experience or training with the technology

2 – Minimal training received; minimal experience with the technology; below average level of expertise

3 – Medium level of experience and expertise (able to competently use key functionality)

4 – Significant experience with the technology; above average level of knowledge, skill, and confidence; but not yet in senior, trainer, or mentor role

5 – Experienced, confident, and skilled; able to train or mentor others; considered expert in field on this technology

1. Web Technologies (*WT*)

HTML	1	2	3	4	5
XML	1	2	3	4	5
JavaScript	1	2	3	4	5
SPARQL	1	2	3	4	5
Web Ontology Language	1	2	3	4	5

2. Developer Tools (*DT*)

ARKit	1	2	3	4	5
Android studio	1	2	3	4	5
Core Machine Learning	1	2	3	4	5
Tizen Studio	1	2	3	4	5
Visual Studio	1	2	3	4	5

3. Relational Database Technology (*RD*)

Power BI Report Server	1	2	3	4	5
SQL Server 2016	1	2	3	4	5
Oracle Mobile Cloud	1	2	3	4	5
Google Cloud	1	2	3	4	5
iCloud	1	2	3	4	5

4. Software Design (*SD*)

User Interface Design	1	2	3	4	5
Process Modeling	1	2	3	4	5
Object Orientation	1	2	3	4	5

5. Blockchain Technology (upon which Bitcoin is based) (*BT*)

	1	2	3	4	5

6. Operating Systems and Server Technologies (*OS*)

Android (Chrome OS)	1	2	3	4	5
iOS	1	2	3	4	5
Tizen	1	2	3	4	5
Mac OSX	1	2	3	4	5
Linux	1	2	3	4	5
Windows 10 Pro	1	2	3	4	5

7. Server Software (*SS*)

McAfee Antivirus	1	2	3	4	5
McAfee Mobile Security	1	2	3	4	5
Symantec Antivirus	1	2	3	4	5
Vipre Mobile Security	1	2	3	4	5

8. Virtualization (*VZ*)

Hypervisor	1	2	3	4	5
VMware Mobile	1	2	3	4	5
Hyper-V	1	2	3	4	5
Microsoft Hyper-V Server	1	2	3	4	5
Microsoft Virtual PC	1	2	3	4	5

9. Use and reliance on HCI Devices

Rate your use of and reliance on an HCI Device within the categories provided:
1 – Device not used
2 – Minimal use of the device
3 – Moderate use of the device
4 – Significant use of and reliance on the device
5 – Heavily reliant on the device most of the time; cannot be apart from the device

Desktop (*DTR*) (e.g., stationary workstation)	1	2	3	4	5
Laptop (*LTR*) (e.g., portable computer)	1	2	3	4	5
Tablet (*TTR*) (e.g., touchscreen capable)	1	2	3	4	5
Smartphone (*SPR*) (e.g., hand-held computer)	1	2	3	4	5
Wearable (*WBR*) (e.g., VR headset)	1	2	3	4	5

10. Competence with HCI Devices

Rate your competence with an HCI Device within the categories provided:
1 – No competence with any functions
2 – Competence and confidence with some functions
3 – Competence and confidence with many functions
4 – Competence and confidence with most functions
5 – Expert on all functions

Desktop (*DTC*) (e.g., stationary workstation)	1	2	3	4	5
Laptop (*LTC*) (e.g., portable computer)	1	2	3	4	5
Tablet (*TTC*) (e.g., touchscreen capable)	1	2	3	4	5
Smartphone (*SPC*) (e.g., hand-held computer)	1	2	3	4	5
Wearable (*WBC*) (e.g., VR headset)	1	2	3	4	5

Thank you for completing the Web 3.0 Technological Skill Matrix.

Appendix B: Protecting Human Subject Research Participants

Certificate of Completion

The National Institutes of Health (NIH) Office of Extramural Research certifies that **Robbie Walker** successfully completed the NIH Web-based training course "Protecting Human Research Participants".

Date of completion: 03/23/2013

Certification Number: 1149422

Appendix C: Occupation Titles of Engineering Participants

Title	Frequency
Aerospace Engineer	1
Aerospace Engineer II	1
Architect Engineer	1
Biomedical Engineer	6
Chemical Engineer	3
Civil Engineer	6
Cloud Engineer	5
Cloud Customer Engineer	1
Cloud Operations Engineer	1
Cloud Partner Engineer	1
Cloud Platform Devops Engineer	1
Controls Engineer	2
Data Center Engineer	1
Data Engineer	6
Desktop Engineer	3
Director of Engineering	1
Director of Engineering Quality	1
Electrical Engineer	9
Engineer	6
Engineer II	1
Engineer III	3
Engineer IV	1
Engineering Leader	1
Forensic Engineer	1
Full Stack Engineer	1
Full Stack JavaScript Engineer	1
Head of Engineering	1
Humanist Engineer	1
Industrial Engineer	5
Inside Systems Engineer	1
IT Engineer	3
Lead Software Engineer	1
Materials and Process Engineer	1
Mechanical Design Engineer	13
Mechanical Engineer	14
Multifaceted Engineer	1
Network Engineer	11
Nuclear Engineer	3
Operations and Supply Chain Engineer	1
Operations Engineer	1

Title	Frequency
Plant Engineering Supervisor	1
Pre-Sales Engineer	1
Process Engineer	4
Product Engineer	1
Production Support Engineer	1
Project Engineer	12
QA Automation Engineer	1
QA Engineer	9
Remote Asset Process Engineer	1
Research Engineer	4
Sales Engineer	14
Senior Engineer	1
Senior Mechanical Engineer	1
Senior Mobile Application Engineer	1
Senior Network Engineer	1
Senior Process Engineer	1
Senior Production Engineer	1
Senior Software Engineer	1
Senior Technical Support Engineer	1
Software Engineer	12
Software Automation Engineer	1
Software Developer Engineer	1
Solutions Engineer	8
Splunk Engineer	1
Structural Engineer	4
Support Engineer	1
Systems Engineer	5
Systems Support Engineer	1
Technical Implementation Engineer	1
UI Engineer	4
UX Engineer	3

Appendix D: Sequential Regression—SPSS Runs 10 to 23

I performed a sequential regression analysis of the six independent variables and the 15 2FIs. This appendix shows the model summary and coefficient tables from run 10 to run 23, except run 22 which is shown in the main body of this document.

Table D1 displays the model summary generated from run 10, which included the six independent variables and 15 2FIs. Table E2 shows the coefficients. The adjusted R^2 = .205, F = 3.63, p < .001.

Table D1

Sequential Model Summary—Run 10

Run	R	R Square	Adjusted R Square	Std. Error of the Estimate
10	.532	.283	.205	.572

Table D2

Sequential Regression—Run 10 Coefficients

Model		Unstandardized B	Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	.928	.531		1.75	.082
	DTR	.119	.234	.212	.510	.611
	LTR	-.135	.238	-.235	-.569	.570
	TTR	.032	.237	.054	.136	.892
	DTC	.512	.287	.863	1.78	.076
	WBC	.011	.204	.020	.053	.958
	LTC	.361	.327	.613	1.10	.272
	DTR*LTR	-.007	.033	-.067	-.197	.844
	DTR*TTR	.046	.039	.464	1.18	.238
	DTR*DTC	-.029	.040	-.284	-.735	.463
	DTR*WBC	.027	.033	.252	.801	.424
	DTR*LTC	-.035	.042	-.340	-.822	.412
	LTR*TTR	-.001	.035	.013	.036	.971
	LTR*DTC	.021	.040	.206	.529	.598
	LTR*WBC	-.016	.033	-.152	-.474	.636
	LTR*LTC	.055	.040	.524	1.37	.174
	TTR*DTC	-.027	.039	-.270	-.701	.484
	TTR*WBC	.032	.033	.314	.979	.329
	TTR*LTC	-.033	.044	-.311	-.749	.455
	DTC*WBC	-.030	.035	-.309	-.852	.395
	DTC*LTC	-.060	.037	-.509	-1.64	.103
	LTC*WBC	-.008	.032	-.080	-.240	.810

Table D3 displays the model summary generated from run 11. The adjusted $R^2 = .209$, $F = 3.83$, $p < .001$. Table D4 provides the coefficients for this model.

Table D3

Sequential Model Summary—Run 11

Run	R	R Square	Adjusted R Square	Std. Error of the Estimate
11	.532	.283	.209	.570

Table D4

Sequential Regression—Run 11 Coefficients

Model		Unstandardized B	Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	.929	.529		1.757	.082
	DTR	.122	.221	.217	.553	.581
	LTR	-.139	.218	-.241	-.636	.526
	TTR	.030	.227	.050	.132	.895
	DTC	.514	.284	.866	1.810	.072
	WBC	.011	.204	.020	.052	.958
	LTC	.362	.325	.615	1.110	.267
	DTR*LTR	-.007	.032	-.070	-.210	.834
	DTR*TTR	.046	.038	.461	1.200	.229
	DTR*DTC	-.029	.040	-.284	-.737	.462
	DTR*WBC	.027	.033	.251	.802	.423
	DTR*LTC	-.035	.042	-.342	-.834	.405
	LTR*TTR	.021	.039	.013	.036	.971
	LTR*DTC	.021	.039	.203	.532	.595
	LTR*WBC	-.016	.033	-.150	-.476	.635
	LTR*LTC	.055	.040	.524	1.37	.172
	TTR*DTC	-.028	.039	-.272	-.717	.475
	TTR*WBC	.032	.033	.313	.981	.328
	TTR*LTC	-.033	.043	-.312	-.754	.452
	DTC*WBC	-.030	.035	-.309	-.856	.393
	DTC*LTC	-.060	.036	-.589	-1.64	.102
	LTC*WBC	-.008	.032	-.080	-.244	.808

Table D5 displays the model summary generated from run 12, the adjusted R^2 = .213, F = 4.05, p < .001. Table D6 provides the coefficients for this model.

Table D5

Sequential Model Summary—Run 12

Run	R	R Square	Adjusted R Square	Std. Error of the Estimate
12	.532	.283	.213	.569

Table D6

Sequential Regression—Run 12 Coefficients

Model		Unstandardized B	Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	.940	.525		1.790	.075
	DTR	.117	.219	.207	.532	.595
	LTR	-.168	.167	-.292	-1.005	.316
	TTR	.044	.216	.074	.205	.837
	DTC	.525	.278	.884	1.885	.061
	WBC	.021	.197	.039	.105	.916
	LTC	.355	.322	.603	1.100	.273
	DTR*TTR	.043	.036	.436	1.204	.230
	DTR*DTC	-.031	.039	-.299	-.791	.430
	DTR*WBC	.025	.032	.233	.777	.438
	DTR*LTC	-.034	.042	-.332	-.817	.415
	LTR*DTC	.021	.039	.206	.541	.589
	LTR*WBC	-.015	.033	-.144	-.459	.647
	LTR*LTC	.055	.040	.523	1.37	.172
	TTR*DTC	-.029	.038	-.281	-.748	.456
	TTR*WBC	.031	.033	.306	.966	.335
	TTR*LTC	-.032	.043	-.306	-.744	.458
	DTC*WBC	-.031	.035	-.314	-.874	.383
	DTC*LTC	-.060	.036	-.591	-1.65	.099
	LTC*WBC	-.008	.032	-.079	-.239	.811

Table D7 displays the model summary generated from run 13, the adjusted R^2 = .217, $F = 4.29$, $p < .001$. Table D8 provides the coefficients for this model.

Table D7

Sequential Model Summary—Run 13

Run	R	R Square	Adjusted R Square	Std. Error of the Estimate
13	.532	.283	.217	.568

Table D8

Sequential Regression—Run 13 Coefficients

Model		Unstandardized B	Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	.958	.519		1.85	.066
	DTR	.124	.216	.220	.575	.566
	LTR	-.164	.166	-.285	-.988	.324
	TTR	.050	.214	.083	.233	.816
	DTC	.548	.260	.923	2.11	.036
	WBC	.007	.188	.013	.037	.970
	LTC	.315	.276	.535	1.14	.255
	DTR*TTR	.042	.035	.419	1.18	.238
	DTR*DTC	-.032	.039	-.309	-.825	.410
	DTR*WBC	.024	.031	.222	.751	.453
	DTR*LTC	-.032	.040	-.310	-.785	.433
	LTR*DTC	.020	.038	.193	.513	.609
	LTR*WBC	-.016	.033	-.149	-.480	.632
	LTR*LTC	.056	.040	.529	1.40	.165
	TTR*DTC	-.029	.038	-.290	-.775	.439
	TTR*WBC	.032	.032	.310	.982	.327
	TTR*LTC	-.031	.043	-.300	-.732	.465
	DTC*WBC	-.033	.034	-.336	-.970	.333

Table D9 displays the model summary generated from run 14, the adjusted $R^2 = .220$, $F = 4.55$, $p < .001$. Table D10 provides the coefficients for this model.

Table D9

Sequential Model Summary—Run 14

Run	R	R Square	Adjusted R Square	Std. Error of the Estimate
14	.531	.282	.220	.566

Table D10

Sequential Regression—Run 14 Coefficients

Model		Unstandardized B	Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	.958	.518		1.850	.066
	DTR	.136	.214	.241	.635	.526
	LTR	-.194	.153	-.337	-1.26	.208
	TTR	.053	.214	.088	.247	.805
	DTC	.575	.253	.969	2.270	.024
	WBC	-.015	.182	-.029	-.084	.933
	LTC	.323	.275	.549	1.17	.242
	DTR*TTR	.041	.035	.416	1.18	.241
	DTR*DTC	-.032	.039	-.309	-.827	.409
	DTR*WBC	.021	.031	.201	.689	.492
	DTR*LTC	-.032	.040	-.313	-.795	.428
	LTR*DTC	.017	.038	.162	.439	.661
	LTR*LTC	.052	.039	.495	1.33	.185
	TTR*DTC	-.030	.038	-.292	-.783	.435
	TTR*WBC	.030	.032	.296	.945	.346
	TTR*LTC	-.031	.043	-.297	-.727	.468
	DTC*WBC	-.038	.032	-.391	-1.195	.234

Table D11 displays the model summary generated from run 15 the adjusted R^2 = .223, F = 4.84, p < .001. Table D12 provides the coefficients for this model.

Table D11

Sequential Model Summary—Run 15

Run	R	R Square	Adjusted R Square	Std. Error of the Estimate
15	.530	.281	.223	.565

Table D12

Sequential Regression—Run 15 Coefficients

Model		Unstandardized B	Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	.932	.513		1.82	.071
	DTR	.117	.209	.207	.558	.577
	LTR	-.159	.131	-.276	-1.22	.226
	TTR	.059	.213	.098	.276	.783
	DTC	.617	.234	1.04	2.64	.009
	WBC	-.014	.182	-.026	-.077	.939
	LTC	.275	.252	.467	1.09	.276
	DTR*TTR	.042	.035	.419	1.19	.236
	DTR*DTC	-.030	.038	-.286	-.774	.440
	DTR*WBC	.021	.031	.199	.683	.496
	DTR*LTC	-.029	.040	-.286	-.736	.462
	LTR*LTC	.059	.036	.559	1.64	.103
	TTR*DTC	-.030	.038	-.293	-.789	.431
	TTR*WBC	.030	.032	.294	.940	.349
	TTR*LTC	-.032	.043	-.309	-.759	.449
	DTC*WBC	-.038	.032	-.389	-1.19	.234
	DTC*LTC	-.056	.035	-.552	-1.60	.110

Table D13 displays the model summary generated from run 16, the adjusted R^2 = .225, F = 5.15, p < .001. Table D14 provides the coefficients for this model.

Table D13

Sequential Model Summary—Run 16

Run	R	R Square	Adjusted R Square	Std. Error of the Estimate
16	.529	.279	.225	.565

Table D14

Sequential Regression—Run 16 Coefficients

Model		Unstandardized B	Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	.911	.512		1.780	.077
	DTR	.166	.196	.295	.849	.397
	LTR	-.164	.130	-.286	-1.26	.208
	TTR	.029	.083	.048	.139	.889
	DTC	.594	.231	1.00	2.56	.011
	WBC	.051	.155	.095	.329	.743
	LTC	.233	.244	.395	.954	.341
	DTR*TTR	.042	.035	.423	1.20	.231
	DTR*DTC	-.026	.038	-.255	-.697	.486
	DTR*LTC	-.025	.039	-.241	-.630	.529
	LTR*LTC	-.060	.036	.572	.168	.094
	TTD*LTC	-.029	.038	-.289	-.777	.438
	TTR*WBC	.031	.032	.304	.975	.331
	TTR*LTC	-.027	.042	-.259	-.648	.518
	DTC*WBC	-.035	.031	-.353	-1.010	.274
	DTC*LTC	-.057	.035	-.563	-1.640	.103

Table D15 displays the model summary generated from run 17, the adjusted R^2 = .227, F = 5.50, p < .001. Table D16 provides the coefficients for this model.

Table D15

Sequential Model Summary—Run 17

Run	R	R Square	Adjusted R Square	Std. Error of the Estimate
17	.527	.278	.227	.564

Table D16

Sequential Regression—Run 17 Coefficients

Model		Unstandardized B	Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	.946	.508		1.863	.064
	DTR	.101	.166	.180	.609	.543
	LTR	-.167	.130	-.290	-1.29	.200
	TTR	.081	.191	.135	.424	.672
	DTC	.639	.220	1.08	2.91	.004
	WBC	.081	.147	.153	.553	.581
	LTC	.149	.204	.253	.729	.467
	DTR*TTR	.042	.035	.417	1.19	.237
	DTR*DTC	-.032	.037	-.310	-.873	.384
	LTR*LTC	.060	.036	.568	.167	.096
	TTR*DTC	-.033	.037	-.329	-.901	.369
	TTR*WBC	.028	.032	.269	.877	.382
	TTR*LTC	-.032	.041	-.301	-.763	.446
	DTC*WBC	-.038	.031	-.387	-1.22	.223
	DTC*LTC	-.056	.035	-.549	-1.61	.110

Table D17 displays the model summary generated from run 18, the adjusted R^2 = .229, $F = 5.89$, $p < .001$. Table D18 provides the coefficients for this model.

Table D17

Sequential Model Summary—Run 18

Run	R	R Square	Adjusted R Square	Std. Error of the Estimate
18	.525	.276	.229	.563

Table D18

Sequential Regression—Run 18 Coefficients

Model		Unstandardized B	Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	.955	.507		1.88	.061
	DTR	.142	.157	.252	.902	.368
	LTR	-.166	.130	-.288	-1.28	.203
	TTR	.055	.188	.093	.296	.768
	DTC	.700	.204	1.18	3.43	.001
	WBC	.097	.145	.182	.668	.505
	LTC	.052	.160	.088	.326	.745
	DTR*TTR	.033	.033	.326	.987	.325
	DTR*DTC	-.033	.037	-.316	-.892	.374
	LTR*LTC	.060	.036	.567	1.67	.096
	TTR*DTC	-.043	.035	-.425	-1.24	.216
	TTR*WBC	.021	.030	.200	.683	.495
	DTC*WBC	-.035	.031	-.361	-1.15	.252
	DTC*LTC	-.063	.033	-.620	-1.88	.061

Table D19 displays the model summary generated from run 19, the adjusted $R^2 = .231$, $F = 6.36$, $p < .001$. Table D20 provides the coefficients for this model.

Table D19

Sequential Model Summary—Run 19

Run	R	R Square	Adjusted R Square	Std. Error of the Estimate
19	.524	.274	.231	.562

Table D20

Sequential Regression—Run 19 Coefficients

Model		Unstandardized B	Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	.895	.499		1.79	.074
	DTR	.119	.153	.210	.773	.440
	LTR	-.178	.128	-.310	-1.39	.167
	TTR	.113	.167	.189	.679	.498
	DTC	.664	.196	1.12	3.38	.001
	WBC	.158	.114	.298	1.39	.166
	LTC	.038	.158	.065	.241	.810
	DTR*TTR	.033	.033	.335	1.02	.310
	DTR*DTC	-.029	.036	-.276	-.790	.430
	LTR*LTC	.064	.035	.610	1.83	.068
	TTR*DTC	-.040	.034	-.396	-1.17	.245
	TTR*WBC	.021	.030	.200	.683	.495
	DTC*WBC	-.031	.030	-.319	-1.04	.301
	DTC*LTC	-.063	.033	-.625	-1.91	.058

Table D21 displays the model summary generated from run 20, the adjusted $R^2 = .233$, $F = 6.89$, $p < .001$. Table D22 provides the coefficients for this model.

Table D21

Sequential Model Summary—Run 20

Run	R	R Square	Adjusted R Square	Std. Error of the Estimate
20	.522	.272	.233	.562

Table D22

Sequential Regression—Run 20 Coefficients

Model		Unstandardized B	Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	.980	.487		2.013	.045
	DTR	.044	.121	.079	.366	.714
	LTR	-.166	.127	-.288	-1.30	.194
	TTR	.180	.144	.300	1.25	.214
	DTC	.594	.175	1.00	3.39	.001
	WBC	.155	.114	.291	1.36	.174
	LTC	.062	.155	.105	.400	.690
	DTR*TTR	.026	.031	.257	.819	.414
	LTR*LTC	.060	.035	.570	1.73	.084
	TTR*DTC	-.050	.032	-.494	-1.56	.120
	DTC*WBC	-.029	.030	-.299	-.977	.330
	DTC*LTC	-.066	.033	-.652	-2.00	.047

Table D23 displays the model summary generated from run 21, the adjusted R^2 = .236, $F = 7.60$, $p < .001$. Table D24 provides the coefficients for this model.

Table D23

Sequential Model Summary—Run 21

Run	R	R Square	Adjusted R Square	Std. Error of the Estimate
21	.521	.271	.236	.561

Table D24

Sequential Regression—Run 21 Coefficients

Model		Unstandardized B	Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	1.02	.474		2.150	.033
	LTR	-.158	.125	-.275	-1.26	.208
	TTR	.153	.124	.255	1.23	.219
	DTC	.616	.164	1.04	3.75	< .001
	WBC	.163	.111	.306	1.46	.145
	LTC	.074	.152	.126	.488	.626
	DTR*TTR	.037	.010	.367	3.85	< .001
	LTR*LTC	.058	.034	.554	1.70	.090
	TTR*DTC	-.053	.031	-.526	-1.74	.084
	DTC*WBC	-.031	.030	-.318	-11.05	.293
	DTC*LTC	-.067	.033	-.662	-2.04	.042

Table D25 displays the model summary generated from run 23, the adjusted $R^2 = .235$, $F = 9.23$, $p < .001$. Table D26 provides the coefficients for this model. The best predictive model was run 22 (found in Table 25 and Table 26).

Table D25

Sequential Model Summary—Run 23

Run	R	R Square	Adjusted R Square	Std. Error of the Estimate
23	.514	.264	.235	.561

Table D26

Sequential Regression—Run 23 Coefficients

Model		Unstandardized Coefficients B	Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	1.38	.401		3.44	.001
	LTR	-.192	.107	-.334	-1.79	.074
	TTR	.207	.111	.346	1.87	.062
	DTC	.553	.151	.931	3.67	< .001
	WBC	.058	.035	.108	1.67	.097
	DTR*TTR	.037	.009	.366	3.89	< .001
	LTR*LTC	.070	.028	.669	2.53	.012
	TTR*DTC	-.068	.028	-.675	-2.47	.014
	DTC*LTC	-.062	.028	-.615	-2.24	.026