5-2023

Artificial Intelligence Superteams & Augmentation Strategies: Increasing Performance of High-Functioning Virtual Team Members Via Human Machine Teaming Enhancements

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Artificial Intelligence Superteams & Augmentation Strategies: Increasing Performance of High-Functioning Virtual Team Members Via Human Machine Teaming Enhancements

by

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A dissertation submitted to the Nathan M. Bisk College of Business

of Florida Institute of Technology

in partial fulfillment of the requirements

for the degree of

Doctor

of

Business Administration

Melbourne, Florida

May, 2023

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Abstract

Title: Artificial Intelligence Superteams & Augmentation Strategies: Increasing Performance of High-Functioning Virtual Team Members Via Human Machine Teaming Enhancements

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Artificial intelligence (AI) can impact future workforce business operations in extraordinary ways through human-machine teaming. A human-machine teaming revolution will unleash enormous change upon businesses by merging humans and AI. For years, scholars and mainstream thought leaders have argued that firms must embrace AI and human-machine teaming to advance employee performance and deliver a high-performance, cost-effective, comprehensive business strategy (Raisamo, Rakkolainen, Majaranta, Salminen, Rantala, & Farooq, 2019). The era of human inadequacy, human-only teams, and human performance ceilings is disappearing as AI rapidly augments work and teams (Ashley & Sahota, 2019). AI augmentation and human-machine teaming will drive tomorrow's blended teams and organizations. AI technologies will augment human skills and senses (Ashley & Sahota, 2019; Raisamo et al., 2019). Peter Drucker, the renowned management consultant, and educator, memorably said, what is measured, improves (Drucker, 2002). The ability of AI to quantify decisions and actions with big data analytics and improve a firm's outcome and ability to maximize success in the future (Duan, Edwards, & Dwivedi, 2019) is essential to firms. This research defines how high-functioning virtual team members (HFVTMs) (Hill, Demirjian, & Walton, 2023), augmented with AI, can become superteams. This study uses an exploratory sequential mixed methods analysis to define and establish HFVTMs as a proxy for superteams to determine how to augment low-performing, moderate-performing, and high-functioning virtual team members with AI at the fundamental job task level to increase ROI. Finally, this study establishes a process and framework to examine jobs to elucidate which job tasks require AI.

Keywords: artificial intelligence, human-machine teams, virtual teams, augmentation, O*NET, Superteams, AI-Able, human-autonomous teams

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List of Abbreviations

Abbreviation	Definition
AI	Artificial Intelligence
CMC	Computer-Mediated Communications
CMT	Computer-Mediated Technologies
DC	Dynamic Capability
DWA	Detailed Work Activities
HF	High-Functioning
GVT	Global Virtual Team
HFVTM	High-Functioning Virtual Team Member
HMT	Human Machine Teams
HP	High-Performing
JTBN	Jobs to be done
KSAC	Knowledge, Skills, Abilities, Competencies
O*NET	Occupational Information Network
ODI	Outcome Driven Innovation
QWL	Quality of Work Life
RBV	Resource Based View
ROI	Return on Investment
SOC	Standard Occupational Classification
VT	Virtual Team
VTM	Virtual Team Member
WPE	Workplace Essential

Acknowledgement

This doctoral dissertation represents the conclusion of three years of passionate effort, extreme self-growth, and overcoming challenges. To say that this cannot be done alone is an understatement. Friends, family, work colleagues, faculty, and my cohort have supported me in this journey. Thank you to my mother and father for a lifetime of support and love. Additionally, I was reminded of my grandfathers, Reigh Porter, and Deran Demirjian, and their galactic-size inspiration for me to make the most of this life.

I want to thank my chair, Dr. Abram Walton, for his assistance on the theoretical constructs and the practical matters of mixed methods testing of my propositions. I thank my committee, including Dr. Bryant, Dr. Eskridge, and Dr. Patel, for their dedication to guidance. I thank Dr. Emily Vogt and Taylor Weaver for their leadership, vision, and consistent support of the DBA program at Florida Tech. I also could only have completed this with the participation of the many peers who participated in the study.

I especially thank Dr. Kate Hill for her complete support, eternal friendship, and unwavering dedication to this analytical effort. Your steel trap memory saved me more times than I remember and has allowed this research to become a diamond under the stress and pressure of this program. As we always said, everyone should have at least one person to complete a doctoral program with. For me, you were the equivalent of four trips to Vermont and three executive principal secretaries.

Dedication

This dissertation is dedicated to my sons, Patrick and Parker, and my daughter, Evelyn. I hope the time and effort taken to create this dissertation serve as an inspiration for the importance of lifelong learning, dedication, and innovation. Anything you decide is worth doing in this life that matters to you, no matter the amount of time or effort, is something you never give up on. Anything is possible in this life. I hope you find the mountains you want to conquer and find the path to achieve all you want in this life. Few are those that see with their own eyes, feel with their own hearts, and think with their own minds. Finally, I hope you remember that you are always young enough to learn something new. I love each of you!

Chapter 1

Introduction

Overview

Domestic and international organizations increasingly rely on teams to conquer and overcome a change-driven business environment and deliver a positive return on investment (ROI) (Ye, Wang, & Guo, 2019). Combining those factors with the growing use of artificial intelligence (AI) in the modern workplace adds a new emphasis on the ability of scholars to define the optimal ways humans and AI can work together to increase ROI. The ability of scholars to define the AI and human-machine team (HMT) fundamental job characteristics required by teams in a change-driven business environment is vital for the future workplace. With the ever-adapting changes in the world, such as pandemics, digitalization, supply chain disruptions, increased focus on health and safety, and economic downturns, the shift to virtual teams (VTs), AI-aided technology, and integrated HMTs are driven by the opportunities of AI in the marketplace. As a result, the research field of the skills required by HMTs and AI to operate in this new dynamic requires a significant shift in the analysis (Larson & DeChurch, 2020).

Over the last ten years, academic research about AI as collaborative teammates has moved out of science fiction and into the academic and business worlds because of significant advances in AI and computing power (Phillips et al., 2011; Seeber et al., 2020). Effective HMTs depend on the complicated interactions between human employees, AI tools, and the environment (Stowers et al., 2017). However, developers and current HMTs have found it challenging to create, design, code, and manage these complex interactions and their related fundamental work activities to achieve the critical ROI threshold (Sukthankar, Shumaker, &

Lewis, 2012). HMT and AI augmentation has failed to demonstrate strong ROI at the individual, team, or organizational level (Ransbotham, Khodabandeh, Fehling, LaFountaine, & Kiron, 2019; Stowers, Brady, Maclellan, Wohleber, & Salas, 2021).

Psychologists, coders, and engineers have long investigated machines to augment and increase team performance (Fitts, 1951; Dekker and Woods, 2002). From basic team augmentation and management to superteaming, the evolution of AI in teams continues (Stowers et al., 2021). The idea of superteams often invokes visions of sports teams loaded with rosters full of hall-of-fame caliber players. However, popular press and trade authors coined the term 'superteams' to describe integrated organizational teams combined with AI, which helps firms to produce transformative results (Deloitte, 2021; Mallon, Durme, & Hauptmann, 2022). However, scholarly literature on superteaming ignores any attempt at defining superteaming and instead focuses on HMTs, AI code development, and the ROI gap within current business AI use (Ransbotham et al., 2019). This research defines superteams as high-functioning virtual team members integrated with artificial intelligence tools, capabilities, and team members capable of surpassing the performance levels of human-only teams. This ROI gap ultimately leads to the question, how do business and AI researchers, organizations, and HMTs actively innovate, create, and strategize to augment current teams with AI and also create superteams?

There is an abundance of academic research on the impacts of computer-mediated technologies (CMTs) and computer-mediated communications (CMCs) on teams and VTs (Fjermestad, 2004; Rains, 2005). Furthermore, communication, coordination, and adaptation have been academically shown to be broad-level requirements for HMTs (Matthews et al., 2021; Stowers et al., 2021). However, there has been no academic attention paid to researching what specific, detailed characteristics of work HMTs or AI superteams require, what general or detailed work activities (DWAs) VTMs necessitate AI augmentation, and how AI can augment low-, moderate-, and high-performing teams to improve performance. For example, a recent experiment into AI-blended technologies in teams found that the work context is critical to understanding, affecting, and measuring the effectiveness of AI assistants within teams (Shaikh & Cruz, 2020). Analysis by Stowers et al. (2017) shows these are vital literature gaps, and research is required to refine the technological requirements for HMTs, AI VTM augmentation, and effective teamwork performance. Academic research must systematically research and define HMT behaviors, tools, and work processes using premier systems such as the occupational informational network (O*NET) in order to understand, invest, and recommend areas of study thoroughly. The O*NET job characteristics and requirements content model provides this study with a solid conceptual foundation and framework for AI job definitions.

Past studies have shown disparate results on AI use and ROI with HMTs (Jackson & Madsen 2004; Ransbotham et al., 2019). This study attempts to take a novel approach to analyze HMTs, VTM augmentation, and superteams. By dissecting the highest performing human VTM jobs to be done (JTBN) using outcome-driven innovation (ODI) and job mapping, this study will create both an O*NET Standard Occupational Classification (SOC) profile of superteams and a rank-ordered investment list of AI augmentable job characteristics that are capable of delivering the highest levels of ROI for future firms. Defining new O*NET job functions and types, like superteams and AI augmentable job characteristics, continues to be called for by trade groups but has not been accomplished to date (Lund, Madgavkar, Manyika, & Smit, 2020). This study uses O*NET general work activities (GWAs) and workplace essentials (WPEs) in the job characteristics O*NET-SOC ontology. GWAs are “an aggregation of similar job activities/behaviors that underlie the accomplishments of major work functions” (Jeanneret, Borman, Kubisiak & Hanson, 1999, p.106). WPEs are foundational skills individuals require to be successful irrespective of the job they are performing, or are required for successful performance within a job, irrespective of the person doing the job (SkillsEngine, 2023). This study uses high-functioning virtual team members (HFVTMs) (Hill, 2023) as a proxy for superteams to understand HMT augmentation and superteam job profiles. Utilizing VTM performance (VTMP) as the independent variable and AI augmented activities index as the dependent variable, this study will examine the moderating capacity of AI VTM augmentation through task perception measured through outcome-driven innovation opportunity scoring.

Background and Rationale for the Study

The section specifies an overview of the problem statement, the purpose of the study, questions that guide the research, definitions of terms, and the study's significance.

Statement of the Problem

Many fundamental questions remain despite extensive scholarly research, company investment, and AI development, such as why AI ROI is low for human-machine teaming in modern businesses (Ransbotham et al., 2019). Ransbotham et al. (2019) report in their MIT Sloan article that 70 percent of firms do not see any impact from AI, and 40 percent of firms making significant investments in AI do not see a ROI (Ransbotham et al., 2019). The information technology productivity paradox states that while ROI is always mixed, businesses that do not invest are left behind (Brynjolfsson, 1993). If everything is capable of AI augmentation in the future (Lee & Qiufan, 2022; Revell, 2017), with enough money, data, and time, what work characteristics do programmers innovate first to enable high performance and strong ROI? How should humans and AI work together to solve fundamental work activities for HMTs to be productive (Zhang, McNeese, Freeman, & Musick, 2020)? How should scholars examine AI superteams, HMTs, and VTM augmentation, and are there proxies best suited for this analysis? How do scholars advise modern businesses, increasingly driven to use VTMs, to possibly augment low-, moderate-, and high-performing VTMs with AI? How do scholars define superteams at a basic O*NET-SOC profile level, including WPEs and GWAs? This exploratory sequential mixed methods analysis will examine these issues by tackling AI at the fundamental work level.

Purpose of the Study

The purpose of this research is to illustrate how the Hill (2023) construct of HFVTMs can be used as a proxy to analyze VTM augmentation, human-machine teaming, and superteam creation at a fundamental work level. This study's findings highlight how low- and moderate-performing VTMs may be augmented with AI, how HFVTMs may be augmented with AI to create superteams, and what fundamental O*NET-SOC profile factors AI should perform to provide maximum ROI. The use of AI-augmented virtual team members (VTMs) and superteams holds great promise as these teams can do things collectively that other human-only teams cannot. The ability of scholars to fully define superteams and their related job-oriented descriptors requires a rank-ordered index of fundamental occupational requirements and job characteristics supported by theory, research methodologies, and empirical findings.

Questions that Guide the Research

The key research questions that this study sets out to answer are:

RQ1. What is the effect of artificial intelligence augmentation on low-performing virtual team member performance?

RQ2. What is the effect of artificial intelligence augmentation on moderate-performing virtual team member performance?

RQ3. What is the effect of artificial intelligence augmentation on high-functioning virtual team member performance?

RQ4. Which high-functioning virtual team member O*NET-SOC profile factors have the highest outcome-driven innovation opportunity score for artificial intelligence augmentation desirability?

Definitions of Terms

Throughout this paper, many terms are used that are specific to human-machine teaming, artificial intelligence, virtual teams, superteams, and outcome-driven innovation. The definitions for each of the key terms are summarized below:

Artificial Intelligence: "The field of artificial intelligence, or AI, is concerned with not just understanding but also building intelligent entities — machines that can compute how to act effectively and safely in a wide variety of novel situations" (Russell & Norvig, 2020).

Artificial Intelligence (Business and Team Augmentation Dissertation Definition): Adaptation with insufficient knowledge and resources" (Wang, 2019).

High-Functioning Virtual Team Members (HFVTMs): High performing virtual team members with high levels of quality of work life (Hill, Demirjian, & Walton, 2023).

Global Virtual Teams (GVT): Teams whose members are geographically distributed across multiple countries and cultures, interact primarily using communication technologies, and collaborate on an interdependent task (Gibbs, 2009) – are often assembled to enhance innovation by bringing together members with varied expertise and perspectives (Gibson & Gibbs, 2006).

General Work Activities (GWA): "an aggregation of similar job activities/behaviors that underlie the accomplishments of major work functions" (Jeanneret, Borman, Kubisiak & Hanson, 1999, p.106).

Job: "A task, goal or objective a person is trying to accomplish or a problem they are trying to resolve. A job can be functional or emotional" (Ulwick, 2011, p. 14).

Job Map: "A visual depiction of a functional job, deconstructed into its discreet process steps, that explains in detail just what it is the customer is trying to get done" (Ulwick, 2011, p. 14).

Opportunity Algorithm: "The formula used to determine the degree to which a specific job or outcome is under- or overserved. It is defined as opportunity = importance + max (importance satisfaction, 0)" (Ulwick, 2011, p. 15).

Outcome-Driven Innovation (ODI): "ODI is an effective needs-first approach to innovation. It corrects the flaws in the methods that have been used to date" (Ulwick, 2011, p15).

Quality of Work Life (QWL)**:** "employee satisfaction with a variety of needs through resources, activities, and outcomes stemming from participation in the workplace" (Sirgy et al, 2001, p. 242).

Occupational Information Network (O*NET): A government-owned, free, web-based database containing universal job descriptions and occupational characteristics to assist organizations, governments, and employees in understanding and defining the world of work across the United States.

Superteams: High-functioning virtual team members (HFVTMs) integrated with artificial intelligence tools, capabilities, and team members capable of surpassing performance levels of human-only teams.

**** Superteams Contemporary Business Definition:*** AI integrated into teams to produce transformative business results (Mallon et al., 2022).

Virtual Teams (VT): "groups of geographically, organizationally and/or time dispersed workers brought together by informational technologies to accomplish one or more organization tasks" (Alavi & Yoo, 1997; Powell, Piccoli, & Ives, 2004, p. 7).

Virtual Team Member (VTM): member of a team: geographically, organizationally and/or time dispersed…brought together by informational technologies to accomplish one or more organization tasks (Alavi & Yoo, 1997; DeSanctis & Poole, 1997; Jarvenpaa & Leidner, 1999; Powell et al., 2004, p. 7).

Workplace Essential (WPE): Foundational skills required by individuals to be successful irrespective of the job they are performing, or are required for successful performance within a job, irrespective of the person doing the job (SkillsEngine, 2023; Sandall, 2023).

Significance of the Study

The significance of this study is to understand how to use HFVTMs, O*NET, and AI to study and characterize HMTs, VTM AI augmentation, and superteaming. Research investigating the capability of AI to augment VTM work factors will allow for more significant ROI by firms. Furthermore, the ability of scholars to provide occupational data and analysis to augment low-, moderate-, and high-performing teams is critical to global firms and VTM success. The ability of this study to define under what conditions AI can successfully enhance the highest functioning VTMs is critical to understanding, building, modifying, and improving VT and firm performance through a wide array of deep learning, machine learning, and other novel AI capabilities. Superteams and AI-augmented VTM performance may be considered valuable dynamic capabilities and sustained competitive advantages defined by the resource-based view (RBV) (Barney, 1991). The impact of AI augmentation on VTMs, and superteaming through HFVTMs, may suggest a valuable, rare, non-imitable, and non-substitutable (VRIN) advantage capable of delivering enhanced firm competency and success.

Organization of the Remainder of the Study

Chapter two is a review of the academic literature pertinent to this dissertation. The review includes an investigation of the academic foundations and the theoretical models in the topics of 1) AI, 2) superteams, 3) VTMs, 4) HFVTMs, and 5) AI augmentation moderators. The review provides support for the definition of AI-VTM augmentation, VTM performance, ODI, and the conceptual research diagram that will serve as the exploratory model for the study. Seven propositions are proposed as a means of testing the concept of VTM augmentation, human-machine teaming, and the creation of superteams to construct a definable AI O*NET-SOC profile.

Chapter three, Methodology, justifies and delineates the use of an exploratory sequential mixed methods research method as the optimum avenue for testing the proposed dissertation's seven propositions. A qualitative tandem interview and quantitative survey technique is justified as the dissertation study instrument. The chapter specifies an overview of the methodology, research design, population identification, data analysis and collection processes, and the planned method for ensuring validity, reliability, and generalizability. Chapter four delivers' details on the findings from the qualitative and quantitative research study, while chapter five examines conclusions and recommendations for future research.

Chapter 2

Literature Review

Overview

Chapter two investigates the literature underlining this dissertation's focus on VTMs, HMTs, VTM performance, AI, AI augmentation, ODI, O*NET, job mapping, RBV, and Dynamic Capabilities (DC). This chapter will construct a scholarly basis and understanding of the: 1) Extant literature supporting the proposed mechanism for examining this study's RQs and propositions on VT augmentation performance, 2) AI superteams, 3) The significance of AI tools on VT augmentation, and 4) The O*NET-SOC factors for AI and superteams. The overall purpose of the literature review is to support an exploratory sequential mixed method study to provide a theoretical foundation for building the study's conceptual model and propositions (Creswell, 2014).

In order to achieve a comprehensive understanding of how AI can augment the business environment, use HFVTMs as a surrogate for human-machine teaming, perform superteam analysis, augment VTs through AI, define O*NET AI-able work factors, and investigate ODI analysis essential to HMTs, it is necessary to engage in a thorough unpacking of the relevant information critical to HMTs, VTM augmentation, and AI superteam research. The literature review provides an extensive scope on VTMs, AI, HMTs, ODI innovation, satisfaction, criticality and frequency, O*NET, RBV, and DC because (1) they allow for an avenue of examining HMTs and superteams, (2) they allow for a definition of AI superteam O*NET-SOC profiles and factors, (3) and they allow for a normative and illustrative way in which AI investment of superteaming can occur from a risk, value, and requirement-based analysis. Exploring the literature related to human-machine teaming and HFVTMs helps formulate implications for AI team augmentation for firms and VTMs. The following questions were investigated: 1) What theoretical frameworks are used to understand HFVTMs and human-machine teaming? 2) What are the O*NET general work activities, workplace essentials, or attributes of HFVTMs that can be used for AI team members, and 3) What findings can assist firms in designing, developing, implementing, and/or advancing HMT, VTM augmentation, and AI superteams?

Organization of the Remainder of the Chapter

This chapter's first section restates the four research questions guiding this exploratory sequential mixed method study. The second section evaluates the principal theoretical support for this dissertation. Thirdly, the literature review contains a review of the literature on VTMs, AI, HMT, ODI innovation, satisfaction, criticality, frequency, O*NET, RBV, and DC. Lastly, the final section of this chapter investigates the conceptual models and proposition for this dissertation study.

Questions that Guide the Research

To reiterate, the research questions that are guiding this study are:

RQ1. What is the effect of artificial intelligence augmentation on low-performing virtual team member performance?

RQ2. What is the effect of artificial intelligence augmentation on moderate-performing virtual team member performance?

RQ3. What is the effect of artificial intelligence augmentation on high-functioning virtual team member performance?

RQ4. Which high-functioning virtual team member O*NET-SOC profile factors have the highest outcome-driven innovation opportunity score for artificial intelligence augmentation desirability?

Relevant Models, Theories, and Theoretical Frameworks

Virtual Teams & Virtual Team Members

Up until the global COVID-19 pandemic, the ever-increasing demand for VT employees was driven by factors such as international business, globalization, organizational competition, CMTs, and CMCs (Alaiad, Alnsour, & Alsharo, 2019). The compounding factor of COVID-19 pandemic policies only continues to increase the fervent demand for VTs and VT employees. For instance, while 83 percent of white-collar employees in the US worked virtually in May of 2020, that number has only dropped to 67 percent by September of 2021 (Saad & Wigert, 2022). By 2022, 78 percent of all workers work virtually in a hybrid or full-time remote status (Wigert & Agrawal, 2022). Of these virtual workers, 90 percent prefer to work remotely and anticipate continuing to work virtually for the next 12 months (Saad & Wigert, 2022).

During a review of extant (441 articles and 200 journals) VT and VTM literature and research from 2005 to 2015, Gilson, Maynard, Young, Vartiainen, and Hakonen (2014) outline ten years of empirical work around ten themes and ten unanswered theoretical opportunities (Gilson et al., 2014). Of particular attention for this study's analysis of AI is the focus on technological innovation, team virtuality, emergent technologies, team adaptation, and creativity to advance how VTMs interact and ways to enhance VT and VTM success; an area the researchers argue shows intense promise to academia and organizations (Gilson et al., 2014). This paper will add to the VTM and AI scholarly research above (Gilson et al., 2014) by directly adding to VT adaptation through AI augmentation, VTM use of AI technologies and their types, the virtuality of VT and VTMs, and creative and novel fundamental work factors VTMs may use to increase performance using AI.

To begin the examination the literature review first addresses VTs. VTs are geographically dispersed collaborations between workers who rely on technology to communicate, cooperate, and achieve synchronous and asynchronous shared goals (Morrison-Smith & Ruiz, 2020). Some figures show that as many as 85 percent of professionals are historically in a VT, and these VT members face many cognitive, distance, social, and emotional challenges (Morrison-Smith & Ruiz, 2020) that can be aligned with those of the AI superteams. When VTs do not work properly, firms spend immense amounts of money to relocate team members to avoid VT distance difficulties and other challenges (Morrison-Smith & Ruiz, 2020). For example, the relocation business is a $14 billion dollar industry in the U.S. (Novak, 2022). Morrison-Smith and Ruiz's (2020) recent literature examination of challenges and barriers in VTs include an overview of these challenges to include awareness of colleagues and their perspective, motivation, trust, technical competence, technical infrastructure, work functions, explicit management, finding common ground, competitive/cooperative cultural issues, and alignment of incentives and goals (Morrison-Smith & Ruiz, 2020). The promise of AI is that it may help solve these challenges, reduce costs to firms, reduce the requirements for costly relocations, and alleviate the issues that arise when VTs are not functioning properly (Lee & Qiufan, 2022; Revell, 2017). As discussed in the AI portion of this literature review, AI can help solve all these issues (Lee & Qiufan, 2022; Revell, 2017); however, this study will attempt to decipher these challenges through the lens of an HFVTM at the O*NET-SOC WPE and GWA work factor level.

Research on CMT tools within VTs has predominantly examined traditional tools, such as the internet, computers, and telephones, and new and emerging technologies have not been commonly examined (Gilson et al., 2014). Generally, research has shown that emerging technologies such as CMT tools within the VT scope has not been commonly examined to the extent that traditional tools have (Gilson et al., 2014) and as a result has demonstrated a gap in academic research that has not focused on CMT tools being used in practice (Koutsabasis, Vosinakis, Malisova, & Paparounas, 2012). According to Gilson et al. (2014), cloud technologies, computing platforms, and newer technologies have not received attention in the literature and represent an excellent opportunity for future research (Gilson et al.,2014). This study will shed light on new and emerging AI tools capable of VTM augmentation.

The argument for future researchers can be made that VTs and superteams, consisting of HFVTMs in combination with AI, will be the two predominant team types in the next phase of humanity. The effect of CMTs and globalization decreasing the need for collocated teams (Martins, Gilson, & Maynard, 2004) must be examined within the modern-day realm of AI inclusion. Specific green shoots of AI's effect on VTMs are beginning to be noted in the literature. For example, CMTs "can decrease social loafing" (Bryant, Albring, & Murthy, 2009, as cited in Gilson et al., 2014), reduce task complexity obstacles (Kock & Lynn, 2012), increase overall intragroup strength (Suh & Shin, 2010), and increase general satisfaction of VTs (Chi, Jia, Li, & Gursoi, 2021). The research gap between new and emerging technologies' effect on VTs and VTMs is directly noted by Gilson and colleagues (2014). Out of the scope of this research is the effect cultural diversity may have on AI adoption and acceptance. Cultural diversity may play a role in team construct, AI adoption, interdependence, and identification, as shown in previous findings (Hoch & Kozlowski, 2012 & Au & Marks, 2012). Future research may also focus on how AI, superteaming, and team augmentation may impact VTM's well-being and QWL.

Finally, this study's focus on AI, VTMs, and HFVTMs is a critical first step. The increased use of VTMs in organizations has traditionally been propelled primarily through advances in CMC and CMT, which have profoundly altered how organizational members collect, communicate, share, and distribute data and the dynamics and relationships among team members (Aliad et al., 2019). This VTM research is only the beginning, and this paper will attempt to begin the scholarly link between AI, HMTs, VTs, and VTM augmentation.

Virtual Team Faultlines & Subgroups

VTs and teams have formal structural faults, such as team hierarchy and assigned work teams, and informal, naturally occurring, informal faults that form subgroups (Lau & Murnighan, 1998; Carton & Cummings, 2012; 2013). This section will examine VT faultlines and subgroups to decode and decipher what VTM work factors, such as WPEs and GWAs, AI may help increase VTM performance. Analyzing VTM work at the formal and informal work levels is vital to improving AI, VTM performance, and superteaming ROI.

Traditional teams and VTs have naturally occurring dividing lines that hypothetically fault similarly to earthquake faultlines (Lau & Murnighan, 1998). These fault lines, first coined by Lau and Murninghan (1998), may form teams of homogenous subgroups based on identity, knowledge, resources, and QWL (Lau & Murnighan, 1998; Hill, 2023). The faultline model is the most pertinent, well-researched, and scholarly constructed theory concerning work team subgroups (Homan, van Knippenberg, Van Kleef, & De Dreu, 2007; Lau & Murnighan, 2005; Li & Hambrick, 2005). This section will summarize faultline theory and the theory of subgroups, their relation to current HFVTMs, AI superteaming performance, and their impact on VTM augmentation.

Faultlines are "hypothetical dividing lines that may split a group into subgroups" (Lau & Murnighan, 1998, p. 328). The faultline theory scholarly argument is faultlines produce subgroups, and subgroups directly influence team outcomes and success (Lau & Murnighan, 1998). Faultline theory is a two-decade-old team diversity concept theorizing that teams with a moderate level of diversity have stronger effects on teams than homogenous or heterogenous teams because they allow for the creation of subgroups (Lau & Murnighan, 1998). Since this first academic effort, multiple deep analytical dives have backed faultline theory and focused on growing the theory's scope through new moderators, mediators, and performance metrics (Bezrukova, Jehn, Zanutto, & Thatcher, 2008; Gibson & Vermeulen, 2003; Lau & Murnighan, 2005; Li & Hambrick, 2005; Molleman, 2005; Thatcher, Jehn, & Zanutto, 2003).

Faultline communication and membership are essential aspects of faultline theory that have both negative and positive outcomes (Gibbs, Boyrax, Sivunen, & Nordback, 2020). Gibbs et al. (2020) delve into the discursive nature of VT communication that is too often painted with a brush of negativity due to demographics and team identity (Lau & Murnighan, 1998; Jehn & Bezrukova, 2010; Gibbs et al., 2020). Gibbs et al.'s (2020) analysis offer a contrasting viewpoint of faultlines within VTs by focusing on the dynamic nature of team communication, membership, and processes that change and adapt over a VT lifecycle (Gibbs et al., 2020). For AI to build superteams and provide for effective team augmentation, work function needs to be able to overcome the fragmentation, changing membership, and evolving processes of teams along faultlines (Cramton & Hinds, 2005). In fact, AI may look to create new positive faultlines and take advantage of other positive faultlines to solve work-related activities beneficial to the firm.

However, Carton and Cummings (2012) argue that Lau and Murnighan's (1998) seminal work and subsequent research on faultline models incorrectly focuses too much on the idea that subgroups mediate the relationship between faultlines and team results by analyzing outcomes of the team. Carton and Cummings (2012; 2013) realized the importance of the individual forming an informal collective team based on identity, knowledge, and resources, and this link to overall goals (Carton & Cummings, 2012; 2013). This research study follows this tradition by performing analysis at the individual member level on structures related to work activities and goals and AI's replacement and augmentation of certain member activities. In Carton and Cummings (2012; 2013) study of leaders managing faultlines, the authors demonstrate research at the member level using a theory that embraces individual team members, and the role they play in informal subgroups within VTs to meet team goals is most appropriate. Using this precedent, this research contends that the study of high-functioning VTM subgroup processes and the augmentation of these activities by AI must also occur at the member level (Carton & Cummings, 2012; 2013).

As thoroughly documented above, the crucial argument of faultline theory is that faultlines produce subgroups, and subgroups directly influence team outcomes and success (Lau & Murnighan, 1998). The theory of subgroups' critical argument is that certain subgroup traits produce informal and highly impactful subgroups in all organizations. Subgroups are subsets of team members that are uniquely interdependent (Carton & Cummings, 2012) and are an output of faultlines. Therefore, high-functioning VT subgroup members may be the most relevant example scholars have to superteams due to high levels of interdependence, inter-subgroup behavior, performance, and virtuality.

Subgroups can also display entrenchment characteristics that increase positive effects, length of subgrouping, reinforcement, and team strength. Subgroup entrenchment or the agreement among team employees about the presence and composition of strong and stable subgroups (Meister, Thatcher, Park, & Maltarich, 2019) is another area AI can assist team member performance.

You and Robert (2022) researched subgrouping between humans and robots driven by AI-like technologies (You & Robert, 2022). In this case, AI have physical embodiments that work with humans through the use of Lego Mindstorms EV3 robots (You & Robert, 2022). This unique use of AI allows You and Robert (2022) to investigate robot identification and team identification associated with the likelihood of subgroup formation, teamwork quality, and performance. This study provides a basis for AI-enabled subgroup formation and extends the theory of subgroups to include AI-enabled technologies like robots and their moderating effects on team performance and quality (You & Robert, 2022).

One area this study will delimit is the effect of AI technology acceptance in VTMs. For example, Thatcher and Patel (2012) illustrate how technology use, norms, and preferences can create adverse task conflict effects. The preference for technology tools, such as AI, may become a source of faultline creation due to unresolved differences and forced compromises over tool selection. These findings align with research from Hinds and Mortensen (2005), who show that common or standard technology adoption facilitates shared context, reduces misunderstandings, and reduces task conflict. This reduction in negative decision-making and team activities increases task productivity and team performance (Hinds & Mortensen, 2005). Therefore, this study suggests that for AI to become a positive source of ROI for VTMs, team augmentation, and AI superteams, scholarly research into HFVTMs faultlines, subgrouping, team performance, and QWL is critical to maximizing team performance.

Virtual Team Quality of Work Life

AI will need to support VTMs to successfully augment and integrate with VTMs in employee well-being, satisfaction, and overall QWL (Hill, 2023). AI augmentation, including assistance with VTM QWL, is critical because research shows VTMs suffer from unique interpersonal conflict, problems, stress, and misunderstandings due to a variety of uncertainty, culture, and communication reasons (Adamovic, 2018; Daim et al., 2012; Nurmi, 2011; Crisp & Jarvenpaa, 2013). Using the conclusion from literature that HFVTMs are an appropriate surrogate for AI-augmented teams means these HMTs are expected to have similar difficulties when AI members are added to the VT. For example, VTM research demonstrates that just combining VTM experts virtually "provides no guarantee that they will be able to work effectively and innovate" (Gibson & Gibbs, 2006, p. 452–453). However, when combined effectively in virtual teaming and telecommuting, studies demonstrate these VTMs see an increased perception of autonomy (Dambrin 2004; Wilson & Greenhill 2004), productivity, work-life stability, employee satisfaction, job performance (Wheatley 2012; Kemerling 2002; Fonner & Roloff, 2010) and less stress (Felstead et al., 2002; Raghuram and Wiesenfeld 2004; Sullivan & Lewis 2006; Azarbouyeh & Naini 2014). Using VTMs as an example, HMT augmentation will require AI to help reduce social isolation (Sparrowe et al., 2001).

VTM challenges affecting employee QWL fall into five primary categories: technology, workload, manager-employee relationship, social connections, and work-home boundary (Graves & Karabayeva, 2020). For example, VTMs have a significant reliance on information and communication technologies, CMTs, and CMCs that create increased job demands (Graves & Karabayeva, 2020) due to the need for VTMs to stay up to date on these ever-changing technologies (Ragu-Nathan, Tarafdar, Ragu-Nathan, and Tu, 2008). Using HFVTMs as a surrogate, AI-augmented VTMs will face similar challenges.

The ability of AI to deliver sustained ROI is critical for member adoption and team augmentation. Chapter three discusses how this study performs tandem interviews with a co-researcher focusing on QWL life-based effects on VTMs and their impact on VTM performance (Hill, 2023). This study will provide a short overview of the QWL survey instrument developed by Sirgy et al. (2001) to align with this parallel research and its use in defining and measuring HFVTMs. QWL includes seven factors to measure workplace dimensions' effect on employee satisfaction with work-life, non-work life, personal happiness, and well-being (Sirgy et al., 2001). Danna and Griffin (1999) layer these QWL concepts starting with employee satisfaction with pay, supervisors, and co-workers at the bottom, tiered next with job satisfaction, and finally, life satisfaction. Sirgy et al. (2001) measure seven factors: satisfaction with health and safety, economic and family, social, esteem, actualization, knowledge, and aesthetic needs (Sirgy et al., 2001). The researcher examines these seven QWL factors, and any possible additional factors, during the tandem interview qualitative interviews. The researcher and tandem interviewer explore additional QWL factors such as mission.

This validated measure, possible additions, and literature connections are critical to this study as multiple studies demonstrate that employees with high levels of QWL are not only loyal, productive, and dynamic employees (Greenhaus, Bedeian, & Mossholder, 1987), but also positively impacts factors such as worker behavioral, firm identification, job involvement, task effort, task performance, and retention (Carter et al., 1990; Efraty & Sirgy, 1990; Efraty et al., 1991; Lewellyn & Wibker, 1990). The positive impacts on these factors are required for AI team augmentation of low- and moderate-performing VTMs, for high-performing VTMs to remain predictively high-performing, and for AI to deliver significant levels of ROI. Because this study uses the VTM as the unit of analysis, future researchers should examine the role AI may have on increasing VT subgroup well-being, QWL, and health.

Virtual Team Performance (HFT & HPT)

A scholarly understanding and measure of VTM and HFVTM performance are critical to this study as the independent variable of this research is VTMP, and the dependent variable is AI Augmented Activities Index. This section will demonstrate the vast array of factors impacting VTMP. Numerous research studies examine the performance of AI and HMTs, human-integrated teams (HITs), human-autonomous teams (HATs), and human-machine systems. However, a wide variety of these studies (Stowers, Oglesby, Sonesh, Leyva, Iwig, & Salas, 2017) operationalize performance by focusing on completing specific goals. Others focus on situation awareness, cognitive workload, error rates, and scores (Prinzel, Freeman, Scerbo, Mikulka, & Pope, 2000; Kaber, Perry, Segall, McClernon, & Prinzel, 2006; Parasuraman, Cosenzo, & De Visser, 2009; Glas, Kanda, Ishiguro, & Hagita, 2012). On account of the large number of factors impacting AI performance, this study will argue that analyzing HFVTMs at the O*NET GWA and WPE level is critical to examining what work factors are most ideal to AI to increase member performance. This approach is a novel and critical difference from existing literature.

This study examines VTMP in VTs from four angles. First, it measures VTMP using a novel performance survey instrument derived from the Andersson, Rankin, and Diptee's (2017) validated survey. Next, performance augmentation is examined using VTM ranking of workplace O*NET augmentable characteristics and how VTMs rate these activities' importance or criticality, frequency, and satisfaction. What do low-, moderate-, and high-performing VTMs require to increase VTM performance? Later in this chapter, this study examines the literature behind importance versus frequency scoring, importance versus satisfaction scoring as measured through ODI, job mapping, and jobs to be done (JTBD). For the remainder of this section, VTM performance, its measurement, and the definition of high-functioning VTMs is discussed.

Examining ways to improve VTM performance has been a critical theme in literature since 2005 (Gilson et al., 2014). However, much of this research centers on mitigating employee barriers when using technologies (Gilson et al., 2014). However, like Gorman, Nelson, and Glassman (2004) noted, current and future generations of workers will grow up with a thorough understanding of computers, CMTs, and new attitudes toward technology adoption (Morris & Venkatesh, 2000). As a direct result of these new generations of workers' views toward speed, technology, and information access, the requirement for instantaneous access is often expected (Hershatter & Epstein, 2010). This view of information access is expected to drive AI to be preferred by the next generation of worker who sees anything less as a waste of effort and an unnecessary roadblock, the same way millennials see CMT as a way to reduce boundaries and improve collaboration (Myers & Sadaghiani, 2010). Next, this study will review the factors, features, and attributes of VTs and VTMs that impact performance.

An overview of factors impacting high-performing VTMs is critical to this study's goal of defining AI O*NET-SOC GWAs and WPEs that can facilitate the creation and development of AI VTM augmentation and superteams. Jackson and Madsen's (2004) research on common work factors of high-performing teams explores the fundamental areas of interest, including goals, aptitude, skills, ethics, incentives, motivations, efficiency, management, conflict, communication, power, customs, and values (Jackson & Madsen, 2004).

Academic research into the characteristics and attributes of high-performing VTMs suggests numerous factors. Shared purpose, as defined by Katzenback and Smith (1993), demonstrates the importance of short- and long-term goals that motivate and challenge team members. Applicable to AI augmentation, Knight, Durham, and Locke (2001) demonstrate that teams using computer simulation with challenging goals achieved the highest level of team function and performance. Goal difficulty has also been shown to positively impact VTM performance, reduce strategic risk, and increase tactical implementation (Knight & Durham, 2001). Shared team goals are critical contributors to high-performing teams (Guzzo & Dickson, 1996). Shared goals and missions offer direction, which increases productivity (Nelson, 1997). Furthermore, shared goals often provide a purpose to VTM's existence, leading to high performance (Holmes, 2005; Nelson, 1997; Sundstrom, DeMeuse, & Futrell, 1990; Dina, 2010). Shared VTM mental models are often antecedents to shared goals as they provide for shared cognitive representations, understanding, task requirements, procedures, and role responsibilities (Mohammed & Dumville, 2001).

However, shared and difficult goals must also be specific, achievable, and collectively agreed upon to deliver direction and motivation, and result in performance increases (Nelson, 1997; Sax, 2012). The development of specific goals permits VTMs to realize small achievements, building VTM's commitment and motivation (Katzenbach & Smith, 1993). However, some research suggests stretch or impossible goals should be utilized because if the goal is more than one member can handle individually, the need for team resourcing, inter-dependent behavior, and collaboration increases team efficiency and results in greater performance (Regan, 1999; Gully, Incalcaterra, Hoshi & Beaublen, 2002).

The ability of VTMs to reach high levels of performance relies heavily on the ability of members to perform the tasks required (Nelson, 2010). This ability necessitates the need for VTM role clarity (Nelson, 2010). Clear VTM responsibilities, authorities, and role definition are highly correlated with performance (Nelson, 1997; Holmes, 2005; Chong, 2007; Dina, 2010). These attributes can be summed up by a range of literature supporting how VTMs must manage healthy conflict and communication. Research demonstrates that properly managed conflict improves decision-making and performance (Rainey, 1991; Jehn & Chatman, 2000; Sampson & Clarke, 2011; Kozlowski & Ilgen, 2006). VTMs who use open communication and coaching reduce miscommunication, increase feedback, reduce message distortion, and improve listening, which increases performance (Reagan, 1991; Gordon, 1990; Brown, 2003; Weiss, 2002; Dina, 2010; Holmes, 2005; Nelson, 1997).

However, conflict avoidance should be shunned to increase communication, reduce message distortion, and increase performance. Research has shown that high-performing VTMs often rely on constructive conflict to moderate and focus members (Sampson & Clarke, 2011). Conflict helps reveal different points of view, information, and solutions to complex problems (Sampson & Clarke, 2011). For example, research by Sampson and Clarke (2011) reveals that employees in high-performing teams often used significantly more challenging and conflict-oriented comments than employees in low-performing teams. This communication is a unique takeaway for the VTM performance instrument development as well as AI construction and integration of AI within teams, as correct answers alone may not allow VTMs to reach their full potential.

Decision-making and problem-solving empowerment are also critical to performance (Katzenbach & Smith, 1993; Holmes, 2005). Another critical takeaway highlighting the requirement of this paper to identify and rank work factors required for AI human-machine teaming, the ability of members to prescribe their own process, is often critical to increased performance. Just as General Patton once said, "Never tell your soldiers how to do a job. Tell them the results you want, and they will surprise you with their ingenuity" (Regan, 1999); it also may be said that AI cannot prescribe solutions to HMTs. AI must empower VTMs and become an integral part of HMT's autonomy (Nakata & Im, 2010) for true superteaming and AI VTM augmentation to be successful. This decentralization of decision-making directly impacts VTM work processes and performance (Pfeffer, 1998). Kirkman and Rosen (2000) provide five critical elements to empowerment: a sense of potency leading to team efficacy; tighter relationships and encouraging behaviors; a sense of meaningfulness that ties members to each other; a sense of autonomy; and a sense of mission importance.

Additionally, leadership is critical to performance. Leaders should avoid secrecy, be flexible, treat members with respect, listen, address problems, provide focus, encourage collaboration, provide praise and recognition, and display tolerance (Larson & LaFasto, 1989; De Vries, 1999; Holmes, 2005). A leader's ability to disseminate information and successfully share leadership responsibility is also essential (Nelson, 1997; Chong, 2007). Mutual respect from leaders and team members is also essential (Nelson, 1997; Salas, Burke, & Cannon-Bowers, 2000; Holmes, 2005;).

Multiple factors such as solidarity, motivation, incentives, cohesion, belief, and positive climate, which researchers suggest provide for positive performance (Deci, 1972; Katzenbach & Smith, 1993; Mullen & Cooper, 1994; Guzzo & Dickson, 1996; Nelson, 1997; Salas, Burke, & Cannon-Bowers, 2000; Brown, 2003; Steers, Mowday & Shapiro, 2004; Holmes, 2005; Kozlowski & Ilgen, 2006), may be difficult for AI to augment. For example, the desire to work with others within the team to achieve goals is imperative to high-level team performance (Sax, 2012). These collaborations may be too elusive for AI augmentation in the short term. Literature notes several other such factors critical to performance but challenging for AI to provide, include respect, the creation of norms and standards, commitment, accountability, dedication, flexibility, diversity, minimum levels of competence, and the ability to seize opportunities (Larson & LaFasto, 1989; Katzenbach & Smith, 1993; Nelson, 1997; Jehn & Mannix, 2001; Hackman, 2002; Annunzio, 2005; Kozlowski & Ilgen, 2006; Chong, 2007).

The above research demonstrates dozens of team factors that impact performance. However, the core reasons for teams and their members to work, likely do not change due to AI augmentation. These core reasons, such as increased complementary skills and experience, real-time problem solving, flexible and responsive change, and the enhancement of administrative and social aspects of work to overcome task difficulties (Katzenbach & Smith, 1993), remain viable goals for HMTs, AI augmentation, and superteams. The above performance factors are explored during the qualitative interviews and in the development of a novel VTMP instrument.

To develop a novel VTMP instrument sufficient for this study's research goals, a review of historic VTMP measurement tools are discussed. Although there is a wide range of VTMP measures, numerous surveys like the North Atlantic Treaty Organization (NATO), National Aeronautics and Space Administration (NASA), and QinetQ models are highly complex, lengthy, and do not effectively operationalize VTMP according to this study's requirement (Andersson et al., 2017). This study develops a novel survey instrument using the Andersson et al.'s (2017) validated 16-question survey as a scholarly starting point to assess VTMP, as it is the most appropriate tool to use to develop and operationalize this study's dependent variable of AI Augmented Activities Index and captures the performance factors discussed in this section. This survey identifies and measures low-, moderate-, and high-VTM performance on a continuous scale based on the 5-point Likert scales (Andersson et al., 2017).

The Andersson et al. (2017) original survey included a single 11-point Likert scale question that allowed the developers to perform a repeated measure evaluation within the experimental design phase of the survey's development (Andersson et al., 2017). The 11-point Likert scale allowed respondents to distinguish more options in their response (Andersson et al., 2017). For use in the current study, the survey does not require a measure at this fidelity and therefore the scale is adjusted to a 5-point Likert. Content and face validity of these changes, along with minor adjustments to the wording of the survey's questions, was confirmed in the pilot study. The original instrument was developed for the medical field (Andersson et al., 2017). The VTM and AI use of this survey requires adjustments and contextual wording adaptations to anchor questions in a broader contextual environment. Adjustments to questions centering on VTMP, and additional VTMP factors required for this study were validated through an expert qualitative panel and quantitative pilot test to further ascertain face and content validity and is discussed further in chapter four.

The total score from the survey determines the AI Augmented Activities Index serving as the dependent variable and will be discussed further in chapter three. Next, this study will review the definition and measure of VTM QWL and the establishment of HFVTMs as a critical component of creating superteams. The measure of high-performing VTMs, as defined by this study's novel VTMP instrument (Andersson et al., 2017), singularly focuses on performance. However, this study's emphasis on superteam creation through AI augmentation requires the highest performing VTM definition. Superteams require another level of collaboration amongst HMTs consisting of high-performing VTMs and AI. For the unit of analysis of this study, the researcher will use the definition of HFVTMs as defined by Hill et al. (2023) for AI superteaming. In this study of VTMs, Hill et al. (2023) demonstrates the highest levels of QWL as defined by Sirgy et al. (2001) in combination with the highest performing VTMs form HFVTMs. This combination of performance and QWL leads to next-level social and worker functionality that is required for the formation of AI superteams and an increase in performance. The use of functioning versus performing is critical to this study as multiple studies indicate that HMTs and AI augmentation of teams need to take into account social interactions and team-building amongst teammates (Walliser, de Visser, Weise, & Shaw, 2019). The use of social interactions and team building around quality of work life play a direct role in improving performance (Walliser et al., 2019).

Artificial Intelligence

At the epicenter of the discussion on human-machine teaming, VTM augmentation, superteams, and VTMP augmentation is AI. AI is frequently viewed as a human-like cutting edge technology that improves efficiency, increases effectiveness, enables novel discovery, and delivers unique opportunities and innovations (Dwivedi et al., 2019). AI can construct text, audio, and pictures to the point that individuals now have difficulty determining AI and human productions (The AI Index Report, 2021). The world is at the beginning of the third wave of the intelligence technology revolution, driven by AI, which is driving economic opportunities and firm capabilities that exceed traditional human Knowledge, Skills, Abilities, and Competencies (KSACs), disrupt firm competitive advantages, unsettle business operations, and influence firms to reassess how humans and machines will work together (Porter & Heppelmann, 2014; Porter & Heppelmann, 2015). AI creates opportunities for firms to take a novel and distinctive strategic position (Porter & Heppelmann, 2014). Research supports the idea that AI will become a team member with unique competencies allowing it to accomplish specific team roles (Rammert, 2008; Rijmenam & Logue, 2020; Stingl et al., 2021).

Academic literature and popular culture provide multiple definitions for AI ranging from highly defined to ambiguous. As a basic level one might say AI is doing the things people do. One seminal definition from Russell and Norvig (2020) is AI is "concerned with not just understanding but also building intelligent entities — machines that can compute how to act effectively and safely in a wide variety of novel situations" (Russell & Norvig, 2020). With this study's focus on team augmentation and business ROI, this research will define business and VTM use of AI as "adaptation with insufficient knowledge and resources" (Wang, 2019). Modern AI tools include multiple types and capabilities, including machine learning, deep learning, reasoning under uncertainty, automated reasoning and inference, intelligent robotics, commonsense reasoning, constraint processing, case-based reasoning, heuristic search, computer vision, multi-agent systems, and natural language processing, and cognition (Doherty & Thiebaux, 2021). This study does not focus on automation or preprogrammed technologies that dynamically process and transforms data to control team procedures within a highly constrictive, well-documented, and well-defined environment (Lee & See, 2004). Automation is not AI (Lyons, Sycara, Lewis, & Capiola, 2021) as these tools only perform in areas where instructions are programmed, and capabilities and decision making outside of the tool's specific role and context are not viable (Lyons et al., 2021).

Porter and Heppelmann (2014) describe this new smart connected AI-driven environment as a combination, or stacks, of physical and digital components, brought together to achieve one-to-one (1v1), one-to-many (1vM), many-to-one (Mv1), or many-to-many (MvN) connectivity (Porter & Heppelmann, 2014). This stacking allows for tremendous data exchange, processing, and evaluation, increasing team and firm functionality (Porter & Heppelmann, 2014). The capability of these technology stacks to deliver advanced applications, engines, databases, and AI capability through connected cloud operations is vital for modern firms (Porter & Heppelmann, 2014).

Virtual team members, team augmentation, and superteams will require multiple external information tools, CMT integrations, CMC integrations, and advanced security features to deliver an array of smart connected tools capable of monitoring, participating, and optimizing team performance (Porter & Heppelmann, 2014). AI products now allow businesses and teams to realize data performance efficiencies that impact processes, products, and firm capabilities (Porter & Heppelmann, 2014). Porter (2014) suggests that these advanced tools and partners are already having a transformative effect on businesses, teams, and competition. The impact of AI on the Five-Force's framework (Porter, 1996) redefines competition (Porter & Heppelmann, 2014). The promise of AI to create sustainable competitive advantages (SCAs) within business and technology activities (Porter & Heppelmann, 2014) must also be understood at the HMT, team augmentation, and superteam levels. A more thorough examination of these studies link to business strategy is examined later in this chapter.

Creating AI requirements for organizations, virtual teaming, firms, and employees have traditionally centered on a bottom-up approach. Researchers and AI developers have focused on what employee and business processes can be done through AI. However, given enough funding, data, and time current technology levels allow AI to take over nearly any business requirement (Lee & Qiufan, 2022; Revell, 2017). This bottom-up approach is not only backward-facing, but it does not take into account ROI, future requirements, and rank-ordered assessment of what teams and employees will need to from the top-down. This same philosophy has occurred repeatedly with virtual teaming technology analysis and research. For example, according to a Gibbs et al., (2017) review of 265 VT articles with 70.9 percent mentioning specific technologies and 53.6 percent measuring technology impact, the research focused on past use of older technologies which often resulted in contradictory findings (Gibbs et al., 2017).

This research study takes an innovation approach to job activities required for AI augmentation and superteaming. This study does not focus on the technology effects, process, or comparative approaches (Gibbs et al., 2017), instead it uses job analysis and employees' perception of work activities to determine the rank ordered requirements needed from AI to create superteams or augment and improve VTMs. Past effect studies often use technology as an input or mediating variable to measure reception and understanding (Lee & Watson-Manheim, 2014), collaborative mental model creation (Andres, 2012), communication failures (Daim et al., 2012), data and knowledge sharing methods (Pinjani & Palvia, 2013; Minas, Potter, Dennis, Bartelt, & Bae, 2014), and performance (Montoya-Weiss, Massey, & Song, 2001; Venkatesh & Windeler, 2012; Bradley, Baur, Banford, & Postlethwaite, 2013). Past process approach studies analyze the role of technology within VTs and organizations, such as structures in inter-organizational VTs (Majchrzak et al., 2000), role in VT knowledge sharing (Klitmøller & Lauring, 2013), configurations of program use over time (Maznevski & Chudoba, 2000), relationship building (Pauleen & Yoong, 2001), and multiple-media structures (Bélanger & Watson-Manheim, 2006). Finally, the comparative studies approach compares face-to-face teaming with VTs technology use. However, none of these approaches offer an affordance-type approach (Gibbs et al., 2017), which provides a method for understanding what a future superteam or augmented HFVTM will need from AI within the definition of work. For this reason, this dissertation will name this study's approach the innovation needs-based approach to superteaming and AI augmentation.

The growth of machine learning, deep learning, and AI tools will rapidly alter the workplace. The rapid growth rate in at-home work environments, driven by COVID-19, will require in-depth analysis and extensive research focusing on the long-term effects of such sudden and drastic change. The rapid onslaught of digital innovation, at-home work products, the move to the cloud, and software-as-a-service drives much greater demand for AI and automation services (Nattermann & Sauer-Sidor, 2020). Research within these growth areas will provide managers a way ahead to meet new digital innovation, cloud, and software-as-a-service obstacles and challenges.

The current AI technology level provides the ability of these novel tools to transform multiple firm value chains and processes (Porter & Heppelmann, 2015). Although AI continues to impact product development, cost, variability, design, operation, quality management, interoperability, manufacturing, and logistics to provide an AI-driven value chain (Porter & Heppelmann, 2015), the ROI for AI and HMTs is not being realized (Ransbotham et al., 2019). Iansiti and Lakhani (2014) demonstrate that digital transformation forces firms to compete in innovative ways (Iansiti & Lakhani, 2014). The coming omnipresence of AI technologies in the work environment, their novel ability to create new value, and their ability to move the boundaries of what firms are capable of must also be realized for VTMs (Iansiti & Lakhani, 2014). The promise of advanced AI HMTs requires collaboration across AI and VTM functions and work activities (Porter & Heppelmann, 2015). Although the mix of data monitoring and AI algorithm optimization enables autonomy (Porter & Heppelmann, 2015), what are the augmentable components, characteristics, and functions of work VTs and businesses want and need AI to increase performance? This study takes a top-to-bottom approach versus a bottom-up approach to answering this study's RQs.

AI Type, AI Style, AI-Ability, Gartner's Hype Cycle,

To examine VTM augmentation, a brief review of AI styles and types is required. Digital teaming, AI, AI-human connectivity, and AI communication technologies will likely become essential for VTM capabilities, impacting research to include internalization theory (Banalieva & Dhanaraj, 2019). Temporally distributed VTMs and multinational enterprises (MNEs) that use AI technologies are predicted to bring down firm costs, increase coordination, and advance decision-making (Banalieva & Dhanaraj, 2019). AI has the ability to develop VT-, firm-, and VTM-specific advantages through digitally developed AI technologies (Banalieva & Dhanaraj, 2019).

Currently, AI can perform a large number of VTM related member and lesser activities, including CMC, CMT, collaboration tasks, and structured and spontaneous communication leadership while increasing trust and setting expectations (Lee & Qiufan, 2022; Revell, 2017). Smart data discovery, HMTs, instantaneously delivered data, and pattern analysis is transforming how businesses analyze and consume data. AI's ability to automate analytics for human employees and firms, called smart data discovery or augmented analytics, is beginning to reduce the VTM's reliance on employee judgment (Davenport & Fitts, 2021). This study will focus on understanding what VTMs and HFVTMs require to predict what AI should do, not focus on what AI can do. Future researchers should examine the effects of high- and low-level task differences in VTM augmentation and superteaming.

Artificial intelligence is more than a buzzword or a business tool. AI is a diverse set of capabilities, types, and functionalities destined to maximize VTM speed, precision, and efficiency (Biswal, 2022). However, despite its social, firm, and theatrical links in modern society, AI is still a difficult to define and comprehend concept to the general public (Kaplan & Haenlein, 2019). This study will examine the different types of AI-based on both capability and function. The type of AI can be split into three categories: narrow AI, general AI, and super AI (Kaplan & Haenlein, 2019). AI functionality is split into four major categories: reactive machines, limited theory, theory of mind, and self-awareness (Biswal, 2022). The range of AI learning can be summarized into three categories: supervised learning, unsupervised learning, and reinforcement learning (Kaplan & Haenlein, 2019). Finally, the AI system type may also be classified by intelligence type: cognitive intelligence, emotional intelligence, social intelligence, and artistic creativity (Kaplan & Haenlein, 2019). These types lead to various AI applications that broadly fall into three major categories analytical AI, human-inspired, and AI humanized AI (Kaplan & Haenlein, 2019). This literature review will focus on the three major AI types and four main functionalities.

Narrow AI, weak AI, or Artificial Narrow Intelligence (ANI) focuses on a singular job without the ability or scope to perform jobs outside of its initial limitations (Kaplan & Haenlein, 2019; Biswal, 2022). Narrow AI is a targeted solution built on particular cognitive capabilities. ANI is highly prevalent in modern society through such tools as IBM's Watson, Amazon's Alexa, and Apple's Siri (Kaplan & Haenlein, 2019). ANI cannot resolve problems in other areas autonomously and often cannot outperform humans in the job arena (Kaplan & Haenlein, 2019). ANI may outperform humans in specific jobs such as Think Go, Chess, or job scheduling.

General AI, also known as strong AI or Artificial General Intelligence (AGI), possesses the capability to comprehend and learn any human intellectual job (Kaplan & Haenlein, 2019). AGI can be used in many business areas to solve VTM and firm issues in other areas autonomously, can outperform human employees in numerous areas, and is likely to be a key driver for firm ROI moving forward (Kaplan & Haenlein, 2019). The ability of machines to apply algorithms, learned knowledge, and human-like skills within a wide range of job contexts has not been fully realized (Biswal, 2022). For example, Fujitsu's K and China's Tianhe-2 supercomputers take nearly 40 minutes to perform one second of human neural activity. These computers are required to perform one billion calculations per second to reach the capability of the human brain (Biswal, 2022). Current large supercomputers such as the Oak Ridge and Tianhe-s supercomputers can already perform well over one billion calculations per second.

In theory, Super AI, or Artificial Super Intelligence (ASI) can perform any job task faster and better than a human, which is a capability that will require AI to become near-human (Kaplan & Haenlein, 2019; Biswal, 2022). ASI is unique because it applies to any business area, it can solve firm problems in nearly all areas instantaneously, and ASI can outperform humans (Kaplan & Haenlein, 2019). While controversial, some argue the ability of AI to have emotions, needs, desires, frustrations, and other human characteristics is essential to problem-solving, reasoning, judgment, and other human-like characteristics (Biswal, 2022).

Reactive machine AI is the current principal functionality of AI. This type of AI does not store experiences, events, or experiences to evaluate future actions; it singularly focuses on data captured at the moment. This type of AI functionality is essential to job tasks with specific and repeatable events. Limited memory AI or the ability of AI to perform jobs and make decisions based on recent past data, is the next AI functionality type. This offline learning can only draw on a library of past events and experiences available to the AI (Biswal, 2022). Theory of mind AI is the next class of AI, existing only as a concept, and requiring AI to understand and act on human emotion. More precisely, this AI must be able to think about other's actions and explain why they did something or predict what they will do. Finally, AI self-awareness, a hypothetical AI system where AI develops internal characteristics, perceptions, and emotions, is theorized to provide machines with the ability to perform far superior to the human mind (Biswal, 2022).

AI often follows Gartner's hype cycle (Bini, 2018), and therefore it is helpful to analyze AI through the five-stage cycle (Gartner, 2021). Gartner's hype cycle is developed by the Gartner research and advisory firm, who publish yearly reviews of individual technologies along a technology hype cycle curve (Bini, 2018; Gartner, 2021). The cycle is often used to express adoption experiences for emerging technologies (Sodhi, Seyedghorban, Tahernejad, & Samson, 2022). These five stages are the innovation trigger, the peak of inflated expectations, the trough of disillusionment, the slope of enlightenment, and the plateau of productivity (Gartner, 2021). Often emerging technology characteristics do not adequately allow customers to appropriately set expectations at the early stages of adoption (Sodhi et al., 2022). This disconnect between AI characteristics and promises or expectations can often explain the inflated expectations and trough of disappointment phases (Sodhi et al., 2022). The follow-on shared experiences can assist the user in beginning the long slope of the enlightenment phase (Sodhi et al., 2022). Superteaming and AI augmentation capabilities will likely follow this same cycle.

Figure 1 shows the AI hype cycle for 2021 (Gartner, 2021). This study will place identified O*NET-SOC GWA and WPE factors, superteams, and AI-augmentable HMT activities along the most recent Gartner hype cycle to align investment opportunities with development status. This process will add a timeline dimension to the AI-ability of recommended factors.

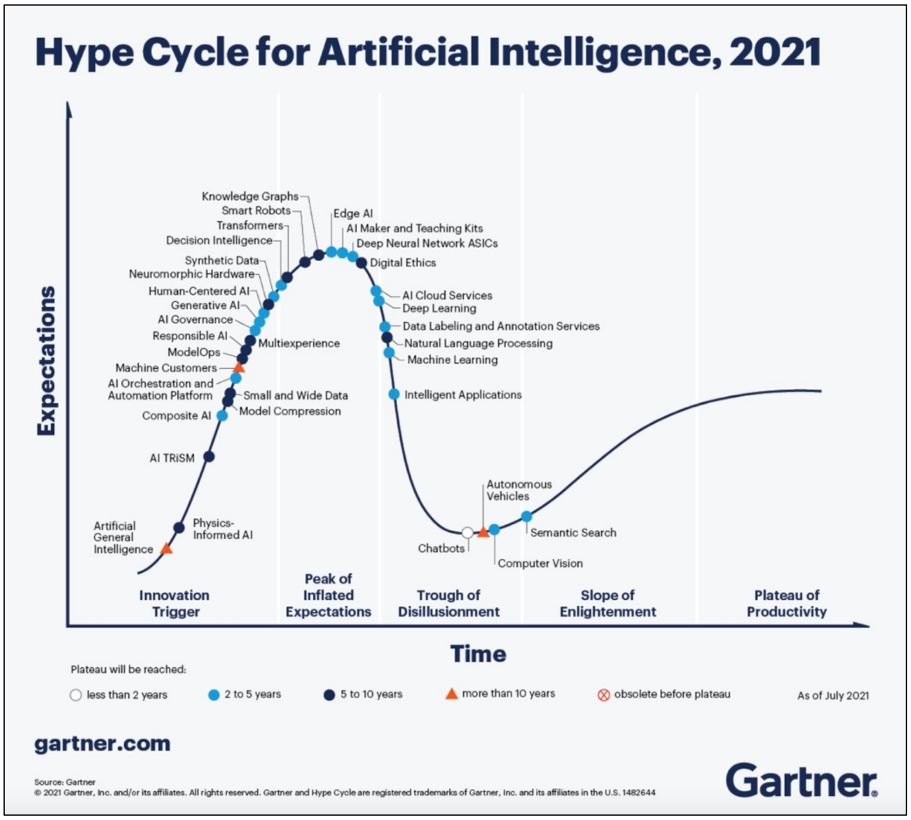


Figure 1 – Gartner's Hype Cycle for Artificial Intelligence – 2021

Figure 1 demonstrates AI is predominantly in the innovation trigger and peak of inflated expectations. This exhibits the research performed in this dissertation is timely and may assist critical AI technologies to move more swiftly into the slope of enlightenment and plateau of productivity. Using the above literature on AI this study will now lay out a series of five conclusions from literature that will govern this study.

Conclusions from Literature

- *Conclusion from Literature 1* – HFVTMs is an appropriate measure for analyzing human-machine teaming.
    - Conclusion from Literature 1 is supported by all the findings in this chapter.
- *Conclusion from Literature 2* – HFVTMs are an appropriate measure for analyzing team augmentation and Superteams.

    - Conclusion from Literature 2 is supported by all the findings in this chapter.
- *Conclusion from Literature 3* – HFVTMs are an appropriate measure for analyzing AI-Human Superteams.
    - Conclusion from Literature 3 is supported by all the findings in this chapter.
- *Conclusion from Literature 4* – AI tools and capability added to a team are at least as good as a human VT.
    - Conclusion from Literature 4 is supported by findings from McNeese, Demir, Cooke, and Myers (2018) that highlight human-autonomous teams (HATs) performed at least as well as human-only teams (McNeese, Demir, Cooke, & Myers, 2018).
- *Conclusion from Literature 5* – AI tools and capability added to a team is better than human-only VTs.
    - Conclusion from Literature 5 is supported by findings from McNeese, Demir, Cooke, and Myers (2018) that highlight human-autonomous teams (HATs) performed at least as well as human-only teams (McNeese, Demir, Cooke, & Myers, 2018).

Human-Machine Teaming (HMT)

The long history of academic research into HMTs continues to note variations in overall team performance. HMT research ranging from human factors, awareness, trust, communication, and computer science, continues to pick up speed; however, scholarly understanding is still limited (McNeese, Demir, Chiou, & Cooke, 2021). The number of AI tools that can function in HMTs is likely to increase significantly, especially as work becomes more virtual (McNeese et al., 2021). For example, NASA and the collaborating countries involved with the International

Space Station (ISS) introduced the first AI conversational tool to assist astronauts and cosmonauts with daily tasks in 2018 (Hauswald, Laurenzano, Zhang, Li, Rovinski, Khurana, Dreslinski, Mudge, Petrucci, Tang, & Mars, 2015; Hoy, 2018).

More commonplace in society is the Amazon Echo, Apple Siri, and Microsoft Cortana AI tools that assist human teams across a variety of personal and business environments (Canbek & Mutlu 2016; Crook 2017; Wall 2018; Wilson & Daugherty 2018; Bogers, Chesbrough, Heaton, & Teece, 2019). AI teammates and AI intelligent assistants are expected to be a $25.63 billion business by 2025 (Business Wire, 2019). This paper attempts to accelerate learning into HMTs by focusing on the intersection of VTMs, HFVTMs, and performance viewed through O*NET-SOC work factors. This ultra-refinement of what fundamental work characteristics is required by performance variation within VTMs allows for a top-down understanding of AI's required tasks for HMT augmentation.

Human-machine teaming is academically defined as an activity in which a human and a machine have interdependent responsibilities requiring mixed interactions to achieve a common teaming goal (McNeese et al., 2021). Although this definition allows for the machine to be varying levels of technologies ranging from a warning system to a virtual agent (ex. Siri or Alexa), a decision-making support system (ex. IBM's Watson), or an AI robot, this study will solely focus on AI partners (McNeese et al., 2021). Additionally, the definition of HMTs includes two subfactors: Human-machine interaction (HMI) and human–autonomy teaming (HAT). Each definition depends on how much freedom is given to the machine (McNeese et al., 2021). This study uses HATs because they are defined as the technology with the authority to make choices on its own (McNeese et al., 2018). This distinction is critical because, from a VTM perspective, HATs are comparable to human teaming, like those in HFVTMs, as the VTMs each have their own knowledge and authority to act. This peer-to-peer relationship at the member level is critical to this study's level of analysis, the VTM.

Little is known about HATs (McNeese et al., 2021). Scholars note that the research community needs validated, translatable, and transferable findings and research methods about human-human teaming characteristics applicable to HMTs and AI augmentation (McNeese et al., 2021). For example, little is known about HMTs and trust. McNeese et al. (2021) analyzed HMT performance and noted that trust played an important role. The results from this Wizard of Oz experimental approach demonstrate lower levels of trust in the AI partner in low-performing teams, loss of trust in AI over time across all levels of performing teams, and low- and moderate-performing teams demonstrating lower levels of trust in their human partners. This study intends to provide a novel and validated approach to examining HMTs that include HAT interactions. Additionally, this dissertation will delimit the examination of AI trust and reliability because these effects are widely known to impact AI performance (McNeese et al., 2021). Furthermore, the primary goal of this study is to examine which areas stand to benefit the most from AI augmentation, or the top-down requirement, not to determine the exact AI solution and embodiment of the technology, algorithm, or type.

Another reason VTMs and HFVTMs are appropriate for analyzing AI augmentation is the theoretical framework of computer are social actors (CASA) (Shaikh & Cruz, 2020). The CASA framework explains why, how, and when humans treat and interact with computers (Reeves and Nass 1996; Nass and Moon 2002; Nass et al. 1994). CASA concludes that humans apply social rules, norms, and categories to computers, machines, and AI, just as they would human teammates and partners, even though they know they are machines (Nass et al. 1994; Nass and Moon 2002). The importance of defining and using HFVTMs versus solely HPVTMs is essential when viewed through this theoretical lens. Employees will treat AI as human-like and extend and expect human-like behavior like politeness, QWL, health, well-being, and reciprocity toward computers (Nass & Moon, 2002).

Multiple studies on HMTs and human-machine collaboration centering on performance have come to similar conclusions (Zhang et al., 2020). AI with higher-than-average performance are likely to grow and encourage trust with humans to increase collaboration (Jones & George, 1998; Yin, Vaughan, & Wallach, 2019). Further, AI and employees who have a shared understanding are critical to HMT's collaborative performance (Hong, Benjamin, & Müller-Birn. 2018; Kaur, Williams, Lasecki, 2019). Moreover, AI should be considered a subject rather than a tool. The use of VTMs and HFVTMs satisfy expectations of human-AI teaming.

AI Superteams & Teaming Intelligence

The ability of members to be effective in a teaming environment is critical. For many years only humans were examined through teaming intelligence (Johnson & Vera, 2019). Only now is AI beginning to be examined through the theoretical foundations of teaming intelligence (Johnson & Vera, 2019). Teaming intelligence is critical because it impacts team performance, viability, and resilience (Johnson & Vera, 2019). Like other technologies, AI does not work in isolation (Johnson & Vera, 2019). Teaming intelligence involves using knowledge, skills, and strategies to manage interdependence (Johnson & Vera, 2019). In this respect, AI provides an augmented interdependence, or virtual teammate, making up for the limitation of humans and playing a critical role in performance. Failure to account for teaming intelligence will increase costs to firms and employees (Johnson & Vera, 2019). This interdependence, or mutual backing, and its support from team intelligence, gives this study another theoretical backing for using VTMs as proxies for HMT and VTM augmentation (Johnson & Vera, 2019).

The highest-level HMT will be referred to as a superteam member. HFVTMs are used as surrogates for HMT and VTM augmentation with AI capabilities for this study. Because AI has only basic teaming intelligence capability with small ROIs (Ransbotham et al., 2019), the ability of this paper to decipher and define critical HMT requirements at a fundamental O*NET-SOC factor level is critical for future research and business success. Trade groups originally coined the term 'superteams' as AI integrated into teams to create transformative business effects (Deloitte, 2021; Mallon et al., 2022). However, this definition does not consider academic testing, interdependence theories, teaming intelligence, human-machine teaming, or other theoretical foundations. For this study, superteams are defined as HFVTMs integrated with AI tools, capabilities, and team members capable of surpassing the performance levels of human-only teams. Trade groups contend superteams can help organizations create value, employees the ability to reinvent careers, and firms the ability to reduce costs (Deloitte, 2021; Mallon et al., 2022). These trade groups found that 65 percent of firms view the shift from AI hierarchy to team-centric models as vital (Deloitte, 2021; Mallon et al., 2022).

The role of AI in VTs cannot be examined without a thorough understanding of the role interdependence plays. Multiple academic articles note the role that task interdependence can have in improving VTMP (Chi, Chang, & Tsou, 2012) and that ratification of decision making is related to decision process quality (Bourgault, Drouin, & Hamel, 2008). CMTs and CMCs are vital to VTM's success currently. CMC and CMT enhance how VTMs collect information, communicate, share information, distribute data, and enhance VTM communication dynamics and relationships (Alaiad, Alnsour, & Alsharo, 2019). All of these items can be accomplished using AI to achieve the same goals of collaboration, coordination, and communication among team members (Alaiad et al., 2019).

Recent analysis centers on identifying major themes of VT research from 149 studies. One of these research themes is CMC tools in VTs (Alaiad et al., 2019). According to the authors, CMC tools can take multiple forms, from the primary such as email, videoconferencing, and phone calls, to advanced virtual worlds (Alaiad et al., 2019). Additionally, role virtuality interdependence is partially mediated by trust (Penarroja, Orengo, Zornoza, & Hernandez, 2013). For example, Cummings, Espinosa, and Pickering (2009) demonstrated that synchronous CMT reduced coordination delays while knowledge sharing, deep-level diversity (Pinjani & Palvia, 2013), and frequency of interaction (Suh & Shin, 2010) were found to be critical mediators. Trust is linked to knowledge sharing (Liu & Li, 2012), transfer, and exchange (Quigley, Tesluk, Locke, & Bartol, 2007). The combination of interpersonal trust and technology trust is critical for knowledge sharing (Golden & Raghuram, 2010), as research suggests the lack of trust in technology leads to inadequate knowledge sharing (Breu & Hemingway, 2004).

Outcome Driven Innovation and Job To Be Done Theory

Outcome driven innovation (ODI) is a theory driven process developed by Anthony Ulwick in 1999 and first proposed in 1991 (Ulwick, 2011). The fundamental idea behind ODI is individuals and firms purchase products and services to complete jobs (Ulwick, 2011). These jobs to be done (JTBD) have identifiable and measurable outcomes that purchaser's endeavor to reach (Ulwick, 2011). ODI connects a firm's value creation activities to consumer-prescribed metrics (Ulwick, 2011). For example, in this study, the researcher will argue AI developers should not assume what superteams and HMTs want or need. It is not what is AI-able, from a ODI perspective, what VTMs need is more important. Using the ODI process, this paper will look to examine what HFVTMs, HMTs, and VTMs require by focusing on the JTBD instead of AI product improvements and developments (Ulwick, 2002). Using the O*NET database to translate HMT needs into a ranking of definable GWAs and WPEs these VTMs need, ODI provides an innovation methodology to convert low-, moderate-, and high-functioning VTM needs into a definable and rank ordered work factor task list using the opportunity algorithm.

The ODI opportunity equation requires this study to measure and rank the possible AI HMT augmentable innovation opportunities using a simple equation. This equation relies on a standard gap analysis using survey participant data measuring importance and satisfaction metrics (Ulwick, 2011). Ulwick's (2011) ODI opportunity formula, listed below in equation one, weighs importance twice as much as satisfaction:

$$\textbf{Opportunity} = \textbf{Importance} + (\textbf{Importance} - \textbf{Satisfaction}) \qquad \textbf{(1)}$$

Equation 1 - Opportunity Formula

This simple equation provides a series of opportunity scores for AI augmentable JTBD for VTMs using the ODI framework (Ulwick, 2011). Survey response participants use a scale from one to ten to quantify the equation inputs (Ulwick, 2011). Importance is defined as the importance of the desired outcome and satisfaction is defined as the degree to which this outcome is presently being satisfied (Ulwick, 2011). This unique framework provides an equation that focuses innovation opportunities on those with the highest importance and lowest satisfaction scores from survey participants (Ulwick, 2011).

The process of turning customer input into innovation motivators turns traditional outside-in innovation methodology on its head (Ulwick, 2002; 2011). Customers cannot be relied upon to describe solutions, instead customers can only deliver outcomes they require (Ulwick, 2002; 2011). The process of turning customer outcomes into innovations includes outcome-based interviews, research capturing of desired outcomes, and organizing outcomes; all performed in the qualitative portion of this study (Ulwick, 2002; 2011). Next customers must rate these outcomes importance and satisfaction. This step is accomplished during the quantitative process of this study and is followed by the final step of recommending the most competitive outcomes customers ranked as important, but were also least satisfied with (Ulwick, 2002).

The next step in the JTBD theory is a strategic framework that allows for the phenomena of critical products and services to be ranked according to whether they help customers get a job done more effectively, efficiently, or more cheaply (Ulwick & Hamilton, 2019). This fundamental connection uses five central growth strategies developers can use to innovate successfully in markets (Ulwick & Hamilton, 2019). This study uses the JTBD matrix to develop five possible strategies for AI augmentation and superteaming. These include a differentiated, dominant, disruptive, discrete, and sustaining strategies (Ulwick & Hamilton, 2019). This survey delivers a JTBD matrix on possible AI augmentable HMT GWAs and WPEs focusing on better and less expensive possibilities and better and more expensive possibilities. This focus on dominant and differentiated strategies is necessary as AI HMT augmentation is in its infancy and the importance on ROI is critical (Ransbotham et al., 2019).

Job Mapping

Job mapping, or the systematic process of revealing innovative products, processes, and ideas to accomplish JTBD, requires researchers to examine work in a fundamentally different way (Bettencourt & Ulwick, 2008; Ulwick, 2011). Job mapping breaks down a job, task, or customer need into high-resolution discrete steps allowing firms and academics to identify the easiest, fastest, and most rewarding developments (Bettencourt & Ulwick, 2008; Ulwick, 2011). This study uses the essence of job mapping in combination with O*NET to identify the fundamental AI-augmentable GWAs and WPEs. Next the study uses an ODI survey framework to identify rank ordered opportunities for VTM augmentation.

Job mapping has eight definable steps that are utilized to transform the qualitative responses within this exploratory sequential mixed methods study to the quantitative survey instrument questions. Job mapping steps include defining, locating, preparing, confirming, executing, monitoring, modifying, and concluding (Bettencourt & Ulwick, 2008). The process of deconstructing a VTM and HFVTM job from start to finish allows researchers to view the entirety of possible gains AI may deliver at all levels of the job (Bettencourt & Ulwick, 2008). An O*NET job map allows this research to analyze all possible solutions for AI augmentation using a systematic framework. This possibility is based on the fact all jobs are processes, with a universal structure, and are not solutions (Bettencourt & Ulwick, 2008). Understanding what HFVTMs are trying to accomplish at fundamental level using O*NET will provide this study with theoretical backing for innovation process evaluation of HFVTM GWAs and WPEs.

Job Statements

The tandem interview qualitative portion of this exploratory sequential mixed methods study will formulate the O*NET GWAs and WPEs utilizing the process of capturing job statements outlined by Ulwick and Bettencourt's (2008). Job statements are requirement statements captured from qualitative interviews of customers and employees used to inform and guide decisions and are optimized for creation of customer value (Ulwick & Bettencourt, 2008). Job statements must mirror the customer's definition of value, have universal acceptance, be pertinent now and in the future, indicate a course of action, be unambiguous, and not be confusing (Ulwick & Bettencourt, 2008).

To create job statements Ulwick and Bettencourt (2008) describe four essential questions that assist interviewers in capturing job statement details during interviews. This study utilizes the following questions to unpack the GWA and WPE of HFVTMs and VTMs that will help formulate the O*NET-SOC profiles and what factors may be most suited to AI augmentation:

1) What make your job as a VTM, or certain parts of it, challenging, troublesome, or frustrating?
2) What makes your job as a VTM, or certain aspects of it time consuming?
3) What causes your data, job and work activities to go adrift, deviate, or be derailed?
4) What aspects of your VTM job are wasteful?

Finally, this study uses Ulwick and Bettencourt's (2008), rules for structuring job statements to guide the creation of the data captured during the qualitative VTM and HFVTM interviews.

Dynamic Capabilities & Resource-Based View

An overall discussion on AI-augmentable VTMs, HMTs, and superteams' impact on strategic management must begin with a historical account of strategy. Beginning with the 1960's single organizing framework of strategy (Andres, 1971; Asnoff, 1965, Hofer & Schendel, 1978) where academia advised firms to acquire competitive advantages by developing and instituting strategies based on exploiting internal firm strengths by responding to environmental opportunities, firms, and scholarly research has advanced the science of business strategy. From external to internal with operational effectiveness, total quality management (Juran, 1967; 1970; 1974 & Deming, 1993; 2000) driven by the early prophets of quality, to Five Forces (Porter, 1980; 1996), to the inside out strategies of DC (Teece et al., 1997), and RBV (Barney, 1991) an evolution of epic proportions has taken place. Debates still occur from industry to academia to firm leadership on whether to focus on isolating firms' opportunities and threats (Porter, 1980; Porter, 1985), focusing on strengths and weaknesses (Penrose & Penrose, 1958; Stinchcombe, 1965; Hofer, 1978), to developing an RBV strategy focusing on sustained competitive advantages (Barney, 1991), to integrating and reconfiguring internal and external competencies in a DC strategy (Teece et al., 1997), is the most appropriate for today's firms. This paper addresses two of these theories, DC and RBV.

AI's ability to augment VTMs can be considered a DC, as described by Teece et al. (1997). DCs are a firm's ability to integrate, build, and reconfigure internal and external competencies to meet and overcome rapidly evolving business environments (Teece et al., 1997). This inside-to-outside strategy focuses on the innovative ability of an organization to develop new core competencies that align current and future firm business directions (Teece et al., 1997). HFVTMs, superteams, and AI-augmentable VTMs can be considered hard to replicate resources, assets, and employees. These hard-to-replicate VTMs and AI superteams may allow firms to quickly learn, integrate, and transform to meet critical new challenges. Additionally, superteams fit the definition of essential corporate agility skills that allow the firm to sense and shape opportunities and threats, seize opportunities, and enhance the competitiveness of both tangible and intangible assets (Teece et al., 1997).

DCs traditionally require managers to learn, seek new assets, transform existing assets, combine or co-specialize assets, and reorchestrate assets. Results from this research may suggest that superteams and AI-augmented VTMs provide bountiful opportunities for asset agility, extension, and modification to increase performance. For example, AI and augmented HFVTMs may be able to provide business model modification to accommodate local preferences (Bolt, 2005), transfer business models, knowledge, and best practices (Teece, 2014), improve leadership and long-range planning (Teece 2016; 2018), improve culture and loyalty (Augier & Teece, 2019), and dynamically improve managerial capabilities (Helfat & Martin, 2015). location and skill preference. This research will determine AI-augmented VTMP, and if fundamental O*NET-SOC factors and work activities increase performance, this study will look to acknowledge these teams as a DC.

Another inside-outside strategy that centers on building organizational advantages to outperform rivals is RBV. RBV looks to strategically outperform rival businesses by developing sustain competitive advantages (SCAs) to add value, increase competitive advantages, and sustain SCAs over rival firms (Barney, 1991). RBV suggests that these SCAs must be valuable, rare, imperfectly imitable, and non-substitutable (Barney, 1991). In this study, AI-augmentable VTMs and superteams may be considered bundles of tangible and intangible assets, team routines, and critical information and knowledge that meet the definition of SCA as provided by Barney (1991). For example, this study will attempt to show that AI-augmentable VTMs and superteams allow firms to create and sustain heterogeneous resources that are long-lived and difficult to reproduce. Furthermore, these VTMs and AI capabilities provide great potential for organizations to move beyond temporary competitive advantages (D'Aveni, Dagnino, & Smith, 2010; Sirmon, Hitt, Arregle, & Campbell, 2010). RBV and DC are at the epicenter of this study's exploration into the AI-augmentable VTMs, and their ability to deliver competitive advantages.

Occupational Information Network (O*NET)

How can scholars define the most vital skills for the 21st-century workforce at a fundamental member level (Sandall, 2023)? Mismatches between team members, discrepancies in skills, and low- and medium-functioning teams unable to perform to the level of high-functioning team (HFTs) or high-performing team (HPTs) are plagues on modern businesses focused on expanding VT and AI use (Hill, 2023). The promise of HMTs and the creation of superteams requires analysis at the essential work and skills level. What are the necessary job analysis factors, including WPEs and GWAs, required by future workforces (Hill, 2023)?

To begin this discussion, the study will first examine the type of job analysis system and structure best to use for this dissertation. The study's selected database and taxonomy is the O*NET-SOC. To examine why the O*NET is a suitable job analysis tool for identifying, documenting, and ranking HFVTMs, team augmentation, and superteaming dimensions, a thorough understanding of the model, tool, taxonomies, and usefulness is required. First, the U.S. Department of Labor (DOL) views O*NET as the national benchmark providing a shared language for occupational information (US Web Based Job Analysis 7 Department of Labor, 1993, p. 6). This common set of taxonomies and language allow this study to analyze multiple jobs across nearly every small and large organization. Next, O*NET specifies an amalgamation of critical job analysis research based on the aggregate knowledge and research on job analysis (Campion, Morgeson, & Mayfield, 1999). Finally, the O*NET content models' use of multiple descriptors allows for numerous inferences (Mumford & Peterson, 1999) required for this study.

The O*NET content model includes a database operated and maintained by the US DOL for job analysis. It is an online open-source platform and encompasses data for almost all occupations in the US through consistent collection and database revisions (Hanna et al., 2019). Burris, Jackson, Xi, and Steinburg (2013) describe O*NET as a persistently updated and wide-ranging database of employee and occupational characteristics of modern workers. The free database includes details of the Detailed Work Activities (DWAs), Intermediate Work Activities (IWAs), KSACs, and GWAs associated with numerous occupations. The ability of this study to use O*NET to identify and define the competencies and factors required for AI, VTMs, and employers to augment teams and create AI superteams in the current workforce is essential. O*NET can serve as a tool to categorize HMT and AI superteaming factors. This study determines the new and legacy O*NET-SOC factors to define AI and VTM augmentable behaviors and outcomes.

Taxonomy

O*NET origins were created from the Dictionary of Occupational Titles (DOT), a U.S. DOL job competencies tool crafted after the Great Depression. Containing tens of thousands of occupations and existing for more than 50 years, the tool specified information on worker temperaments, interests, training, and more (Dunnette, 1999). To overcome numerous deficiencies including too many jobs, lack of competencies required to be successful, difficulty in updating, overly job-specific job types, and a database structure that does not easily allow for the comparisons of jobs (Peterson et al., 2001) the Advisory Panel for the Dictionary of Occupational Titles (APDOT) and DOL developed O*NET to meet the next generation of employer and employee needs (Peterson et al., 2001).

O*NET was envisioned to provide job requirements, attributes, and contextual information about modern occupations yearly (Dye & Silver, 1999). The O*NET database contains definable variables describing job characteristics, occupation codes, and SOC. The model contains six comprehensive domains; three domains concentrate on variables relating to the job, and three relate to the employee. The key classifying framework of O*NET is a set of taxonomies containing occupational descriptors known as the O*NET content model (Tippins & Hilton, 2010). O*NET provides this study with an established theoretical framework founded on job and organizational research and principles to categorize, organize, and define the most critical types of occupational information. The O*NET model was developed to deliver a universal language of work that can be applied across all occupations, with the capacity to define occupations in multiple ways within a taxonomic classification system (Peterson et al., 2001).

O*NET uses worker-oriented and job-oriented descriptors that are classified into six domains. Worker-oriented descriptors, or competencies employee characteristics, requirements, and experience requirements. Job competencies are occupational requirements, workforce characteristics, and occupation-specific information. The O*NET structure provides this study with a model with an explicit focus on specific worker attributes and characteristics (Research Triangle Institute, 2007).

The O*NET taxonomy structure is hierarchical, with the abilities of one level nested in more general levels (Tippins & Hilton, 2010). O*NET abilities are employees' capability to complete various job tasks, verbal, physical, sensory, mathematical tasks (Tippins & Hilton, 2010). Employee requirements are descriptions of work-related characteristics that are developed through employee education, experiences, and training. The O*NET work characteristics category subdomains include skills, knowledge, and education (Tippins & Hilton, 2010).

O*NET Structure

The O*NET content model provides the conceptual foundation and framework for the job analysis requirement of this study. This framework identifies the critical details surrounding work by integrating these into a theoretically and empirically consistent model (O*NET, 2022). The O*NET content model provides job-oriented descriptors that address the character of occupations, worker-oriented descriptors focusing on the employee, cross-occupational descriptors delivering cross-sector and industry occupational information, and occupational-specific descriptors focusing internally on occupations (O*NET, 2022). These four descriptors are organized into six major domains focusing on critical attributes and characteristics of workers and occupations, including worker requirements, experience requirements, occupation-specific information, workforce characteristics, worker characteristics, and occupational requirements (O*NET, 2022).

The critical focus of this study is the occupational factors and requirements, or the comprehensive set of job elements that detail what each occupation requires (Sandall, 2023). For this study, HFVTMs (Hill, 2023) occupational requirements and other legacy factors will be utilized, as well as the development of any new AI factors. Occupational requirements include specifics about HFVTM activities required across HFVT occupations (Hill, 2023). The study expands on the O*NET approach of identifying GWAs, and a related set of work factors called WPEs, of HFVTMs to encapsulate the small to large types of job behaviors and tasks that HFVTMs perform. This study's use of O*NET allows it to develop a single set of descriptors to define AI factors, capabilities, and functionalities involved in VTM augmentation (Hill, 2023). This study will also include contextual variables such as the physical, social, or structural context of work that create demands on the HFVTM employee.

The definition of GWA for this study is HFVTM activities that are common across a HFVTM and VTs (Sandall, 2023; Hill, 2023). GWAs are likely to be executed by most HFVTMs (Hill, 2023). IWAs are HFVTM activities that are shared across many HFVTMs (Sandall, 2023). DWAs are unambiguous work activities performed across a small to moderate number of HFVTMs (Hill, 2023). In this study, DWAs are not defined within the organizational context or the work context, such as physical and social factors that guide the very nature of work. WPEs are related to the O*NET construct. However, they were created by scholars and applied researchers. WPEs are “foundational skills required by individuals to be successful irrespective of the job they are performing, or are required for successful performance within a job, irrespective of the person doing the job (Sandall, 2023; SkillsEngine, 2023)". WPEs and GWAs will be the driving goal of this study.

The O*NET structure includes over 974 occupations, with over 255 descriptor ratings for each occupation (Hanna et al., 2019). The O*NET structure is a suitable tool for this study because the Office of Management and Budget (OMB) requires all US government agencies to use and collect occupation-related information using a classification compatible with the O*NET-SOC (Office of Management and Budget, 2010). This study will add a new category of AI, AI-augmented VTMs, and those features that are most AI-able. The current O*NET-SOC structure includes four aggregate levels: 23 major groups, 96 minor groups, 449 broad occupations, and 821 detailed occupations. The O*NET taxonomy structure allows the study to define further a unique level of specificity appropriate for its groundbreaking purposes in superteaming and HMT augmentation.

Beyond a common language, structure, taxonomy, and descriptors, O*NET provides for specific workers' characteristics, or KSACs, that are enduring attributes and are critical to understanding, defining, and examining HMT augmentation and superteams. This study will begin the discussion on abilities and KSACS, or the largely long-term employee's fundamental capacity to complete a diverse set of diverse responsibilities (Carrol, 1993; Fleishman, 1982; Peterson et al., 2001) in chapter five. O*NET abilities are based on Fleishman's research and are stable, essential, and developable within the employee (Fleishman, 1975; Fleishman & Reilly, 1992; Peterson et al., 2001). O*NET abilities include primary level items such as cognitive, psychomotor, physical, and sensory abilities (Peterson et al., 2001). Secondary level abilities include verbal, reasoning, idea generation, quantitative, memory, perception, spatial, attentiveness, reaction time, physical strength, visual, and auditory abilities (Peterson et al., 2001). Abilities allow O*NET to organize link job task characteristics with the details required for successful job performance.

Knowledge within O*NET, again based on Fleishman's research, describes 86 areas of employee's ownership of factual and procedural information that is linked to task performance (Fleishman, 1975; Peterson et al., 2001). Knowledge is grounded in education, training, and on-the-job experiences that are specific and can apply to a wide range of jobs (Peterson et al., 2001).

Skills are illustrative of an employee's competency to perform fundamental and high-level tasks (Peterson et al., 2001). The separations of skills into basic and cross-functional types allow for a thorough understanding of how skills can account for content and process proficiencies that are required for performance across job contexts, problems, and employer types (Peterson et al., 2001). These content, process, problem-solving, social, technical, systems, and resource management skills are critical for AI-augmented VTMs, superteams, employers, and skill classification.

These four KSAC taxonomical descriptors allow for a GWA taxonomy within O*NET. This GWA aggregation of employee capabilities and behaviors, defined through O*NET, provides the basic principles for modern work. Future studies should further attempt to define DWAs that will be used in this research to examine legacy DWAs and HFVTM DWAs that are AI-able within the context of superteams and team augmentation. This study will focus on GWA and WPE taxonomy characteristics such as information input, mental processes, work output, interacting with team members, coordination, and team administration. Further, this study will dig deeper to examine the WPEs and GWAs in a scholarly attempt to rank and define the key AI characteristics that require reproduction within superteams and AI augmentable teams.

Chapter 3

Methodology

Overview

This paper has defined the study's theoretical underpinnings by reviewing the literature on HMTs, ODI, VTs, HFVTMs, job mapping, job statements, JTBN, O*NET, and AI. Furthermore, the literature encompassing the concept of superteaming using O*NET-SOC profiles to define AI WPE and GWA factors has been explored. The third chapter delivers methodological details proposed by the researcher for the execution of this study. The rationale behind using exploratory sequential mixed methodology using a qualitative tandem-interview, quantitative VTM performance instrument, quantitative importance versus frequency survey, and a quantitative ODI opportunity score survey instrument required for analysis into a rank-ordered AI investment profile will be made. This chapter describes the proposed participant selection process, data collection processes, and how validity and reliability to be achieved.

Worldview

Creswell (2014) advises that researchers distinguish their philosophical views or worldview that will ultimately guide the research. The researcher for this study advocates a pragmatic worldview. The pragmatic worldview ascends from activities, actions, and outcomes versus antecedent conditions (Creswell, 2014). By focusing on the research problem and all available approaches, the researcher uses this philosophy through an exploratory sequential mixed methods study. This study uses all available scholarly tools to focus attention on the RQs and propositions (Creswell, 2014) surrounding AI superteams, VTM augmentation, HMTs, the surrogate use of HFVTMs, and finally, the study's goal to derive knowledge on the opportunities that exist to use O*NET to define AI-augmentable O*NET-SOC GWA and WPE factors.

Organization of the Remainder of this Chapter

The proposed design of the exploratory sequential mixed method study is described in five principal segments that encompass this third chapter. The first segment of this chapter presents the RQs and propositions. The second segment of this chapter outlines the proposed exploratory sequential mixed method research design, variable design, the rationale for tandem interviewing, and the rationale for the ODI opportunity score and importance versus frequency quantitative survey instrument. The third segment outlines the study population of VTM participants, the proposed sample size, and the method to be used to cultivate participants. The fourth segment demarcates the proposed methods used for data collection, procedures, and statistical techniques that are employed. The fifth segment covers qualitative and quantitative ethical considerations as well as study validity, common method variance (CMV), and trustworthiness factors.

Research Questions and Propositions

To reiterate, the research questions that are guiding this study are:

RQ1. What is the effect of artificial intelligence augmentation on low-performing virtual team member performance?

RQ2. What is the effect of artificial intelligence augmentation on moderate-performing virtual team member performance?

RQ3. What is the effect of artificial intelligence augmentation on high-functioning virtual team member performance?

RQ4. Which high-functioning virtual team member O*NET-SOC profile factors have the highest outcome-driven innovation opportunity score for artificial intelligence augmentation desirability?

The researcher has identified seven propositions from which to explore these research questions. The researcher has chosen to use propositions in this study because the study is explorative and no test currently exists to test hypotheses (Creswell, 2014).

- *Proposition 0 – No O*NET-SOC profile components are significantly desirable for artificial intelligence augmentation and therefore do not play a significant role in virtual team member performance improvement.*
- *Proposition 1a – There are statistically significant O*NET-SOC profile components desirable for artificial intelligence augmentation that leads to low-level virtual team member performance improvements.*
- *Proposition 1b – There are statistically significant O*NET-SOC profile components desirable for artificial intelligence augmentation that leads to moderate-level virtual team member performance improvements.*
- *Proposition 2 – There are statistically significant O*NET-SOC profile components desirable for artificial intelligence augmentation that leads to high-functioning virtual team member performance improvements creating superteams.*
- *Proposition 3a – A definable O*NET-SOC profile consisting of legacy factors (GWAs and WPEs) can be created to define artificial intelligence augmented high-functioning virtual team members.*
- *Proposition 3b – A definable O*NET-SOC profile consisting of new factors (GWAs and WPEs) can be created to define artificial intelligence superteams.*
- *Proposition 4 – An outcome driven innovation rank-ordered O*NET-SOC profile index exists to guide the creation, investment, and research of AI superteams.*

The researcher has identified five conclusions based on literature from which to explore these research questions and propositions.

- *Conclusion from Literature 1 – High-functioning virtual team members are an appropriate measure for analyzing human-machine teaming.*
- *Conclusion from Literature 2 – High-functioning virtual team members are an appropriate measure for analyzing team augmentation and superteams.*
- *Conclusion from Literature 3 – High-functioning virtual team members are an appropriate measure for analyzing artificial intelligence human superteams.*
- *Conclusion from Literature 4 – Artificial intelligence tools and capabilities added to a team are at least as good as human virtual teams.*
- *Conclusion from Literature 5 – Artificial intelligence tools and capabilities added to a team are better than human-only virtual teams.*

Research Design

This study utilizes an exploratory sequential mixed method research procedure. The procedure mixes two data forms into one study to capitalize on the qualitative method's open-ended exploratory information discovery data and the close-ended data found in the quantitative method. (Creswell, 2014). The blending of data allows the researcher to reduce limitations and capitalize on the strengths of each method (Creswell, 2014). The researcher selected this procedure because it delivers a stronger understanding of the RQs than a single method on its own (Creswell, 2014). Creswell (2014) defines mixed methods research as the rigorous collection, analysis, and procedure of applying qualitative and quantitative tools to integrate, connect, and merge distinct data to address a study's RQs and propositions (Creswell, 2014). Mixed methods research began in the late 1980s and finds it roots in researcher analysis in distinct fields such as evaluation, education, business, sociology, and health sciences (Creswell, 2014). This method provides a complete understanding of this emerging topic, allows for the integration of previous theoretical foundations on HMTs and VTMs, and incorporates individual perspectives vital to understanding VTM augmentation, O*NET-SOC profiles, and superteaming.

This study performs qualitative tandem interviews and a quantitative survey assessment centering on VTMs in the U.S. and worldwide western governments and firms with populations exceeding 500. The model variables subsist of VTMP, AI augmented activities index (AIA-AI), and VTM task perception (VTM-TP) as measured through the ODI opportunity score. The model's dependent variable is AIA-AI and VTMP as the independent variable. Virtual team member task perception of fundamental and definable O*NET work profile components will be the moderating variable for AI-augmented VTM performance and superteam creation. The moderating variable is measured through an ODI Opportunity Score.

Independent Variable

The independent variable will be called VTM performance (VTMP). VTMP is measured by assessing the performance of a VTM prior to AI augmentation. VTMP is the independent variable for the quantitative and qualitative analysis. For the quantitative survey, measurement of VTMP is derived using a novel VTMP self-assessment survey instrument. The researcher begins development of the novel VTM performance questionnaire using new qualitative data gathered from VTMs, leaders, and experts post-COVID-19. The novel VTM performance survey is fully developed using 30 qualitative expert interviews, a prior validated team member self-assessment report survey from Andersson et al. (2017), and scholarly research on VTMP. The researcher primarily uses qualitative interviews and quantitative pilot testing to build this unique survey instrument to accomplish this study's goals. The survey will result in statistically significant scores evaluating VTMP, and the scores will be split into three categories: low-VTMP, moderate-VTMP, high-VTMP using equal cut points from the representative survey respondents at the 33.3rd and 66.7th percentiles. For the qualitative tandem interviews, the interviewee will ask the survey respondent to evaluate their VTMP.

Dependent Variable

AI augmented activities index is the dependent variable for the study. The dependent variable is called AI augmented activities index (AIA-AI). The measurement of AIA-AI is derived from the ODI opportunity score rankings for specific work factors, as discussed in chapter two. Based on ODI literature, VTM-TP opportunity scores of 10.00 or greater is designated as possible AIA-AI factors at each VTM performance level (Ulwick, 2011). For the qualitative tandem interviews, the interviewee asks the survey respondent to evaluate to what degree VTMP would be increased through a specific AI-augmentable activity. For the quantitative survey, the study uses the ODI equation listed below (Ulwick, 2011).

$$\textbf{Opportunity Score} = \textbf{Importance} + (\textbf{Importance} - \textbf{Satisfaction}) \qquad \textbf{(2)}$$

Equation 2 - Opportunity Score

AI augmented activities fall into four categories of possible VTMP improvement based on: no opportunity for AI improvement (9.99 or less), solid opportunity for AI improvement (10.00 – 11.99), high opportunity for AI improvement (12.00 – 14.99), and extreme opportunity for AI improvement (15 or above). AIA-AI characteristics of HFVTMs capable of a 10 or greater improvement are considered superteaming factors. The use of linear regression statistical evaluation of the AI-augmented activities using VTMP and ODI scores is discussed later in this chapter.

Moderating Variable

The moderating variable will be Virtual Team Member Task Perception (VTM-TP) measured through an ODI Opportunity Score. VTM-TP O*NET GWA and WPE activities will be first reduced to the relevant factors using the qualitative tandem interview portion of this study. VTM-TP will first be quantitatively analyzed for this study through the importance and frequency scores. As discussed in chapter two, the criticality and frequency of tasks is critical to understanding which AI-augmentable O*NET factors are most impactful to VTMP. This study will rank order the VTM-TP O*NET-SOC GWA and WPE factors using the combination of the importance and frequency scores to determine a priority list. VTM-TP will consider O*NET activities with a score 5 or greater for frequency and 5 or greater for importance as viable AI-augmentable activities.

In the unique case of superteam creation, the moderating variable will also be VTM-TP. VTM-TP will be analyzed through the importance and frequency scores and the ODI Opportunity score. As discussed in chapter two, the criticality and frequency are critical to understanding which AI-augmentable O*NET-SOC factors are most impactful to VTMP. VTM-TP O*NET-SOC GWA and WPE factors that originate from HFVTMs and are capable of an ODI Opportunity Score greater than 10, will be referred to as viable superteam factors.

Control Variables

The researcher collects multiple data points for the survey including VTM experience, frequency, tenure, type, location, leadership level, industry, education, and demographic data. Because the goal is to establish the most generalizable proxy and method of analysis for HMTs and superteams, only VT experience will serve as a control variable. However, given enough data the researcher will explore all variables as each have been shown to impact VTM performance, VT faultlines, and VT subgroup formation (Carton & Cummings, 2012; 2013). For example, VTM tenure may be critical to control as VTMs must have a suitable time to operate within a VT environment (Meyer, Glenz, Antino, Rico, & González-Romá, 2014).

Conceptual Diagram Variables

Figure 2 below shows the conceptual diagram for this study. The exploratory sequential mixed methods procedure requires a clear visual model to comprehend the study's details and research flow (Creswell, 2014). Additionally, this study will test for a direct relationship between the moderating variable of VTM-TP and the dependent variable of AIA-AI using the data collected in the quantitative survey.

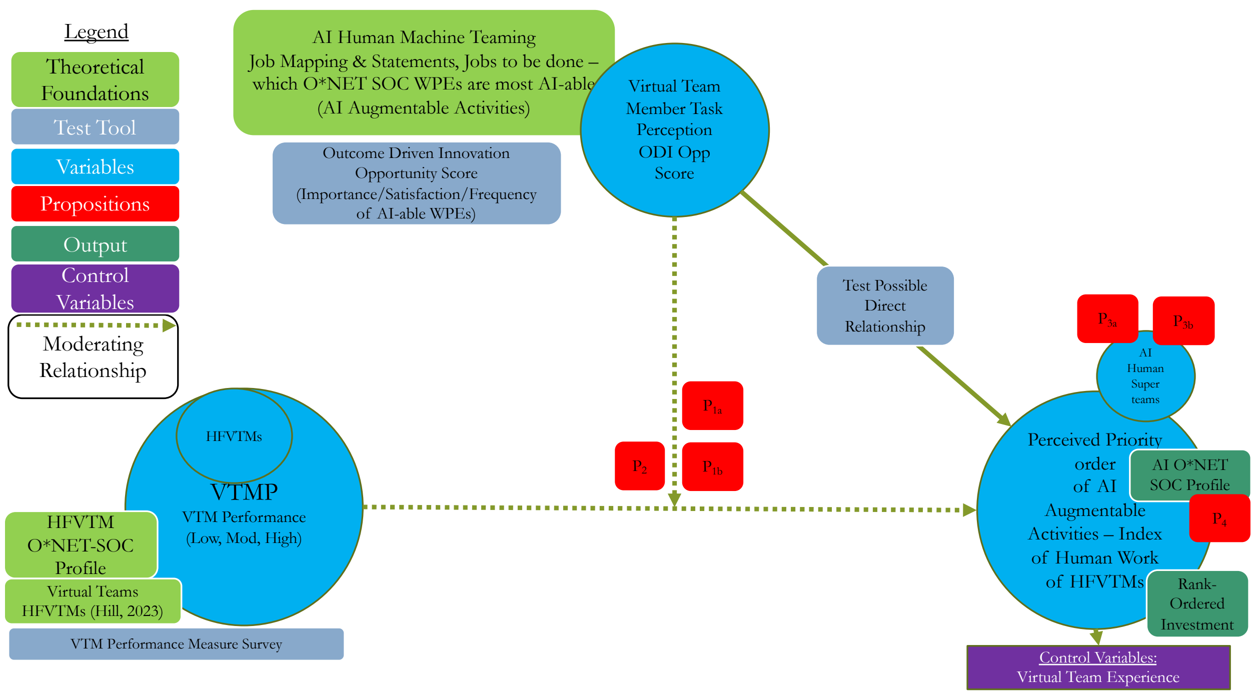


Figure 2 - Study Conceptual Diagram Flow and Variables

Research Approach

To assess VTMP improvement possibilities, rank-ordered AI HMT augmentation potentials, and O*NET-SOC AI teaming WPE and GWA factors, the study will require an exploratory sequential mixed method approach (Hill, 2023). This exploratory sequential mixed method approach supports the researcher's worldview. The pragmatist often uses mixed methods to understand and then test theories, frameworks, and models to decipher the world around them (Creswell, 2014). The exploratory sequential mixed methods design begins with a qualitative exploration of the data points and inquiry, followed by a quantitative stage (Creswell, 2014). The quantitative stage will build on the qualitative stage to cultivate appropriate measurements from small sample populations to understand if the data from a minor population is expandable to large population samples (Creswell, 2014). The study builds a descriptive survey using the knowledge gained from the qualitative interviews with VT and AI experts at the center of the field.

This study develops and implements a qualitative tandem interview exploration in stage one. This tandem interview process, also known as two-on-one interviewing, follows the interview processes described by Matteson and Lincoln (2009) and use Monforte and Úbeda-Colomer (2021) to alleviate possible methodological issues. Following the exploratory sequential mixed method approach, the quantitative survey instrument utilizes the stage one data to build the survey instrument. This process is required to understand the moderating impact of VTM task perception on AI augmentation and VTMP. The research methodology allows for a well-proven, all-inclusive, exhaustive, and practical method that will allow the researcher to maximize understanding of the expansive ODI job opportunity score data (Ulwick, 2011).

Population and Sample

VT research over the last 15 years has overwhelmingly occurred in laboratory-type settings with student-team populations (Gilson et al., 2014). This study uses real and diverse VT and AI members, experts, and leaders in field-type settings to ascertain key aspects vital to HFVTMs, AI augmentation, HMT, and superteams. The research population includes participants from a minimum of 20 countries from across Europe, Australia, Canada, and the U.S. The population includes full and hybrid VTMs, VTMs with experience ranging from a minimum of two years to over 20 years, and VTMs with no VT leadership roles to senior executives and subject matter experts (SMEs). Additionally, the VTM population includes participants from over 14 industries with education levels ranging from a high-school diploma to the doctorate level. Finally, this study includes low-, moderate-, and high-functioning VTMs to ascertain AI needs and VTM differences in O*NET-SOC GWA and WPE profiles based on performance and other factors.

For this study's qualitative study, the researcher evaluates the required number of interview participants based on McIntosh and Morse (2015). To ensure data adequacy and sufficiency of the data during the semi-structured interviews where every participant is asked identical questions a sample size of 30 is required. The use of 30 participants allows for significant academic analysis by the researcher and for the data derived from the qualitative interviews to be transformed into quantitative survey instrument to be discussed below (Morse & Niehaus, 2009). Therefore, the qualitative pilot study utilizes seven participants including three AI and four VT experts. The exploratory sequential, semi-structured interviews will include 23 participants for a total of 30 interviews (McIntosh & Morse, 2015) allowing for adequate quantitative analysis.

To ascertain the quantitative sample size required for this research study, academic and statistical research suggests analyzing the population size as a complete set. This study focuses on VTMs in businesses and governments with the capability to have multiple VTs, AI augmentable teams, and are likely to execute AI integration projects within virtual teaming in the future. The study will assume that the firm's size can be used as a proxy for the existence of AI-integration and virtual teaming conditions. Therefore, a cutoff of 500 employees will be used to estimate the population of firms for this analysis. According to NAICS of 2021, the number of U.S. businesses with more than 500 employees is 42,977 (NAICS, 2021). The first estimate for sample size calculation uses Yamane's (1967) formula (Equation 3).

$$\mathbf{n = N / (1 + N{*}e^2)} \qquad \mathbf{(3)}$$

Equation 3 - Yamane's (1967) Sample Size Formula

For Yamane's (1967) formula n is the sample size for this study, N is the population size (43,000) and e is the level of precision (0.05). When this calculation is performed, n equals 397.

For an additional assessment this study will now calculate the required sample size using Cochran's (1977) formula for estimating the sample. Because this study does not use categorical data, Cochran's (1963) sample size formula is also appropriate (Equation 4) (Israel, 1992 & Israel, 1992; Bartlett et al., 2001).

$$\mathbf{n_0 = (Z^2{*}p{*}q)/e^2 \quad or \quad = t^2s^2/d^2} \qquad \mathbf{(4)}$$

Equation 4 - Cochran's (1963) Sample Size Formula

For this non-categorical data study, a five percent margin of error is within guidelines and is acceptable (Krejcie & Morgan, 1970). This study will assume a confidence level of 95 percent, a 0.5 maximum variability, a margin of error of 0.05, and a Z^2 equal to 1.960 representing the abscissa of the normal curve that cuts off an area alpha at the tails. Bartlett et al. (2001)

demonstrates that for populations above 43,000, the sample size should be 385. This calculation is in line with Yamane (1967).

To double-check the above assessment, the sample size reasonableness G*Power (Faul, Erdfelder, Lang, & Buchner, 2007) will be used to ascertain the statistical power of the sample size of 397 with an alpha of 0.05 and a power of 0.95. At a power of 0.95 this means there is a 95 percent chance of finding an effect if there is one. The Cohen (1988) effect size formula for multiple regression is defined as $f^2 = R^2 / (1 - R^2)$. Assuming a medium effect as defined by an R^2 of 0.13, the f^2 should be near 0.1494 (Cohen, 1988). To achieve that, a minimum sample size of 74 is required. Therefore, the researcher concluded that a quantitative sample size between 385 and 397 is acceptable for this analysis. This researcher expects a response rate of around 20 percent to 30 percent. A 25 percent response rate would require 1,588 surveys to be distributed. For this study to meet this requirement, the researcher begins by delivering a total of 1,600 surveys in 400 count chunks. Additional survey invites were sent until the study quota was met.

The quantitative study utilizes a pilot survey to estimate the construct validity and the reliability of the VTM performance, ODI analysis, and O*NET survey instruments. The academic literature analyzing pilot study sample size is not clear and provides a range of guidelines for study leads to consider. The use of ten participants is recommended as a quantitative pilot study's minimum size for a study sample size of 100 (Treece & Treece, 1982). Multiple research citations suggest pilot studies use between 12 and 30 (Isaac & Michael, 1995; Hill, 1998; van Belle, 2002; Julious, 2005). An attempt to understand the ramifications of Principal Component Analysis (PCA), Exploratory Factor Analysis (EFA), and Confirmatory Factor Analysis (CFA) statistical analysis techniques is also required. However, because the PCA, EFA, and CFA analytical guidelines are not conclusive, and the number of O*NET survey

ODI questions is so large, the pilot test may not be able to fully determine VTMP and other statistical relationships until the full survey.

Literature supports multiple sample ratios to include 2:1 (Kline, 1979), 3:1 (Cattell, 1978), 5:1 (Gorosuch, 1983; Bryant & Yarnold, 1995), and 6:1 (Cattell, 1978). This study uses Dochteman and Jenkins's (2011) computer simulation research showing that a sample size of 19 is adequate in 90 percent of the testable cases. This study utilizes 20 responses for the quantitative pilot study portion of this research. The researcher anticipates an elevated response rate for the pilot study because the participants will originate from a random selection of members from the researcher's individual network of over 150 VTs, as well as from the tandem interviewer VT network that the researcher is a member of as well. Because of these connections, 70 surveys will be distributed in batches of 20 as part of the quantitative pilot study until 20 usable pilot test responses are received. Additional responses received after the pilot study are automatically added to the full study count assuming no statistically significant changes to the survey.

Selection of Participants

The study involves sending a survey instrument to VTMs to test the propositions and RQs proposed in this study. A VTM is a virtual team member of an organization virtually responsible for individual and team operations, functions, and activities within a firm (Piccoli, & Ives, 2004). A sample of 20 from the more than 150 VTMs in the researcher's personal and co-tandem interviewer network of VTMs were selected to conduct the qualitative tandem interview and the quantitative pilot study. This database contains VTMs from diverse industries, governments, and types. The selection of study participants was chosen from firms within the researchers and co-tandem interviewer database within U.S. governments, NATO governments, and U.S. businesses including the oil and gas, defense, financial, medical, and telecom industries.

For the quantitative survey pilot study, the researcher utilizes a random sampling process by assigning potential respondents' unique numbers and then randomly determining participants using the random number generator in the Microsoft Excel macro. This study must address nonresponse bias. Nonresponse bias centers around specific demographics or specific business units responding, resulting in a study population with skewed population characteristics not reflected in the sample characteristics (Creswell, 2014). One such example for this study is that only VTMs with strong VT performance respond. However, two essential factors are critical to understanding and mitigating the potential for nonresponse bias (Groves & Peytcheva, 2008). According to Groves and Peytcheva's (2008) literature review, nonresponse bias is reduced when the sample population has increased experience with the survey requestor and increased when the population is generalized. This study will take advantage of two populations that are in multiple ways connected to the researcher. The VTM aspect of the research is less generalizable and therefore the study expects nonresponse bias to be low.

Instrumentation

This exploratory sequential mixed methods study began with a qualitative tandem interview to use the findings from this stage to build the quantitative measures. According to Creswell (2014), the researcher must pay vigilant attentiveness to the qualitative data analysis steps to successfully define the proper conclusions to build on in the quantitative stage (Creswell, 2014). The goal of this process is to conclude if the qualitative findings, themes, and codes are generalizable to the larger sample population. Additionally, the researcher uses a semi-structured interview structure in combination with tandem interview process to gain as much insight into the topic as possible. The tandem interviews are descriptive-interpretative as defined by McIntosh and Morse (2015).

This study develops and utilizes a quantitative survey to collect the VTMP and ODI importance, frequency, and satisfaction data. The survey is created, refined, and pilot tested to collect data on VTMs, their performance, and the moderating factor of AI VTM augmentation. The researcher develops the full survey based on previously validated VTM performance and O*NET questions, the qualitative interview key takeaways, and newly established questions on AI GWAs and WPEs. All legacy and novel questions within the final research study measuring ODI importance, frequency, and satisfaction are evaluated for validity and reliability prior to distribution to the research population. Furthermore, the opportunity for bias is minimized by confirming that the survey questions are unambiguous. The use of a semi-structured interview style, within an exploratory sequential mixed methods study, to create a quantitative survey instrument has strong academic foundations (McIntosh & Morse, 2015). These qualitatively constructed questionnaire's yield useful data and have strong content analysis (McIntosh & Morse, 2015).

Tandem Interviewing and Coding

Traditional qualitative one-on-one interviews typically utilize a solitary interviewer as researchers do not regularly ask how many interviewers should be considered (Monforte & Úbeda-Colomer, 2021). However, tandem interviewing, sometimes referred to as two-to-one interviewing, may allow for unexplored benefits for researchers (Monforte & Úbeda-Colomer, 2021). Monforte and Úbeda-Colomer (2021) referred to these unexplored benefits as tinkering or consistent questioning within each moment of the research interview that allows for coherent researcher adjustment for what to ask, what is appropriate, and what is best. This researcher flexibility is in line with this study's researcher pragmatic worldview and with the scholar's malleable methodological approach. Just as face-to-face interviews are giving way to digital interviews (Thunberg & Arnell, 2021), tandem interviewing offers a unique opportunity beyond the one-on-on, dyadic, group, and focus group interviewing to address critical VTM attributes jointly with another researcher investigating HFVTMs (Monforte & Úbeda-Colomer, 2021).

Interviewees are humans that are conversational beings built on conversing through languages (Monforte & Úbeda-Colomer, 2021). As such, interviewing is a social activity that, when viewed through social constructionism, allows for engaging discussion to develop a collaboratively constructed knowledge about the social world (Smith & Sparkes, 2016). This method allows the researcher to use consistent discussion to fuse and understand different actions and understandings necessary for this exploratory phase of this study. This study uses the concepts, practices, and framing outlined by Monforte & Úbeda-Colomer (2021), combined with the semi-structured style of Matteson and Lincoln (2009), to guide the qualitative tandem-interview process. In addition, this style increases qualitative interview validity as some of the participants may know one of the interviewers. As shown in Matteson and Lincoln's (2009) investigation into teachers and middle school students, when one researcher has a rapport with the participant, tandem interviewing is a possible efficient means to collect data to avoid any influence from previous researcher interactions and ethics of care with the interviewee (Matteson & Lincoln, 2009).

Qualitative analysis is critical to developing initial insight and a basic understanding of how scholars can use HFVTMs as a proxy for AI Superteams for VTM and HMT augmentation analysis. To begin the qualitative interview process, a series of tandem interview questions are developed and pilot tested with a fellow HFVTM researcher to analyze this dissertation's fundamental RQs and those of HFVTMs. This study develops a series of questions, follow-up questions, and a tandem-interview protocol based on the combined HFVTM and AI RQs. The original proposed tandem interview questions, formulated from job statements (Ulwick & Bettencourt, 2008) and concept mapping (Moon, Hoffman, Novak, & Canas, 2011) are listed below. These semi-structured questions were updated during the tandem interview pilot testing and finalized prior to the final qualitative tandem interviews. The final tandem interview questions and semi-structured script is in Appendix B.

1) HFVTMs – Begin by setting a definition and a context for a high-performing virtual team member using Andersson's (2017) 16 items for the interviewee.
   a) Do you agree/disagree with this definition of a high-performing virtual team member, or would you add anything to it?
2) Continue by setting a definition and context for high-functioning using Sirgy's (2001) seven quality of work life characteristics for the interviewee.
   a) Do you agree/disagree with this definition of a high-functioning virtual team member, or would you add anything to it?
   b) How do you describe high-functioning versus high-performing (ask interviewee, have them define)?
   c) Have you worked on a high-functioning / high-performing Team?
3) Do you feel you would group along quality of work life or pre-group along quality of work life?
   a) How do you as a virtual team member view quality of work life, well-being?
4) Is it desirable to be on a high-functioning virtual team member or / high-performing virtual team member? (They may not want to be on high-functioning virtual team but want to be on

high-functioning virtual team (Transition to high-functioning virtual team member only for rest of interview)

5) O*NET questions
   a) What makes your job as a virtual team member, or certain parts of it, challenging, troublesome, or frustrating?
   b) What makes your job as a virtual team member, or certain aspects of it time consuming?
   c) What causes your data, job, and work activities to go adrift, deviate, or be derailed?
   d) What aspects of your virtual team member job are wasteful?
6) What capabilities does a virtual team member need that a non-virtual team member may not need?
   a) How do you know when to ask someone a question/coordinate/collaborate?
7) It sounds like you're describing certain functions that you are happy with or not (provide examples based on O-NET workplace essentials). Would you be okay with AI performing these functions or solving these issues at the same level or 20 percent better than a human (partnered high-functioning virtual team member)?
   a) Would you use an automation framework? (Is the removal of the work process and connections helpful (ex: Docusign)

After researching multiple coding software programs for the qualitative portion of the mixed methods dissertation, this study uses MAXQDA for coding. The ability to process audio recordings, code, create researcher memos, perform qualitative data analysis, and merge with future quantitative data collections is ideal for the mixed methods portion of this study (MAXQDA, 2022). The software has multiple unique features that allow easy use and research into dissertation RQs.

MAXQDA software was chosen for a variety of scholarly and performances reasons. The software can use various data formats from documents, Microsoft Excel tables, PDFs, JPEGs, website data, audio, video, and even YouTube and Twitter input (MAXQDA, 2022). Other features, including transcriptions of audio and video recordings and data analysis features for qualitative and quantitative analysis in one tool, deliver the optimum performance for this researcher's mixed methods study (MAXQDA, 2022). This study utilizes the audio software and transcription service TEMI.com.

The study utilizes content and thematic analysis and coding (Creswell, 2014). Coding analysis includes identifying early connections and insight into critical study areas (Creswell, 2014). Primary tandem interview themes include HMT, superteaming, HFVTMs, AI, and team augmentation. Secondary themes include business operations, stress, communication technologies, AI types, knowledge, and resources.

The researcher uses a four-step process to initially delimit legacy O*NET-SOC GWA and WPE factors. First, O*NET-SOC GWAs and WPEs are reviewed through two seminal O*NET experts using the technique for order of preference by similarity to ideal solution (TOPSIS) method. All TOPSIS categories are equal weighted, backed by literature, and ranked on a score from one to ten for ease of subject matter expert evaluation and future statistical analysis. Total WPE scores above 80 percent are retained for survey analysis. Second, any single WPE and GWA TOPSIS category with a rating above an 80 percent threshold are additionally retained for survey analysis. Third, face validity testing of all WPE and GWA factors using the qualitative expert panel is performed with a threshold of 80 percent agreement in WPE and GWA factors. Finally, a second phase filter for all WPE and GWA factors is performed to rank factors according to their AI-ability using AI solution type and the Gartner Hype Cycle.

Survey Instrument

The descriptive survey instrument combines a series of ODI opportunity score questions, importance versus frequency score questions, and VTM performance survey questions created by the researcher into a single survey instrument (Appendix D & E). By performing a pilot test of this novel survey instrument, the researcher can test for CMV, validity, and reliability (Creswell, 2014). The development of the survey instrument utilizes the qualitative coding, theming, and O*NET-SOC factors to fit the sample population (Creswell, 2014).

The survey first uses a new VTM performance measurement survey to identify low-, moderate-, and high-performing VTM using questions developed during the qualitative interviews and adapted from 16 validated performance Andersson et al. (2017) questions (Appendix D1). Next, the researcher uses ODI opportunity score questions and importance versus frequency score questions covering the O*NET-SOC factors to identify statistically significant profile component differences on what HFVTMs vote for versus lower performing non-HFVTMs. The researcher expects to identify that there are different factors the low-, moderate-, and high-performing VTMs want help with within the teaming environment.

The importance and frequency O*NET task data is used to identify the VTM-TP augmentation opportunities and what AI developers can contribute to performance (Appendix E). To identify what is profitable for AI innovation, the VTM-TP questions are used to identify what factors contribute to performance and which tasks are the most difficult to perform. The ability of the study to identify the importance of the O*NET-SOC profiles WPEs and GWAs, and how satisfied different VTMs are with them is essential to create this study's rank-ordered AI augmentable index.

Procedures & Data Collection

This study's pilot study and quantitative survey are collected using Qualtrics, the online survey website. The Qualtrics participant requests are sent out via Qualtrics, email, social media, LinkedIn, and company and government network portals. Each invite includes instructions for the survey, respondent rights, and directions to the Qualtrics survey. All necessary data for the study, pilot study, and analysis are collected from the Qualtrics online survey. Cooper and Schindler (2006) show that online surveys are a valuable means to rapidly collect data, increase response rates, and share information with the respondent. The use of a random drawing for gift cards are not offered to increase participation rates. Research on AI bots, discussed in chapter four, demonstrates that while incentives increase participation rates in surveys (Cooper & Schindler, 2006), AI bots increase the risk to data quality greatly. Finally, all participants will be instructed to use this study's definitions of a VT and VTM.

Data Analysis

The pilot and final study utilizes JASP and Microsoft Excel to conduct the data analysis portion. JASP is an acronym for Jeffreys' Amazing Statistics Program, a gesture to Sir Harold Jeffreys, a famous Bayesian statistician. JASP allows the researcher to dissect the moderating and mediating variable interaction between the dependent and independent variables. Multiple researchers confirm the use of JASP in understanding variable interactions, such as those found in moderating and mediating variable relationships (Agawin, 2020). This statistical tool is appropriate for this study as it is developed and supported by the University of Amsterdam (Agawin, 2020). Furthermore, research shows that both Excel and JASP are useful for analyzing the importance, frequency, and satisfaction connections that are analyzed in this study (Agawin, 2020).

This study uses PCA, common EFA, CFA, clustering analysis, classical Linear Regression analysis, T-Tests, unidimensional reliability, and correlation as statistical tools to conduct this study's data analysis. PCA is used as a data reduction technique to eliminate items with an examination of the linear combination of all variants. PCA assumes that variance across variables is shared and performs the data computations without respect to the primary hidden structure of the variables (UCLA, 2022). The ability to decipher the maximum amount of variance among the set of variables with the purpose of ascertaining the minimum number of linear functions necessary to explain the total variance is required. EFA serves as the primary statistical tool to evaluate VTMP and HFVTM survey question factor analysis and loading. Using EFA, which recognizes that the model may contain both shared and unique variance across variables, allows for a more thorough understanding of the theoretical framework that conceptualizes the fundamental structure of the variables (UCLA, 2022). CFA is appropriate for this study when investigating whether the theoretical model and its relationships is consistent with the data collected.

Overall factor analysis allows for a more thorough mapping of latent constructs and variable effects, increase the analyses validity and reliability, and allows for a greater understanding of the measures at play within the study. The equation for EFA and CFA is below (Equation 5). Component loadings and EFA factor loadings are represented by a_{ij} and considered strong if above 0.6.

$$X_i = a_{i1}F1 + a_{i2}F2 + a_{ij}Fm + e_i \qquad \textbf{(5)}$$

(aij is component loadings; m = # of factors; e = unique variability)

Equation 5 – Generalized Factor Analysis Equation

PCA assumes there is no unique variance with the total variance equal to the common variance. However, EFA assumes that the total variance can be divided into common and unique variance (UCLA, 2022). PCA, EFA, and CFA will be used together because this study tests instruments containing both well-specified models, novel models, and an initial data reduction with possible low levels of unique variance.

Although this study uses the O*NET importance and frequency scores to determine VTM-TP first, the study also performs an ANOVA and linear regression analysis between low-performing VTM, moderate-performing VTM, and HFVTM performance scores and the ODI O*NET-SOC WPE and GWA Opportunity scores to assess statistical significance and proposition 1a, 1b, and 2. Cluster analysis, or the process of identifying natural groupings inside multidimensional data, will help the research identify the O*NET profiles based on similarity measures (Dubes & Jain, 1980; Madhulatha, 2012). Proposition 3a and 3b will be determined using the cluster analysis technique used by the seminal O*NET experts. Additional statistical analysis and results are discussed in chapter four.

Ethical Considerations

The researcher applied for and received an Institutional Review Board (IRB) exempt application for this study that seeks a waiver (Creswell, 2014). The study collects all research data anonymously, and no company, personal, or government identifying data is collected. Furthermore, this study does not collect personal data about the survey respondents. For the qualitative tandem interview informed consent will be requested at the beginning of all tandem interviews (Creswell, 2014). Each subject is read the informed consent statement from Appendix F. At the end of each interview, the interviewer notes if the subject completed all questions voluntarily and if there were any issues with the questions. Finally, this study's researcher has successfully completed online ethical research training offered through the Florida Institute of Technology by the Collaborative Institutional Training Initiative.

Researcher Positionality

This study's researcher is a government civilian aerospace engineer, VTM, and VT leader within the U.S. The researcher has more than 22 years of leadership, VT, and software experience in Defense and has held vital AI roles within the U.S. government. The researcher has also been a part of multiple VTs, often as both a leader and a member, including roles within and outside of the U.S. for years at a time. Because of this vast VT and AI experience, the researcher has exceptional insight into the factors affecting VTMs, VT augmentation, human-machine teaming, and AI technologies.

Validity and Trustworthiness

This study uses an exploratory sequential mixed methods phased approach to develop an understanding of the study topic and the instruments. The researcher utilizes academic literature, scholarly experience, and exploratory qualitative discussions to develop an initial version of the qualitative tandem interview questions. These questions are adapted from previously published research and developed by the researcher to assess the research topic and the dependent, independent, control, and moderating variables.

Upon completion of the qualitative portion of the mixed methods analysis, a second phase enveloping the quantitative survey instrument was developed to exhaustively research the importance versus frequency and ODI opportunity scores for relative AI O*NET-SOC factors. These questions are based on qualitative tandem interviews, previous research, and researcher experience. The importance and frequency questions seek to elucidate fundamental VTM and HFVTM AI-augmentable work processes and the moderating effect of AI augmentation on the dependent variable of AIA-AI. The ODI opportunity score portion of the quantitative survey seeks to identify the importance and satisfaction scores for the fundamental AI-augmentable O*NET-SOC factors using the tenets of ODI (Ulwick, 2011).

The researcher assembled an expert panel of VT and AI members to establish face and content validity in the initial pilot study survey instrument. The expert panel consisted of four VT experts and three AI experts with at least an average of a decade of experience. The panel members were not compensated for their participation. The recommended changes to the pilot survey instrument were incorporated into the survey, and a pilot study was performed. Typical questions in this pilot study centering on HFVTM WPEs and GWAs were developed in collaboration with two O*NET thought leaders and experts with over 20 years of experience.

Face validity is established by the pilot test panel, independent discussions with O*NET-SOC experts, and survey responses. Face validity is established for each question in the survey. Expert discussions to date, including VT experts, O*NET-SOC leaders, AI experts, and VT seminal authors, support the premise behind this study, the challenges within organizations to increase performance and show ROI on AI. These experts agree that the study's RQs and propositions are challenges in academic research and applied science management arenas.

Content validity is established using the content validity ratio (CVR) first proposed by Lawshe (1975). CVR is a widely used method for researchers to calculate content validity (Wilson et al., 2012). For an expert panel of seven members and a P=0.05, this study expects to exceed the minimum value of 0.741 for CVR (Wilson et al., 2012).

This study examines the component factor analysis using the PCA, EFA, and CFA to evaluate the construct validity, including discriminate and convergent validity. The study uses the PCA, EFA, and CFA assessment of the instrument's reliability using the Cronbach Alpha and

McDonalds Omega coefficients. When using ODI and importance and frequency scales, the Cronbach Alpha coefficient is an appropriate reliability measure (Whitley, 2002; Robinson, 2009). The Cronbach Alpha coefficient quantifies reliability for measures with multiple items and is the most widely used internal consistency measure (John & Soto, 2007).

The study involves VTM's self-reporting quantitative survey methodology, and therefore the researcher manages and addresses common method variance (CMV). Given the challenge of measuring performance augmentation against the moderating variable of VTM-TP to examine the opportunity score of work, the survey remains the best vehicle to achieve the research objectives. To address CMV, the study uses a large number of surveys, varies survey format type, and varies CMV question style. Varying quantitative survey question type is shown to reduce CMV (Chang et al., 2010). The researcher varies survey response formats using both matrix & drop-down menus to alleviate additional CMV methodological concerns (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003).

Chapter 4

Findings

Overview

This exploratory sequential mixed methods research aimed to construct a scholarly basis for using HFVTMs as a proxy for VTM augmentation, human-machine teaming, and superteam analysis at a fundamental work level. This analysis intended to demonstrate how low- and moderate-performing VTMs can be augmented with AI, how HFVTMs can be augmented with AI to create superteams, and what fundamental O*NET-SOC GWA and WPE factors AI should perform to provide maximum ROI. The exploratory sequential mixed methods research includes five main phases: O*NET expert panel review, qualitative tandem interviewing pilot study, master qualitative tandem interviewing, quantitative survey pilot study, and master quantitative survey. The subsequent sections describe the outcomes and findings from each phase and the statistical support for the propositions.

Research Questions and Propositions

To reiterate, the research questions that are guiding this study are:

RQ1. What is the effect of artificial intelligence augmentation on low-performing virtual team member performance?

RQ2. What is the effect of artificial intelligence augmentation on moderate-performing virtual team member performance?

RQ3. What is the effect of artificial intelligence augmentation on high-functioning virtual team member performance?

RQ4. Which high-functioning virtual team member O*NET-SOC profile factors have the highest outcome-driven innovation opportunity score for artificial intelligence augmentation desirability?

Expert Panel Findings

A preliminary set of tandem interview questions is developed using the exploratory sequential mixed methods literature review, O*NET and AI expert panel discussions, and the author's experience. The researcher refined these preliminary questions with the co-tandem interviewer and dissertation committee. The goal of the refined questions was to build high-functioning VTM O*NET-SOC survey questions, a qualitative scholarly backing for QWL-based VTM subgrouping, and to explore and understand how to use HFVTMs as a proxy for human-machine teaming and superteam creation. Finally, the researcher aimed to investigate possible AI-able O*NET factors specific to AI and human-machine teaming.

The O*NET-SOC survey required convening a panel of O*NET experts to review, establish face and content validity, and delimit the number of factors addressed by the qualitative interview. The study required the author to delimit the number of O*NET factors due to the overwhelming size of the combined taxonomy and to reduce the length of the master survey. During discussions with two seminal O*NET experts with a combined experience of over 40 years and the committee chair, the expert panel agreed to examine GWA and WPE types first. Starting at the top of the O*NET taxonomy, with GWA and WPE types, allows the researcher to define a process for establishing HFVTM factors for this study and future research with more detailed work factors.

A three-step process was conducted to delimit the number of suitable O*NET GWA and WPE factors was designed to demonstrate a high degree of rigor and rationale and allow for the maximum number of factors attributable to HFVTMs to be included in both the qualitative and quantitative portions of this research. The first step in this process was a TOPSIS ranking by the two O*NET experts, the tandem interviewers, and the dissertation committee chair. A total of 41 GWAs and 34 WPEs, with approximately 44-53 applicable to all occupations, were ranked using Qualtrics by the five experts. The O*NET expert TOPSIS process included a 1-10 ranking of each WPE and GWA factor along two categories: impact on QWL and impact of virtual team member performance and collaboration. After external testing and extensive dialogue with the O*NET experts, impact on performance, impact on teaming and collaboration, and impact on communication and information technology were combined into one category to reduce duplication, unanticipated outcomes, and survey length. Initially, the expert panel suggested a minimum score of 0.80 to inclusion in the final master survey. By stratifying and reducing the survey questions into smaller numbers, the researcher added to the amount of data available for evaluation while reducing survey data loss.

During the tandem interview pilot phase, it was determined that O*NET factors that achieved a total TOPSIS score of greater than 0.70 or O*NET factors with a score of greater than 0.70 in an individual category were deemed appropriate for inclusion in the qualitative master portion of this study to allow for additional data clarity into the factors. All 75 WPEs and GWAs, were evaluated on a one to ten scale by a total of 27 participants. During the qualitative tandem pilot study, seven participants ranked the O*NET factors. During the master qualitative tandem interview study, 23 participants rated the O*NET factors. WPE and GWA factors with a score of 0.80 or greater from the above three-step process were automatically included in the master quantitative portion of this research study. After reviewing the pilot test data, the decision was made to include WPE and GWA factors with a score of 0.70 – 0.80 in the master interview stage.

At the conclusion of both the pilot test interviews and the master tandem interviews, the compiled list of WPE and GWA factors was reviewed for face validity with the O*NET experts to determine if there were any disagreements regarding the O*NET category types chosen. In addition, the O*NET experts and researcher could add factors for analysis in the next stage of this research. Notably, GWAs and WPEs are appropriate for the qualitative master stage as they are occupationally neutral and apply to nearly every occupation (Sandall, 2023). The O*NET expert panel and the researcher agreed that WPE and GWA factors are an appropriate starting point for the first stage of developing AI-able O*NET factors, research into VTM augmentation, a more thorough understanding of using HFVTMs as a proxy for HMT analysis, and building the required HFVTM O*NET profile because they are more general, applicable, discrete and define attributes specific to a job position through behavioral anchors.

Qualitative Pilot Study

Interview Process, Sample Selection & Participant Profiles

The section is organized sequentially to include a discussion of the interview process and sample selection, a profile of each of the tandem interview participants, and a review of the interview questions and O*NET factor refinement. The pilot study interview findings are discussed and synthesized, and a summary of the refined master tandem interviews is provided. During one-hour interviews, the tandem interview pilot study was administered using the video teleconference platform, Zoom. Zoom allowed participants to discuss their lived experiences, journeys, and individual interpretations of virtual teaming, human-machine teaming, and AI (Madsen, 2008). The researcher sought to understand participants' feelings, thoughts, and practices. The researcher explored the pilot study's primary goals by understanding the AI, human-machine teaming, and virtual teaming experiences associated with the participants. Zoom interviews allowed the interviewers to include participants from multiple countries and continents at a low cost and within a time frame not possible with face-to-face interviews (McIntosh & Morse, 2015).

The tandem interview pilot study panel consisted of three AI and four VTM experts averaging over a decade of experience from three countries and four industries. The tandem interview team used a semi-structured interview format (Appendix B Figure 3), the most common qualitative method used by mixed methods researchers (Morse, 2012; Povee & Roberts, 2015). This format allowed the interview team to ask open-ended questions adding scope to the data collection process and allowing multiple researcher perspectives from their rich VT and AI history (Arskey & Knight, 1999). The interviewer team explored VT and AI O*NET factors, human-machine teaming, and AI central themes relevant to performing, resulting in recommendations and lessons learned to refine the semi-structured tandem interview questions and process for use in the master qualitative interview sessions. Notably, no participants in the qualitative phase are included in the quantitative survey to reduce validity issues by introducing unwanted duplication of responses. The qualitative participants provide instrument and variable design and help reduce data validity concerns (Creswell, 2014).

During the data analysis portion of the pilot test interviews, the researcher provided each participant with an interview transcription through email for review and comment. All seven participants agreed with the interview transcription without changes. Additionally, each participant was allowed to provide additional feedback on the process, elaborate on their career history and association with AI, and use a pseudonym.

Participant Background, Coding and Discussions

Sandy

Sandy has a Ph.D. in Physics and is widely regarded as an expert in his field as an astrophysics and data scientist. Sandy owns a technology company and has eight years' experience as a full or hybrid virtual team member. His work experience includes technical astrophysicist, senior scientist duties, and data science and large volume digital signal/data processing and analysis frameworks with NASA and two additional companies. Sandy's current duties include employee performance management, employee acquisition and evaluation, hybrid and virtual team development, big data and document management systems, database development, intelligent search tools, modeling and simulation, natural language processing for engineering requirements analysis, and demand forecasting supply chain logistics. Sandy and his teams have worked on two U.S.-based software development projects focusing on missile defense machine learning software prototyping. Most recently, his virtual projects are based in the southeast region of the U.S. and have lasted just over four years. His expertise in AI, machine learning, and virtual teaming is ideal for this study.

Veronica

Veronica works at a Fortune 500 telecommunications company as a project manager supporting hybrid and fully virtual teams across the continental U.S. and Central Europe. Veronica has over ten years of VT experience and is an expert in process and automation development, implementation engineering, account management, marketing management, project management, and experimental marketing coordination. Veronica's experience as an automation developer and end-user, VT leader, problem solver, and advanced communication leader makes her a model interview choice.

Becky

Becky's experience includes 26 years of military, government, and engineering work, often based in virtual teaming environments. Her experience as a GVT leader focusing on reverse engineering, modeling and simulation, and virtual support to U.S. warfighters globally brings a new dynamic to this research. Becky's virtual team and AI experience with international partners from Australia, Canada, New Zealand, the United Kingdom, and multiple NATO countries allow for a broader examination of multiple site HMT and VTM analysis. In addition, her experience successfully integrating highly complex modeling environments, digital twins, and software into over ten labs across multiple nations using only virtual team working and one on-site visit per year allows for a deep understanding of the mix between highly complex scientific and technical work and virtual teaming.

Becky has found that her past virtual teaming experience has become increasingly important during the COVID-19 pandemic. The requirement to work virtually in her field has become essential over the last five years. This evolution as a VT employee and leader makes her an ideal candidate for this pilot test.

Itor

Itor has a Ph.D. in engineering, focusing on aircraft signatures and UV detection. Itor is a defense scientist at a United Kingdom government laboratory. He has diverse AI and virtual teaming experiences across numerous countries, industries, and types of AI. His experience using multiple AI, machine learning, and automation frameworks within a virtual environment makes him a critical asset to the pilot study phase.

Most recently, Itor's AI experience includes developing and delivering cross-organizational tools and capabilities that use AI and machine learning technologies to investigate and analyze large quantities of data. With over 13 years of experience, he has been part of multiple GVT and AI teams. His understanding of AI and software engineering development through in-person, hybrid, and fully virtual teams allows the researcher to thoroughly investigate this pilot study's AI and human-machine teaming goals.

Jake

Jake is a principal investigator with experience in AI and machine learning-based analytics dating back to 2004. In addition, Jake has hybrid and fully virtual teaming experience on distributed simulation software development teams. Uniquely, Jake is a stand-alone expert who has no direct managerial authority, instead relying on collaboration and teaming with nearly 80 employees and subcontractors for all work functions spanning four time zones and eight U.S. states. Jake seldomly sees co-workers face-to-face.

Lucie

Lucie is the second international member of the pilot study interview team and the first from a central European country. She is unique to this study as she started her career primarily working face-to-face before transitioning to a hybrid-based team structure. She is now a fully remote VTM for a Fortune 500 telecommunications company. Her experience as a VT worker working globally offers insight into the advantages and disadvantages of virtual teaming. In addition, Lucie has experience with automation development, process improvements, and rapidly moving to new virtual teams.

Rachel

Rachel is a medical sales virtual consultant with over ten years of experience working entirely remotely. This distinctive work experience and the fact that she has never worked on a high-performing or high-functioning team make her a supreme candidate for this pilot study as the researcher can investigate further the differences between low-, moderate-, and high-performing VTMs. This experience brings greater knowledge of the deficiencies and challenges VTMs on low- and moderate-performing teams require to increase value and performance contributions. This avenue of research allows this study to elucidate different ways AI can assist with virtual team augmentation, a primary goal of this analysis.

Qualitative Interview Question & O*NET Refinement

The goals of the qualitative tandem interview pilot test were to finalize the semi-structured interview instrument, delimit the number of O*NET GWA and WPE factors, determine a scholarly research basis for the use of high-functioning VTMs as a proxy for VTM augmentation, human-machine teaming, and superteam analysis at a fundamental work level. Testing of this study's propositions will occur at the quantitative stage. The pilot study was administered to three AI and four VT experts. This descriptive-interpretive semi-structured interview pilot study was evaluated based on McIntosh and Morse's (2015) guides. The co-interviewers evaluated the pilot study based on six crucial questions (Chadwick, Bahr, & Albrecht, 1984 as cited in McIntosh & Morse, 2015):

- Are all the interview questions required?
- Do the interview questions produce anticipated responses?
- Are the interview questions meaningful to the participants?
- Do the questions accidentally insert problems or double meaning?
- Are the interview questions and script in a logical order?
- Did the script motivate participants to contribute to the research?

During the pilot study, 42 GWAs and WPEs scored higher than 70 percent, and five GWAs were added post-analysis to the master tandem interview by the O*NET expert committee. These 5 GWAs were added because they scored above 50 percent by the O*NET experts, and their addition adds O*NET AI variation and clarity. Furthermore, the total survey time was analyzed, and minimal data reduction loss was observed.

A total of 11 semi-structured interview script and process changes were agreed to with the co-tandem interviewer for use in the master tandem interview stage. Changes applicable to the AI and research study goals include adding participant generation and VTM experience to the demographic questions, using Microsoft PowerPoint slides for intentional visual support, elimination of problems, reduction in interview time, participant support, and finally, refinement of VTM performance questions using Andersson et al. (2017). Furthermore, the original AI questions seeking whether the interviewee would accept AI was removed due to total acceptance, likely due to social change technology acceptance, and because they were not parsimonious. These questions were adapted into a broader dialogue on AI, asking participants if they agree with using HFVTMs as a proxy for HMT and team augmentation analysis, the scholarly definition of superteaming, exploring in more detail what low-, moderate-, and high-performing VTMs require, moving AI discussions to after the O*NET discussions, and finalizing the use of a post participation survey using Qualtrics for rating O*NET GWAs and WPEs. The development of the VTM performance questions included modification of the Andersson et al. (2017) 16 performance questions to include: adding the word ‘virtual’ to all 16 questions, eliminating medical framing in the first question, and illuminating to the participant that the workload was ‘too’ high for question two and three (Appendix D2). The final qualitative instrument survey script and PowerPoint, with goals and purpose for each section and question, are available in appendix B, Figure 3, and Figure 4.

Pilot Study Summary, Data Synthesis, & Key Takeaways

The above changes to the qualitative pilot test interview script directly result from testing and indicate multiple findings. This section will provide a short overview of the pilot study data, its synthesis, and critical takeaways relevant to this study's research goals. All seven participants agreed with this study's scholarly definition and measurement of VTM performance and HFVTMs. Defining VTMs with a combination of high levels of QWL and high levels of performance as HFVTMs, by the co-tandem interviewer (Hill, 2023), a critical requirement for HMT analysis, was agreed to by all seven participants.

This study is unique and distinct from other AI and HMT studies because it focuses on AI and HMT topics from a top-down approach. Although multiple participants suggested possible AI-able additions to the O*NET GWA and WPE factors, at this stage in the research, these were noted but not added without further evidence during the master qualitative tandem interviewing stage.

A few noteworthy observations are made about high-performing VTMs and AI. First, all participants willingly agreed with AI's capability to deliver performance improvements and the study's definition of performance. Veronica contends that low-performing VTMs would enthusiastically accept AI tools because of its capacity to make their job easier. However, high-performing VTMs may reject AI assistance due to control factors and fear of prestige loss. Additionally, Veronica assesses that AI must be individualized for each employee to be highly accepted. This assertion leads to the following critical observation. A few participants, such as Jake, noted that AI's ability to be empathetic and social was critical to adoption. This data is in line with the CASA framework noted in chapter two.

Tandem Interviews

Full Tandem Interview Process & Sample Selection

This section is organized in the following manner. The number and process for tandem interview participant selection, adaptations from the pilot study, and procedure for the tandem interviews begins this section. Next, a profile of each of the tandem interview participants to include key takeaways and findings from each interviewee is discussed. Key takeaways include agreements and additions to research definitions, face validity, content validity, critical analysis of themes and codes relevant to this dissertations subject, and interviewee rankings of O*NET GWAs and WPEs. Finally, a synthesis and summary of the data relevant to the research and the creation of the quantitative survey is presented. All findings and the contribution of these discoveries to applied practice are discussed during data synthesis.

According to McIntosh & Morse (2015), a total of 30 interviews are required for the qualitative portion of this mixed method analysis (McIntosh & Morse, 2015). Therefore, the researcher conducted an additional 24 interviews with 23 different subjects during the master tandem interview process to achieve the desired interview totals. This study's tandem interviews were conducted primarily using the video teleconference tool Zoom, with two subjects requiring the use of Microsoft Teams. The use of these virtual tools permitted the researchers and interviewees to examine the lived VT experiences, detailed work practices, and personal interpretations of virtual teaming related to member performance, human-machine teaming, and AI and virtual team O*NET work factors (Madsen, 2008). The video teleconference interviews allowed the interviewers to include participants from countries on three continents at a low cost and within a time frame not possible with face-to-face interviews (McIntosh & Morse, 2015).

The researcher's primary interview goals are to understand the virtual teaming experiences associated with the participants relevant to VTM performance, AI augmentation, O*NET work factors, human-machine teaming, and team augmentation. The ability of the researcher to examine what factors of work could best benefit from AI team augmentation required an extensive discussion of O*NET GWA and WPE factors. To meet the O*NET factor requirement one primary goal was delimiting the O*NET factors necessary for continued analysis in the quantitative portion of this study. The interviews allowed the researcher to continue the delimitation process of the relevant O*NET GWA and WPE factors to be asked during this study's quantitative survey phase. Next, a discussion between the tandem interviewers and the interview subjects permitted a thorough examination of possible new AI and VTM O*NET work factors not in existence. To accomplish this goal, the tandem interviews included a section on virtual team job statements (Ulwick & Bettencourt, 2008) and jobs to be done centering on the virtual team member frustrations and challenges?

Next, creation of the VTM performance self-assessment reporting survey questions using the Andersson et al. (2017) self-assessment reporting was necessary. This process included the review of not only the definitions of VTMs and high-performance VTMs, but also a review of each of the validated questions from Andersson et al. (2017). At the conclusion of this portion of the interview participants were also able to propose additional questions for use within the VTM performance survey. The combination of these questions allows the researcher to create a novel survey instrument for this study.

Additionally, a discussion centering on VTM QWL and VTM QWL-based subgrouping was necessary for the tandem interviewer in order to set the definition of a HFVTM. The ability to set the definition of an HFVTM is appropriate due to the use of this definition in developing superteams and HMT augmentation. Finally, the qualitative interview provided an opportunity to explore face and content validity of the goals of this dissertation, the definition of superteams, and the use of HFVTMs as a proxy for HMT, superteams, and team augmentation analysis.

The master tandem interview study phase consisted of 23 VTM and AI individuals ranging from high-performing experts with more than a decade of experience, to moderate and low-level performance VTMs. The tandem interview team used a semi-structured interview format (available in appendix B Figure 3), the most common qualitative method used by mixed methods researchers (Morse, 2012; Povee & Roberts, 2015). The semi-structured format allowed the interview team to ask open-ended questions adding scope to the data collection process and allowing multiple researcher perspectives from their rich VT and AI history (Arskey & Knight, 1999). The interview explored more than 47 VT and AI O*NET factors, human-machine teaming requirements, and AI central themes relevant to performance. The resulting qualitative analysis, to be discussed in this section, is used to create this study's quantitative pilot study survey. The qualitative interview process also provided instrument and variable design validity to help reduce potential data validity concerns (Creswell, 2014). Just as in the qualitative interview pilot study, none of the 23 participants in the master qualitative interview phase were included in the quantitative survey to reduce validity issues by introducing unwanted duplication of responses.

At the conclusion of the interviews, the researcher provided each participant with an interview transcription through email for review and comment. Only one participant required a single change to the transcription and at the conclusion all 23 participants agreed with the interview transcriptions. Keeping with best practices, each interview participant was allowed to provide additional feedback on the process, elaborate on their VT career history and association with AI, and choose a name or pseudonym for reporting in this research study.

Interview Script, Data Collection & Participant Summary

Following the successful pilot study, a series of changes to the interview process were made by the researchers. First, the tandem interviewers intentionally used Microsoft PowerPoint to eliminate any misinterpretations. This was a prescribed and intentional decision that not only reduced interview time, but PowerPoint also increased the quality of the interview discussions. Additionally, the flow of the interview was intentionally amended to allow the interviewers to move from virtual teaming, to performance, to subgrouping, to high-functioning VTMs, to O*NET work factors, and finally to AI team augmentation and superteaming. The goal is to allow interviewees to shift gears to recall the VTM setting and proceed into performance and what is needed by AI without the interviewers verbally saying AI until the very end of the interview. This interview flow change was made because during the pilot test after it was observed that interviewees were having a difficult time transitioning away from QWL and subgrouping and to discussions centered around the fundamental work activities of a VTM. This important and intentional decision allowed for the interview subject to begin to provide critical insights into O*NET work factors, VTM difficulties, human machine teaming, and AI team augmentation. The goals, changes, and flow of the interview fit ideally with the semi-structured interview technique.

Second, the ability to create new instruments such as the VTM performance survey to ensure each of the questions fit contextually within the new instrument is critical. In addition, the need to reduce erroneous data, anchor respondents' situational awareness, and possibly add new performance questions appropriate for this study's research questions is important. The ability of the master qualitative tandem interviews to validate the new performance survey to measure low-, moderate-, and high-performing VTMs is critical to this study's quantitative survey because this study expects to see statistically significant profile differences in what each of these VTM performers require.

The final critical step of the quantitative interviews is to begin to dissect VTM tasks at the fundamental O*NET work level. This study expects to see statistically relevant differences in not only low-, moderate-, and high-performing VTMs, but additionally HFVTMs versus non-HFVTMs. The ability of this survey to delimit the current list of 47 WPEs and GWAs from the pilot test stage, and possibly reveal new VTM and AI O*NET GWAs and WPEs relevant to virtual teamwork, team augmentation, human-machine teaming, and superteaming is critical.

Each of the interviewee recaps attempt to clearly state their lived experience as a VTM, their views on team augmentation, superteaming, and human machine teaming, the fundamental O*NET work activities required by VTMs, and those O*NET work factors that could possibly be replaced by AI. Furthermore, an analysis of each of the VTM frustrations unpacked using job statements and JTBD (Ulwick & Bettencourt, 2008) will be synthesized to address each VTM task perception critical to the development of the ODI opportunity score portion of the final survey. Understanding VTM fundamental GWA and WPE work activities, how important they are, how satisfied they are, and how frequently they perform these activities is critical to the underlining this study's research questions and propositions.

The master tandem interview participants include VTM and AI SMEs from three countries and eight industries with an average of over ten years of experience. Interviewee diversity was essential as the research requires members that are geographically dispersed with performance variations in order to ensure the parsimonious aims of this study (McIntosh &

Morse, 2015). With the above interview goals, changes, and motivations in mind, this section will now transition to an overview of each of the 23 interviewees. This review addresses each participant and discuss the major tandem interview takeaways from each member. One note on interview naming. At the close of each interview, the participants were provided the option of choosing a pseudonym or name for participant discussions. Each participant is referred to by the name they provider the interview team.

Finally, transcriptions of the Teams and Zoom interviews were provided to all interview subjects and each was offered the opportunity to add or clarify responses, confirm the accuracy of the transcript, and add any additional details. All conclusions discussed below were confirmed with each participant during this process.

Adam

Adam is a Vice President at a Southern U.S. financial investment company. Adam has more than 22 years of experience in institutional investing. Adam is relatively new to virtual teaming, having begun at the start of the COVID-19 pandemic two and a half years ago. However, Adam's expertise coordinating financial work, meeting, and performing technical facets of the job virtually with clients makes him an ideal candidate. For example, Adam noted some of his major struggles were working virtually with older clients and attempting to bring clients up to speed on technology usage. Adam claims to be a high-performing virtual team member and continues to work with many high performing, well-educated, and highly experienced teammates.

Adam provides multiple recommended changes to the Andersson et al. (2017) performance survey. For example, he recommends the addition of performing consistently and recommends questions five and six remove the word low and replace it with adequate or on par.

Additionally, Adam notes the O*NET factors with the impact to HFVTMs, of which he considers himself one, were oral communication, critical thinking, multi-tasking, processing information, attention to detail, written communication, adaptability, and integrity. While only two O*NET factors were the least important: conflict management and influencing.

Furthermore, initiative, adaptability, attention to detail, written communication, learning orientation, multitasking, time management, and work ethic were likely to vary the most based on VTM performance. Interestingly, Adam argued that VTMs required the capability to speak up, and have a voice, to meet the requirements of VTM participation and interaction contrary to the traditional in-person employee. Adam states the most challenging aspects of the HFVTM job profile is team time coordination. Adam finds it difficult for VTMs to schedule and coordinate meetings. Finally, Adam agrees with the superteam definition, the use of HFVTMs as a useful proxy for the study's goals and recommends AI should focus on assisting VTMs where it can achieve the highest level of ROI and productivity. For example, Adam recommends AI be used to improve probability, scenario, and factor analysis.

BAK

BAK is an Associate Director of Technology in Engineering & Operations at a major U.S. telecom firm managing a diverse set of geographically diverse VTMs located across the country. As a 20-year veteran and member of a high-performing team, she speaks openly of the drive to increase performance at her company by regularly laying off low-performers to increase performance. She believes AI may be able to help some of these low performers without the need for costly layoffs, hiring, and training cycles.

Although agreeing to the HPVTM definition, she recommends the performance questionnaire be adapted by removing the word low from questions two and three. As she stated, 'because she is a virtual team member' her workload is always too high for her and her team. In addition, BAK believes VTMs require consistent multi-tasking, perseverance, and multiple means of communication to be successful. BAK believes the following O*NET factors are the most important for HPVTMs: multitasking, teamwork, planning, written communication, interpersonal skills. technology & tool usage, scheduling work & activities, organizing, planning and prioritizing work, communicating with peers, supervisors & subordinates, and developing and building teams. The least important HFVTM O*NET factors according to BAK are pride in work, math application, learning orientation, and adaptability.

BAK agrees with the superteam definition, the use of HFVTMs as a useful proxy for the study's goals and recommends AI should focus on context clues, empathy, and time management assistance in a virtual setting is required. BAK struggles with getting in touch with managers, keeping people's attention in a virtual environment, and with the disrespect and lack of empathy in a virtual environment.

Brian

Brian is a 10-year veteran of virtual teaming and currently is an Area Manager for within a Fortune-500 telecom engineering firm. Brian has experience with AI applications that assist him in managing his teams, automating team reporting, and GPS routing. Brian believes when managing VTM performance it is necessary to rely on AI tooling due to lack of personal observations and face to face contact.

Brian believes VTMs require assistance with new employee training as well-trained VTMs lead to high performance. When discussing the Andersson et al. (2017) statements, Brian believes the workload is never evenly distributed and recommends ‘reasonably distributed’ for question four. Additionally, he recommends modifying question 8 and changing the word equally for the same reasons. Brian contends higher performance requires high levels of QWL.

Brian ranks the following O*NET factors as the most important to HFVTMs: conflict management, teamwork, planning, written communication, leadership, oral communication, making decision & solving problems, developing objectives & strategies, organizing, planning & prioritizing work, coordinating the work & activities of others, and guiding, directing & motivating subordinates. Brian states thinking creatively, creativity, and establishing & maintaining interpersonal relationships are the least important to an HFVTM.

Brian expresses frustration with managing employees across diverse time zones and time keeping requesting support in making sure employees are doing what they are supposed to be doing instead of allowing management to learn that through performance measures. Finally, Brian agrees with the superteam definition, the use of HFVTMs as a useful proxy for the study’s goals, and AI support with team augmentation to meet critical ROI goals.

Byron

Byron has a doctorate in electrical engineering and has supported the DoD for over nine years with seven of those years being a hybrid or full time VTM. Much of Byron’s VT experience resides with multinational defense, modeling, simulation, and engineering virtual teaming between the U.S. and Allies such as Australia and England. Byron has a mix of high-, moderate-, and low-performing virtual team experience. Byron states building AI to support the goals of an HFVTM is ideal as the high levels of QWL and performance can assist to reduce burnout.

Byron contends time management, attention to detail, and organizing, planning & prioritizing are the most important O*NET work factors. The least important O*NET work factors are technology & tool usage and updating & using relevant knowledge. This rating is because of the large variety of computer and technology tools. Employees have little patience and drive to use these tools well and to communicate effectively in community forums. Byron would like to see assistance with active feedback, reading the room, spin-up support and task management tools leading to learning curves, dependency management, and interactive support and training. For example, can AI help VTMs to analyze and summarize the consequences to decisions makers.

Byron agrees with the superteam definition, the use of HFVTMs as a useful proxy for the study's goals, the top-down approach utilized by this study, and AI support with team augmentation to meet critical ROI goals. For example, Byron suggests help with identifying, recognizing, communicating poor uses of tools while also providing suggestions.

Daniel

Daniel has a long career as a hybrid team member working with teams in the U.S and Europe for a Fortune 500 telecom company. For Andersson et al. (2017) he recommends question four be adapted to state 'reasonably' distributed. He agrees with the definition of an HFVTM but has never been on a high-functioning virtual team. Daniel rates the following O*NET characteristics as the more important: multitasking, teamwork, planning, communication, creativity, processing information, training & teaching others, and time management. Whilst David rates adaptability, influencing, leadership as the least important O*NET GWAs and WPEs. However, David argues patience is essential and recommends it to be added as a work factor.

David argues communication is vital for VTMs and is much more important to hybrid and virtual employees than their in-person colleagues. Interestingly, David suggests that as AI is integrated on a team, if it is too helpful, employees will have little reason to reach out and communicate, collaborate, or subgroup with each other. However, if AI could facilitate, create, and form employee teams with similar interests of members working together, that may be very useful. AI could also assist in reducing virtual team meetings, especially those that unnecessary, relieve employees from repetitive tasks and those that don't require a lot of thinking. This would allow humans perform troubleshooting and AI to perform mundane work tasks and functions. Daniel agrees with the superteams definition, the use of HFVTMs as a useful proxy for the study's goals, the top-down approach utilized by this study, and AI support with team augmentation to meet critical ROI goals.

David 2

David2 is a Senior-Advanced Technical Specialist at a Fortune 500 telecommunications company with 8 years of VT experience. He has a mix of hybrid, geographically dispersed and co-located, and full virtual teaming. With his experience as a high-performer, David1 suggests adapting the Andersson et al. (2017) statements to include consistency. For example, 'I have been a consistent high performer'. On the subject of HFVTMs, David2 not only agrees with the definition, but he believes the addition of QWL, and subgrouping is a performance enhancer. As he states it, employees need to have that higher QWL to have an overall quality of life as a high performer.

When discussing the Andersson et al. (2017) O*NET work factors, David2 rates work ethic, pride in work, communication with persons outside of the organization, and coordinating the work activities of others as those factors that are most important to HFVTMs. However, customer service and multi-tasking are the least important. David2 suggests the most challenging aspect of VTM is the lack of experience of new and sometimes existing VTMs and their large lack of formal training and a VT training process. Additionally, David2 suggests frustration with the amount of time it takes him to sift through automated problem and troubleshooting reports and the amount of coordination time with other VTMs required to solve the problem. He finds large levels of waste associated the high volumes of automated reports that come into a VTM environment. Finally, David2 agrees with the Superteams definition, the use of HFVTMs as a useful proxy for the study's goals, the top-down approach utilized by this study, and AI support with team augmentation to meet critical ROI goals.

David1

David1 is a Senior-Business Level II Project Manager at a Fortune 500 Telecom company with 25 years of experience in addition to 10 years of US Army Tactical Communications experience. David1 also holds a nano degree in AI Project management, has eight years of virtual teaming experience, and has three years of AI experience. This VT and AI experience, combined with his high performance, makes him an ideal candidate for this research.

With this experience, David1 suggests rewording questions five and six to requalify the stress level of a VTM, and delimiting thinking creatively and coordinating the work and activities of others. He sees making decisions and solving problems and establishing & maintaining interpersonal relationships as critical O*NET factors. David1 would like to help with time zone difficulties and structuring meetings. David1 agrees with the superteams definition, the use of HFVTMs as a useful proxy for the study's goals, the top-down approach utilized by this study, and AI support with team augmentation to meet critical ROI goals. Done correctly, David1 argues proper AI tool development for VTMs could greatly assist humans significantly increase ROI. However, he does state that generally speaking there are VTM activities that AI cannot replicate at this time. Finally, David1 suggests adding comradery, project scope, clear communication of tasks, and adaptability to the O*NET work factor evaluation list.

Jeremy

Jeremy is a chief scientist within the U.S. DoD and his staff and teams are widely dispersed. Jeremy has a doctoral degree, has been on a total of three separate VTs, has consistently been a high-performer, and has been both hybrid and fully virtual at different parts of his career. When discussing the Andersson et al. (2017) statements Jeremy recommends adding the phrase 'focusing on your most recent experience' to the introduction instructions.

During discussion on the 47 O*NET work factors, Jeremy rates the following factors as highly important to HFVTMs: teamwork, work ethic, perseverance, creativity, integrity, technology and tool usage, interacting with computers, critical thinking, and problem solving. Although Jeremy deems all 47 O*NET work factors as important and cannot delimit any, he does suggest adding the ability to dictate constructive criticism.

Jeremy suggest HFVTMs need increasing levels independence, the capability to be a self-starter and willing to take initiative and finds coordination as one of the most challenging aspects. Although Jeremy believes AI is a buzz word in today's society, he is accepting of the definition, the use of HFVTMs as a proxy for the study's goals, the top-down approach utilized by this study, and AI support with team augmentation to meet critical ROI goals. In fact, Jeremy believes the use of HFVTMs as a proxy for this analysis is 'necessary in the future' as teams must accept modern technology as a way to do their jobs more efficiently.

Fab

Fab has been a member of, on average, six VTs for the last three years. This complex set of mixed VTs is another critical component of the interview population.

The mix of meetings, brainstorming, aims, issues, collaboration, and feedback provide this study with unique perspectives. He identifies as a high-performance VTM and views these individuals as subject matter experts. From the interview it is postulated that future AI human machine teammates may be viewed similarly to a modern-day VT subject matter expert.

Fab believes HFVTM and performance may fluctuate according to the VTM stage of life. Fab contends decision making, critical thinking, and leadership are the most important O*NET work factors, while pride in work, integrity, perseverance, and multi-tasking are the least important. He suggests the lack of facial context expression and recognition reduces the ability for VTMs to read the energy and vibe of teammates and situations. Additionally, Fab suggests AI could assist with whistle blowing, or calling out, reporting, and fixing VTMP and personnel issues. Fab, broadly agrees with this study's definition of superteams, the use of HFVTMs as a useful proxy for HMTs, the top-down approach utilized by this study, and with AI support with team augmentation to meet critical AI ROI goals. Finally, Fab recommends O*NET factors such as AI speed, adaptability, motivation, and empathy be added.

Nicole

Nicole is a Senior Level Business Manager for the Engineering & Operations at a Fortune 500 telecommunication conglomerate. Her experience in data management and analytics reporting at the local, national, and international VT level makes her an ideal candidate for this study. Nicole's 10 years of experience provides her a perspective ranging from nascent virtual teams without dedicated support to the modern COVID-19 era. Nicole makes frequent use of effective collaboration methods, such as Teams and SharePoint sites to share information, as well as collaborative work sites.

Nicole suggests numerous changes to the Andersson et al. (2017) performance questionnaire. First, Nicole recommends question four be adapted to read ‘fair and equitable distribution’ based on skill set because in her lived experience workloads ebb and flow daily. During discussions on question, four it was noted by the tandem interview team that Nicole changes her work style to focus more on innovation when workloads are lower. She states, as a high performer you know what to do with that time (i.e., innovate) rather than having to be micromanaged like a lower performing team member. This is a novel area of AI exploration to be noted for future research in chapter five pending outcomes from the survey.

Similarly, to other interview participants, Nicole believes HPVTMs have an aptitude toward higher levels of stress. She states higher stress is because if there is no stress at all then what she is doing is unimportant. For the stress questions, Nicole suggests rephrasing the word low to ‘adequate’. For question nine, Nicole suggests rewording the question to provide greater participation framing: ‘I was active in the virtual team’s decision-making and direction process of the team’. The daily active participation within team and individuals’ tasks, the participation in daily decision making, individual innovation, increasing effectiveness or gained efficiency, all represent HPVTMs proactive nature. Nicole associates high performance and high functionality VTMs with proactive capacity that improve the direction of the team.

Nicole rates the following O*NET GWA and WPE factors as the most important: adaptability, math application, teamwork, planning, getting information, processing information, making decisions and solving problems, interacting with computers, establishing and maintaining interpersonal relationships, and training and teaching others. Nicole only rates resolving conflicts and negotiating with others as the single least important O*NET work factor. Nicole focuses heavily on collaboration due to her belief that the ability of VTMs to collaborate and edit as a shared team leads to outperformance and is more critical in a VT environment. Because of this belief, Nicole recommends AI focus on collaboration tools, quick collaboration and feedback, improving the process of sending and receiving information, whiteboarding, and instant messaging. Additionally, she believes HPVTMs have a tendency to overwork themselves and therefore contends more should eb done to ease VTM work pressures.

Nicole agrees with this paper's proposed definition of a superteam, the use of HFVTMs as a useful proxy for the study's goals, the top-down nature of this study's methods, and AI support to team augmentation to meet critical ROI goals. She contends machine learning will be highly useful for highly mundane tasks, responses, and forecasting that have the capacity to ease VTM workload and decision making. Furthermore, from her experience AI is essential to creating a future positive work-life balance. For example, BOTs would be helpful in answering simple questions opposed to consistent interruptions. It is AI capability to increase VT adaptability, refine team performance monitoring and measuring, and improve communication, and relate all activities to organization goals that Nicole says should be reflected better in the O*NET work factors. AI adaptability and other possible WPEs and GWAs will be discussed in the data synthesis portion of this chapter.

Tina

Tina is a senior technical program manager inside a Fortune 500 telecommunications mobility construction & engineering department. With more than 25 years of experience, Tina has over 15 years of experience with virtual teaming and over seven years of Al experience specific to BOTs. Her experience ranges from entry level to senior management and her personal experiences present a unique point of view not offered by other interview subjects. It is these specific experiences, views, and personal experiences that add a layer of face validity required for this study.

Tina recommends the Andersson et al. (2017) questions be adapted in five key areas. First, during discussions on question two, Tina states certain personalities take on more and therefore the survey should be modified to consider those VTMs who take on more responsibility. In a similar vein, Tina initially misinterpreted questions five and six believing it was saying VTMs are more stressed than regular teams. This theme of equality appears also in question eight. The phrasing of equal is not appropriate in her judgement, instead wording representing a VTMs performance up to their capability is suggested. She uniquely discusses the lack of a 50/50 relationship by using euphonism of marriage. Finally, question ten should be adapted to focus on the majority of decisions.

Tina provides teamwork, computer skills, creativity, adaptability, relationship building, work ethic, problem solving, thinking creatively, and communication as the most essential O*NET factors for an HFVTM. The only work factors Tina suggests as not essential is math, influencing, use of tools, and learning because in Tina's view, anything a business can teach a VTM is not important. This is because Tina associates a VTMs tenacity and willingness to learn as critical to high performance. It is in this belief that Tina suggests adding a new O*NET VTM factor of being a self-starter to include willingness to ask questions and learn. It is this autonomy that is critical. She says she doesn't take enough personal time.

Tina agrees with this paper's proposed definition of a superteam, the use of HFVTMs as a useful proxy for the study's goals, the top-down nature of this study's methods, and AI support to team augmentation to meet critical ROI goals. She would like to see AI help with a VTMs ability to take a break as this will lead to increased health and performance. In her view proper breaks are a major VT requirement and would be an excellent use of AI. Finally, Tina suggests assistance with time management and improved willingness and tenacity of VTMs working together as these are antecedents to seeking help and collaborating.

Timothy

Timothy is a senior wireless translations engineer at a major U.S. telecommunications company with eight years of VTM experience traditionally with overseas VTs. Timothy considers working with other VTMs and deliberately constructing underlining friendships as the hardest thing to sustain and build on a VTM. This level of relationship building includes empathy and may be a place where AI can help. For example, could AI provide a better process for introducing new VTMs?

Timothy suggests numerous O*NET factors are important to HFVTMs. These include time management, work ethic, oral communications, leadership, attention to detail, relationship building, making decisions and solving problems, communicating with supervisors, peers, subordinates, establishing and maintain interpersonal relationships, and training and teaching others. Only math application, planning, and written communication are the least important WPEs and GWAs. Timothy suggests multiple problems with VTM performance. For example, VTMs lack of time management is a critical issue to virtual performance and needs to be addressed immediately. Additionally, the lack of communication in VTMs often require teammates to go on highly time-consuming deep dives. Timothy also suggests the number of meetings and inefficiency of VT meetings are difficult to deal with for him. Tim suggests rating meetings, assistance hosting meeting, and help with email is also necessary. These suggestions continually center on VTMs need for clear communication of task and coordination. Finally, Timothy agrees with this paper's proposed definition of a superteam, the use of HFVTMs as a useful proxy for the study's goals, the top-down nature of this study's methods, and AI support to team augmentation to meet critical ROI goals.

Stephanie

Stephanie is a six-year veteran of virtual teaming and consistently looks for virtual job opportunities over that of an office setting due to her ability to be more productive. Stephanie is a unique member of the interview participants because she is the only administrative assistant with responsibilities to manage a team of four administrative participants. She directly supports four virtual sales representatives as an executive administrative assistant. Stephanie finds work ethic and open lines of communication are an essential part of the virtual team productivity.

From Stephanie's experience, she advises question five of the Andersson et al. (2017) performance questionnaire remove the word low from stress. She would prefer that this question say the stress level was on par with her virtual teammates. This is because VTMs do not clock out, its 24/7 position. Stephanie rates computer fundamentals, teamwork, time management, attention to detail, critical thinking, multi-tasking, oral communication, communication with peers, supervisors, and subordinates as the most important O*NET factors. She recommends delimiting scheduling activities and establishing and maintaining interpersonal relationships.

During discussions on JTBD, Stephanie states VTMs need to have the capability to think outside the box, because it is hard to get help and find answers quickly as a VTM. This self-reliance requirement is on par with other difficult job duties such as the analytical part of her job which often consists of financial analysis summaries. The most difficult part of her job is dealing with employees who do not check their work properly forcing her and her staff to repeat the work. Lack of training, training absorption, and lack of communication cause significant delays.

It is these teamwork experiences, use of thinking outside the box, and training difficulties that lead to Stephanie to say that using HFVTMs as a proxy for HMT analysis, team augmentation, and AI augmentation is an imperative. Stephanie agrees with this paper's proposed definition of a superteams, the top-down nature of this study's methods, and AI support to team augmentation to meet critical ROI goals.

John

John is a professional-wireless translations engineer at a Fortune 500 telecommunications company with over 15 years of VT experience. Since 2012, John's senior level virtual team role includes leading mobile telecommunications teams in both the U.S and the Czech Republic to optimize network performance. This role includes numerous automated functions that assist VTs in making network changes. John has engaged with multiple worldwide VTs from England, Mexico, and Puerto Rico. John had no issues or changes with the Andersson performance questionnaire.

Prior to discussions on virtual team O*NET factors, John mentioned the difficulty he has experienced functioning virtual teams across different time zones, cultures, and companies due to the differences in how each location, company, and culture views work. He believes time management, stress management, interpersonal skills, relationship building, and adaptability are the most essential HFVTM O*NET factors. John rated conflict management and developing and building teams as the least important work factors. When discussing possible additions and workplace frustrations, John discusses his view that ethics and integrity are critically important for VTMs as these virtual employees have no one looking over their shoulder during remote work. Can AI have a role in ethics, integrity, outside environmental factors such as doorbells in a similar fashion as data analysis, data coalescing, report development, and automation. John expresses hope for AI with all work roles. He says dealing with 10 different locations, with 10 different individuals, and 10 different morning reports is difficult and time consuming. Could AI help with follow the sun and cycle production, believes so. However, in his view, the human portion of the HMT must understand why AI is making its choices as automation sometimes goes off the rails and when you don't know what it is doing, correcting it is hard. The impact of AI on human factor performance is a future research item to be discussed more in chapter five. Finally, John agrees with this paper's proposed definition of a superteams, the top-down nature of this study's methods, and AI support to team augmentation to meet critical ROI goals.

Sam

Sam is a 25-year veteran of the telecommunications industry. He has been virtual teaming for the last 13 years of his career in the wireless engineering of a Fortune 500 company. As an above average performer he has a broad range of experience from first job as an entry level telecom engineer, to a technician, to being a manager of a small team of 15 engineers, to now being a technical Project Manager. Sam's varied experience as a full-time VTM from project management, to cross country and cross continent teaming, is an essential part of this study's goals.

Sam entirely agrees with the Andersson et al. (2017) performance questionnaire. Of the 47 O*NET GWAs and WPEs Sam believes multitasking and time management are the most important work factors because Sam believes VTMs are consistently doing numerous jobs at the same time and is key to working remotely. He believes creativity, influencing, getting information, and thinking creatively are the least important O*NET work factors. Finally, Sam agrees with this paper's proposed definition of a superteam, the top-down nature of this study's methods, and AI support to team augmentation to meet critical ROI goals.

Russ

Russ has been a virtual employee since 2011 on multiple international and US teams in the telecommunications industry. Early in the interviews Russ mentions missing the ability to attend break out discussions as a VT employee. He would like the ability to go into rooms with digital whiteboards to engage in critical collaboration and brainstorming. This theme of Russ seeking knowledge and collaboration first, to become more efficient and reduce his stress, to allow him to maximize his personal time is consistent.

For the Andersson et al. (2017) performance questionnaire, this theme continues. For questions two, three, and five, Russ discusses adding in the words too high, with regards to stress and workload, is critical. He argues high-performing and high-functioning VTMs can handle higher stress and workload levels. These VTMs require additional tools and tooling to aid their individual, or internal drive, to maximize their performance. These tools can aid in the prevention of burnout and ensure longer term VTM success. This theme continues with Russ's rating of the most important O*NET work factors: critical thinking, integrity, written communications, initiative (self-motivated), and organizing planning and prioritizing work. Russ rates math application, computer fundamentals, and training and teaching others as the least important O*NET factors.

Finally, coding of Russ's comments reveal multiple opportunities for AI within team augmentation, human machine teaming, and team augmentation. For example, Russ consistently discusses the need for effective virtual teaming tools that directly support VT roles. These tool ideally would allow for general discussions, effective collaboration, building up internal resource groups, access to supplies, reduction in multi-tasking. These capabilities ideally would ease misunderstandings on actions, goals, and directions, maximize VTM engagement, improve change management, improve visual and collaboration queuing, and reduction or elimination of easily repeatable and performed activities. The goal of top-down analysis and tool delivery has a significant effect on VTM stress reduction thereby increasing VTM performance. Russ agrees with this papers proposed definition of a Superteam, the top-down nature of this study's methods, and AI support to team augmentation to meet critical ROI goals.

Melanie2

Melanie2 has vast experience as a VTM and leader. Her leadership of multiple U.S. and international VT within the telecommunications industry offers unique insight into women-led virtual teaming leadership. For example, a consistent point Melanie2 makes is the recognition of leadership of high-performers and the value they provide to an organization, to allow for the maximization of these unique individuals. For example, first Melanie2 points out during discussion around question four of the Andersson et al. (2017) questionnaire that the workload is never evenly distributed. Next, she points out that those high-performing and high-functioning VTMs need to be supported better with increased mental breaks, management support, and efforts to reduce or at least manage high stress levels.

These themes continue with her additions to the O*NET work factors. Melanie2 recommends patience and flexibility is added as these are bespoke to a VTM. She rates organizing planning and prioritizing work, training and teaching others, stress management, adaptability, resolving conflict and negotiating with others as the most important O*NET factors. While multi-tasking, perseverance, and judging the qualities of things people are the least important. She would like to see AI help with reading employee mannerisms, unique international wording and phrases, and time zone support and meeting scheduling to accommodate internal and external scheduling. Melanie2 agrees with this paper's proposed definition of a superteam, the top-down nature of this study's methods, and AI support to team augmentation to meet critical ROI goals.

Melanie1

Melanie1 was one of the most unique interview subjects. Melanie1was recently promoted to a senior executive position in the U.S. federal government. She is one of the youngest senior executives in her organization and has had to manage a full move of her organization of one-hundred individuals from 100 percent in person, to 100 percent virtual. The closing of this office and move to an entire virtual environment dispersed across four U.S. states has resulted in new levels of workload and high demand stresses on her teams. Her and her teams continue to experience unique communication challenges outside of the team and their lack of ability to establish and maintain trust. This inability to consistently work externally, manage expectations, convince leadership, and manage VTM availability and expectations in a 'go, go, go environment' leads to extensive burnout. She feels as those the goals of this research will help her build HFVTMs and high-performing teams and sees this research as essential to her solving current problems within her organization.

Melanie1's list of most important O*NET factors include integrity, influencing, creativity, interpersonal skill, attention to detail, adaptability, relationship building, decision making, how you make decisions as a team, critical thinking, time management and stress management, teamwork, conflict management, computer fundamentals, and written and oral communication. The least important factors were information gathering and multi-tasking. Melanie1 would like to see help with tool usage, collaboration in a whiteboard environment, capture transcripts of meetings, real-time help reading tones and feelings, building relationships, tracking progress toward goals and accomplishments, and brainstorming across both internal and external teams. Two unique areas of help include relating overall VTM activities to organizational goals and the larger mission and improving the VTM experience with regards to back-to-back meetings with no breaks. She also suggests AI HMT assistance may be better across certain industries versus others. Finally, Melanie1 ‘absolutely’ agrees with this paper’s proposed definition of a superteam, the top-down nature of this study’s methods, and AI support to team augmentation to meet critical ROI goals.

Carl

Carl is the first member of the insurance and banking sector within the research population. Carl has five years of experience as virtual team member and leader in both the military and the commercial sectors. As a 20-year Navy veteran, Carl offers the most recent experience of any of the interview subjects.

As a leader, Carl continually challenged the interview team to explore salary versus hourly, supervisor versus worker, and organization versus employee viewpoints during the Andersson et al. (2017) questionnaire and O*NET work factor discussions. Carl rates communicating with peers, subordinates, and superiors, relationship building, influencing, and time management as the most important O*NET work factors and choses to not delimit any work factors. This lack of a delimit choice by Carl is because he strongly believes low, moderate, and high performers need different things to be successful. However, Carl suggests adding reliability to the O*NET work factors. He would also prefer to see help with certain frustrations as a virtual team leader. For example, VTMs are enormously busy and team members can rarely meet quickly. This slow response, combined with a typical virtual setting involving back-to-back meetings leaves little time to ‘get creative juices going’ and deliver alignment of effort within the team. Carl agrees with this paper's proposed definition of a superteam, the top-down nature of this study's methods, and AI support to team augmentation to meet critical ROI goals.

Mark

Mark is one of the only international AI and VT practitioners in the research population. Mark has 32 years of international collaboration and virtual teaming in a large variety of technical contexts. Having begun his career with the U.K. Ministry of Defence at the age of 16, Mark has numerous accolades and degrees to include a Master of Engineering, Chartered Engineer (CEng) status and an engineering Fellowship (FIET). Mark is unique because he virtual teams across over 32 countries many of which are members of NATO.

Mark recommends a few important changes to the Andersson et al. (2017) performance survey. First, Mark suggests question four be adapted because work is never even. Both in question four and question eight he recommends appropriately distributed or some other 'fit for purpose' terminology. Mark believes that AI can significantly help VTMs if it can assist with keeping these human machine teams mind clear, with the ability to focus on the task. It is this clarity that allows his highest performing employees to perform at a high level, be an effective teammate, and deliver on a task. Additionally, he strongly believes individuals go through peaks and valleys just like teams, and AI may be able to help with this roller coaster of events. For example, can AI help managers bring employees in and out of high-performing and high-functioning teams more effectively.

Mark's list of most important O*NET factors include communication, leadership, training and teach others, and adaptability. The least important factors include multitasking, computer fundamentals, and communication. Mark, consistent with others in the population, suggest empathy be added to the O*NET factor list. Additionally, Mark suggests he has issues with encouraging his employees to have freedom of thought, knowing when to interject and when to listen as a VT. Additionally, understanding how you're their VT work fits into others work, and potentially causes delays in other teams' efforts is critical. Finally, improving the ability of VTMs to share documents easily and prevent the re-inventing of the wheel is critical.

He believes he would look at AI as another teammate. Just as when he constructs a team, he would look for AI team members based on the specific skills it offers to his team. This observation may play critical roles in AI's perceived lack of ROI in some situations. Mark states, in his experience, just adding AI to the team without a proper motivation is bad. This motivation, and possible combination with roll speed, is essential with AI HMTs. Mark agrees with this paper's proposed definition of a superteam, the top-down nature of this study's methods, and AI support to team augmentation to meet critical ROI goals.

Jana

Jana is a 21-year veteran of virtual teaming with a Fortune500 telecommunications company. Jana provided numerous comments that when coded, established a link to where AI can help and how these statements fit in with what other interview subjects were discussing. For example, her statement of not everyone does the same job, not everyone has the same abilities, and not everyone is the same wise phrasing when viewing AI HMT ROI. The comparison of different job types, functions, and responsibilities is important to the examination of what AI can provide and how it can deliver tangible and economic benefit. A second critical observation Jana provides is the brutal, but beneficial results, layoffs and firings have on team performance. If VT employees do not perform, they are fired. How do AI platforms and tools run their course of life and how are AI tools and teammates retired. Finally, what is the financial benefit of a facial expression on team performance? These questions and comments are vital to understanding the human-machine teaming ROI in modern businesses.

Jana provides numerous recommended changes to the Andersson et al. (2017) performance questionnaire consistent with other interview subjects. For example, in line with other subjects, Jana recommends question four be updated to read workload was reasonable or adequate versus even. She argues workload in a VT environment can experience peaks and valleys. For questions two and three Jana argues the workload is always too high. This experience, that VT work is never level loaded, and plans regularly change is the argument for adapting the questionnaires wording. Jana believes high performing teams and employees know their strengths and weaknesses and know how their personal lives influence performance. Can AI assist, replicate, and possibly improve the highest functioning VTMs, Jana believes this.

Jana rates the most important O*NET work factors as relationship building, leadership work ethic, decision making, and communication. Jana argues there are no least important factors, but offers learning, math application, and computer fundamentals. Jana's interview can be summed up by three key themes: relationship building, empathy and team building. AI must be able to team with her in these ways to achieve positive ROI. Jana agrees with this paper's proposed definition of a superteam, the top-down nature of this study's methods, and AI support to team augmentation to meet critical ROI goals.

Sandra

Sandra is a Senior Level Executive in the U.S. federal government. With many years of experience hybrid and virtual teaming, she benefits the research population as her experiences as long-term, successful, but reserved senior executive. In addition, Sandra is a doctoral trained leader who offers opportunities for extensive process, method, and survey face validity. For example, for the Andersson et al. (2017) performance questionnaire, Sandra contends the survey requires an additional question centering on team results, deliverables, or success. She argues it is critical for teams to meet objectives in an allocated timeline in an efficient and effective manner.

Sandra rates updating and using relevant information and knowledge, task management, information gathering, and information processing as the most important. She rates math application and computer fundamentals as the lowest factors. She recommends AI support for white boarding and brainstorming as these are vital for VTs. Additionally, she recommends virtual sticky notes, software that identifies and assists with employees not paying attention in virtual environment, assistance with follow-up questions, and support with meeting minutes, actions, data capture, and action trackers. This ability to be a high-performance virtual teammate, automatically facilitating discussion satisfaction and enrichment would be highly useful for her and her teams. AI augmentation of virtual meetings, meant to enrich and organize virtual discussions is a much-needed requirement for the challenges she faces. Finally, Sandra says that AI needs to provide assistance with soft and emotional skills. Sandra agrees with this paper's proposed definition of a superteam, the top-down nature of this study's methods, and AI support to team augmentation to meet critical ROI goals.

Mitch

Mitch is a Senior Level Executive in the U.S. federal government focusing on critical defense and government capabilities. He has knowledge of U.S. AI efforts, AI, and virtual teaming. As a regular survey designer, user, and reviewer, Mitch provides much needed face validity of this study's survey questions. For example, Mitch expresses support for many of the Andersson et al. (2017) performance questions such as question 11, 'my virtual team was wasting time'. Additionally, he recommends adding trust to the performance questionnaire due to its critical importance to VTM performance. Finally, he believes the survey needs to be repeatable.

Mitch's impact on the O*NET work factors begins with a discussion of wanting help with adding time after meetings to discuss and capture critical actions. Restricting people's ability to go off topic, intervene in good discussion, and talking too long is critical to performance and team ROI. Mitch believes a lot of virtual meetings are sidetracked from bloviating participants and expresses the need for help with this problem. He recommends software that gives a nudge to individuals if they are talking too long or too much in an effort to move the discussion forward. He rates computer fundamentals, multitasking, teamwork, customer service, work ethic, and information gathering are the most important. He recommends the delimitation of math application and learning orientation. Finally, Mitch agrees with this paper's proposed definition of a superteam, the top-down nature of this study's methods, and AI support to team augmentation to meet critical ROI goals. He believes HMTs are the future of work.

Tandem Interview Data Synthesis, Coding Summary, and O*NET Factors

This qualitative interview summary begins by discussing the goals and findings of each major section of the interviews. This overview will include the coding summary, observations, viewpoints, and synthesis of the VTM performance questionnaire, definition of HFVTMs, VTM needs, VTM JTBD, VTM job statements, and the definition of superteams. In addition, this section states the definitions of a VTM, high-performance VTM, QWL, and subgrouping performed by the co-tandem interviewer that are relevant to this study. Finally, this section will conclude with an expert overview and face validity review for this research study's analysis process, recommended VTM and AI O*NET factor delimiting, use of HFVTMs as a proxy, and any new fundamental O*NET GWAs and WPEs relevant to human machine teaming, team augmentation, and superteaming.

Virtual Team, Virtual Team Members, and HPVTM Definitions

Hill (2023) defines virtual teams as groups of geographically, organizationally, and/or time dispersed workers brought together by informational technologies to accomplish one or more organization tasks (Powell, Piccoli, & Ives, 2004, p. 7). The co-tandem interviewer's qualitative interview analysis demonstrated reliable and extensive backing for this definition. A VTM is a member of a geographically, organizationally, and/or time dispersed virtual team brought together by informational technologies to accomplish one or more organization tasks (Hill, 2023).

Hill (2023) modified Scase's (2003) definition of a HPVTM. Scase (2003) originally defined HPVTMs as one who excels higher than the average employee in a specific industry (Scase, 2003). Hill (2023) defined HPVTMs as "one who consistently excels significantly higher than the average employee in a specific industry". Hill's (2023) addition of the term consistency is based on scholars' definition of effort. Effort is measurable in three ways: persistence, intensity, and direction (Kafner, 1990; Locke & Latham, 1990; De Cooman, Gieter, Pepermans, Jegers, & Van Acker, 2009). The validated definition of effort, defined as definition of energy exerted over a unit of time (De Cooman et al., 2009), affords Hill (2023) the scholarly backing for the addition of consistency. This study will also use the Hill (2023) definition of QWL and QWL-based subgrouping in defining HFVTMs.

HPVTM Performance Questionnaire

A central requirement of this study is the development of the self-reporting VTM performance scale questionnaire using Andersson et al., (2017) and the qualitative takeaways from these interviews. To determine whether the VTM performance scale and questions are a generally sufficient scale to identify and classify low-, moderate-, and high-performing VTMs each of the 23 interview subjects were first asked whether they have ever worked on a high performing VT and whether they considered themselves high-performing VTMs. Next, the tandem interview team reviewed Hill's (2023) definition of high-performing VTMs to set the interviews definition and context. Finally, the interview subjects were asked to review each of the proposed 16 performance items and answer two questions. First, did they agree that this was holistically a generally sufficient measures of high performance for a VTM? Second, each participant was asked to think back on their time as a low-, moderate-, or high-performing virtual team member and the high-performing virtual team definition. At this point each interviewee was asked to respond to the extent to whether they agreed to the each of the 16 items, hereafter referred to as questions, and their ability to determine VTM performance. Finally, the interviewer asked whether there were any questions they would add to help determine VTM performance. This section will now discuss the 23 interview subjects' noteworthy adaptations and additions to the novel VTM performance questionnaire.

The interview team began the discussion on the modified 16 questions developed from Andersson et al. (2017) by asking each interview subject to focus on their most recent VTM experience. Anchoring the interview subject was critical for subject evaluation of each VTM performance question. It is noted that only VTM performance survey questions with potential modifications suggested by the pilot study participants will be discussed. The analysis revealed questions one, seven, 12, 13, 14, 15, and 16 should remain in their pilot study wording. It is noted that the majority of interview subjects provided positive feedback during the master tandem interviews process for these questions.

However, question two and three evoked a modest number of stimulating responses. Two respondents, BAK and Jana, noted a VTMs workload was always too high. One respondent, Carl, recommended the team research hourly versus salary workload. Another interview subject, Russ, suggested defining workload from either the leadership or worker point of view. In conclusion, participants were broadly accepting of the addition of the word ‘too’ from the pilot study as the need to clarify the workload was more than just high was deemed appropriate. Wording for questions two and three will stay the same with the only addition ‘too high’ being noted as face validated through this interview process.

Unlike questions two and three, question four’s original version, the workload was evenly distributed within the virtual team, was a consistent problem with nearly every participant. A couple of notable observations include Jana commenting workload is ‘never even’. Mark and Brian agreed with Jana’s critique with all three recommending evenly be changed to reasonably, adequately, or appropriately distributed. Melanie2 noted that unless every VTM was high performing she would recommend adjusting the question. The two tandem interviewers agreed to modify question four to say, the workload was reasonably distributed within the VT, after a careful review of thematic coding and literature.

Interview subjects routinely grappled with question five and six and their use of the word ‘low’ from in the VTM performance questions. Respondents often stated the stress level was not low for high or moderate performing virtual team members. For example, Tina stated VTMs are always stressed. In fact, Tina noted VTMs are often more stressed than their in-person colleagues. Timothy stated higher performers always having higher stress levels. Stress performance curve literature and the significance of stress measures in QWL measurement (Martell & Dupuis, 2006) provide scholarly backing for the revision of question five. Multiple interview subjects suggested wording changes. For example, Nicole recommended changing low to fair and equitable. Stephanie and Adam each recommended the changing the word low to on par, or adequate. For the quantitative pilot study survey, the tandem interviewers agreed to modify question five and six. Question five will now read, the stress level was reasonable for me as a virtual team member. Question six will now read, the stress level was reasonable for the virtual team members in general.

The theme of interview subjects taking issue with the terminology and theme of equal work continued in question eight. Tina flatly stated she does not like the word equal. Mark, who continued to discuss the need for fit for purpose of each question in the survey recommended equal be changed to appropriately distributed. Brian recommended the survey use the phrase reasonably distributed. However, after a review of literature and each respondent responses and coding, the researchers agreed question eight will now read, all virtual team members participated adequately.

After careful thematic coding and review, questions nine and ten remain unchanged after review of the pilot test and full interview data. These questions, which focus on the decision-making process produced only a few noteworthy comments. Nicole recommended changing the focus of the question entirely and aim at the direction of the team. Others like Tina and Brian suggested wording changes focusing on VTMs participation in the majority of decisions or the ability to be part of the decision-making process respectively.

The one question to evoke a bar bell response from interview subjects was question 11. Mitch was enormously supportive of the question and said waste was a necessary element of the performance survey. However, Adam and Tina suggested phrasing changes to alleviate the directness of the term waste, suggesting a focus on use of time. After thematic and tandem interview review, question eleven will remain my virtual team wasted time.

As part of the interview process, respondents were asked for recommended improvements to the novel VTM performance questionnaire. As noted above by De Cooman et al. (2009), numerous interviewees suggested the need for consistency in effort (David2) mission accomplishment (Carl), or addition of VTMs deliverables (BAK). David1, Sandra and others continued with the theme of a performance question focusing on results, deliverables, goals, or objectives. With the scholarly backing and noteworthy interview evidence, the quantitative pilot test will include the question, I consistently met my virtual team goals.

One final performance question, focusing on trust, is suggested after review of the interview data. Predictably, literature on the importance of trust factors in both performance and VTs is significant (Holton, 2001), and multiple respondents such as Mitch pointed this out. The pilot test performance survey will now include a second additional question, my virtual team has high trust in me. These two survey questions, combined with the modified 16 validated self-reporting VTM performance questions are pilot tested during the next stage of this research. A variety of scholarly backing for trusts impact on VTM performance exists (Wildman & Griffith, 2015). Links to VT trust relating to information sharing and its positive impact on performance is broadly supported (Politis, 2003). Trust can reduce interpersonal conflict (Peterson & Behfar, 2003), increase VTM satisfaction (Costa, 2003), and support VTMs meeting deadlines and improving communication (Wildman & Griffith, 2015).

HFVTM Definition, HFVTM Proxy Analysis, and Methods Face Validity

A significant portion of the master tandem interviews focused on the definition of a HFVTM and its appropriate use for AI, human machine teaming, and team augmentation research. To begin, each participant was read the definition of a HFVTM from Hill (2023); high performing virtual team members who have a high level of QWL. They were asked whether they agreed that this is a generally sufficient definition of a HFVTM and whether they would add anything to the definition or describe high-functioning versus high-performance in a different way? Finally, interviewees were asked if they have worked on a high-functioning VT and whether it was desirable to be on either a high-functioning or high-performing VT.

Hill's (2023) novel research and definition of HFVTMs demonstrates strong lived experience roots. Hill's analysis is exhibited with 22 of the 23 participants in the tandem interview agreeing with the HFVTM definition (Hill, 2023). However, this research requires the study to use the definition of HFVTMs, or 'high performing virtual team members who have a high level of quality of work life' (Hill, 2023), as a proxy for HMTs, team augmentation, and superteam creation. It is in this area, and the analysis of these members fundamental work factors and its impact on ROI, that the rest of this section will focus on.

HFVTMs use as a proxy for HMTs, team augmentation, and superteam creation was explored during the tandem interviews. The goal of the HFVTM discussion was to elicit whether the use of these individuals was as a suitable proxy for superteam, team augmentation, and HMT analysis. Each interview subject was asked to think back on the interview's discussion and definition of an HFVTM, how it is being used to analyze human-machine teaming and team augmentation, and how it is being used to explore the creation of superteams. At this point each participant was asked whether HFVTM needs and wants can serve as a proxy for this study's analysis. Additionally, each interview was specifically asked 'do you generally agree that using HFVTMs as a proxy for human machine teaming, superteaming, and virtual team member augmentation analysis is useful?' All 23 participants agreed, and provided extensive face validity, with using HFVTMs as a proxy for this study's research questions and propositions.

Next, each interview participant was asked an additional question: 'broadly do you agree, analyzing HFVTMs and their fundamental work activities as discussed in the above slide, is a useful way of analyzing ROI and Human Machine Teaming, Superteams and team augmentation?' All 23 participants agreed, and provided extensive face validity, with using the fundamental O*NET work activities of an HFVTMs to analyze ROI, human machine teaming, Superteams, and team augmentation.

One final note relevant to the frequent use of mission during the QWL, HFVTM, and performance questions. The survey uses mission only in the areas of QWL and QWL-based subgrouping. A review of literature demonstrates that although mission is discussed by Sirgy, Reilly, Wu and Eftaty (2008), this use focuses on ethical corporate mission and culture. The Sirgy et al. (2008) definition of mission, providing employees with resources that contribute to fulfilling work roles while serving to increase meaning and a sense of purpose in work role identity (Sirgy, et al., 2008), does not exemplify the lived experiences the researcher team uncovered during the interview stage of the research study. As a result, this study defines mission needs as one's personal commitment to the work mission on behalf of the organization that leads feelings of purpose, value or making a difference (Hill, 2023). During discussions with the dissertation chair, the decision was made to pilot test this eighth QWL factor centering on mission, vision, and value (Hill, 2023).

AI O*NET Delimiting and Refinement

The most critical discussions of the qualitative interview process took place around O*NET factors. This exploration into the fundamental work activities of an HFVTM occurred in two separate and deliberate actions. The O*NET factor discussion began by reminding the participants of the interviewers' HFVTM definition followed by showing them a single slide with each of the 47 delimited pilot test O*NET GWA and WPE titles. As the study is interested in the participants specific VTM personal experiences, the interview subjects were asked to think back on their time as a VTM and the definition of an HFVTM. Next, the interview team and interviewee began a discussion on the most and least important O*NET GWAs and WPEs titles relative to an HFVTM. Although the survey's deliberate set of questions revealed insight into the most important and least important O*NET factors, the central goal of this discussion was the delimitation of O*NET factors. Math application, computer fundamentals, multi-tasking, conflict management & resolving conflicts, influencing, thinking creatively, and learning orientation were brought up repeatedly by the interview subjects as the least important O*NET factors related to HFVTM activities. The interview team noted each of the O*NET factors for inclusion during the final analysis and the creation of the quantitative survey.

Next, each participant was asked if there were any factors they believe, low-, moderate-, and high performers would differ on, regarding its importance to performance and ROI. All participants agreed that different O*NET factors would be required based on VTMP. For example, stress management may be more critical for some VTM performers than others. The O*NET factor differences impacting VTMP is a central goal of the quantitative survey.

The second deliberate action taken by the researchers to parse the O*NET data occurred at the conclusion of the tandem interviews. Each interviewee was asked to complete a short

Qualtrics survey that was sent to them at the conclusion of the interview. The O* NET survey asked the respondent to rate all 47 WPE and GWA factor definitions on a 10-point Likert scale. The use of definitions at this stage of the research allowed the team to test the use of both O*NET titles and definitions, and which would be best for use in the quantitative survey. Although the results were roughly comparable, interview subjects often requested the definition of the O*NET factor during the interviews and therefor the team made the deliberate choice to use the O*NET definitions in the pilot test survey.

The exact question asked of interview subjects as part of the Qualtrics O*Net survey was:

> *'Thinking back on your time as a full or hybrid virtual team member and the definition of high-functioning virtual team members from the research interview, please respond on a scale of 1-10, with 10 being maximum and 1 being minimum, on how important each work function is to a high-functioning virtual team member.'*

The use of two techniques, an in-person O*NET title discussion and post-interview O*NET definitions ranking, to delimit O*NET factors was a deliberate choice by the researcher. This methodological choice allowed for an extensive, high-confidence, and thorough review of each O*NET GWA and WPE factor and the establishment of which factors were suitable for the survey stage of this research. To finalize the O*NET delimiting process, the tandem interview team coordinated two meetings with the two O*NET experts. Each Zoom meeting allowed for the review, fine tuning, and approval of the O*NET factor refinement process, collected data, and research analysis to include four possible O*NET factor additions. This process helped establish methodological and face validity by allowing the two O*NET experts to review the collected data against legacy O*NET data that was third party validated. An overview of both meetings and the outcomes will now be discussed.

To begin the first meeting, the researcher presented an overview of the qualitative data from the interviews. The researcher, dissertation chair, co-tandem interviewer, and O*NET experts primarily discussed critical takeaways and findings from the 30 total interviews concentrating on the O*NET factors and observed differences between responses from low-, moderate-, and high-performing VTMs. At the conclusion of the first meeting the team collectively decided to analyze the verbal ranking of the least important 47 O*NET title factors alongside a statistical analysis of the 47 Qualtrics O*Net definition survey ranking. Statistical analysis of the Qualtrics 47 O*NET factors included two methods. First the O*NET factors would be analyzed using the same methodology as the pilot test delimitation. Second, upon agreement with an outside quantitative statistical expert, the 47 variables were analyzed using a 95 percent confidence interval performed with the JASP software.

The examination of the O*NET factor data using the pilot test process involved equal weighting the O*NET GWAs and WPEs from both the 23 individual interviews and the mean of the five member O*NET expert panel. Using this analysis, both groups received 50 percent of the weighting. O*NET GWA and WPE factors with average scores equal to or above 7.0, or those with a single group mean above 8.0 were preserved. This process resulted in the delimitation of 11 factors including Math application, Information Gathering, Attention to Detail, Creativity, Influencing, Judging the Qualities of Things Services or People, Processing Information, Thinking Creatively, Scheduling Work & Activities, Training & Teaching Others, Guiding, Directing, & finally Motivating Subordinates. However, the equal rating of both groups produced the undesirable mathematical effect of outliers.

The second process used to delimit the O*NET factors used weighting each of the 23 interview subject rankings and the five O*NET expert responses equally at the individual level versus by group. JASP was used to determine each of the 47 factors 95 percent confidence interval. Using the upper- and lower-95 percent confident interval bounds, the researcher delimited the factors that did not reach an upper bound confidence interval score of greater than 8.0. Using the above statistical process and data, eight of the 47 WPE and GWA factors were delimited. Importantly, when compared with the interview title rankings and discussions, the O*NET factors recommended for delimit aligned. The eight factors delimited using the confidence interval process are Math Application, Information Gathering, Influencing, Judging the Qualities of Things Services or People, Thinking Creatively, Scheduling Work & Activities, Resolving Conflicts and Negotiating with Others, and Training & Teaching Others.

Despite both delimit processes being comparable, the 95 percent confidence interval process using the equally ranked individual O*NET data was chosen because of the strength of the statistical support, the alignment with the interview data, ability to have the data reviewed against legacy O*NET expert data, the ability for third party validation, and the exclusion of outliers. Furthermore, this statistical process was reviewed with an outside statistics expert resulting in face validity of the process and the resulting O*NET factors recommended for removal.

The second O*NET expert panel meeting occurred at the conclusion of the statistical analysis of the O*NET factors recommended for delimitation. The expert O*NET panel agreed with the researcher analysis and the 8 O*NET delimitations. Additionally, at the conclusion of the second meeting a conversation on including an additional four VT and AI O*NET factors ensued. These unique O*NET factors will be discussed further during the section to follow. It was regularly noted during the qualitative interviews VTMs experienced four possible additional O*NET GWAs or WPEs. These possible new O*NET factors centering on VTMs and AI are:

- Role Independence and Adaptation - Ability and motivation to consistently act independently and adapt to a virtual team independent environment.
- Empathy - Ability to understand, sympathize, and engage with empathy toward colleagues to build camaraderie, fellowship, and collaboration.
- Role Diversity - Ability to act and engage in a role diverse environment requiring high levels of adaptability.
- Role Speed - Ability for automation tools to perform activities with high speed (above that of a human).

During the second call, the full O*NET expert panel agreed to include these four additional O*NET factors for analysis in the quantitative pilot test survey. This process also allowed for face and construct validity of the new O*NET variable definitions and process validity of the analysis steps. In addition, the researcher validated the use of 42 total O*NET factors was within survey timing expectations to achieve minimal data loss. The process resulted in 42 total O*NET WPEs and GWAs were used in the quantitative survey pilot study as part of this study's exploratory sequential mixed methods analysis. The final set of 42 O*NET factors are investigated in the quantitative survey portion of this chapter.

VT and AI O*NET Work Activities, JTBD, & Job Statements

As the interview continued, the tandem interview team were able to build a more thorough scholarly understanding of the VTM job requirements. Building on the understanding of job statements and JTBD from chapter two, the interview team was able to ask a series of questions on VTM vs non-VTM needs. For example, the participants were asked what capabilities a VTM needs that a non-VTM may not need. Next, they were asked what makes their job as a VTM, or certain parts of it challenging, troublesome, or frustrating. Subsequently, the VTMs were asked what makes their job as a VTM, or certain aspects of it time consuming. After the interview subjects were asked what aspects of their VTM job were wasteful, or cause your data, job and work activities to go adrift, deviate, or be derailed. Finally, each participant was asked what job activities they would want automation or AI to perform.

The goal of this section was to uncover what, if any, O*NET factors AI might perform that are missing from the current O*NET GWA and WPE lists. The ability to decipher work activities that VTMs might be most in need of using AI for, is a central role of this interview. During this discussion, participants noted multiple fundamental work activities that are different, or missing, for a VTM. This full list and participant contributions is below:

- Need to be a self-starter (Tina)
- Willingness to ask questions (Tina)
- Collaborate a lot (Tim, Melanie1, Matt)
- Thinking outside the box
- Self-reliance (Stephanie)
- Patience (Stephanie, Melanie, Byron, Daniel)
- Clear communications (Stephanie, Nicole)
- Ethics and Integrity (John)
- Understanding across cultures (Melanie2)
- Time Zone Patience (Melanie2)
- Flexibility (Melanie2)
- Lots of trust and reliability (Matt)
- Empathy (Mark)
- Freedom of thought (Mark)

- Mastery (David2)
- Time management (David2)
- Role Diversity (David2 & Pilot)
- Motivation (David2 & Pilot)
- Comradery (David2 & Pilot)
- Independence (Werner)
- Self-Starter (Werner)
- Restraint (Nicole)
- Focus (Nicole)
- Back-to-Back meetings (Melanie1)
- People are nicer F2F (can be mean)
- Role adaptability (Mitch)

The researcher then coded each interview focusing on these possible novel O*NET additions and four central themes were uncovered. Each theme was discussed with two seminal O*NET experts and four possible novel O*NET GWA and WPE work factors uncovered. These proposed O*NET additions, titles, and their definitions are listed below. It is the goal of the quantitative survey to test these four new O*NET factors with the full VTM survey population.

- Role Independence and Adaptation - Ability and motivation to consistently act independently and adapt to a virtual team independent environment.
- Empathy - Ability to understand, sympathize, and engage with empathy toward colleagues to build camaraderie, fellowship, and collaboration.
- Role Diversity - Ability to act and engage in a role diverse environment requiring high levels of adaptability.

- Role Speed - Ability for automation tools to perform activities with high speed (above that of a human).

Additionally, coding of the full and pilot test qualitative interviews revealed a long list of items the interviewee team observed VTMs may want assistance from AI on within their daily duties. This full list of AI recommended role assistance is listed below (Figure 3). These VTM assistance additions will be discussed further with the full survey free response responses allowing for a wider view of a large number of quantitative responses.

Reduction of bloviating (VTMs stuck on topics during meetings) (Mitch)
Help getting answers fast (Stephanie, Nicole)
Getting Supplies (Russ)
Collaboration via white board - Coordination (Melanie1, Sandra, Matt, Jeremy, Nicole)
- Establishment of meeting break out rooms (Russ)
- Brainstorming (Melanie1, Sandra)
- Speed (Nicole)
- Action tracker & capturing data in meetings (Sandra)

Tool usage, training, and interactive additions (Melanie1, Byron)
- Change management of tools (Russ)

Capability to see VTMs faces (Jana, Fab, Mark)
- Participation, interaction, and body language (Adam)
- Assistance reading the room (Byron)
- Visual cues (Russ)
- Sensing vibe & energy (Fab)
- Read tones - feedback in real-time (Melanie1)
- When to interject (Mark)

Contact and getting in touch with other VTMs
Time zone assistance and collaboration (David1, Melanie2, Brian, Byron)
Sifting through automatic reports (David2)
Relating work to overall goals and activities (Nicole, Melanie1, Mark)
Comradery (Scott)
Project scope (limit and understanding)
Communication (Tim, Daniel)
- Clear communication of task and coordination (Nicole, Tim)

Filter out material not needed (Mark)
Relationship building (Jana)
Empathy (Jana)
Team building (Jana, BAK)
Scheduling (Byron)
Dependency Management (Byron)
Follow up questions & pull up data automatically (Sandra)
Monitoring and measuring (Nicole)
Help VTMs taking breaks and setting personal time (Tina, Nicole)
- Reduction of overwork (Nicole)

Time management & coordination (Tina, Tim, Scott, Adam, BAK)
Introducing new team members (Tim)
Reduction of number of meetings (Tim)
Rating meetings (Tim)
Analytics & coalescing of data (Stephanie, Scott)
- Follow the sun production

Double checking other VTMs work to reduce task repetition (Stephanie)
Training (Stephanie)
Teamwork (Stephanie)
Managing outside environment (work/home) (Scott)
Motivation (Scott, Fab, Mark)
Help establish quality of work life boundaries (Russ)
Help reduce VTM multi-tasking (Russ)
- Low engagement often leads to misunderstandings

Speed of business roll speed (Mark)
Adaptability (Fab)
Assistance with or reduction of back-to-back meetings (Melanie1, Carl)
- Establishment of time after meetings for coordination and other activities (Mitch)

Capturing transcripts (Melanie1)
Track VTM accomplishments (Melanie1)
People are slow – help VTMs quickly meet up (Carl)
Prevent reinventing the wheel and other nonstarters (Mark)
Assistance in interjecting in meetings
Time coordination (Adam)
Probability, factor, and scenario analysis
Know when someone is listening (BAK, Sandra)
Analyze and summarize consequences (Byron)
Help with VTM soft skills and emotional skills (Sandra)
Visual sticky notes (Sandra)

Figure 3 - Qualitative Interviewee List of VTM Assistances for AI

Finally, two overall AI and HFVTM ROI opportunities for future research were noted. These included the exploring of some industries, including those surveyed in the next stage of this research, might be best suited virtual teaming and AI assistance. Understanding which industries may or may not be best suited for AI assistance may reveal additional threads related to ROI. Related to this, future research should also explore VTM, organization, and industry desire for AI assistance.

Superteams Definition

Next, the tandem interview team focused on the heart of this dissertation study's methods. First, interview subjects were introduced to this paper's novel definition of a superteam. For this paper, superteams are defined as high-functioning virtual team members integrated with AI tools, capabilities, and team members capable of surpassing performance levels of human-only teams. Each participant was asked if this was a generally sufficient definition of a superteam to establish face validity. The goals of these discussions was to provide face validity for this new definition of Superteams. All 23 participants agreed that this study's definition of a Superteam was generally sufficient.

Quantitative Pilot Study Survey

The primary objective of the quantitative pilot study is to validate the survey instrument developed using the qualitative interview portion of this mixed methods exploratory research. Because this study is attempting innovative additions to O*NET, a seminal O*NET expert panel is employed to provide supplemental face validity. At this stage of the research, the intent of the pilot study is to test the instrument's capability to examine the propositions (Creswell, 2014). The pilot study survey overview will provide a thorough overview of the process, O*NET and expert panel input, sample selection, data collection, survey updates, use of CMV, and preliminary statistical analysis of the data collected.

The sample size of 20 participants does not allow for a complete analysis of the survey instrument using rigorous statistical analysis to include regression techniques. Due to the complexity and exploratory nature of the research study, to include O*NET GWAs and WPEs, VTMs perception of AI, and using HFVTM as a proxy for superteams analysis, there are higher than normal levels of variability. The variability in how questions can be answered in the pilot study does not provide the researcher with enough degrees of freedom to fully dissect the full population bell curve. The researcher expected this and predicted the full survey population will provide enough power to fine tune the breadth of variability using statistical analysis. With this expectation the researcher made the informed decision with a known risk that parts of the survey may fail, and therefore would be removed or adapted during the master survey statistical analysis. This research decision was made with dissertation chair and expert panel that the study's quantitative analysis is expected to hold together statistically, and the researcher will reevaluate all data and survey questions during the master survey analysis phase.

Survey Development Process

The development of the pilot survey occurred over multiple expert and dissertation committee meetings with the researcher's doctoral chair, dissertation committee, O*NET experts, and qualitative pilot interview participants. The researcher first developed the pilot survey using the questions discussed in chapter three and projected during the dissertation proposal. Using these questions as the starting point, the researcher used the qualitative interview takeaways discussed earlier in this paper to refine and add to the proposed pilot study survey. Subsequently, the researcher met with the doctoral chair and three volunteer participants from the qualitative portion of this exploratory sequential mixed methods analysis to review the pilot study survey. The pilot test volunteers from the qualitative interview stage included Sandy, Becky, and Veronica.

During the pilot survey review stage, the researcher made a series of changes to improve survey functionality, improve flow, reduce survey length, reduce the time it took participants to take the survey, improve CMV effectiveness, and reduce the non-response rate. First, the dissertation chair recommended adding a midpoint value in each Likert scale, bolding necessary instructions to the participant, making small grammatical changes, modifying language to past tense for performance and virtual team questions, adding a slide bar for participant observation of progress, and finally updates in granularity of the demographic questions at the end of the survey.

Additionally, the chair recommended that the survey take less than 21 to 22 minutes for participants to finish. With survey use significantly increasing, optimum survey length continues to be an area of much academic discussion. Recent studies suggest the maximum length of an internet survey be between 20-28 minutes, with most practitioners arguing for 20 minutes or less (Revilla & Höhne, 2020). Survey completion time can be critical as survey fatigue can negatively affect data and response with a lengthy survey (Liu & Wronski, 2017). To analyze survey time and ease the burden on the participant, the researcher analyzed the survey time before pilot testing and added a statement telling the participant, ‘in order to ensure your responses are included in the final analysis, please complete the survey in full.’ Additionally, the researcher used additional techniques such as survey deadlines (Porter & Whitcomb, 2005), invitation personalization (Heerwegh, Vanhove, Matthijs, & Loosveldt, 2005), prenotification and reminders (Shih & Fan, 2008), and target population relevance to increase response rates (Crawford, McCabe, & Pope, 2005).

The survey structure and questions play a significant role in survey fatigue. The survey fatigue estimation process used by the researcher followed a set of assumptions. First, the researcher assumed from the literature that it would take approximately 7.5 seconds to answer an online survey question (Versta Research, Inc, 2011). Second, the researcher assumed from the literature that if the question is simple, eight questions can be answered in one minute by the survey participant. As the proposed pilot study survey question structure includes a majority of simple versus complex questions, the simple survey calculation is used. This research decision is because the pilot study survey predominantly utilizes simple questions layered in a matrix-style structure. A matrix-styled question is considered a simple question and thus is assigned a point for each question. For this pilot study survey, the researcher calculated that the survey contained approximately 131 points. Dividing this point total by eight allows the researcher to estimate that the pilot study survey would take approximately 19-22 minutes to complete.

This pilot study survey estimation of 19-22 minutes was validated when a test check was accomplished by conducting the live pilot study survey. During pilot testing, survey time was confirmed to be approximately 20 minutes reaching the upper bounds of researcher goals to maximize data while reducing data loss. The response rate per email invite sent for the pilot test was 60 percent and was in line with researcher expectations. This section will now discuss the changes made to the survey and the methodological, data, and validity backing for the changes.

First, the dissertation committee chair suggested refining the survey introduction and informed consent statement to provide a cleaner presentation and to introduce the respondent to the fact that some questions may be reverse-worded. The researcher added the following three sentences to the introduction ‘Some items are worded in reverse. All items are intended to read as written. Please do not overthink the questions.’

Next, the researcher held a series of meetings with each committee member to review the survey and make recommendations before the pilot test was administered. After the pilot test, the researcher reviewed the data with each committee member and sought and received approval prior to the complete study rollout. This section will now review the committee feedback before and after the pilot test. The first committee member recommended no changes prior to the pilot survey but contributed heavily to the survey data analysis discussed later in this chapter. For example, the researcher and committee member reviewed the data post-pilot test using JASP. The committee chair recommended providing additional methodological and literature backing for the VTM performance and QWL mission questions including the additional questions formulated from the qualitative interviews. The suggestion focuses on validating questions developed from the qualitative interviews using outside scholarly sources. However, the observations made during the qualitative interviews were new. After thoroughly reviewing the literature and possible questions, the researcher determined that the qualitative discoveries did not fit easily into prior research. Therefore, the scholarly backing for these additional performance questions are accomplished using the dissertation chair method captured below.

The pilot study tested adding two new performance questions to the end VTM performance survey that were not considered as part of the Andersson et al. (2017) survey or other VTM performance surveys. The two additional questions are ‘I consistently met my virtual team goals’ and ‘My virtual team has high trust in me’. The addition of these two VTM performance questions is accomplished using the below logic process.

First, as discussed in the qualitative interview coding, the reason why these questions are required is the theme of meeting the VT goals and the VT having high trust in the VTM are consistent. These themes of trust and meeting goals consistently erupted from the 30 participants. The themes of trust and meeting goals are not only qualitatively coded, but they were also validated from the SMEs and consistently present in AI and VT performance literature. For example, as discussed in chapter two, AI analysis using results from a Wizard of Oz approach demonstrates lower levels of trust in the AI partner in low-performing teams, loss of trust in AI over time across all levels of performing teams, and low- and moderate-performing teams demonstrating lower levels of trust in their human partners. Similarly, for VTMs, trust impacts performance greatly due to its links to knowledge sharing (Liu & Li, 2012), transfer, and exchange (Quigley, Tesluk, Locke, & Bartol, 2007). Trust is a key component in performance of VTMs in respect of AI due to the combination of interpersonal trust and technology trust greatly impacting knowledge sharing (Golden & Raghuram, 2010). Literature demonstrates strong backing for the lack of trust in technology leading to inadequate knowledge sharing (Breu & Hemingway, 2004) and lower performance (Hill, 2023).

The researcher uncovered multiple trust and goal accomplishment themes in the qualitative interviews. Furthermore, searches of all study interviews unveiled additional support. These research observations combined with the lack of validated questions in other VTM performance instruments, allows the researcher to determine this study unveiled a uniquely identifiable gap in literature. Supported by this study's exploratory goals the researcher made the decision to create and test these two new VTM performance questions.

By borrowing the same language used by Andersson et al. (2017) that was tested and refined in this study's qualitative interviews, the researcher provides additional justification for the wording of these two additional VTM performance questions. The researcher did not create these questions, instead the combination of the above logic from literature, previous phraseology, and validated measurement method provides further justification to the wording of these two questions. Finally, methodical justification for the validation of these two questions is formulated using SME review, qualitative pilot participant review to assess if the questions captured what the interview subject was discussing in the interview, and review of extant literature for the creation of new survey items (Creswell, 2014).

Methodologically, specific items are purposefully inverted by the researcher and original instrument developer. For example, Andersson et al. (2017) use question inversion for the intent of quality control, and the researcher continued this for multiple VTM performance and CMV survey questions. These items were explicitly identified, such that in the event they were answered in the opposite that was expected (i.e., answering five verses one), those surveys were pulled for further research analysis to evaluate whether or not the rest of that participant's answers could be trusted, or it was only the inverted questions that were answered incorrectly. Whether the participant was not paying attention or there was another cause of the inverted answer, this/these CMV question(s) provided a binary parity check to evaluate that participant's poll response of consistency.

Discussions with the second committee member primarily focused on the survey design, O*NET ODI section, and the five free-response AI-centric questions. This committee member, whose background is that of an AI researcher, approved the methods, survey design, and approach taken in the first meeting. In the post-pilot test meeting, the committee member approved of the final release and expressed excitement at the data captured to date by the pilot test.

Notably, the CMV effectiveness rate for the pilot study was estimated to be too high due to the CMV question complexity. During meetings with the third committee member, discussions primarily centered on the low rate of CMV effectiveness and possible question confusion. It was determined during emails and meetings with this committee member that respondents were likely to overthink survey CMV questions. The initial version of the survey used multiple types of CMV questions. One, in particular, focusing on fridge size in the GWA ODI section elicited positive reactions from respondents and effectively captured whether the respondent was paying attention. The decision was made to update all CMV questions and focus on entertaining and fun questions, keeping the respondent engaged while still allowing the researcher to determine whether the respondent was paying attention. According to Champagne (2017), this CMV method is appropriate because research demonstrates that using humorous questions provokes the respondent to be more engaged, and therefore higher response rates are attainable. The following questions were changed to improve survey CMV effectiveness while giving the respondents a chuckle (Champagne, 2017) to increase response rate and engagement.

- Original: 1) DELAYS in team communication led to INCREASED team performance (Rate 1 if you think delays in team communication leads to low performance, rate 5 if you think high levels of communication leads to optimum performance).
    - New: The color of my co-workers' cars effect my mood?
- Original 2) Human Capital - The ability to achieve LOW levels of education, training, and new skills to REDUCE performance, service, knowledge, soft skills, and creativity that limit organizational success. (Rate 0, very low, if this is not applicable and you desire higher performance)

    - New: Staplers - The ability to operate red staplers in the basement. (Rate 0, very low, if this is not applicable)
- Original 3) My management's HIGH level of control over my job allows me to achieve optimum performance. (Rate 1 if you think oppressive bosses are bad, rate 5 if you think micromanagement achieves optimum performance).
    - New: I feel the COLOR of my printer affects my performance?

Additionally, the third committee member recommended that the researcher review cross-loading specifically within the VTM performance scale. Therefore, the researcher analyzes cross-loading using PCA and EFA during the pilot and final survey data analysis process, focusing on understanding VTM performance in both the 'teaming' and 'individual' factor analysis.

During discussions with outside experts, the researcher attempted to reduce data loss. For example, an outside qualitative survey expert suggested adding statements such as, ‘Rate 0, very low, if this is not applicable’, to provide further respondents clues on how they should answer CMV questions if they were paying attention. These changes were possible because the CMV goal was to determine whether participants were paying attention and whether survey results deliberately would not be impacted by a more positive or well-understood respondent. While there is no one way to handle CMV, with the changes made during the pilot test process, the researcher can successfully analyze the final survey data of each participant instead of throwing out respondent data and reducing collection opportunities. During the data analysis phase, the researcher provides what impact the degrees of freedom certain respondents with inconsistent CMV responses have on the overall statistical power. Then, if it has little effect, the data responses is removed. The researcher also provides how many responses were removed because of CMV error checks. The data is kept if the statical data is consistent even when including the possible invalid CMV participants.

During the pilot study, participants were encouraged to provide feedback after taking the survey. The researcher received immediate feedback, via email and telephone, from five of the 20 participants. These participants, in particular Yelena, advised the researcher on small wording changes, such as adding definitions of satisfaction, importance, and frequency, along with comments on minor grammatical errors. In addition, these participants commented on the successful use of the CMV questions discussed above and their ability to increase participant concentration due to the comedic nature of the questions providing an additional layer of face validity. Additionally, the researcher added a generational demographic question to be able to analyze data across ages or generations.

Further, the researcher added hospitality alongside the service industry option and additional country options for the location of the VTM. Next, the WPE section was broken into two separate pages as respondents struggled to tackle the section due to length. The researcher added two additional occupations, student and teacher, into the demographic question section. Finally, the researcher sought feedback from multiple work conferences centering on AI and virtual teaming on survey refinement, CMV success, and overall additions.

Sample Selection

The breadth of pilot study participants, covering three continents and six countries, combined with the COVID-19 pandemic impact, required the researcher to email survey participants. The researcher focused on the defense, technology and telecommunication, and a variety of other industries from the researcher and co-tandem interviewer's network. The researcher decided to randomly select 70 names from the researchers and co-tandem interviewer network of 214 VTMs using the Microsoft Excel random number generator function. The random sample selection produced a distribution covering three continents, six countries, and over 16 different business organizations that allowed the researcher to assume generalizable results. Table 1 displays the frequencies of VTM industries invited in the pilot study random selection.

Table 1 - Frequencies of VTM Industry for Pilot Study Random Emails

Industry	Frequency	Percent	Cumulative Percent
Defense	23	32.86	32.86
Technology & Telecommunications	11	15.71	48.57
Other Industry	36	51.43	100

Data Collection

The pilot study survey requests were sent to the selected random survey participants by email. Two sequential invites to the first 20 and subsequent 20 random selectees were emailed. The survey email invite requests were sent by Florida Institute of Technology and the researcher's organization email. The email messages identified the researcher as a doctoral student at the Florida Institute of Technology and a fellow virtual team member. The researcher noted zero returned or bounced emails leading to the assumption that all emails reached the recipient's email network. However, with the significant prevalence of spam and email filters, it is impossible to determine whether all study recipients received or read the survey email. The survey pilot ran from 9/22/22 to 9/30/22. After the first request, only one additional follow-up email was sent to the recipients. After the pilot study data collection phase, the goal of 20 survey responses was achieved. Because the pilot study was anonymous, no representative distribution tests, industry tests, or regional analysis was performed. The researcher did note the requirement to provide a follow-up email to assure participants that the invite was not a cyber scam or network vulnerability within specific defense networks.

A review of the pilot study data demonstrated the fourth participant to complete the survey answered all data responses with a maximum value and failed each of the CMV tests. This participant data was removed due to CMV failure and data reliability issues.

Upon review of the first 20 valid data recipients, the researcher tabulated and analyzed the data to determine if the sample collected represented a random set of respondents. Each of the 20 participants had experience as either a full or hybrid VTM. Further, 14 of the 20 respondents had experience as a VTM prior to COVID-19. To determine additional data points on whether the collected sample represented a random set of respondents across industry, location, and virtual team leadership level the researcher performed multiple respondent frequency checks. The resulting frequency tables are presented in the below tables. First, the researcher performed a frequency check to understand the sex of the responding VTM. Table 2 demonstrates a distribution in the sex of the VTMs that responded to the pilot survey.

Table 2 - Pilot Study Respondent Frequencies for Virtual Team Member Sex

Male/ Female	Frequency	Percent	Cumulative Percent
Male	14	70	70
Female	6	30	100

The researcher performed additional checks to understand the location of the responding VTM. Table 3 demonstrates a distribution in the residency reach of the VTMs that responded to the pilot survey.

Table 3 - Pilot Study Respondent Frequencies for Virtual Team Member Location

Residency	Frequency	Percent	Percent
United States	16	80	80
Europe	3	15	95
Australia	1	5	100

The researcher performed additional analysis to understand the education level of the responding VTM. Table 4 demonstrates a distribution in the education level of the VTMs that responded to the pilot survey.

Table 4 - Pilot Study Respondent Frequencies for Virtual Team Member Educations

Highest Degree	Frequency	Percent	Cumulative Percent
High School diploma or equivalent degree	2	10	10
Bachelor’s degree	11	55	65
Master's degree	6	30	95
Doctorate degree	1	5	100

Next, the researcher performed frequency checks to understand the industry of the responding VTM. Table 5 demonstrates a distribution in the industry reach of the VTMs that responded to the pilot survey.

Table 5 - Pilot Study Respondent Frequencies for Industry

Industry	Frequency	Percent	Cumulative Percent
Telecommunications	8	40	40
Defense	4	20	60
Defense & Government	3	15	75
Medical/Healthcare	2	10	85
Telecommunications & Technology/Information Technology	1	5	90
Service / Hospitality,Teacher,Student	1	5	95
Technology/Information Technology	1	5	100

Finally, the researcher performed a final series of frequency checks to understand the leadership level of the responding VTM. Table 6 demonstrates a distribution in the leadership level of the VTMs that responded to the pilot survey.

Table 6 - Pilot Study Respondent Frequencies for Virtual Teaming Leadership Level

Industry	Frequency	Percent	Cumulative Percent
No Virtual Team Management Experience	5	25	25
Subject Matter Expert	2	10	35
First Level Manager	6	30	65
Second Level Manager	5	25	90
Senior Leader	2	10	100

The random sample produced from the pilot study confirmed a distribution that would allow the researcher to assume generalizable results for the pilot study.

O*NET and Expert Panel Input

The researcher not only met with each committee member to review data, statistical analysis techniques, and survey design, the researcher also engaged two outside O*NET experts and three outside survey design and quantitative statistical analysis experts. This section will review the input provided by these experts and the changes made during this rigorous review.

The first outside expert provided input on survey design to maximize linear regression analysis. This expert advised being able to analyze the data using multiple factors combined in linear regression and the ability to perform SEM using JASP in future research. The first outside expert agreed that both avenues of statistical analysis would be possible using the survey as designed.

The second outside statistical expert advised analyzing data reliability to include Cronbach Alpha α and McDonald's ω in the pilot test and full survey data analysis. The researcher will perform these statistical analysis techniques as appropriate in the pilot and final study analysis sections.

The third outside expert advised the researcher to consider and protect against automated and AI BOTS. While the researcher investigates and accounts for natural warnings such as speed of survey completion and duplicate time stamps to determine BOT use, the outside expert encouraged additional efforts to aid in data confidence. BOTs are becoming a widespread threat to quality responses (Zhang, Zhu, Mink, Xiong, Song, & Wang, 2022). BOTs are software or AI algorithms that perform automated tasks, such as survey taking to collect compensation for the developer, that can result in Type 1 and Type 2 errors (Huang et al., 2015; Marjanovic, Struthers, Cribbie, & Greenglass, 2014; Storozuk, Ashley, Delage, & Maloney, 2020). Data from 2021 suggests that nearly half of the global internet traffic resulted from BOTs (Imperva, 2022), with malicious BOTs making up 27.7 percent of worldwide internet activity (Imperva, 2022, p.4). Because compensation is a driving factor in BOT use, the researcher does not offer money or rewards to take the survey (Teitcher, Bockting, Bauermeister, Hoefer, Miner, & Klitzman, 2015).

As discussed previously, the researcher uses multiple attention checks as part of the CMV questions. Attention checks not only ascertain thoughtless responses from humans but also successfully detect BOTs not trained to read questions (Yarrish, 2019; Storozuk et al., 2020; Zhang et al., 2022). This survey uses three attention checks discussed in the CMV section of chapter four. Finally, the survey also includes five open-ended responses at the conclusion of the survey to detect fraudulent responses while collecting additional feedback from humans. Open-ended questions help define if a survey response is a BOT or human-created (Griffin et al., 2022; Storozuk et al., 2020). These five open-ended responses are:

- What makes your job as a virtual team member, or certain parts of it, challenging, troublesome, or frustrating?
- What capabilities does a virtual team member require that a non-virtual team member may not require?
- What makes your job as a virtual team member, or certain parts of it, time-consuming?
- Is there any part of your virtual team job you would like assistance from artificial intelligence tools to improve job satisfaction?
- What virtual team or artificial intelligence training, if any, you would suggest for you and your team?

The researcher engaged two outside O*NET experts during a review of the survey instrument. Throughout two Zoom calls, the O*NET seminal experts reviewed responses from the qualitative interviews and researcher coding, mainly focusing on the VT and AI additions to O*NET to include new AI and VTM WPEs and GWAs. The experts agreed on the addition of four testable WPEs and GWAs, measurement wording for the WPEs and GWAs, the delimitation of certain WPEs and GWAs not germane to the research analysis goals, and approved of the pilot study survey instrument and pilot study data. Finally, the researcher received the go-ahead from the outside O*NET and quantitative survey data experts. Each expert and committee member agreed that the survey addresses this study's propositions and that the results align with this dissertation's research goals.

Statistical Analysis of Pilot Study Instrument Validation

During the pilot study analysis with the dissertation chair, an outside JASP statistical expert, and the co-developer of the survey, reviewed numerous data points, survey constructs, and validity measures. The survey was reviewed with a focus on how each of the propositions was addressed and if the results were in line with expectations, scholarly evidence, and this dissertation's research goals. A discussion of each survey improvement and recommended changes will now be discussed.

First, descriptive statistics for each critical survey component is displayed below (Table 7). The descriptive statistics for the VTM performance, QWL, and QWL-based subgrouping scores relevant to VTMP ranking to include HFVTMs is shown below. The data shows that the researcher is achieving a mix of VTM performers. A mix of high-, moderate-, and low-performers is required for the propositions. The mean and standard deviation statistics are in line with what was expected. The values for skewness and kurtosis indicate normal univariate distribution as they are within a range of plus or minus two (George & Mallery, 2019).

Table 7 - Pilot Study Performance, QWL, and QWL Subgrouping Descriptive Statistics

	Valid	Median	Mean	Std. Deviation	Skewness	Std. Error of Skewness	Kurtosis	Std. Error of Kurtosis	Minimum	Maximum
VTM Performance Score	20	74	71.2	10.506	-0.915	0.512	1.44	0.992	43	87
Quality of Work Life (QWL) Score	20	104	103.2	8.05	-0.842	0.512	1.171	0.992	82	115
QWL Subgrouping Score	20	23	22.3	4.953	-0.482	0.512	1.017	0.992	10	32

The descriptive statistics for the O*NET importance scores relevant to ODI scores are below (Table 8). The mean and standard deviation statistics are in line with what was expected. The values for skewness and kurtosis vary somewhat for a few of the O*NET importance factors indicating a lack of normal univariate distribution as some range outside of plus or minus two (George & Mallery, 2019). This was expected with the smaller pilot study population.

Table 8 - O*NET GWA and WPE Importance Pilot Study Scores

O*NET Factor Importance	Valid	Mean	Std. Deviation	Skewness	Std. Error of Skewness	Kurtosis	Std. Error of Kurtosis
WPE1 Importance	20	9.3	0.865	-0.663	0.512	-1.347	0.992
WPE2 Importance	20	8.55	1.432	-1.008	0.512	0.583	0.992
WPE3 Importance	20	9.45	0.887	-1.592	0.512	1.854	0.992
WPE4 Importance	20	9.45	0.999	-1.785	0.512	2.117	0.992
WPE5 Importance	20	8.45	2.235	-2.11	0.512	5.695	0.992
WPE6 Importance	20	9.05	1.05	-1.017	0.512	0.068	0.992
WPE7 Importance	20	8.7	1.38	-0.464	0.512	-1.286	0.992
WPE8 Importance	20	9.35	0.988	-1.536	0.512	1.503	0.992
WPE9 Importance	20	9.05	0.999	-0.813	0.512	-0.236	0.992
WPE10 Importance	20	9.35	0.933	-1.24	0.512	0.523	0.992
WPE11 Importance	19	9.211	0.976	-0.868	0.524	-0.468	1.014
WPE12 Importance	20	8.95	1.05	-0.498	0.512	-1.001	0.992
WPE13 Importance	20	9.25	1.118	-1.302	0.512	0.305	0.992
WPE14 Importance	20	9.1	1.294	-1.014	0.512	-0.828	0.992
WPE15 Importance	20	9	1.076	-0.563	0.512	-1.061	0.992
WPE16 Importance	20	8.8	1.005	0.097	0.512	-1.509	0.992
WPE17 Importance	20	8.9	1.373	-1.023	0.512	-0.044	0.992
WPE18 Importance	20	8.7	1.38	-1.131	0.512	1.102	0.992
WPE19 Importance	20	9.35	0.813	-0.766	0.512	-1.002	0.992
WPE20 Importance	20	8.7	1.302	-1.285	0.512	2.051	0.992
WPE21 Importance	20	7.9	1.683	-0.636	0.512	0.083	0.992
WPE22 Importance	20	9.85	0.489	-3.436	0.512	11.885	0.992
WPE23 Importance	20	9.2	0.894	-0.432	0.512	-1.672	0.992
WPE24 Importance	20	9.3	0.865	-0.663	0.512	-1.347	0.992
WPE25 Importance	20	8.4	1.231	-0.12	0.512	-0.962	0.992
WPE26 Importance	20	8.8	1.673	-1.597	0.512	2.311	0.992
GWA1 Importance	20	9.15	1.089	-0.869	0.512	-0.694	0.992
GWA2 Importance	20	8.1	1.586	-0.533	0.512	-0.393	0.992
GWA3 Importance	20	9.2	0.834	-0.412	0.512	-1.434	0.992
GWA4 Importance	20	8.55	2.114	-1.97	0.512	4.005	0.992
GWA5 Importance	20	8.35	1.461	-1.134	0.512	1.052	0.992
GWA6 Importance	20	9.1	1.294	-1.501	0.512	1.523	0.992
GWA7 Importance	20	8.6	2.479	-2.527	0.512	7.352	0.992
GWA8 Importance	20	9.15	0.933	-0.756	0.512	-0.391	0.992
GWA10 Importance	20	8.8	1.281	-0.587	0.512	-0.764	0.992
GWA11 Importance	20	8.75	1.251	-0.548	0.512	-0.67	0.992
GWA12 Importance	20	8.85	1.182	-0.318	0.512	-1.541	0.992
GWA13 Importance	20	8.25	1.888	-0.557	0.512	-1.087	0.992
New O*NET Factor 1 Importance	20	8.35	1.785	-1.454	0.512	2.949	0.992
New O*NET Factor 2 Importance	20	8.9	1.165	-0.896	0.512	0.33	0.992
New O*NET Factor 3 Importance	20	8.35	1.348	-0.146	0.512	-1.007	0.992
New O*NET Factor 4 Importance	20	7.4	3.016	-1.541	0.512	2.017	0.992

The descriptive statistics for the O*NET frequency scores relevant to ODI scores are below in Table 9. The mean and standard deviation statistics are in line with what was expected.

The values for skewness and kurtosis vary somewhat for a few of the O*NET frequency factors indicating a lack of normal univariate distribution as some range outside of plus or minus two (George & Mallery, 2019). This was expected with the smaller pilot study population.

Table 9 - O*NET GWA and WPE Frequency Pilot Study Scores

O*NET Factor Frequency	Valid	Mean	Std. Deviation	Skewness	Std. Error of Skewness	Kurtosis	Std. Error of Kurtosis
WPE1 Frequency	20	9.35	0.875	-1.321	0.512	1.289	0.992
WPE2 Frequency	20	4.85	2.323	0.062	0.512	0.362	0.992
WPE3 Frequency	20	7.75	2.468	-1.221	0.512	1.412	0.992
WPE4 Frequency	20	7.7	1.922	-0.661	0.512	0.385	0.992
WPE5 Frequency	20	8.85	2.277	-2.528	0.512	7.081	0.992
WPE6 Frequency	20	8.6	1.314	-0.396	0.512	-1.129	0.992
WPE7 Frequency	20	6.9	1.774	-0.461	0.512	-0.106	0.992
WPE8 Frequency	20	8.55	1.791	-1.312	0.512	1.165	0.992
WPE9 Frequency	20	8.85	1.461	-0.838	0.512	-0.737	0.992
WPE10 Frequency	20	9.15	1.182	-0.956	0.512	-0.742	0.992
WPE11 Frequency	19	7.895	1.696	-1.267	0.524	2.676	1.014
WPE12 Frequency	20	8	2.026	-0.928	0.512	0.396	0.992
WPE13 Frequency	20	8.2	1.436	-1.099	0.512	2.623	0.992
WPE14 Frequency	20	8.25	2.245	-1.433	0.512	1.758	0.992
WPE15 Frequency	20	8.85	1.814	-2.103	0.512	3.964	0.992
WPE16 Frequency	20	7.65	1.899	-0.667	0.512	0.228	0.992
WPE17 Frequency	20	7.85	1.814	-0.81	0.512	1.132	0.992
WPE18 Frequency	20	8	1.835	-1.022	0.512	1.3	0.992
WPE19 Frequency	20	8.8	1.322	-0.656	0.512	-0.859	0.992
WPE20 Frequency	20	6.9	2.693	-0.96	0.512	0.616	0.992
WPE21 Frequency	20	6	2.714	-0.895	0.512	0.687	0.992
WPE22 Frequency	20	9.35	1.137	-1.737	0.512	2.594	0.992
WPE23 Frequency	20	7.85	2.11	-1.015	0.512	1.582	0.992
WPE24 Frequency	20	9.05	1.356	-1.365	0.512	0.776	0.992
WPE25 Frequency	20	8.1	1.944	-1.015	0.512	0.946	0.992
WPE26 Frequency	20	8.5	2.115	-1.669	0.512	3.338	0.992
GWA1 Frequency	20	8.8	1.436	-0.796	0.512	-0.717	0.992
GWA2 Frequency	20	7.05	2.188	0.164	0.512	-1.346	0.992
GWA3 Frequency	20	8.15	2.033	-1.186	0.512	1.087	0.992
GWA4 Frequency	20	7.45	2.417	-1.511	0.512	3.629	0.992
GWA5 Frequency	20	6.75	1.803	0.715	0.512	-0.397	0.992
GWA6 Frequency	20	8.7	1.593	-1.101	0.512	0.148	0.992
GWA7 Frequency	20	8.25	2.653	-1.915	0.512	3.844	0.992
GWA8 Frequency	20	8.5	1.395	-0.516	0.512	-1.077	0.992
GWA9 Frequency	20	7.7	2.452	-0.542	0.512	-1.287	0.992
GWA10 Frequency	20	8.35	1.496	-0.568	0.512	-0.443	0.992
GWA11 Frequency	20	7.65	2.231	-0.679	0.512	-0.521	0.992
GWA12 Frequency	20	7.85	1.663	0.111	0.512	-1.243	0.992
GWA13 Frequency	20	6.7	2.319	-0.213	0.512	-0.678	0.992
New O*NET Factor 1 Frequency	20	8.2	1.765	-0.783	0.512	-0.528	0.992
New O*NET Factor 2 Frequency	20	8.1	1.619	0.069	0.512	-1.678	0.992
New O*NET Factor 3 Frequency	20	7.7	2.408	-0.964	0.512	0.051	0.992
New O*NET Factor 4 Frequency	20	6.2	3.35	-0.753	0.512	-0.387	0.992

The descriptive statistics for the O*NET satisfaction scores relevant to ODI scores are below (Table 10). The mean and standard deviation statistics are in line with what was expected. The values for skewness and kurtosis vary somewhat for a few of the O*NET satisfaction factors indicating a lack of normal univariate distribution as some range outside of plus or minus two (George & Mallery, 2019). This was expected with the smaller pilot study population.

Table 10 - O*NET GWA and WPE Satisfaction Pilot Study Scores

O*NET Factor Satisfaction	Valid	Mean	Std. Deviation	Skewness	Std. Error of Skewness	Kurtosis	Std. Error of Kurtosis
WPE1 Satisfaction	20	8.55	1.276	-0.377	0.512	-1.022	0.992
WPE2 Satisfaction	20	7.15	2.661	-1.017	0.512	0.974	0.992
WPE3 Satisfaction	20	8.25	1.743	-0.89	0.512	0.104	0.992
WPE4 Satisfaction	20	7.75	1.713	-0.476	0.512	-0.257	0.992
WPE5 Satisfaction	20	7.4	2.604	-1.126	0.512	0.686	0.992
WPE6 Satisfaction	20	7.85	1.565	0.092	0.512	-0.984	0.992
WPE7 Satisfaction	20	7.45	1.701	0.202	0.512	-0.976	0.992
WPE8 Satisfaction	20	8.45	1.538	-1.342	0.512	2.5	0.992
WPE9 Satisfaction	20	8	1.654	-0.387	0.512	0.087	0.992
WPE10 Satisfaction	20	8.75	1.118	-0.706	0.512	0.305	0.992
WPE11 Satisfaction	19	8.421	1.071	0.532	0.524	-0.99	1.014
WPE12 Satisfaction	20	8.25	1.372	-0.365	0.512	-1.016	0.992
WPE13 Satisfaction	20	7.95	1.638	-0.631	0.512	0.125	0.992
WPE14 Satisfaction	20	8.65	1.496	-1.631	0.512	3.757	0.992
WPE15 Satisfaction	20	8.45	1.395	-0.662	0.512	0.177	0.992
WPE16 Satisfaction	20	8.15	1.496	0.031	0.512	-1.463	0.992
WPE17 Satisfaction	20	8.6	1.635	-1.361	0.512	1.897	0.992
WPE18 Satisfaction	20	8.35	1.531	-0.662	0.512	-0.401	0.992
WPE19 Satisfaction	20	8.5	1.762	-1.058	0.512	0.538	0.992
WPE20 Satisfaction	20	7.85	1.694	-0.606	0.512	-0.021	0.992
WPE21 Satisfaction	20	7.4	2.062	-0.722	0.512	0.388	0.992
WPE22 Satisfaction	20	9.45	0.686	-0.887	0.512	-0.24	0.992
WPE23 Satisfaction	20	8.05	1.932	-0.564	0.512	-0.867	0.992
WPE24 Satisfaction	20	8.3	1.342	0.113	0.512	-1.404	0.992
WPE25 Satisfaction	20	8.25	1.682	-0.88	0.512	0.454	0.992
WPE26 Satisfaction	20	8.5	1.504	-0.876	0.512	-0.151	0.992
GWA1 Satisfaction	20	8.55	1.146	-0.369	0.512	-0.323	0.992
GWA2 Satisfaction	20	7.6	2.113	-0.601	0.512	-0.424	0.992
GWA3 Satisfaction	20	8.45	1.877	-2.221	0.512	6.846	0.992
GWA4 Satisfaction	20	8.1	1.774	-0.607	0.512	-0.771	0.992
GWA5 Satisfaction	20	7.05	1.504	0.319	0.512	-0.279	0.992
GWA6 Satisfaction	20	8.3	1.559	-0.927	0.512	1.434	0.992
GWA7 Satisfaction	20	8.35	1.694	-1.047	0.512	0.199	0.992
GWA8 Satisfaction	20	8.6	1.392	-0.75	0.512	-0.364	0.992
GWA9 Satisfaction	20	8.25	1.832	-0.753	0.512	-0.766	0.992
GWA10 Satisfaction	20	8.7	1.261	-0.592	0.512	-0.703	0.992
GWA11 Satisfaction	20	8.15	1.785	-0.62	0.512	-0.345	0.992
GWA12 Satisfaction	20	8.05	2.038	-1.11	0.512	0.887	0.992
GWA13 Satisfaction	20	7.4	1.875	0.04	0.512	-1.376	0.992
New O*NET Factor 1 Satisfaction	20	8.3	1.455	-0.812	0.512	-0.063	0.992
New O*NET Factor 2 Satisfaction	20	8.2	1.642	-0.593	0.512	-0.519	0.992
New O*NET Factor 3 Satisfaction	20	8	2.471	-1.907	0.512	4.872	0.992
New O*NET Factor 4 Satisfaction	20	6.55	3.12	-0.804	0.512	-0.041	0.992

The unidimensional reliability of the VTMP scale pilot study data using Cronbach α and McDonald's ω was performed (Table 11). Scholars often argue what establishes a suitable and high Cronbach α score. This research uses a score greater than 0.70 as sufficient for research conducted in this study (Green et al., 1977; Devellis & Thorpe, 2021). An additional review for reliability was conducted using McDonald's ω. The Cronbach α and McDonald's ω values exceed the threshold for all VTMP scale items. Of note, performance questions two, three, and 11 are reversed for this analysis as they are reverse scored to measure the full VTM score.

Table 11 - Virtual Team Member Performance Pilot Study Reliability (if item dropped)

Item	McDonald's ω	Cronbach's α
Performance Item_1	0.866	0.871
Reverse Performance Item_2	0.884	0.879
Reverse Performance Item_3	0.882	0.879
Performance Item_4	0.881	0.873
Performance Item_5	0.868	0.872
Performance Item_6	0.87	0.872
Performance Item_7	0.834	0.857
Performance Item_8	0.852	0.863
Performance Item_9	0.875	0.877
Performance Item_10	0.87	0.87
Reverse Performance Item_11	0.886	0.887
Performance Item_12	0.861	0.87
Performance Item_13	0.856	0.863
Performance Item_14	0.866	0.869
Performance Item_15	0.864	0.87
Performance Item_16	0.865	0.868
Performance Item_17	0.861	0.868
Performance Item_18	0.876	0.877

Because the survey develops a novel VTMP survey containing modified Andersson et al. (2017) performance questions, additional VTM changes, and two additional unique questions developed from the qualitative interviews a PCA and EFA is performed to determine factor loading and performance. The latent variable grouping test was performed first using PCA with a promax rotation. PCA is used as a data reduction technique to reduce the number of items. Using

PCA, the component loading values resulted in two items loading with no cross-loading above 0.41. Table 12 exhibits the pilot study PCA results loading for VTMP. The researcher assesses the full population is required to address final VTMP loadings, data reduction, and question removal for the VTMP and HFVTM scores using PCA.

Table 12 - PCA for VTM Performance

Chi-squared Test	Value	df	p
Model	209.123	118	< .001
Component Loadings	**RC1**	**RC2**	**Uniqueness**
Performance Item_15	0.959		0.167
Performance Item_13	0.94		0.158
Performance Item_12	0.877		0.311
Performance Item_7	0.86		0.134
Performance Item_16	0.826		0.317
Performance Item_14	0.805		0.376
Performance Item_8	0.722		0.394
Performance Item_17	0.674		0.417
Performance Item_1	0.617		0.601
Performance Item_10	0.605		0.614
Performance Item_9	0.423		0.835
Rev Performance Item_2		0.919	0.243
Rev Performance Item_3		0.917	0.242
Performance Item_4		0.709	0.474
Performance Item_6		0.655	0.466
Rev Performance Item_11		0.452	0.813
Performance Item_5		0.433	0.606
Performance Item_18			0.817

Note. Applied rotation method is promax.

Next, an EFA analysis is performed by the researcher to evaluate the VTMP construct validity and to confirm latent variable loading onto a single construct, with two factors focusing on the team and individual, for the survey performance measurement. The researcher began by running a promax rotation with principal axis factoring estimation to reveal the level of factor correlations. The oblique method, using promax, was confirmed as the option most suited for the analysis because it allows the research to explore the correlation between the factors (Fabrigar, Wegener, MacCallum, & Strahan, 1999).

The researcher ran an EFA on the 18 items that measures the novel VTMP construct. Using the correlation matrix, the research demonstrated that both factors had at least one correlation coefficient greater than 0.77, exceeding the recommended threshold of 0.3 (Hair et al., 2010). However, as seen in Table 13, not all VTMP questions loaded at a level above 0.45.

Table 13 - EFA for Pilot Test VTM Performance Items

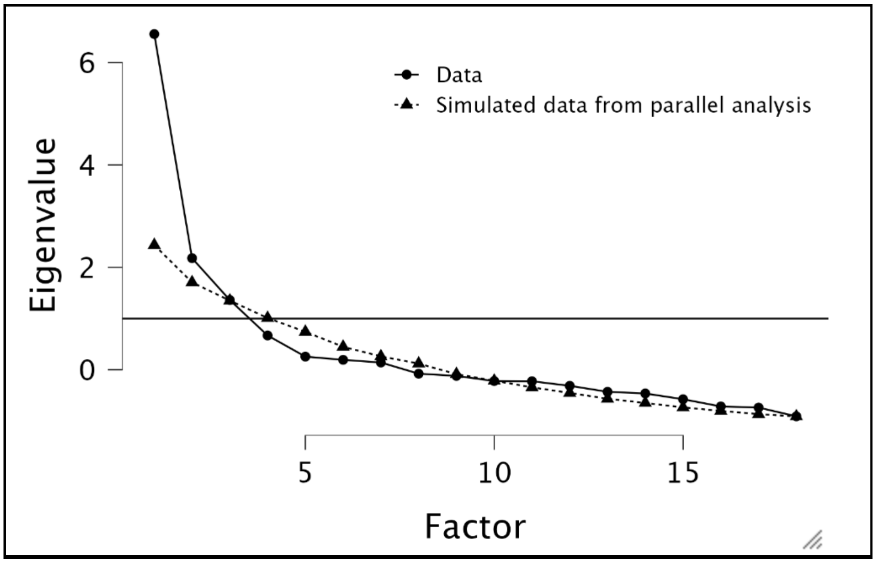
Pilot Factor Loadings VTM Performance	Factor 1	Factor 2	Uniqueness
Performance Item_15	0.957		0.127
Performance Item_13	0.936		0.143
Performance Item_7	0.863		0.085
Performance Item_16	0.751		0.368
Performance Item_14	0.739		0.447
Performance Item_8	0.699		0.472
Performance Item_17	0.696		0.449
Performance Item_1	0.625		0.618
Reverse Performance Item_3		0.771	0.446
Performance Item_6		0.766	0.33
Reverse Performance Item_2		0.723	0.517
Performance Item_5		0.558	0.52
Performance Item_9			0.869
Performance Item_18			0.928
Reverse Performance Item_11			0.856

Note. Applied rotation method is promax.

The EFA in Table 13 demonstrates two factors are loading using a total of 15 of the 18 questions. These factors are discussed in greater detail during the full study analysis. Bartlett's (1954) test of sphericity was demonstrated to be statistically significant ($p < .001$), specifying that the collected data was factorizable. A value of 0.585 was demonstrated using the Kaiser-Meyer-Olkin (KMO) which does not exceed the recommended minimum rate of 0.6 for sampling accuracy (Kaiser, 1974). However, this was theorized by the researcher in the above sections of this chapter. In this case it is assessed numerous additional survey responses are required to fully evaluate the EFA of VTMP questions in a statistically significant manner. Therefore, the researcher assesses this test with low confidence and further evaluation will be performed on sampling accuracy using the full data analysis.

Next, the researcher performed a visual examination of the EFA scree plot in Figure 4 demonstrated that three factors should be retained (Cattell, 1966).

Figure 4 – EFA Scree Plot for Pilot Test VTM Performance Items



However, when analyzing the pilot study data with Eigenvalues set at a threshold of 1.0, five factors were deemed acceptable to retain using EFA (Table 14). In this case, all variables had at least one correlation coefficient greater than 0.527. However, factors three, four, and five only had two questions correlate to the factor suggesting they may need to be clarified using the full distribution of VTMs.

Table 14 - EFA Pilot Study Using Eigenvalues for VTM Performance

Factor Loadings	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Uniqueness
Performance Item_7	0.97					0.005
Performance Item_15	0.893					0.103
Performance Item_12	0.83					0.15
Performance Item_1	0.813					0.458
Performance Item_13	0.69					0.234
Performance Item_17	0.687					0.462
Performance Item_14	0.643					0.38
Performance Item_8	0.595					0.371
Performance Item_16	0.593	0.463				0.198
Performance Item_5		0.978				0.031
Performance Item_6		0.872				0.176
Performance Item_2			0.957			0.05
Performance Item_3			0.9			0.119
Performance Item_10				0.97		0.019
Performance Item_9				0.527		0.685
Performance Item_4					0.758	0.005
Performance Item_18					0.691	0.545
Performance Item_11						0.84

Note. Applied rotation method is promax.

During the overall pilot study EFA analysis, between two and five factors were assessed. The researcher assesses that only two factors, centering on the team and individual performance should load in the final full survey. This analysis was discussed with the expert panel as this result was estimated by the researcher in the above sections of this chapter. The PCA and EFA results demonstrate the number of pilot study responses required to fully evaluate the novel VTMP instrument and 18 VTMP questions in a statistically significant manner were not met due to the complexity of the research. Therefore, the researcher assesses this test with low confidence and further evaluation will be performed on sampling accuracy using the full data analysis.

After the pilot study analysis, the decision was made to move ahead with all 18 VTMP factor items to analyze the results in the full survey using the required 385 to 397 respondents. Analyzing the data from a minimum of 385 to 397 survey respondents allows the researcher to determine the number of factors and VTMP item use across additional respondents, industries, and demographics. A review with the dissertation committee confirmed this conclusion. This also allows the researcher to demonstrate a higher KMO measure suggested rates higher than 0.5 (Kaiser, 1974) and .7 (Hoelzle & Meyer, 2013; Lloret, Ferreres, Hernández, & Tomás, 2017). Additionally, the added respondent data allows for a full evaluation of cross loading between individual and team performance with the goal of no such cross loading between these two factors.

An examination of VTMP and O*NET GWA and WPE frequency, satisfaction, and importance using T-Tests was also performed. Table 15 shows the T-Test for VTMP demonstrating statistically significant p-values for all 18 items.

Table 15 - VTM Performance Item T-Tests

One Sample T-Test	t	df	p
Performance Item_1	26.1	19	< .001
Rev Performance Item_2	15.415	19	< .001
Rev Performance Item_3	15.916	19	< .001
Performance Item_4	12.056	19	< .001
Performance Item_5	22.65	19	< .001
Performance Item_6	21	19	< .001
Performance Item_7	17.118	19	< .001
Performance Item_8	10.559	19	< .001
Performance Item_9	24.106	19	< .001
Performance Item_10	11.943	19	< .001
Rev Performance Item_11	13.708	19	< .001
Performance Item_12	16.624	19	< .001
Performance Item_13	18.783	19	< .001
Performance Item_14	24.907	19	< .001
Performance Item_15	19.648	19	< .001
Performance Item_16	31	19	< .001
Performance Item_17	29.648	19	< .001
Performance Item_18	26.449	19	< .001

Note. For the Student t-test, the alternative hypothesis specifies that the mean is different from 0.

The full study analysis of 393 participants includes a linear regression on VTMP versus O*NET GWA and WPE frequency, satisfaction, and importance. However, with only 20 pilot study participants and over 47 O*NET factors the analysis could only be performed on less than half of the WPEs or GWAs at a time. Analysis of this data showed statistically significant ANOVA and model support for this study's analysis. SEM and Linear Discriminant Analysis (LDA) could not be performed during the pilot test phase due to low number of respondents. Additionally, after discussions with the chair, committee, and other outside experts, SEM and LDA is not performed during the full study analysis stage as it is not required for the analysis of this study's propositions. Finally, a review of the ODI scores from the pilot test are performed as a second method for defining which O*NET factors are most important and most frequently used by VTMs and which of the 47 O*NET factors may impact VTM performance the most. An examination of the ODI scores clearly demonstrates support for using this survey to determine where AI can help improve ROI and performance. For example, using the pilot study data, stress management is shown to be important for both high and low performers, but not for moderate performers.

Additionally, the researcher added four new O*NET work factors from the qualitative interview analysis. Three of the four factors were shown to be performing well from the 20 pilot test survey participants. For example, the first three additional factors show below are highly relevant statistically to VTMP while the fourth AI driven O*NET factor is shown to possibly relate well to human performance. This is expected as only AI can perform this fourth novel factor, Role Speed. By design, the ability for automation tools to perform activities with high speed (above that of a human) was expected to perform low with humans in the survey if this was only a novel AI O*NET factor. Finally, when examining O*NET GWA and WPE ODI survey respondent data, the responses suggest these observations are beginning to demonstrate where generation, education, and management level may play a role in AI choices and the effect it has on VTMP.

Pilot Study Summary

This exploratory sequential mixed methods research developed a pilot study. The pilot study survey uses 20 participants to construct a validated and reliable survey instrument that is used to test this study's propositions centering on human machine teaming, the use of HFVTMs as proxy for AI and human superteams, and the augmentation of low-performing, moderate-performing, and HFVTMs with AI at the fundamental job task level. The pilot study increased the effectiveness of the CMV, VTMP, O*NET, and demographic questions. Of note, the researcher acknowledges the pilot study data does not meet the fully desirable statistical threshold for continuing due to the complexity of the O*NET, VTMP and HFVTM factors. However, while additional PCA, EFA, and CFA data points on the VTMP and O*NET ODI is desirable, the board of outside experts, O*NET SMEs, and expert dissertation committee members determined that the pilot study survey was likely within a safe spectrum and worth proceeding with minimal at risk. With the pilot study results, the researcher moved forward with full data collection and analysis that is examined at the end of this chapter.

Primary Quantitative Survey

The final phase of the exploratory sequential mixed methods research involved a survey of 408 VTMs conducted between 10/3/22 and 2/9/2023. The selection of primary research VTM participants, data collection, and statistical analysis follows the pilot study process and is discussed in detail in this section. Additionally, the researcher discusses the statistical analyses required to test this study's propositions, check CMV, and validate novel instruments.

Sample Selection and Primary Survey Population

This study performed a quantitative survey assessment on VTMs in the U.S. and worldwide western governments and firms. Following generally acceptable scholarly research practice, the sample in the qualitative population was not included in the quantitative survey phase to eliminate the possibility of unnecessary response duplication. The study involves sending a survey to VTMs to test this study's propositions and RQs. The sample of 408 included participants from the researcher's personal and co-tandem interviewer network of VTMs, over 100 businesses, and HR Florida State Council. The participants include VTMs from diverse industries, governments, cultures, and types. The study participants include VTMs from the U.S. government, NATO governments, and U.S. businesses, including the oil and gas, defense, technology, academic, manufacturing, service, retail, financial, medical, and telecommunications industries.

Data Collection

The survey requests were sent to approximately 3,093 recipients using employee network email, LinkedIn posts, Facebook Messenger, Florida Tech email, Instagram, HR Florida email, and through cell phone text messages and business cards containing a QR code link to the survey. All messages, posts, and emails identified the researcher as a doctoral student at Florida Tech and a fellow VTM. Although no bounced emails were received, the researcher cannot conclude that the recipients received all the emails due to the wide use of spam and security filters. Additionally, due to the security threat posed by email phishing, it is unknown how many possible participants did not click on the link due to cyber concerns. In most cases, a second email was sent to confirm the validity and safety of the survey link. Survey responses were received between 10/3/22 and 2/9/2023.

At the conclusion of the primary survey collection phase, a total of 711 participants reached the survey site. Of the 711 participants, 186 did not proceed past the first survey question suggesting the cyber security protections on the email software clicked on the link, and the human participants never visited the survey. This analysis suggests that 525 participants began the survey, and 406 completed the survey in full. This calculation demonstrates that approximately 16.9 percent of the population started the survey, and 13.1 percent completed the survey in full. However, the pure total of 3,093 was likely affected by email security software and other factors. The ability to reach possible participants via email is significantly impacted by the significant use of spam-blocking tools at businesses (Couper, 2000; Couper, Kapteyn, Schonlau, & Winter, 2007). Therefore, because this survey was primarily conducted via email, and it is nearly impossible to calculate the actual percentage of emails routed to the intended VTMs, the only true survey participation percentage known is of the 711 participants that received the email, 57.1 percent or 406 completed the survey in full. According to Cycyota and Harrison's (2006) analysis of prescreened participant response rate, a 28 percent participation rate is the medium response rate. Therefore, the research concludes that the survey received a high response rate.

Next, the researcher performed a two-step process to identify any survey responses requiring removal from the analysis process. First, all 406 responses were reviewed for CMV, participant attention irregularities, maximum straight scoring across the entire survey, and confirmation of VTM experience. Of the 406 responses, 13 participants were removed. The remaining 393 responses were selected for primary study analysis and remained within the optimal range for the number of responses to generalize the results for companies with over 500 employees (Yamane, 1967).

The researcher performed a series of checks to determine the degree to which the collected responses were widely distributed across the industry, gender, generation, residency, education, VTM leadership, VTM frequency, and other demographical categories. The distribution of responses suggests that the study results can be broadly generalized across western industries, gender, generation, residency, education, VTM leadership, VTM frequency, and other demographical categories. For example, a check was performed to determine the degree to which the responses were widely distributed across industries (Table 16). The industry distribution of responses suggests that the study results can be broadly generalized across industries, and specific takeaways can be determined in the telecommunications, defense, government, and information technology industries.

Table 16 - Primary Study Frequencies by Industry

Industry	Frequency	Percent	Cumulative Percent
Telecommunications	136	34.61	34.61
Defense	95	24.17	58.78
Government	35	8.91	67.68
Telecommunications & Technology/Information Technology	38	9.67	77.35
Medical/Healthcare	17	4.33	81.68
Student/Teacher	15	3.82	85.50
Manufacturing/Construction	12	3.05	88.55
Finance	6	1.53	90.08
Service/Hospitality	5	1.27	91.35
Energy	3	0.76	92.11
Retail	3	0.76	92.88
Other	28	7.12	100.00

The researcher performed a comparable check to determine the distribution of responses by VTM generation. Table 17 displays the frequencies by VTM generation. The data indicates a proper distribution across generations, demonstrating that the study results can be broadly generalized. Further, specific takeaways can be determined in each generation except for Generation Z or iGen (Cohen, Manion, & Morrison, 2000).

Table 17 - Primary Study Frequencies by Generation

Industry	Frequency	Percent	Cumulative Percent
The Baby Boom Generation	87	22.14	22.14
Generation X	162	41.22	63.36
Millenial Generation	75	19.08	82.44
Generation Z or iGen	16	4.07	86.51
Other or Prefer Not to Answer	53	13.49	100.00

An additional check is made to determine the distribution of responses by VTM gender. Table 18 displays the frequencies by VTM gender. The data indicates a proper distribution across gender, demonstrating that the study results can be broadly generalized across gender. Further, specific takeaways can be determined in each VTM gender (Cohen et al., 2000).

Table 18 - Primary Study Frequencies by Gender

Male/ Female	Frequency	Percent	Cumulative Percent
Male	261	66.41	66.41
Female	114	29.01	95.42
Other/Prefer not to say	18	4.58	100.00

Because this research study targeted businesses and organizations located in the U.S. and worldwide, data from multiple western countries and four continents were captured in the survey. Table 19 indicates that 89.82 percent of the responses were from VTMs in the United States. As a result, the generalizability of the results can only be determined for the United States and western countries worldwide because 40 VTM responses were obtained from western style countries (Cohen et al., 2000).

Table 19 - Primary Study Frequencies by Residency

Residency	Frequency	Percent	Cumulative Percent
United States	353	89.82	89.82
Europe	23	5.85	95.67
Australia	8	2.04	97.71
Canada	5	1.27	98.98
Other	4	1.02	100.00

A check is made to determine the distribution of responses by VTM education level. Table 20 displays the frequencies by VTM education. The data indicates a proper distribution across education, demonstrating that the study results can be broadly generalized. Further, specific takeaways can be determined within each education level (Cohen et al., 2000).

Table 20 - Primary Study Frequencies by Education

Highest Degree	Frequency	Percent	Cumulative Percent
High School diploma or equivalent degree	59	15.01	15.01
Bachelor's degree	160	40.71	55.73
Master's degree	144	36.64	92.37
Doctorate degree	30	7.63	100.00

VTM work schedule is a critical factor requiring analysis to generalize the results across all VTMs in the production of the HFVTM proxy for human-machine teaming, VTM augmentation, and the creation of superteams. A check was made to determine the distribution of responses by VTM work schedule. Table 21 displays the frequencies by VTM work schedule. The data indicates a proper distribution across the VTM schedule, demonstrating that the study results can be broadly generalized across all VTMs and HMTs. Further, specific takeaways can be determined in each VTM work schedule (Cohen et al., 2000).

Table 21 - Primary Study Frequencies by VTM Work Schedule

VTM Work Schedule	Frequency	Percent	Cumulative Percent
Hybrid VTM for Less than 20% of Work Schedule	125	31.81	31.81
Hybrid VTM for Less than 50% of Work Schedule	67	17.05	48.85
Hybrid VTM for More than 50% of Work Schedule	44	11.20	60.05
Hybrid VTM for More than 80% of Work Schedule	84	21.37	81.42
Full-Time VTM for 100% of Work Schedule	73	18.58	100.00

VTM experience type is another critical factor in determining the generalizability of the results across all VTMs in the production of the HFVTM proxy for human-machine teaming, VTM augmentation, and the creation of superteams. A check was made to determine the distribution of responses by VTM experience type (Table 22). The data indicates a proper distribution across VTM experience types, demonstrating that the study results can be broadly generalized across all VTMs and HMTs. Further, specific takeaways can be determined in both full-time VTMs and hybrid VTMs (Cohen et al., 2000).

Table 22 - Primary Study Frequencies by VTM Type

VTM Experience Type	Frequency	Percent	Cumulative Percent
Experience Only as a Full-time VTM	72	18.32	18.32
Experience Only as a Hybrid VTM	78	19.85	38.17
Experience Both as a Full-Time and Hybrid VTM	243	61.83	100.00

A check was made to determine the distribution of responses by VTM experience by years. Table 23 displays the frequencies by VTM experience in years. The data indicates a proper distribution across VTM experience, demonstrating that the study results can be broadly generalized across all VTMs and HMTs. Further, specific takeaways can be determined at each VTM experience level (Cohen et al., 2000).

Table 23 - Primary Study Frequencies by VTM Total Experience

Total Experience	Frequency	Percent	Cumulative Percent
0-2 years	97	24.68	24.68
3-5 years	123	31.30	55.98
6-10 years	78	19.85	75.83
11-15 years	48	12.21	88.04
16-20 years	22	5.60	93.64
20 or more years	25	6.36	100.00

Finally, a check was performed to determine the distribution of responses across the VTM leadership level. Table 24 displays the frequencies by VTM leadership. The data indicates a proper distribution across VTM leadership, demonstrating that the study results can be broadly generalized across all VTMs and HMT leadership levels. Further, specific takeaways can be determined at each VTM leadership level (Cohen et al., 2000).

Table 24 - Primary Study Frequencies by VTM Leadership

Industry	Frequency	Percent	Cumulative Percent
No Virtual Team Management Experience	101	25.70	25.70
Subject Matter Expert Who Does Not Manage Employees	56	14.25	39.95
First Level Manager Who Manages Multiple Employees	57	14.50	54.45
Second Level Manager Who Manages Multiple Employees	36	9.16	63.61
Senior Leader	50	12.72	76.34
Second-Level Manager Who Does Not Manage Any Employees	47	11.96	88.30
First-Level Manager Who Does Not Manage Any Employees	46	11.70	100.00

Non-Response Bias

Non-response bias is tested two ways. First, the researcher examines an ANOVA with VTMP as the dependent variable. Second, the research analyzes a comparison of the data using the covariate variables VTMP and QWL, the fixed factors of VTM experience, and the dependent variables of HFVTM scores between early responses and later responses. For each case the cut-off is set at half of the 393 respondents in chronological order, resulting in 196 responses residing in the first period and 197 respondents residing in the second.

In this first case, the VTMP means for the first half and second half of this study's population resulted in VTMP scores of 37.204 and 36.157. This first ANOVA and resulting Levene's test suggest that if the primary survey continued to collect data and additional responses were received, the data would not significantly affect the conclusions, assessments, and outcomes determined in this study. In this case the p-value is 0.643 (Table 25).

Table 25 - Non-Response Bias ANOVA

ANOVA - VTM Performance In Split Population					
Population	**N**	**Mean**	**SD**	**SE**	**Coefficient of variation**
1st Half	196	37.204	6.303	0.45	0.169
2nd Half	197	36.157	6.382	0.455	0.177

Test for Equality of Variances (Levene's)			
F	**df1**	**df2**	**p**
0.215	1	391	0.643

Next, an ANCOVA was conducted, establishing no statistically significant differences in the independent or dependent mean scores between the first and second survey submissions. Using Levene's (1960) test for equality of variances, a homogeneity of variances was established, with HFVTM having p=0.503. The ANOVA and Levene's test suggest that if the primary survey continued to collect data and additional responses were received, including the additional respondent data would not significantly affect the conclusions, assessments, and outcomes determined in this study.

CMV

The researcher analyzed the eight CMV questions spread throughout the survey instrument. Each CMV question and participant response was analyzed independently. The researcher performed a two-step process to identify failed CMV survey responses. Focusing on attention irregularities and maximum straight scoring across the complete survey by participants, three participants were removed using this process. The remaining 393 participant survey responses were retained as the statistical data was consistent and expected.

Control Variable Analysis

A control variable analysis was performed using an Analysis of Variance (ANOVA) on the single critical control variable, VTM experience. Table 26 displays the mean value for the control variable VTM experience. Using this analysis for VTM experience, there are no statistically significant variances within the categories.

Table 26 - Mean Value for VTM Experience

ANOVA - VTM Performance Relating to VTM Experience

Cases	Sum of Squares	df	Mean Square	F	p
What is your experience with virtual teaming	1480.666	5	296.133	7.981	< .001
Residuals	14358.937	387	37.103		

Note. Type III Sum of Squares

Descriptives - VTM Performance Relating to VTM Experience

What is your experience with virtual teaming	N	Mean	SD	SE	Coefficient of variation
Participant has a mix of VTM expierence	144	37.535	5.964	0.5	0.159
I have experience as a full time virtual team member	72	39.514	5.099	0.601	0.129
I have experience ONLY as a hybrid virtual team member	72	33.722	6.55	0.772	0.194
I have experience both as a full-time and hybrid virtual team member	92	35.391	6.63	0.691	0.187
I have full-time or hybrid virtual team member experience PRIOR to the COVID pandemic	13	36.692	5.964	1.654	0.163

BOT Detection

The researcher analyzed the full study data set for BOTs using the Qualtrics BOT detection service and literature signs discussed earlier in this chapter. In total two survey respondent data sets were flagged as BOTs and removed from the full study. Neither of the BOT data sets identified and removed completed the survey.

Overview of Analysis

The complexity of the analysis advocates for a short synopsis of the analysis performed using the data collected. The researcher first analyzes the VTMP (Independent variable) data collected. This data is analyzed to build the VTMP score using the statistically relevant questions determined from a PCA, EFA, and CFA analysis. The VTMP score is required to analyze low-performing, moderate-performing, high-performing, and high-functioning VTMs.

Next, the researcher develops a QWL score (Hill, 2023) for each participant from the data collected using the survey. Each of the 18 QWL questions in the survey is analyzed to develop a QWL score only using the statistically relevant questions determined from an EFA, PCA and CFA analysis. The QWL score is required to build an HFVTM score for each participant. The equal-weighted combination of QWL and VTMP determines the HFVTM score for every participant.

Following the development of the VTMP score and an HFVTM score for each VTM respondent, the researcher develops an ODI opportunity algorithm score and opportunity landscape chart for each VTM to determine the low-performing, moderate-performing, high-performing, and high-functioning VTMs. ODI opportunity algorithm scores and opportunity landscapes are developed using the importance, frequency, and satisfaction scores collected from each VTM.

For proposition 1a, the researcher provides a list of the low-VTMP ODI opportunity scores, ANOVA, and a linear regression of the low-VTMP versus ODI opportunity score. Because this is exploratory research, the ODI, ANOVA, and linear regression scores are analyzed. Utilizing VTMP as the independent variable and AI VTM augmentation measured with VTM task perception (VTM-TP) using ODI opportunity scoring as the moderating variable, the dependent variable of AI-augmented activities index (AIA-AI) for low-VTMP is created.

Similarly, for proposition 1b, the researcher provides a list of the moderate-VTMP ODI opportunity scores, ANOVA, and a linear regression of the moderate-VTMP versus ODI opportunity score. Utilizing VTM performance (VTMP) as the independent variable and AI

VTM augmentation measured with VTM-TP using ODI opportunity scoring as the moderating variable, the dependent variable of AIA-AI for moderate-VTMP is created. For completeness, the researcher provides the high-performing ODI opportunity scores, ANOVA, and linear regression of the high-VTMP vs. ODI opportunity score.

Next, the researcher performs an identical procedure to the one outlined above to establish the AIA-AI for HFVTMs. For proposition 2, the researcher provides a list of the HFVTM ODI opportunity scores, ANOVA, and a linear regression of HFVTMs versus ODI opportunity scores. Utilizing the HFVTM VTMP score as the independent variable and AI VTM augmentation measured with VTM-TP using ODI opportunity scoring as the moderating variable, the dependent variable of AIA-AI for HFVTMs is created. The relevant O*NET factors identified in this process are referred to as superteam-creating O*NET factors. AIA-AI O*NET GWA and WPE characteristics of HFVTMs capable of a ten or greater improvement are considered superteaming factors.

Finally, the researcher performs an analysis of the O*NET propositions 3a, 3b, and 4 using a similar methodology. For proposition 3a, the researcher uses the HFVTM O*NET importance, satisfaction, and frequency scores to define an O*NET-SOC profile consisting of legacy factors (WPEs & GWAs) to define AI augmented HFVTMs through a cluster analysis evaluation technique used by two seminal O*NET authors. For proposition 3b, the researcher examines the related cluster analysis to define an O*NET-SOC profile consisting of new WPE and GWA factors to define AI superteams. These possible new factors focus on the four possible O*NET GWAs uncovered from the qualitative interviews. Finally, for proposition 4, the researcher performs a linear regression of the ODI score of legacy and new HFVTM WPEs and

GWAs required to create superteams and cross-lay AI-type and Gartner's Hype Cycle to determine a rank-ordered index to guide the creation, investment, and research of AI superteams.

Statistical Analysis of Instrument Validation & Latent Construct Validation

The study's use of new survey instruments to measure VTMP and QWL, required for developing the novel HFVTM score, requires PCA, EFA, and CFA latent construct validation. A statistical analysis of each instrument, starting with the VTMP survey component, is performed to begin the examination.

Virtual Team Member Performance (VTMP) Survey

The novel VTMP survey is developed using the qualitative tandem interview portion of this study, and refinement during the pilot test requires initial evaluation using PCA for data and question reduction. The researcher aims to discover the number of factor questions influencing the performance variables and to examine which of these questions' hang together' (DeCoster, 1998). Next, EFA is performed to assess the construct validity and confirm that each latent variable is loaded on a single construct (Mason, Classen, Wersal, & Sisiopiku, 2021). Further, EFA assesses the degree to which underlying questions or items load onto a higher-level construct (Van Mierlo, Vermunt, & Rutte, 2009). EFA analysis is appropriate for this study because the recommended sample size is over 300 (Comrey & Lee, 1992). The ratio of respondents to variables should be at least 10:1 (Yong & Pearce, 2013). Having a larger sample size diminishes the error in this survey's data (Yong & Pearce, 2013), using EFA.

Analysis of the 18 questions using PCA is conducted as an initial check to verify that the appropriate latent variable grouping is identified, and question reduction is performed. The PCA is conducted using a promax rotation. PCA components enhance this study's parsimonious data and contribute information to help the researcher decide on the number of question factors to retain for subsequent EFA and CFA analysis (Walkins, 2018).

Tables 27 and Figure 5 display the final PCA results and scree plot after removing nine questions that did not load against either of the two components (RC1 Team and RC2 Individual). For the PCA analysis, the researcher used a value of 0.5 factor loading for newly developed items and 0.6 for established items (Awang, 2014). With these scholarly-backed factor loading values, questions one, seven, eight, nine, 11, 15, 16, 17, and 18 are retained.

Table 27 - PCA for Final VTM Performance Survey Questions

Chi-squared Test	Value	df	p
Model	171.681	19	< .001

Component Loadings	RC1 (Team)	RC2 (Individual)	Uniqueness
Performance Question_7	0.857		0.207
Performance Question_11 Reverse	0.857		0.37
Performance Question_1	0.824		0.411
Performance Question_8	0.762		0.409
Performance Question_15	0.755		0.236
Performance Question_9		0.933	0.333
Performance Question_17		0.786	0.305
Performance Question_16		0.637	0.259
Performance Question_18		0.598	0.436

Note. Applied rotation method is promax.

	Unrotated solution			Rotated solution		
Component Characteristics	Eigenvalue	Proportion var.	Cumulative	SumSq. Loadings	Proportion var.	Cumulative
Component 1 - Team	4.908	0.545	0.545	3.62	0.402	0.402
Component 2 - Individual	1.125	0.125	0.67	2.413	0.268	0.67

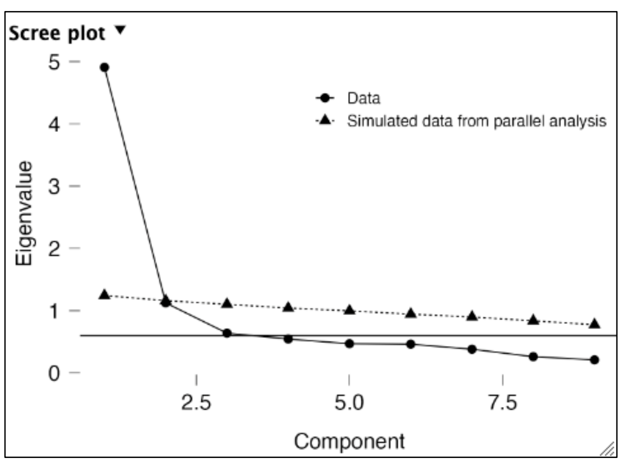


Figure 5 - PCA Scree Plot for VTM Performance

For the EFA analysis of the VTMP survey, promax rotation with principal axis factoring is used to determine the level of factor correlations for the 18 questions that measure VTMP. The oblique rotation technique, promax, is necessary because of its speed in larger databases and its loadings to a power of four, resulting in greater correlations among factors (Gorsuch, 1983). Using Andersson et al. (2017) as a baseline, the researcher evaluated the two factors of the team and individual performance. The researcher assessed these factors required no statistically significant cross-loading and attempted to perform all relevant statistical analyses used by Andersson et al. (2017) to create this novel VTMP survey.

Factor extraction relies on evaluating the scree plot and loading measure, and only factors with greater than two questions loading on the factor are characterized as a factor. The scree plot and eigenvalues above 1.0 allow the researcher to determine how many factors to retain (Yong & Pearce, 2013). The scree plot is only dependable when the sample size exceeds 200 (Costello & Osborne, 2005), making this test appropriate for this study. Scholarly rules of thumb for factor loading thresholds have a wide range of endorsements ranging from a minimum of 0.4 at the lower end (Stevens, 1992) to 0.055 (Comrey & Lee, 1992) to 0.60 (Guadagnoli & Velicer, 1988) at the upper end. Literature suggests that researchers need to establish a statistically meaningful cut-off for factor loading (Yong & Pearce, 2013). For this research, any question with a factor loading between 0.50-0.60 is evaluated based on theory to determine survey inclusion.

Inspection of the EFA results in Table 28 demonstrates only two factors, containing nine questions, centering on the Team (Factor 1) and Individual (Factor 2) load. Although the EFA component loading values were marginally different, the loading results of the EFA analysis affirms and does not disagree with the PCA analysis.

Table 28 - VTM Performance EFA Factor Loading of Survey Questions

Factor Loadings VTM Performance	Factor 1 (Team)	Factor 2 (Individual)	Uniqueness
Performance Question_7	1.046		0.179
Performance Question_1	0.76		0.539
Performance Question_15	0.745		0.251
Performance Question_11 Reverse	0.63		0.492
Performance Question_8	0.543		0.386
Performance Question_17		0.793	0.358
Performance Question_9		0.681	0.53
Performance Question_16		0.63	0.296
Performance Question_18		0.53	0.497
Performance Question_13			0.045
Performance Question_14			0.145
Performance Question_2 Reverse			0.165
Performance Question_3 Reverse			0.298
Performance Question_6			0.169
Performance Question_5			0.329
Performance Question_10			0.182
Performance Question_4			0.585
Performance Question_12			0.414

Note. Applied rotation method is promax.
Note. Factor 8 and 18 kept due to theory and uniqueness value

Figure 6 displays the VTMP EFA scree plot. The scree plot demonstrates that the two factors load above an Eigenvalue of 1.0 affirming PCA analysis.

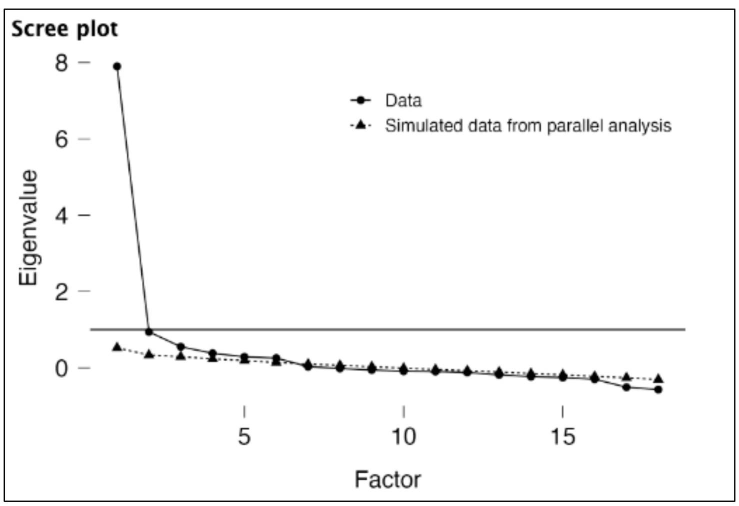


Figure 6 - VTM Performance EFA Scree Plot

Following the above VTMP EFA results, a follow on EFA was run using only the remaining nine questions relating to factors one and two. Examination of the correlation matrix demonstrates that all variables have a least one correlation coefficient greater than 0.6 and only question 18 loads below 0.6 (0.525). The researcher will keep question 18 because question 17 and 18 load onto the same individual performance factor, literature contends that meeting VTM goals are essential to performance in VTMs, and VTM trust and goals are linked (Pazos, 2012). In addition, the high level of statistical EFA uniqueness and meeting VTMs goals was a demonstrative component of the qualitative interview questions. The overall KMO value of 0.930 exceeds the minimum suggested rate of 0.7 (Hoelzle & Meyer, 2013; Lloret et al., 2017). Bartlett's test of sphericity was statistically significant ($p < .001$), revealing the data has patterned relationships among the variables (Yong & Pearce, 2013) and is likely factorizable. Table 29 displays the final VTMP EFA results for the final nine questions.

Table 29 - EFA for Final VTM Performance Survey Questions

Kaiser-Meyer-Olkin test	MSA
Overall MSA	0.903
Performance Question_7	0.942
Performance Question_1	0.884
Performance Question_15	0.92
Performance Question_11 Reverse	0.874
Performance Question_8	0.929
Performance Question_17	0.895
Performance Question_9	0.889
Performance Question_16	0.881
Performance Question_18	0.928

Bartlett's test		
X^2	df	p
1841.658	36	< .001

Chi-squared Test	Value	df	p
Model	44.766	19	< .001

Factor Loadings	Factor 1	Factor 2	Uniqueness
Performance Question_7	0.894		0.203
Performance Question_1	0.746		0.5
Performance Question_15	0.744		0.256
Performance Question_11 Reverse	0.706		0.54
Performance Question_8	0.676		0.506
Performance Question_17		0.801	0.365
Performance Question_9		0.682	0.634
Performance Question_16		0.674	0.279
Performance Question_18		0.525	0.537

Note. Applied rotation method is promax.

Finally, an examination of VTMP using CFA was conducted. The CFA results demonstrate X^2 is 85.514. The results of the overall KMO is 0.903, with a Bartlett's test of sphericity of <0.001, and a Bartlett's test X^2 of 1841.658. The CFA VTMP R-Squared and factor loadings shown in Tables 30 and 31 affirm and do not disagree with the EFA and PCA results.

Table 30 - R-Squared CFA Values for VTM Performance

R-Squared	R^2
Performance Question 1	0.453
Performance Question 7	0.779
Performance Question 15	0.76
Performance Question 8	0.488
Performance Question 11 - Rev	0.478
Performance Question 17	0.581
Performance Question 16	0.755
Performance Question 18	0.454
Performance Question 9	0.31

Table 31 - CFA Factor Loadings for VTM Performance

Factor loadings							95% Confidence Interval		
Factor	Indicator	Symbol	Estimate	Std. Error	z-value	p	Lower	Upper	Std. Est. (lv)
Factor 1	Performance Question 1	λ11	0.621	0.042	14.613	< .001	0.538	0.704	0.621
	Performance Question 7	λ12	0.91	0.042	21.599	< .001	0.827	0.992	0.91
	Performance Question 15	λ13	0.878	0.041	21.166	< .001	0.797	0.959	0.878
	Performance Question 8	λ14	0.857	0.056	15.319	< .001	0.748	0.967	0.857
	Performance Question 11 - Rev	λ15	0.854	0.056	15.13	< .001	0.744	0.965	0.854
Factor 2	Performance Question 17	λ21	0.565	0.034	16.781	< .001	0.499	0.631	0.565
	Performance Question 16	λ22	0.725	0.036	20.214	< .001	0.655	0.796	0.725
	Performance Question 18	λ23	0.494	0.035	14.071	< .001	0.425	0.563	0.494
	Performance Question 9	λ24	0.495	0.044	11.286	< .001	0.409	0.581	0.495

The researcher chose several statistical, extraction, and rotation techniques based on pragmatic reasoning (Yong & Pearce, 2013) to explore the underlying questions that explain the relationships between the VTMP items. The PCA, EFA, and CFA results demonstrate statistical validation for retaining VTMP questions one, seven, eight, nine, 11, 15, 16, 17, and 18. The final statistically significant nine questions focus on VTM duties, effective teamwork, adequate VTM participation, active decision-making, time-wasting, VT performance satisfaction, feeling like part of the team, trust, and meeting VT goals. These nine questions are retained, and the total is the statistically significant VTMP score (independent variable) for this study.

QWL Score

To create the HFVTM proxy required for this study's research questions, the analysis requires the development of a QWL survey and the resulting QWL score for each VTM participant. The QWL survey is developed using the 16 questions from the Sirgy et al. (2001) validated survey combined with two additional mission-centric questions developed during this study's qualitative tandem interview portion (Hill, 2023).

Similarly to the VTMP instrument factor analysis, analysis of the 18 QWL questions begins with PCA. PCA is conducted using a promax rotation to elucidate the appropriate latent variable grouping and reduce the number of questions. PCA is used as a reliability test to assess the totality of the correlation matrix and "is intended to reduce data while preserving as much information from the original data set as possible (Norris & Lecavalier, 2010, p. 9)." Using PCA, component loading values demonstrated two factors should be used. Table 32 and Figure 7 display the final PCA results and PCA scree plot after removing the ten questions that did not load against either of the two components. For the PCA analysis, the researcher used a value of 0.5 factor loading for newly developed items and 0.6 for established items (Awang, 2014). PCA factor loading values suggest questions one through nine and 18 should be removed.

Table 32 - PCA for Final QWL Survey Questions

Chi-squared Test	Value	df	p
Model	200.99	13	< .001

Component Loadings	RC1	RC2	Uniqueness
QWL _10	0.977		0.303
QWL _12	0.924		0.194
QWL _11	0.818		0.217
QWL _14	0.631		0.277
QWL _13	0.625		0.351
QWL _16		0.989	0.246
QWL _15		0.806	0.249
QWL _17		0.659	0.459

Note. Applied rotation method is promax.

		Unrotated solution			Rotated solution	
Component Characteristics	Eigenvalue	Proportion var.	Cumulative	SumSq. Loadings	Proportion var.	Cumulative
Component 1	4.59	0.574	0.574	3.36	0.42	0.42
Component 2	1.114	0.139	0.713	2.344	0.293	0.713

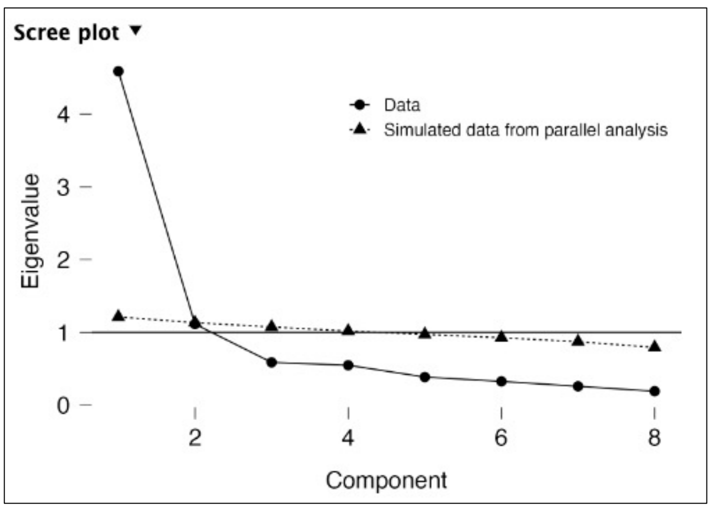


Figure 7 - PCA Scree plot for QWL Survey Questions

Next, am EFA is performed to assess the construct validity and confirm each latent variable loaded on a single construct (Mason, Classen, Wersal, & Sisiopiku, 2021). EFA is used to assess the degree to which each validated and novel question loads onto the higher-level QWL construct (Van Mierlo, Vermunt, & Rutte, 2009). For the EFA analysis of the QWL survey, the researcher uses a promax rotation with principal axis factoring to determine the level of factor correlations for the 18 questions that measure QWL. Promax rotation is appropriate because of its speed in larger databases and its loadings to a power of four, resulting in greater correlations among factors (Gorsuch, 1983). Using Sirgy et al. (2001) as a baseline, the researcher evaluated the eight factors of QWL. The researcher assessed these factors required minimal cross-loading and attempted to perform all relevant statistical analyses used by Sirgy et al. (2001) in the creation of the QWL survey questions (Hill, 2023).

Factor extraction relies on the evaluation of the scree plot and loading measure, and only factors with two questions loading on the factor are determined as a factor. This change is because each of Sirgy et al. (2001) factors rely on between two and three validated survey questions. Scholarly rules of thumb for factor loading thresholds have a wide range of endorsements ranging from a minimum of 0.4 at the lower end (Stevens, 1992) to 0.55 (Comrey & Lee, 1992) and 0.60 (Guadagnoli & Velicer, 1988) at the upper end. Literature suggests that researchers need to establish a statistically meaningful cut-off for factor loading (Yong & Pearce, 2013). For the QWL portion of the survey, any item with a factor loading between 0.50-0.60 is evaluated based on theory to determine survey inclusion.

The scree plot and eigenvalues allow the researcher to determine how many factors to retain (Yong & Pearce, 2013). Inspection of the QWL survey EFA eigenvalues and factor loading results in Table 33 demonstrate that only two factors should be considered. The first factor centering on esteem, actualization, and knowledge, and the second factor centering on aesthetics and mission, are statistically significant according to the EFA. These results are not entirely surprising due to the characteristics of the VTM population (Hill, 2023). The VTM population predominantly comes from higher-paying, white-collar jobs that are likely not to require heavy help with health, safety, economic, or family factors (Hill, 2023). In addition, the low loading of the social component of QWL is not surprising due to the virtual nature of the position (Hill, 2023).

Table 33 - QWL EFA Factor Loading of Survey Questions

Bartlett's test			
X^2	df	p	
2978.342	153	< .001	

Chi-squared Test	Value	df	p
Model	299.15	87	< .001

Factor Loadings	Factor 1	Factor 2	Uniqueness
QWL _12	0.894		0.256
QWL _11	0.761		0.244
QWL _10	0.758		0.428
QWL _13	0.682		0.415
QWL _14	0.674		0.306
QWL _16		0.762	0.39
QWL _17		0.699	0.383
QWL _15		0.638	0.378
QWL _6			0.43
QWL _1			0.898
QWL _2			0.688
QWL _3			0.898
QWL _4			0.513
QWL _5			0.751
QWL _7			0.784
QWL _8			0.709
QWL _9			0.544
QWL _18			0.539

Note: Cutoff at 0.6
Note. Applied rotation method is promax.

Figure 8 displays the QWL EFA Scree plot. As the scree plot demonstrates, only two factors load above an Eigenvalue of 1.0.

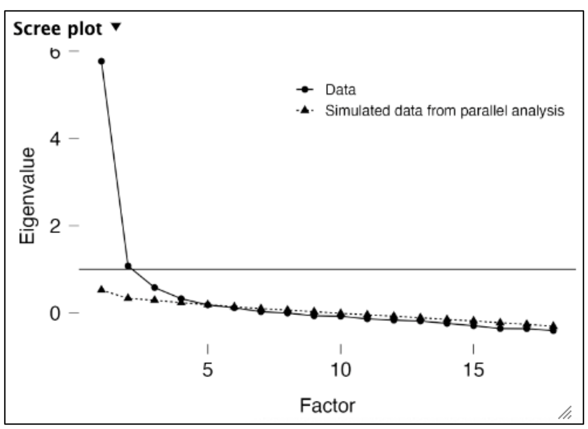


Figure 8 - QWL EFA Scree Plot

The EFA scholarly-backed factor loading values affirm the findings from the PCA analysis. Both techniques suggest questions one through nine and 18 should be removed as they are inconsistent with the PCA and EFA results. Following these QWL analysis results, a second EFA is run using only the remaining eight questions relating to factors one and two. Examination of the correlation matrix demonstrates that all eight variables have a least one correlation coefficient greater than 0.6 and only question 17 loads below 0.6 (0.400). However, the data splits into three factors. The researcher must now examine CFA to consider whether to retain question 17 and the number of factor questions. This additional analysis is required because QWL based on mission was a significant component of the qualitative interview thematic coding, pragmatic exploratory research requires the investigation, and the overall and QWL question 17 KMO measure of 0.930 and 0.948 exceed the minimum suggested rates of 0.7 (Hoelzle & Meyer, 2013; Lloret et al., 2017).

Further, Bartlett's test of sphericity was statistically significant ($p < .001$), revealing that the data was likely factorizable. This test is the most preferable as it is the most easily understood (Tabachnicek & Fidell, 2007) and produces unbiased scores correlated only with their own factor (Yong & Pearce, 2013). Table 34 displays the final QWL EFA results for the final eight QWL questions.

Table 34 - EFA for Final QWL Survey Questions

Kaiser-Meyer-Olkin	MSA			
Overall MSA	0.88			
QWL _10	0.901			
QWL _11	0.877			
QWL _12	0.848			
QWL _13	0.902			
QWL _14	0.892			
QWL _15	0.865			
QWL _16	0.818			
QWL _17	0.948			
Factor Loading	**Factor 1**	**Factor 2**	**Factor 3**	**Uniqueness**
QWL _12	1.015			0.094
QWL _10	0.707			0.514
QWL _11	0.628			0.257
QWL _14		0.905		0.18
QWL _13		0.749		0.347
QWL _16			0.901	0.376
QWL _15			0.745	0.298
QWL _17			0.4	0.613

Note. Applied rotation method is promax.

Finally, an examination of QWL using CFA was conducted. "CFA tests whether a specified set of constructs is influencing responses in a predicted way" (DeCoster, 1998, p. 1). The CFA results demonstrate that overall KMO is 0.880, with a Bartlett's test of sphericity of <0.001, and X^2 of 1802.878, revealing the data has patterned relationships among the variables (Yong & Pearce, 2013). The CFA QWL R-Squared and factor loadings, shown in Tables 35 and 36, affirm the EFA and PCA results.

Table 35 - R-Squared CFA Values for QWL Survey Questions

R-Squared	R^2
QWL _10	0.435
QWL _11	0.774
QWL _12	0.732
QWL _13	0.57
QWL _14	0.66
QWL _15	0.775
QWL _16	0.489
QWL _17	0.381

Table 36 - CFA Factor Loadings for QWL Survey Questions

Factor loadings	95% Confidence Interval							
Factor	Indicator	Symbol	Estimate	Std. Error	z-value	p	Lower	Upper
Factor 1	QWL _10	λ11	0.627	0.044	14.192	< .001	0.54	0.713
(Esteem, Actualization, &	QWL _11	λ12	1.296	0.06	21.539	< .001	1.178	1.414
Knowledge)	QWL _12	λ13	1.198	0.058	20.518	< .001	1.083	1.312
	QWL _13	λ14	0.969	0.057	16.908	< .001	0.857	1.082
	QWL _14	λ15	1.011	0.054	18.833	< .001	0.906	1.117
Factor 2	QWL _15	λ21	1.268	0.065	19.357	< .001	1.139	1.396
(Aesthetic & Mission)	QWL _16	λ22	1.159	0.078	14.772	< .001	1.006	1.313
	QWL _17	λ23	0.987	0.081	12.201	< .001	0.828	1.145

The PCA, EFA, and CFA results demonstrate statistical validation for retaining QWL questions 10, 11, 12, 13, 14, 15, 16, and 17. These eight questions, focusing on esteem, actualization, knowledge, aesthetics, and mission, are retained and become the statistically significant QWL score (Hill, 2023) in developing the novel HFVTM score for this study.

HFVTM Score

This study's definition of an HFVTM is high-performing VTMs with high levels of QWL (Hill, 2023). Using the quantitative data collected from the 393 respondents, the HFVTM score is calculated by summing the statistically significant VTMP and QWL scores determined using the final survey instruments discussed previously in this chapter. This sum-based equal scoring for Likert questions is based on the HFVTM scholarly definition (Hill, 2023) and Kutner, Nachtsheim, and Neter's (2004) analysis. Standardizing the inputs minimizes the influence of different input scales (Kutner et al., 2004) and is appropriate for this exploratory research. Because the VTMP and QWL Likert-scale items are not identical, unequal variance can occur, possibly skewing the analysis toward one question (Low, White, Koschnick, & Elshaw, 2022).

This study measures HFVTMs on a 100-point scale, equally weighted between the QWL and VTMP components (Hill, 2023). Because the number of VTMP and QWL questions varies, the eight questions that comprise the QWL metric are equally weighted by multiplying the score by 9/8 (Kutner et al., 2004). Because the VTMP component is rated using a 5-point Likert scale instead of a 7-point Likert scale, the VTMP score is multiplied by 7/5 (Kutner et al., 2004). At this point, the total score is divided by the total possible score of 126 and multiplied by 100 to get a percentage. The HFVTM equation (Equation 6) is listed below, with the HFVTM scores for each of the 393 VTM participants (Figure 9).

$$\mathbf{HFVTM = (((VTMP * (7/5)) + (QWL) * (9/8)) / 126) * 100 \qquad (6)}$$

Equation 6 - HFVTM Calculation

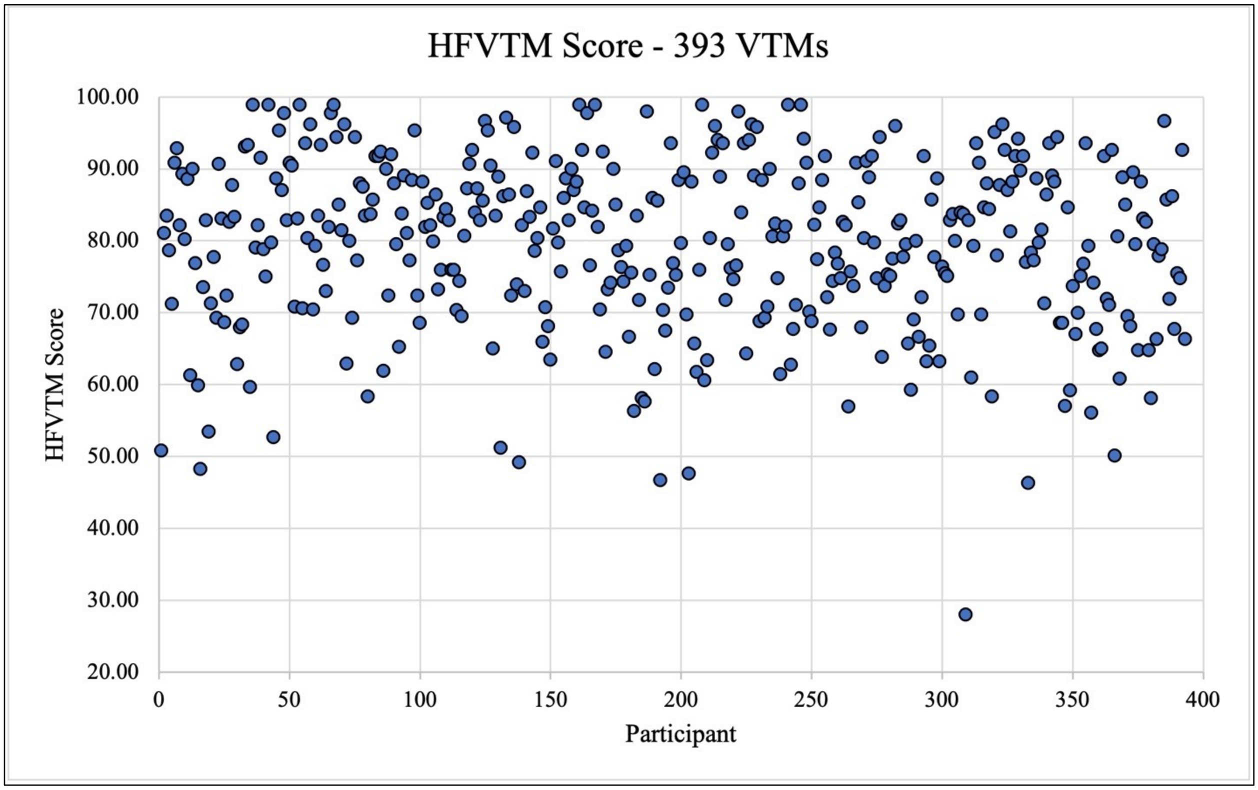


Figure 9 - HFVTM Score by VTM Participant

Of note, participant 311 ranked as an extremely low-performer, low-levels of QWL, and expressed tremendous dissatisfaction with virtual teaming. Finally, of the 132 VTMs designated HFVTMs, 28 of these VTMs fell within the moderate-performing VTM score and 104 were considered high-performing. These moderate-performing VTMs, with a VTMP score between 35 and 41, demonstrate a statistically significant difference in population between HFVTMs and high-performing VTMs.

Outcome Driven Innovation Opportunity Score & Landscape

As discussed in chapter two, the ODI score and opportunity landscapes for the O*NET factors are determined using the ODI opportunity algorithm. The opportunity algorithm determines the degree to which a specific job or outcome is under or over-served. It is defined with the formula listed below (Equation 7).

$$\textbf{Opportunity Algorithm} = \textbf{Importance} + \textbf{Max (Importance - Satisfaction, 0)} \quad \textbf{(7)}$$

Equation 7 - Opportunity Score (Ulwick, 2011, p15)

The ODI opportunity scores is calculated for low-performing, moderate-performing, high-performing, high-functioning VTMs, and all VTM participants. JASP is used to determine three cut points for the VTMP scores. These groups comprise 126 low-performing, 130 moderate-performing, and 137 high-performing VTMs. These scores and the average VTMP and HFVTM ODI opportunity scores are listed below in Table 37.

Table 37 - ODI Opportunity Scores for Low-Performing, Moderate-Performing, High-Performing, High-Functioning VTMs, and All VTM Participants

O*NET Factor	Low VTMP ODI Opportunity Score	Moderate VTMP ODI Opportunity Score	High VTMP ODI Opportunity Score	All VTMP ODI Opportunity Score	HFVTM ODI Opportunity Score
WPE1	11.17	10.66	10.85	10.9	10.71
WPE2	10.85	10.34	9.61	10.25	10.17
WPE3	10.71	10.79	10.49	10.66	10.36
WPE4	11.13	10.58	10.77	10.82	10.83
WPE5	10.42	10.07	10.47	10.33	10.53
WPE6	10.30	10.38	10.38	10.36	10.14
WPE7	10.87	11.15	10.82	10.94	10.83
WPE8	10.76	10.41	10.28	10.48	10.34
WPE9	11.39	11.17	10.86	11.13	10.98
WPE10	10.34	10.28	10.14	10.25	10.22
WPE11	10.39	10.12	10.46	10.33	10.38
WPE12	10.62	10.58	10.32	10.51	10.41
WPE13	10.83	10.63	10.76	10.73	10.42
WPE14	10.63	10.04	10.03	10.23	10.00
WPE15	9.40	10.05	9.77	9.73	9.71
WPE16	9.69	10.20	10.12	10	10.31
WPE17	10.10	10.28	10.32	10.24	10.36
WPE18	9.63	9.63	9.81	9.7	9.73
WPE19	10.10	10.07	10.11	10.09	10.10
WPE20	10.08	9.93	10.29	10.1	10.23
WPE21	8.62	9.18	9.51	9.11	9.57
WPE22	10.17	10.05	10.11	10.11	10.15
WPE23	10.31	10.42	10.34	10.35	10.52
WPE24	10.35	10.38	10.33	10.35	10.37
WPE25	9.40	9.75	10.05	9.73	9.95
WPE26	9.39	9.84	9.64	9.63	9.70
GWA1	10.63	10.98	10.47	10.69	10.57
GWA2	9.71	9.81	9.54	9.69	9.77
GWA3	10.37	10.57	10.13	10.36	10.32
GWA4	10.29	9.99	10.20	10.16	9.98
GWA5	10.00	10.21	9.91	10.03	10.23
GWA6	10.41	10.30	10.07	10.25	10.25
GWA7	9.74	9.73	9.34	9.59	9.62
GWA8	10.29	10.07	10.18	10.18	10.10
GWA9	9.22	9.47	8.98	9.21	9.31
GWA10	9.93	9.86	9.55	9.77	9.88
GWA11	9.33	9.66	9.15	9.37	9.46
GWA12	10.05	10.31	9.89	10.07	10.43
GWA13	9.59	9.55	8.92	9.34	9.54
KE1	9.26	9.21	9.00	9.15	9.44
KE2	9.46	9.26	9.31	9.33	9.52
KE3	8.52	8.55	8.93	8.67	9.24
KE4	8.52	8.51	8.93	8.67	8.80

The ODI opportunity landscape is determined using the O*NET Importance versus Satisfaction score for each WPE and GWA. The opportunity landscape model is analyzed using the areas listed below in Figure 10 and the value opportunity terms discussed in chapters two and three (Ulwick, 2013).

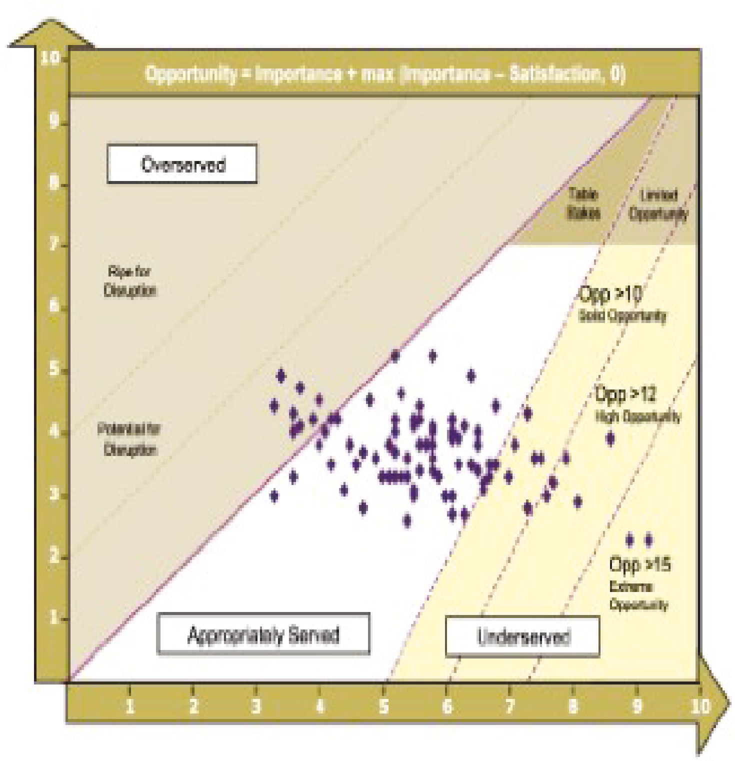


Figure 10 - ODI Opportunity Landscape Model (Ulwick, 2013)

Descriptive Statistics

A key variables' descriptive statistics analysis is first performed and reviewed by the researcher to examine reasonableness (Table 38). The mean and standard deviation statistics of each of the critical variables are in line with researcher expectations. The calculations for variable skewness and kurtosis suggest normal univariate distribution as they are within a range of plus or minus two (George & Mallery, 2019).

Table 38 - Primary Study Descriptive Statistics for Key Variables

	Valid	Median	Mean	Std. Deviation	Skewness	Std. Error of Skewness	Kurtosis	Std. Error of Kurtosis	Minimum	Maximum
VTM Performance Score (All Items)	393	71	69.72	12.274	-0.561	0.123	-0.473	0.246	32	87
VTM Performance Statistically Significant Item Score	393	38	36.679	6.357	-0.803	0.123	-0.102	0.246	16	44
QWL- Based Subgrouping Score	393	24	23.845	7.242	-0.251	0.123	0.093	0.246	8	40
QWL Score (All Items)	393	100	99.003	14.559	-0.582	0.123	0.276	0.246	43	126
QWL Statistically Significant Item Score	393	44	43.405	8.322	-0.858	0.123	1.009	0.246	9	56
HFVTM Statistically Significant Item Score	393	80.6	79.509	11.712	-0.645	0.123	0.47	0.246	28.04	98.89

Additionally, as part of the HFVTM score, the researcher examines the QWL scores. The mean and standard deviation statistics of the QWL variables are in line with researcher expectations (Table 39). The calculations for variable skewness and kurtosis suggest normal univariate distribution as they are within a range of plus or minus two (George & Mallery, 2019).

Table 39 - Primary Study Descriptive Statistics for QWL

	Mean	Std. Deviation	Skewness	Std. Error of Skewness	Kurtosis	Std. Error of Kurtosis	Minimum	Maximum
QWL Score (All Items)	**99.003**	**14.559**	**-0.582**	**0.123**	**0.276**	**0.246**	**43**	**126**
QWL Statistically Significant Item Score	**43.405**	**8.322**	**-0.858**	**0.123**	**1.009**	**0.246**	**9**	**56**
Health & Safety QWL Score	17.827	2.473	-1.067	0.123	2.423	0.246	4	21
Economic & Family QWL Score	15.349	3.722	-0.494	0.123	0.013	0.246	3	21
Social QWL Score	11.031	2.399	-0.902	0.123	0.835	0.246	2	14
Esteem QWL Score	11.74	2.05	-1.048	0.123	1.313	0.246	2	14
Actualization QWL Score	10.865	2.723	-0.964	0.123	0.531	0.246	2	14
Knowledge QWL Score	11.639	2.356	-1.107	0.123	1.047	0.246	2	14
Aesthetic QWL Score	9.616	2.808	-0.482	0.123	-0.085	0.246	2	14
Mission QWL Score	10.936	2.727	-0.986	0.123	0.666	0.246	2	14

Finally, the descriptive statistics for the WPE, GWA, and proposed new GWA factors for importance, frequency, and satisfaction scores are calculated and shown in Tables 40, 41, and 42.

Table 40 – WPE, GWA, and KE Factor Importance Values Descriptive Statistics

O*NET Factor Importance	Valid	Mean	Std. Deviation	Skewness	Std. Error of Skewness	Kurtosis	Std. Error of Kurtosis
WPE1 Importance	393	9.466	0.906	-1.883	0.123	3.724	0.246
WPE2 Importance	393	8.781	1.647	-1.82	0.123	4.264	0.246
WPE3 Importance	393	9.351	1.151	-2.219	0.123	5.512	0.246
WPE4 Importance	393	9.099	1.458	-2.239	0.123	6.591	0.246
WPE5 Importance	393	8.868	1.7	-1.964	0.123	4.6	0.246
WPE6 Importance	393	8.817	1.598	-1.836	0.123	4.465	0.246
WPE7 Importance	393	9.115	1.518	-2.871	0.123	11.515	0.246
WPE8 Importance	393	9.349	1.255	-3.15	0.123	14.008	0.246
WPE9 Importance	393	9.3	1.143	-2.542	0.123	11.824	0.246
WPE10 Importance	393	9.481	1.028	-2.159	0.123	4.33	0.246
WPE11 Importance	393	9.328	1.075	-1.675	0.123	2.32	0.246
WPE12 Importance	393	9.247	1.253	-2.456	0.123	9.051	0.246
WPE13 Importance	393	9.173	1.298	-2.514	0.123	9.936	0.246
WPE14 Importance	393	8.959	1.462	-1.9	0.123	5.205	0.246
WPE15 Importance	393	8.995	1.414	-1.846	0.123	4.941	0.246
WPE16 Importance	393	8.995	1.405	-2.187	0.123	8.223	0.246
WPE17 Importance	393	9.127	1.259	-1.605	0.123	2.778	0.246
WPE18 Importance	393	8.947	1.416	-1.531	0.123	2.64	0.246
WPE19 Importance	393	9.191	1.266	-1.757	0.123	3.075	0.246
WPE20 Importance	393	8.931	1.435	-1.691	0.123	3.347	0.246
WPE21 Importance	393	8.132	1.948	-1.32	0.123	2.025	0.246
WPE22 Importance	393	9.649	1.002	-4.421	0.123	26.124	0.246
WPE23 Importance	393	9.12	1.403	-1.931	0.123	4.363	0.246
WPE24 Importance	393	9.204	1.173	-2.087	0.123	7.1	0.246
WPE25 Importance	393	8.924	1.495	-1.693	0.123	3.433	0.246
WPE26 Importance	393	8.529	2.074	-2.082	0.123	5.146	0.246
GWA1 Importance	393	9.066	1.294	-1.643	0.123	2.478	0.246
GWA2 Importance	393	8.595	1.719	-1.776	0.123	4.322	0.246
GWA3 Importance	393	9.219	1.232	-2.167	0.123	5.69	0.246
GWA4 Importance	393	8.962	1.3	-1.351	0.123	2.039	0.246
GWA5 Importance	393	8.562	1.779	-1.619	0.123	3.157	0.246
GWA6 Importance	393	9.031	1.385	-1.637	0.123	2.714	0.246
GWA7 Importance	393	8.552	2.16	-2.069	0.123	4.537	0.246
GWA8 Importance	393	9.181	1.304	-2.186	0.123	5.925	0.246
GWA9 Importance	393	8.422	2.133	-1.819	0.123	3.582	0.246
GWA10 Importance	393	8.924	1.527	-1.825	0.123	4.239	0.246
GWA11 Importance	393	8.443	2.071	-1.843	0.123	3.907	0.246
GWA12 Importance	393	8.903	1.612	-1.764	0.123	3.345	0.246
GWA13 Importance	393	8.16	2.41	-1.626	0.123	2.506	0.246
New O*NET Factor 1 Importance	393	8.539	1.826	-1.663	0.123	3.489	0.246
New O*NET Factor 2 Importance	393	8.565	1.74	-1.449	0.123	2.456	0.246
New O*NET Factor 3 Importance	393	8.051	2.181	-1.357	0.123	1.793	0.246
New O*NET Factor 4 Importance	393	7.496	2.648	-1.078	0.123	0.664	0.246

Table 41 - WPE, GWA, and KE Factor Frequency Values Descriptive Statistics

O*NET Factor Frequency	Valid	Mean	Std. Deviation	Skewness	Std. Error of Skewness	Kurtosis	Std. Error of Kurtosis
WPE1 Frequency	393	9.303	1.248	-2.376	0.123	6.518	0.246
WPE2 Frequency	393	5.875	2.724	-0.256	0.123	-0.915	0.246
WPE3 Frequency	393	8.043	2.246	-1.334	0.123	1.545	0.246
WPE4 Frequency	393	7.466	2.215	-0.893	0.123	0.356	0.246
WPE5 Frequency	393	8.926	1.539	-1.9	0.123	4.299	0.246
WPE6 Frequency	393	8.097	2.075	-1.08	0.123	0.58	0.246
WPE7 Frequency	393	7.478	2.399	-0.846	0.123	-0.01	0.246
WPE8 Frequency	393	8.702	1.698	-1.63	0.123	2.792	0.246
WPE9 Frequency	393	8.766	1.637	-1.65	0.123	2.886	0.246
WPE10 Frequency	393	9.183	1.339	-1.966	0.123	3.69	0.246
WPE11 Frequency	393	8.664	1.528	-1.322	0.123	1.938	0.246
WPE12 Frequency	393	8.277	1.863	-1.325	0.123	2.021	0.246
WPE13 Frequency	393	8.071	2.066	-1.171	0.123	1.194	0.246
WPE14 Frequency	393	7.952	2.04	-1.028	0.123	0.802	0.246
WPE15 Frequency	393	8.758	1.666	-1.442	0.123	1.638	0.246
WPE16 Frequency	393	8.107	1.879	-0.893	0.123	0.236	0.246
WPE17 Frequency	393	8.435	1.852	-1.408	0.123	1.647	0.246
WPE18 Frequency	393	8.438	1.603	-1.193	0.123	1.567	0.246
WPE19 Frequency	393	8.644	1.738	-1.414	0.123	1.761	0.246
WPE20 Frequency	393	7.786	2.119	-0.988	0.123	0.546	0.246
WPE21 Frequency	393	6.967	2.306	-0.642	0.123	0.045	0.246
WPE22 Frequency	393	9.188	1.589	-2.512	0.123	6.629	0.246
WPE23 Frequency	393	7.929	2.228	-1.09	0.123	0.763	0.246
WPE24 Frequency	393	8.478	1.77	-1.361	0.123	1.823	0.246
WPE25 Frequency	393	8.481	1.803	-1.368	0.123	1.646	0.246
WPE26 Frequency	393	7.656	2.623	-1.201	0.123	0.759	0.246
GWA1 Frequency	393	8.191	1.625	-0.896	0.123	1.076	0.246
GWA2 Frequency	393	7.669	2.158	-1.128	0.123	1.387	0.246
GWA3 Frequency	393	8.209	1.822	-1.236	0.123	1.632	0.246
GWA4 Frequency	393	7.957	1.955	-0.89	0.123	0.292	0.246
GWA5 Frequency	393	6.936	2.379	-0.644	0.123	-0.325	0.246
GWA6 Frequency	393	8.354	1.777	-1.12	0.123	0.744	0.246
GWA7 Frequency	393	8.066	2.629	-1.507	0.123	1.541	0.246
GWA8 Frequency	393	8.593	1.683	-1.377	0.123	1.94	0.246
GWA9 Frequency	393	7.087	2.768	-0.848	0.123	-0.129	0.246
GWA10 Frequency	393	8.232	1.879	-1.148	0.123	1.371	0.246
GWA11 Frequency	393	7.351	2.562	-1.019	0.123	0.424	0.246
GWA12 Frequency	393	7.679	2.309	-1.109	0.123	0.788	0.246
GWA13 Frequency	393	6.473	3.053	-0.711	0.123	-0.414	0.246
New O*NET Factor 1 Frequency	393	7.919	2.131	-1.078	0.123	0.717	0.246
New O*NET Factor 2 Frequency	393	7.634	2.221	-0.908	0.123	0.388	0.246
New O*NET Factor 3 Frequency	393	7.117	2.44	-0.724	0.123	0.09	0.246
New O*NET Factor 4 Frequency	393	6.336	2.864	-0.526	0.123	-0.475	0.246

Table 42 - WPE, GWA, and KE Factor Satisfaction Values Descriptive Statistics

O*NET Factor Satisfaction	Valid	Mean	Std. Deviation	Skewness	Std. Error of Skewness	Kurtosis	Std. Error of Kurtosis
WPE1 Satisfaction	393	8.043	1.907	-1.139	0.123	1.274	0.246
WPE2 Satisfaction	393	7.313	2.302	-0.746	0.123	0.003	0.246
WPE3 Satisfaction	393	8.041	1.992	-1.287	0.123	1.669	0.246
WPE4 Satisfaction	393	7.379	2.35	-0.883	0.123	0.204	0.246
WPE5 Satisfaction	393	7.412	2.452	-0.883	0.123	-0.01	0.246
WPE6 Satisfaction	393	7.277	2.257	-0.845	0.123	0.289	0.246
WPE7 Satisfaction	393	7.28	2.325	-0.866	0.123	0.195	0.246
WPE8 Satisfaction	393	8.219	1.9	-1.478	0.123	2.701	0.246
WPE9 Satisfaction	393	7.468	2.26	-0.955	0.123	0.431	0.246
WPE10 Satisfaction	393	8.71	1.656	-1.679	0.123	3.308	0.246
WPE11 Satisfaction	393	8.333	1.696	-1.405	0.123	2.188	0.246
WPE12 Satisfaction	393	7.992	1.882	-1.151	0.123	1.488	0.246
WPE13 Satisfaction	393	7.606	2.213	-0.953	0.123	0.395	0.246
WPE14 Satisfaction	393	7.692	2.205	-0.936	0.123	0.348	0.246
WPE15 Satisfaction	393	8.247	1.83	-1.182	0.123	1.292	0.246
WPE16 Satisfaction	393	7.982	1.909	-1.133	0.123	1.643	0.246
WPE17 Satisfaction	393	8.015	1.95	-1.24	0.123	1.701	0.246
WPE18 Satisfaction	393	8.201	1.812	-1.367	0.123	2.297	0.246
WPE19 Satisfaction	393	8.288	1.856	-1.352	0.123	2.03	0.246
WPE20 Satisfaction	393	7.758	2.052	-1.045	0.123	0.915	0.246
WPE21 Satisfaction	393	7.15	2.322	-0.807	0.123	0.346	0.246
WPE22 Satisfaction	393	9.188	1.368	-2.319	0.123	7.168	0.246
WPE23 Satisfaction	393	7.885	2.118	-1.16	0.123	1.151	0.246
WPE24 Satisfaction	393	8.053	1.89	-1.194	0.123	1.269	0.246
WPE25 Satisfaction	393	8.107	1.97	-1.252	0.123	1.511	0.246
WPE26 Satisfaction	393	7.433	2.32	-1.099	0.123	1.098	0.246
GWA1 Satisfaction	393	7.445	1.985	-0.778	0.123	0.523	0.246
GWA2 Satisfaction	393	7.509	1.973	-0.858	0.123	0.699	0.246
GWA3 Satisfaction	393	8.084	1.839	-1.321	0.123	2.419	0.246
GWA4 Satisfaction	393	7.763	2.015	-1.005	0.123	0.775	0.246
GWA5 Satisfaction	393	7.089	2.27	-0.78	0.123	0.409	0.246
GWA6 Satisfaction	393	7.807	2.075	-0.996	0.123	0.567	0.246
GWA7 Satisfaction	393	7.506	2.361	-0.91	0.123	0.325	0.246
GWA8 Satisfaction	393	8.183	1.893	-1.352	0.123	2.006	0.246
GWA9 Satisfaction	393	7.626	2.195	-1.08	0.123	1.139	0.246
GWA10 Satisfaction	393	8.074	1.979	-1.247	0.123	1.698	0.246
GWA11 Satisfaction	393	7.509	2.158	-1.019	0.123	1.058	0.246
GWA12 Satisfaction	393	7.728	2.095	-0.99	0.123	0.821	0.246
GWA13 Satisfaction	393	6.98	2.504	-0.838	0.123	0.472	0.246
New O*NET Factor 1 Satisfaction	393	7.926	2.002	-1.114	0.123	1.323	0.246
New O*NET Factor 2 Satisfaction	393	7.786	2.136	-0.989	0.123	0.61	0.246
New O*NET Factor 3 Satisfaction	393	7.43	2.289	-0.924	0.123	0.624	0.246
New O*NET Factor 4 Satisfaction	393	6.333	2.63	-0.486	0.123	-0.174	0.246

Propositions Testing

This study's seven propositions are tested using a mix of ODI opportunity algorithm scoring, ODI landscape analysis, linear regression, O*NET GWA and WPE clustering analyses, and other statistical analysis. As a reminder, the propositions are:

- *Proposition 1a – There are statistically significant O*NET-SOC profile components desirable for artificial intelligence augmentation that leads to low-level virtual team member performance improvements.*
- *Proposition 1b – There are statistically significant O*NET-SOC profile components desirable for artificial intelligence augmentation that leads to moderate-level virtual team member performance improvements.*
- *Proposition 2 – There are statistically significant O*NET-SOC profile components desirable for artificial intelligence augmentation that leads to high-functioning virtual team member performance improvements creating superteams.*
- *Proposition 3a – A definable O*NET-SOC profile consisting of legacy factors (GWAs and WPEs) can be created to define artificial intelligence augmented high-functioning virtual team members.*
- *Proposition 3b – A definable O*NET-SOC profile consisting of new factors (GWAs and WPEs) can be created to define artificial intelligence superteams.*
- *Proposition 4 – An outcome-driven innovation rank-ordered O*NET-SOC profile index exists to guide the creation, investment, and research of AI superteams.*

The complete list of O*NET GWAs, WPEs, and new GWAs (KE1-KE4) analyzed in this study are presented below in Table 43.

Table 43 – Full List of O*NET GWAs, WPEs, and New GWAs (KE1-KE4) Analyzed

Factor Number	O*NET GWA & WPE Factor Name
GWA1	Getting Information
GWA2	Processing Information
GWA3	Making Decisions & Solving Problems
GWA4	Updating & Using Relevant Knowledge
GWA5	Developing Objectives and Strategies
GWA6	Organizing, Planning, & Prioritizing Work
GWA7	Interacting with Computers
GWA8	Communicating with Supervisors, Peers, & Subordinates
GWA9	Communicating with Persons Outside Organization
GWA10	Establishing and Maintaining Interpersonal Relationships
GWA11	Coordinating the Work and Activities of Others
GWA12	Developing and Building Teams
GWA13	Guiding, Directing, and Motivating Subordinates
WPE1	Computer Fundamentals
WPE2	Conflict Management
WPE3	Customer Service
WPE4	Learning Orientation
WPE5	Multi-tasking
WPE6	Organization
WPE7	Stress Management
WPE8	Teamwork
WPE9	Time Management
WPE10	Work Ethic
WPE11	Critical Thinking
WPE12	Decision Making
WPE13	Planning
WPE14	Relationship Building
WPE15	Written Communication
WPE16	Adaptability
WPE17	Attention to Detail
WPE18	Initiative
WPE19	Interpersonal Skills
WPE20	Perseverance
WPE21	Creativity
WPE22	Integrity
WPE23	Leadership
WPE24	Oral Communication
WPE25	Pride in Work
WPE26	Technology and Tool Usage
KE1	Role Independence and Adaptation
KE2	Empathy
KE3	Role Diversity
KE4	Roll Speed

Proposition 1a, 1b, and 2 Testing

The null proposition and propositions 1a, 1b, and 2 are tested using ODI scoring, ODI landscape, ANOVA, and linear regression analysis. Proposition 1a and 1b are first tested using ODI scoring and landscape analysis, followed by linear regression analysis. In Table 44, the low VTMP importance, frequency, satisfaction, and ODI scores are tabulated. Using this case, ODI opportunity scores above 10.0 represent a solid opportunity, and below 10.0 are appropriately served. Table 46 supports proposition 1a that there are statistically significant O*NET-SOC GWA and WPE profile components desirable for AI augmentation that leads to low-level VTMP improvements. For low-performing VTMs, 27 solid opportunities exist, and three near high-opportunities exist.

Table 44 - Low VTMP ODI Opportunity Scores

O*NET Factor	Low VTMP Importance	Low VTMP Satisfaction	Low VTMP Frequency	Low VTMP ODI Opportunity Score
WPE1	9.28	7.39	9.02	11.17
WPE2	8.68	6.52	5.82	10.85
WPE3	8.94	7.16	7.45	10.71
WPE4	8.92	6.71	6.96	11.13
WPE5	8.48	6.53	8.67	10.42
WPE6	8.31	6.32	7.60	10.30
WPE7	8.80	6.73	7.01	10.87
WPE8	9.06	7.35	8.30	10.76
WPE9	9.02	6.64	8.29	11.39
WPE10	9.22	8.10	8.78	10.34
WPE11	9.12	7.85	8.43	10.39
WPE12	9.02	7.41	7.91	10.62
WPE13	8.81	6.79	7.47	10.83
WPE14	8.81	6.98	7.71	10.63
WPE15	8.44	7.49	8.40	9.40
WPE16	8.52	7.36	7.43	9.69
WPE17	8.69	7.28	7.69	10.10
WPE18	8.61	7.60	8.17	9.63
WPE19	8.79	7.47	8.22	10.10
WPE20	8.58	7.08	7.46	10.08
WPE21	7.56	6.51	6.65	8.62
WPE22	9.40	8.62	8.66	10.17
WPE23	8.69	7.07	7.45	10.31
WPE24	8.87	7.38	8.20	10.35
WPE25	8.32	7.24	7.80	9.40
WPE26	8.21	7.04	7.45	9.39
GWA1	8.60	6.58	7.52	10.63
GWA2	8.17	6.63	7.18	9.71
GWA3	8.84	7.31	7.61	10.37
GWA4	8.60	6.90	7.25	10.29
GWA5	8.13	6.27	6.48	10.00
GWA6	8.59	6.76	7.65	10.41
GWA7	8.34	6.94	7.90	9.74
GWA8	8.77	7.25	7.99	10.29
GWA9	8.04	6.86	6.48	9.22
GWA10	8.57	7.21	7.79	9.93
GWA11	7.99	6.66	6.90	9.33
GWA12	8.40	6.76	7.02	10.05
GWA13	7.90	6.22	6.09	9.59
KE1	8.15	7.04	7.26	9.26
KE2	8.06	6.65	6.88	9.46
KE3	7.33	6.15	6.33	8.52
KE4	7.14	5.77	5.77	8.52

Next, the researcher examines proposition 1b using the same method. Table 45 supports AI augmentation that leads to moderate-level VTMP improvements. For moderate-performing VTMs, 27 different solid opportunities exist, and two near high-opportunities exist.

Table 45 - Moderate VTMP ODI Opportunity Scores

ONET Factor	Moderate VTMP Importance	Moderate VTMP Satisfaction	Moderate VTMP Frequency	Moderate VTMP ODI Opportunity Score
WPE1	9.37	8.08	9.25	10.66
WPE2	8.82	7.29	5.76	10.34
WPE3	9.48	8.18	7.97	10.79
WPE4	8.92	7.25	7.43	10.58
WPE5	8.81	7.55	8.81	10.07
WPE6	8.87	7.35	8.02	10.38
WPE7	9.21	7.26	7.52	11.15
WPE8	9.31	8.21	8.59	10.41
WPE9	9.32	7.48	8.73	11.17
WPE10	9.51	8.73	9.12	10.28
WPE11	9.25	8.38	8.68	10.12
WPE12	9.39	8.21	8.46	10.58
WPE13	9.18	7.72	8.23	10.63
WPE14	8.87	7.70	7.66	10.04
WPE15	9.20	8.35	8.61	10.05
WPE16	8.95	7.71	8.12	10.20
WPE17	9.15	8.01	8.45	10.28
WPE18	8.92	8.20	8.30	9.63
WPE19	9.20	8.33	8.48	10.07
WPE20	8.95	7.98	7.72	9.93
WPE21	8.17	7.16	6.99	9.18
WPE22	9.71	9.37	9.36	10.05
WPE23	9.23	8.05	8.07	10.42
WPE24	9.20	8.02	8.41	10.38
WPE25	8.99	8.24	8.57	9.75
WPE26	8.53	7.22	7.40	9.84
GWA1	9.16	7.35	8.12	10.98
GWA2	8.73	7.65	7.61	9.81
GWA3	9.31	8.05	8.25	10.57
GWA4	8.80	7.61	7.84	9.99
GWA5	8.62	7.02	6.85	10.21
GWA6	9.10	7.90	8.38	10.30
GWA7	8.61	7.48	7.97	9.73
GWA8	9.13	8.19	8.62	10.07
GWA9	8.62	7.76	7.37	9.47
GWA10	8.94	8.02	8.20	9.86
GWA11	8.55	7.43	7.52	9.66
GWA12	8.99	7.68	7.86	10.31
GWA13	8.35	7.16	6.82	9.55
KE1	8.47	7.73	7.81	9.21
KE2	8.55	7.85	7.55	9.26
KE3	8.12	7.68	7.24	8.55
KE4	7.32	6.12	6.18	8.51

Table 48 below compares low-, moderate-, and high-VTMP ODI opportunity scores. As demonstrated, the null proposition (P0) is not supported as there are O*NET-SOC GWA and WPE profile components significantly desirable for AI augmentation. The ODI opportunity scores above 10.0 play a significant role in VTMP improvement.

Table 46 - Low, Moderate, and High VTMP ODI Opportunity Scores

O*NET Factor	Low VTMP ODI Opportunity Score	Moderate VTMP ODI Opportunity Score	High VTMP ODI Opportunity Score	All VTMP ODI Opportunity Score
WPE1	11.17	10.66	10.85	10.9
WPE2	10.85	10.34	9.61	10.25
WPE3	10.71	10.79	10.49	10.66
WPE4	11.13	10.58	10.77	10.82
WPE5	10.42	10.07	10.47	10.33
WPE6	10.30	10.38	10.38	10.36
WPE7	10.87	11.15	10.82	10.94
WPE8	10.76	10.41	10.28	10.48
WPE9	11.39	11.17	10.86	11.13
WPE10	10.34	10.28	10.14	10.25
WPE11	10.39	10.12	10.46	10.33
WPE12	10.62	10.58	10.32	10.51
WPE13	10.83	10.63	10.76	10.73
WPE14	10.63	10.04	10.03	10.23
WPE15	9.40	10.05	9.77	9.73
WPE16	9.69	10.20	10.12	10
WPE17	10.10	10.28	10.32	10.24
WPE18	9.63	9.63	9.81	9.7
WPE19	10.10	10.07	10.11	10.09
WPE20	10.08	9.93	10.29	10.1
WPE21	8.62	9.18	9.51	9.11
WPE22	10.17	10.05	10.11	10.11
WPE23	10.31	10.42	10.34	10.35
WPE24	10.35	10.38	10.33	10.35
WPE25	9.40	9.75	10.05	9.73
WPE26	9.39	9.84	9.64	9.63
GWA1	10.63	10.98	10.47	10.69
GWA2	9.71	9.81	9.54	9.69
GWA3	10.37	10.57	10.13	10.36
GWA4	10.29	9.99	10.20	10.16
GWA5	10.00	10.21	9.91	10.03
GWA6	10.41	10.30	10.07	10.25
GWA7	9.74	9.73	9.34	9.59
GWA8	10.29	10.07	10.18	10.18
GWA9	9.22	9.47	8.98	9.21
GWA10	9.93	9.86	9.55	9.77
GWA11	9.33	9.66	9.15	9.37
GWA12	10.05	10.31	9.89	10.07
GWA13	9.59	9.55	8.92	9.34
KE1	9.26	9.21	9.00	9.15
KE2	9.46	9.26	9.31	9.33
KE3	8.52	8.55	8.93	8.67
KE4	8.52	8.51	8.93	8.67

Finally, the researcher examines proposition 2 using the same method. Table 47 supports proposition two that there are statistically significant O*NET-SOC profile components desirable for AI augmentation that leads to HFVTM performance improvements creating superteams. For HFVTMs, 27 solid opportunities exist.

Table 47 - HFVTM ODI Opportunity Scores

O*NET Factor	HFVTM Importance	HFVTM Satisfaction	HFTM Frequency	HFVTM ODI Opportunity Score
WPE1	9.69	8.67	9.62	10.71
WPE2	9.11	8.05	6.33	10.17
WPE3	9.64	8.91	8.67	10.36
WPE4	9.59	8.35	8.20	10.83
WPE5	9.32	8.11	9.28	10.53
WPE6	9.14	8.14	8.61	10.14
WPE7	9.31	7.79	7.82	10.83
WPE8	9.73	9.11	9.23	10.34
WPE9	9.59	8.20	9.28	10.98
WPE10	9.72	9.22	9.58	10.22
WPE11	9.64	8.89	9.08	10.38
WPE12	9.49	8.58	8.68	10.41
WPE13	9.39	8.36	8.69	10.42
WPE14	9.28	8.56	8.53	10.00
WPE15	9.32	8.92	9.07	9.71
WPE16	9.48	8.66	8.73	10.31
WPE17	9.53	8.70	9.01	10.36
WPE18	9.34	8.95	8.89	9.73
WPE19	9.64	9.19	9.22	10.10
WPE20	9.33	8.44	8.33	10.23
WPE21	8.86	8.16	7.57	9.57
WPE22	9.91	9.67	9.62	10.15
WPE23	9.60	8.68	8.64	10.52
WPE24	9.58	8.80	8.89	10.37
WPE25	9.45	8.94	9.18	9.95
WPE26	8.86	8.02	7.98	9.70
GWA1	9.44	8.31	8.86	10.57
GWA2	8.94	8.11	8.23	9.77
GWA3	9.55	8.79	8.83	10.32
GWA4	9.28	8.58	8.59	9.98
GWA5	9.14	8.05	7.64	10.23
GWA6	9.40	8.55	9.01	10.25
GWA7	8.91	8.20	8.46	9.62
GWA8	9.54	8.98	9.11	10.10
GWA9	8.89	8.48	7.60	9.31
GWA10	9.42	8.95	8.80	9.88
GWA11	8.89	8.33	7.67	9.46
GWA12	9.52	8.61	8.35	10.43
GWA13	8.65	7.77	6.89	9.54
KE1	9.17	8.89	8.67	9.44
KE2	9.14	8.75	8.52	9.52
KE3	8.84	8.44	7.98	9.24
KE4	7.89	6.99	6.93	8.80

Figure 11 displays the HFVTM ODI Opportunity Landscape. This visual representation of the opportunities demonstrates the significant ROI opportunities presented to AI developers to innovate in meeting the needs of HFVTMs and superteams.

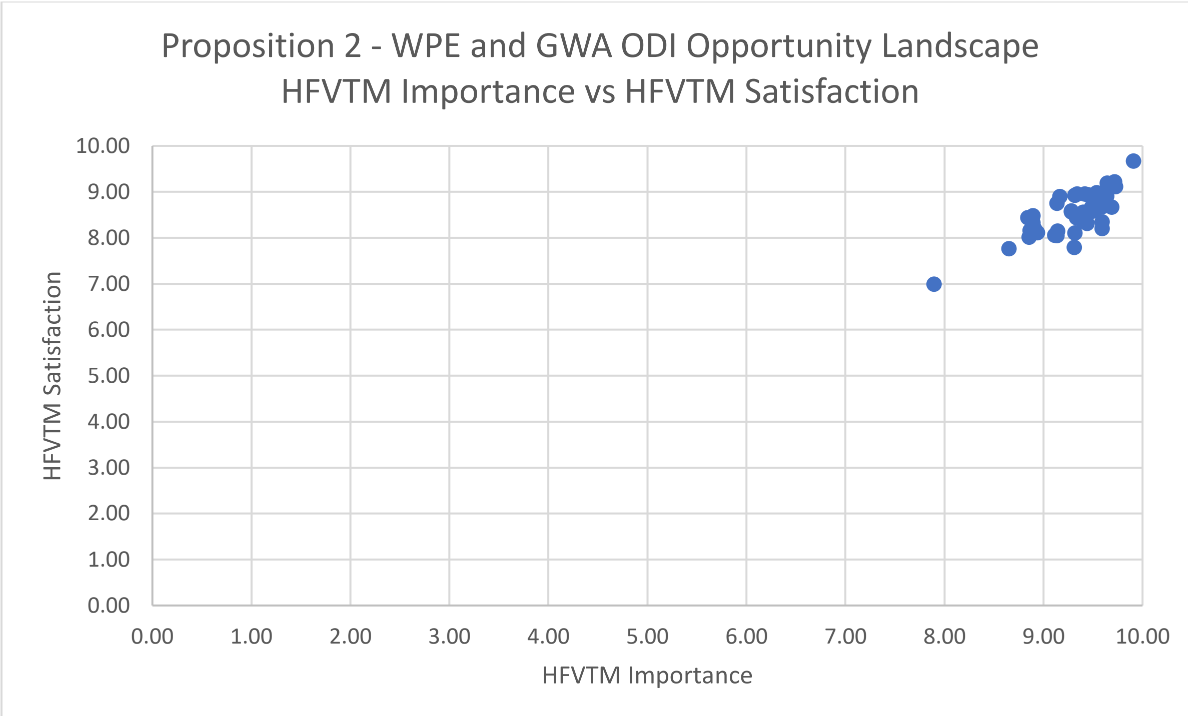


Figure 11 - HFVTM ODI Opportunity Landscape (Proposition 2)

Linear Regression Statistical Checks

Before performing this study's linear regression, the statistical theory requires an examination of the requirements for regression to confirm that the needs were met. Each of the linear regression data sets was examined separately and in totality. First, the Durbin-Watson statistic was analyzed to test the independence of residuals. The Durbin-Watson statistic values of 1.839 for HFVTMs, 1.863 for high-performing VTMs, 2.018 for moderate-performing VTMs, and 1.858 for low-performing VTMs are within the range of 1.5 to 2.5 indicating there is no autocorrelation.

Next, the VIF and tolerance were analyzed to assess multicollinearity in the models. In each case, the VIF value is lower than 5.0, and the tolerances are greater than 0.1, indicating there is no issue with multicollinearity (Hair, 2010; Cohen et al., 2014). Because all analyzed values are outside these set parameters, the researcher can conclude there is no multicollinearity. These values will be displayed as part of the linear regression analysis.

Third, the data was examined for homoscedasticity violations. The researcher visually inspected all performance standardized residuals versus standardized predicted values plots. Observing a balanced distribution of the residuals around the baseline, the researcher concludes that the assumption of homoscedasticity is not violated.

Finally, the normal probability plots were visually inspected to ensure the residuals were normally distributed. As noted in each analysis section below, the Q-Q plot demonstrates that this study's standardized residuals fit along the diagonal. The Q-Q plots demonstrate that the assumptions of normality and linearity are unlikely to have been violated. In summation, the above four techniques confirm that linear regression analysis is warranted for this study.

After the ODI landscape and opportunity scoring analysis, the researcher analyzed the VTMP and ODI data using linear regression. While there is a more or less correct analysis, once the ODI and opportunity scores demonstrated support for the propositions meeting a desirable analysis threshold, the natural next step was linear regression. In this process, O*NET factor ODI scores were removed one by one based on their individual p-values until only factors with individual p-values of less than 0.16 remained. The remaining O*NET factors represent the statistically significant WPEs, GWAs, and possible new factors (KE1-KE4) related to the VTMP or HFVTM statistically significant scores. For each case, the model summary, ANOVA, coefficients, and QQ plots are shown for completeness. Future research should perform additional statistical analysis to include SEM and LDA.

As seen in Table 48 and Figure 12 (Q-Q plot), for low VTMP vs. low ODI linear regression analysis, the R2 demonstrates the WPE1, WPE4, WPE5, WPE15, WPE22, GWA1, GWA3, GWA6, and GWA9 explain 34.3 percent of the data. Further, WPE1, WPE22, GWA1, GWA3, and GWA9 negatively correspond to performance while WPE4, WPE5, WPE15, and GWA6 positively correspond to performance. Therefore, in combination with the individual O*NET ODI scores, WPE4 (Learning Orientation), WPE5 (Multi-tasking), and GWA6 (Organizing, Planning, and Prioritizing Work) have the greatest opportunity to increase low VTMP.

Table 48 - Linear Regression of Low VTMP vs Low ODI Opportunity Scores

Model Summary - Low VTMP vs Low ODI

Model	R	R^2	Adjusted R^2	RMSE
H_0	0	0	0	4.179
H_1	0.586	0.343	0.292	3.516

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
H_1	Regression	749.583	9	83.287	6.739	< .001
	Residual	1433.631	116	12.359		
	Total	2183.214	125			

Note. The intercept model is omitted, as no meaningful information can be shown.

Coefficients

Model		Unstandardized	Standard Error	Standardized	t	p	Collinearity Statistics Tolerance	VIF
H_0	(Intercept)	28.881	0.372		77.572	< .001		
H_1	(Intercept)	36.931	2.331		15.845	< .001		
	WPE1	-0.605	0.134	-0.376	-4.503	< .001	0.811	1.234
	WPE4	0.266	0.101	0.21	2.634	0.01	0.89	1.124
	WPE5	0.216	0.087	0.202	2.482	0.014	0.851	1.175
	WPE15	0.176	0.103	0.139	1.708	0.09	0.859	1.165
	WPE22	-0.339	0.161	-0.187	-2.109	0.037	0.722	1.385
	GWA1	-0.339	0.121	-0.259	-2.797	0.006	0.66	1.516
	GWA3	-0.445	0.157	-0.268	-2.844	0.005	0.638	1.567
	GWA6	0.522	0.146	0.362	3.565	< .001	0.549	1.823
	GWA9	-0.209	0.108	-0.158	-1.937	0.055	0.848	1.179

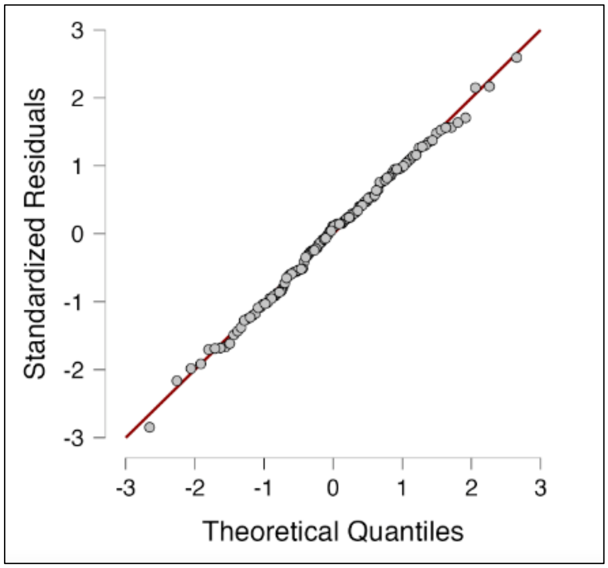


Figure 12 – Q-Q Plot of Low VTMP vs. Low ODI Opportunity Scores Standardized Residuals

As seen in Table 49 and Figure 13 (Q-Q plot), for moderate VTMP versus moderate ODI linear regression analysis, the R^2 demonstrates that the WPE5, WPE18, WPE24, and GWA3 explain only 8.4 percent of the regression. Further, WPE18 negatively corresponds to performance, while WPE5, WPE24, and GWA3 positively correspond to performance. Therefore, in combination with the moderate individual O*NET ODI scores, WPE5 (Multi-tasking), WPE24 (Oral Communications), and GWA3 (Making Decisions & Solving Problems) have the greatest opportunity to increase moderate VTMP.

Table 49 - Linear Regression of Moderate VTMP vs. Moderate ODI Opportunity Scores

Model Summary - Moderate VTM Performance vs Moderate ODI

Model	R	R²	Adjusted R²	RMSE
H_0	0	0	0	1.722
H_1	0.29	0.084	0.055	1.674

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
H_1	Regression	32.148	4	8.037	2.868	0.026
	Residual	350.283	125	2.802		
	Total	382.431	129			

Note. The intercept model is omitted, as no meaningful information can be shown.

Coefficients

							Collinearity Statistics	
Model		Unstandardized	Standard Error	Standardized	t	p	Tolerance	VIF
H_0	(Intercept)	37.677	0.151		249.497	< .001		
H_1	(Intercept)	36.15	0.889		40.683	< .001		
	WPE5	0.084	0.052	0.147	1.603	0.111	0.871	1.148
	WPE18	-0.157	0.069	-0.23	-2.264	0.025	0.71	1.409
	WPE24	0.101	0.07	0.149	1.433	0.154	0.682	1.466
	GWA3	0.109	0.07	0.141	1.543	0.125	0.876	1.141

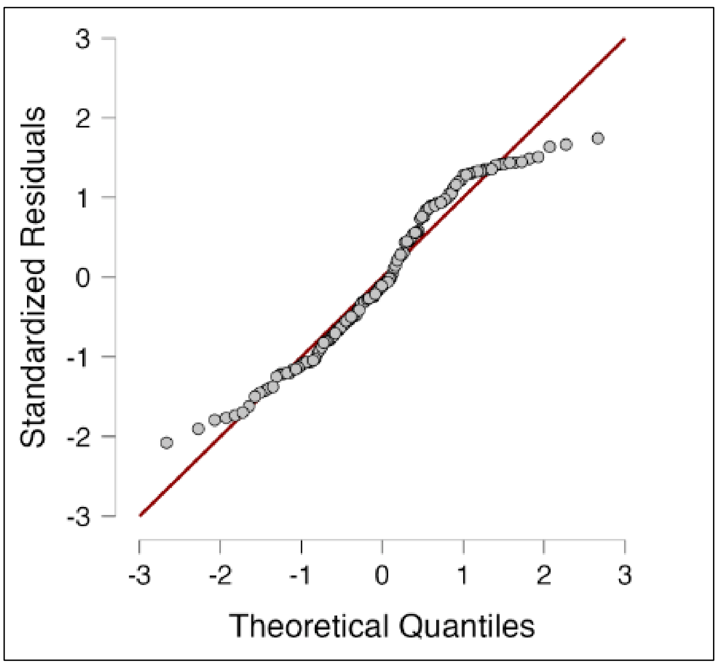


Figure 13 - Q-Q Plot of Moderate VTMP vs. ODI Opportunity Scores Standardized Residuals

As seen in Table 50 and Figure 14 (Q-Q plot), for high VTMP vs. high ODI linear regression analysis, the R^2 demonstrates the WPE1, WPE2, WPE3, WPE4, WPE9, WPE15, WPE16, WPE17, WPE18, WPE19, WPE23, and the new O*NET factors of KE2 and KE4 explain 22.7 percent of the regression. Further, WPE1, WPE3, WPE9, WPE16, WPE19, WPE23, and the new O*NET factor of KE4 negatively corresponds to performance while WPE2, WPE4, WPE15, WPE17, WPE18, and the new O*NET factors of KE2 positively correspond to performance. Therefore, in combination with the individual O*NET ODI scores for high performers, WPE4 (Learning Orientation) and WPE17 (Attention to Detail) have the greatest opportunity to increase moderate VTMP.

Table 50 - Linear Regression of High VTMP vs. High ODI Opportunity Scores

Model Summary - High VTM Performance vs ODI

Model	R	R^2	Adjusted R^2	RMSE
H_0	0	0	0	1.124
H_1	0.476	0.227	0.145	1.039

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
H_1	Regression	38.961	13	2.997	2.776	0.002
	Residual	132.806	123	1.08		
	Total	171.766	136			

Note. The intercept model is omitted, as no meaningful information can be shown.

Coefficients

Model		Unstandardized	Standard Error	Standardized	t	p	Collinearity Statistics Tolerance	VIF
H_0	(Intercept)	42.905	0.096		446.858	< .001		
H_1	(Intercept)	44.245	0.904		48.968	< .001		
	WPE1	-0.084	0.046	-0.155	-1.844	0.068	0.892	1.122
	WPE2	0.068	0.03	0.226	2.287	0.024	0.644	1.553
	WPE3	-0.077	0.043	-0.155	-1.791	0.076	0.836	1.196
	WPE4	0.078	0.044	0.164	1.757	0.081	0.724	1.381
	WPE9	-0.107	0.047	-0.227	-2.268	0.025	0.63	1.588
	WPE15	0.122	0.052	0.23	2.333	0.021	0.645	1.55
	WPE16	-0.131	0.045	-0.298	-2.927	0.004	0.606	1.65
	WPE17	0.117	0.049	0.217	2.373	0.019	0.753	1.327
	WPE18	0.113	0.053	0.225	2.135	0.035	0.567	1.764
	WPE19	-0.171	0.06	-0.291	-2.868	0.005	0.611	1.636
	WPE23	-0.079	0.046	-0.176	-1.734	0.085	0.612	1.635
	KE2	0.083	0.04	0.196	2.106	0.037	0.724	1.381
	KE4	-0.041	0.022	-0.162	-1.905	0.059	0.87	1.15

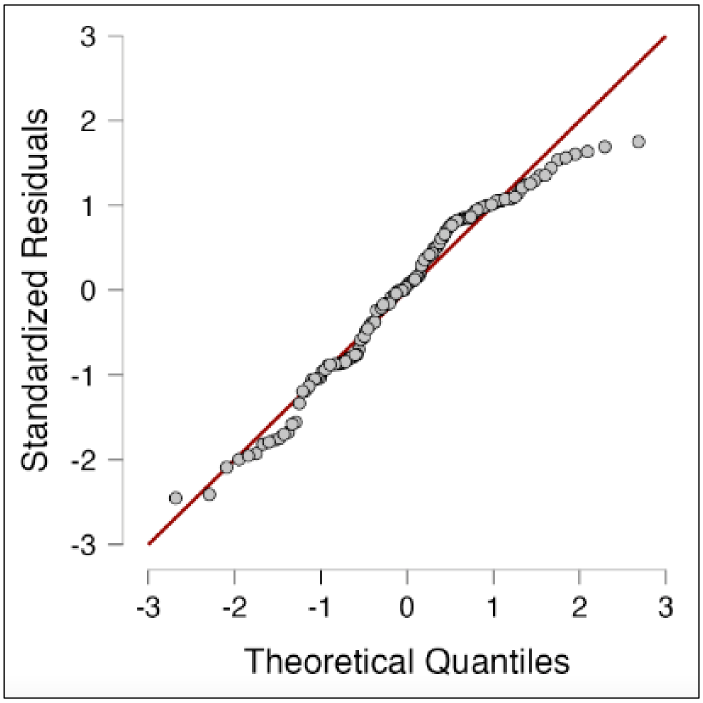


Figure 14 - QQ Plot of High VTMP vs. ODI Opportunity Scores Standardized Residuals

As seen in Table 51 and Figure 15, for HFVTM scores vs. HFVTM ODI linear regression analysis, the R^2 demonstrates the WPE1, WPE5, WPE13, WPE14, WPE15, WPE17, WPE21, WPE24, WPE25, GWA3, and the new O*NET factors of KE3 explain 10.7 percent of the regression. Further, WPE1, WPE13, WPE14, WPE17, WPE24, and GWA3 negatively corresponds to performance while WPE5, WPE15, WPE21, WPE25, and the new O*NET factors of KE3 positively correspond to performance. Therefore, in combination with the individual O*NET ODI scores for HFVTMs, WPE5 has the greatest opportunity to increase HFVTM performance. Finally, the data supports the assessment that WPE5, multi-tasking, is the primary statistically significant O*NET-SOC profile component desirable for AI augmentation that leads to the creation of superteams. AI focusing on multi-tasking, or the ability to handle or switch between multiple tasks and assignments by setting priorities and managing workflow under varying deadlines, is likely a significant activity for HFVTMs.

Table 51 - Linear Regression of HFVTM vs HFVTM ODI Opportunity Scores

Model Summary - HFVTM vs ODI

Model	R	R^2	Adjusted R^2	RMSE
H_0	0	0	0	11.712
H_1	0.324	0.105	0.079	11.239

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
H_1	Regression	5647.489	11	513.408	4.064	< .001
	Residual	48126.44	381	126.316		
	Total	53773.928	392			

Coefficients

Model		Unstandardized	Standard Error	Standardized	t	p	Collinearity Statistics Tolerance	VIF
H_0	(Intercept)	79.509	0.591		134.576	< .001		
H_1	(Intercept)	90.352	4.61		19.599	< .001		
	WPE1	-0.498	0.264	-0.096	-1.886	0.06	0.911	1.098
	WPE5	0.323	0.196	0.09	1.649	0.1	0.792	1.262
	WPE13	-0.668	0.234	-0.164	-2.856	0.005	0.717	1.395
	WPE14	-0.568	0.216	-0.145	-2.628	0.009	0.773	1.294
	WPE15	0.507	0.247	0.114	2.05	0.041	0.761	1.314
	WPE17	-0.443	0.252	-0.093	-1.756	0.08	0.838	1.194
	WPE21	0.498	0.208	0.143	2.391	0.017	0.654	1.529
	WPE24	-0.416	0.274	-0.086	-1.516	0.13	0.733	1.365
	WPE25	0.664	0.279	0.141	2.38	0.018	0.666	1.501
	GWA3	-0.627	0.279	-0.116	-2.25	0.025	0.89	1.124
	KE3	0.418	0.182	0.121	2.302	0.022	0.854	1.171

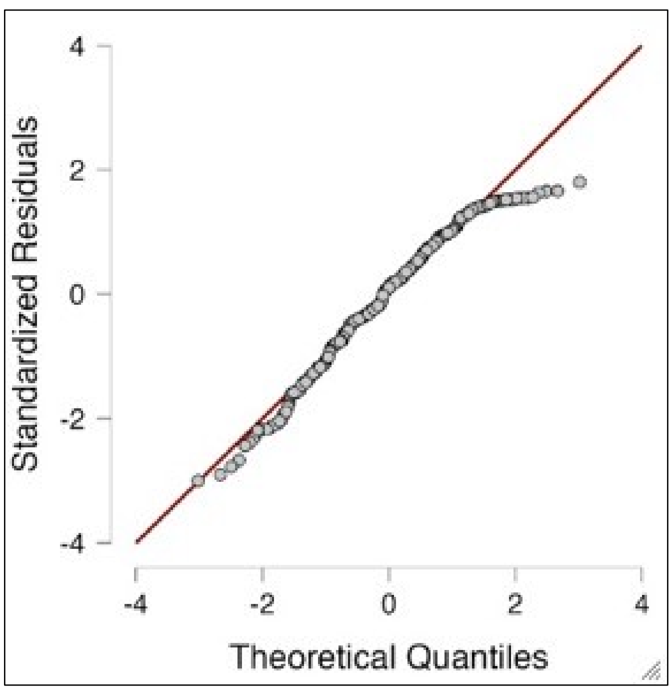


Figure 15 - QQ Plot of HFVTM vs ODI Opportunity Scores Standardized Residuals

Finally, an ANOVA and MANOVA analysis of the high, moderate, and low-performers O*NET ODI importance and satisfaction scores was performed to confirm statistical variance between these groups (Appendix H & Appendix I). The analysis demonstrates there are statistical differences in the score for each O*NET importance work factor ranking except WPE2, GWA7, and GWA13 confirming these performance groups rate the vast majority of work factor importance is different and therefore likely want different things from AI. The analysis demonstrates there are statistical differences in all O*NET satisfaction work factors confirming these groups rate all work factor satisfactions differently across performance levels and likely want different things from AI.

At the conclusion of this part of the analysis, the null proposition can be rejected, and propositions 1a, 1b, and 2 are supported. There are statistically significant O*NET-SOC profile components desirable for AI augmentation, leading to low-level VTMP improvements (P1a). There are statistically significant O*NET-SOC profile components desirable for AI augmentation, leading to moderate-level VTMP improvements (P1b). There are statistically significant O*NET-SOC profile components desirable for AI augmentation, leading to HFVTM performance improvements and creating superteams (P2).

Proposition 3a, 3b, and 4 Testing

In this section, the researcher analyzed the O*NET propositions 3a, 3b, and 4. For proposition 3a, the researcher analyzed the HFVTM O*NET importance and frequency scores to improve and modify for AI analysis, an O*NET-SOC profile originally consisting of the 43 legacy WPE and GWA factors (Hill, 2023). This process defined artificial intelligence augmented HFVTMs through a cluster analysis evaluation technique used by two seminal O*NET authors (Dubes & Jain, 1980; Madhulatha, 2012). For proposition 3b, the researcher uses the same cluster analysis technique to define an O*NET-SOC profile consisting of any of the four new VT and AI GWA factors to define AI superteams. These possible new factors focused on virtual teaming, human-machine teaming, AI-ability of work, and AI-only work factors (AI-able) will focus on the four possible GWAs uncovered from the qualitative interviews. Finally, for proposition 4, the researcher will analyze the ODI score for the legacy and new HFVTM WPEs and GWAs required to create superteams and cross-lay AI-type and Gartner's Hype Cycle to determine a rank-ordered index to guide the creation, investment, and research of AI superteams.

Proposition 3a and 3b

Figure 16 displays the importance versus frequency scores cluster analysis plot for both the legacy (3a) and new (3b) work factors. This process is used to determine the legacy and new work factors using a cluster analysis technique used by two seminal O*NET authors (Dubes & Jain, 1980; Madhulatha, 2012). In the case of the 43 legacy WPEs and GWAs for analysis of proposition 3a, WPE2 (Conflict Management) and GWA13 (Guiding, Directing, & Motivating Subordinates) are removed. In the case of the 47 new and legacy WPEs and GWAs for analysis of proposition 3b, KE4 (Roll Speed) is removed. This analysis supports proposition 3a and proposition 3b.

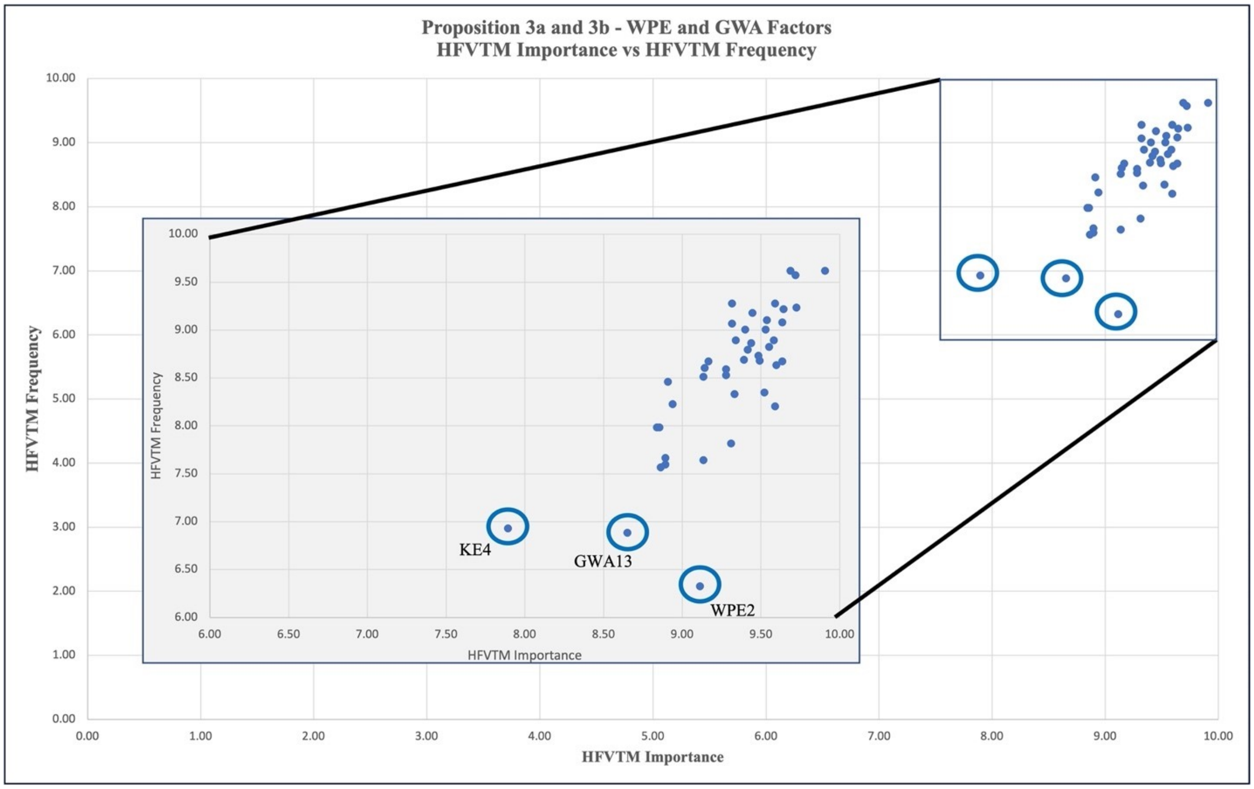


Figure 16 - Cluster Analysis for New and Legacy Work Factors

Therefore, an updated HFVTM O*NET-SOC profile consisting of the 44 WPE and GWA factors can be created to define AI superteam work factors. This superteams O*NET-SOC profile is discussed in chapter five and is available in Table 56.

Proposition 4

For analysis of proposition 4, the researcher analyzed the ODI opportunity score of the legacy and new HFVTM WPEs and GWAs required to create superteams and cross-laid AI-type and Gartner's Hype Cycle to determine a rank-ordered index to guide the creation, investment, and research of AI superteams. Table 56 shows the overlay of AI-Type and Gartner Hype Cycle Status. The work factors in bold represent the GWAs and WPEs available for innovation today. Using this crosswalk, Table 52 displays the rank-ordered index intended to guide AI superteams' creation, investment, and research using five-year spans supporting proposition 4.

Table 52 - HFVTM ODI Score versus AI-Type and Gartner's Hype Cycle

Factor Number	O*NET GWA or WPE Factor Name	Gartner Hype Cycle	AI-Type	HFVTM ODI Opportunity Score
WPE9	Time Management	Peak	Narrow AI / Reactive AI	10.98
WPE4	Learning Orientation	Innovation	General AI / Limited Memory AI	10.83
WPE7	Stress Management	Innovation	General AI / Limited Memory AI	10.83
WPE1	Computer Fundamentals	Peak	Narrow AI / Reactive AI	10.71
GWA1	Getting Information	Peak	Narrow AI / Reactive AI	10.57
WPE5	Multi-tasking	Innovation	General AI / Limited MemoryAI	10.53
WPE23	Leadership	Innovation	Super AI / Theory of Mind AI	10.52
GWA12	Developing and Building Teams	Innovation	Super AI / Theory of Mind AI	10.43
WPE13	Planning	Innovation	General AI / Limited Memory AI	10.42
WPE12	Decision Making	Innovation	Super AI / Theory of Mind AI	10.41
WPE11	Critical Thinking	Innovation	Super AI / Theory of Mind AI	10.38
WPE24	Oral Communication	Peak	Narrow AI / Reactive AI	10.37
WPE3	Customer Service	Peak	Narrow AI / Reactive AI	10.36
WPE17	Attention to Detail	Peak	Narrow AI / Reactive AI	10.36
WPE8	Teamwork	Innovation	Super AI / Theory of Mind AI	10.34
GWA3	Making Decisions & Solving Problems	Innovation	General AI / Limited Memory AI	10.32
WPE16	Adaptability	Innovation	General AI / Limited Memory AI	10.31
GWA6	Organizing, Planning, & Prioritizing Work	Innovation	General AI / Limited Memory AI	10.25
WPE20	Perseverance	Innovation	General AI / Limited Memory AI	10.23
GWA5	Developing Objectives and Strategies	Innovation	Super AI / Theory of Mind AI	10.23
WPE10	Work Ethic	Innovation	General AI / Limited Memory AI	10.22
WPE22	Integrity	Innovation	General AI / Limited Memory AI	10.15
WPE6	Organization	Innovation	General AI / Limited Memory AI	10.14
WPE19	Interpersonal Skills	Innovation	General AI / Limited Memory AI	10.10
GWA8	Communicating with Supervisors, Peers, & Subordinates	Peak	Narrow AI / Reactive AI	10.10
WPE14	Relationship Building	Innovation	General AI / Limited Memory AI	10.00
GWA4	Updating & Using Relevant Knowledge	Peak	Narrow AI / Reactive AI	9.98
WPE25	Pride in Work	Innovation	General AI / Limited Memory AI	9.95
GWA10	Establishing and Maintaining Interpersonal Relationships	Innovation	Super AI / Theory of Mind AI	9.88
GWA2	Processing Information	Trough	Narrow AI / Reactive AI	9.77
WPE18	Initiative	Innovation	General AI / Limited Memory AI	9.73
WPE15	Written Communication	Slope	Narrow AI / Reactive AI	9.71
WPE26	Technology and Tool Usage	Innovation	General AI / Limited Memory AI	9.70
GWA7	Interacting with Computers	Slope	Narrow AI / Reactive AI	9.62
WPE21	Creativity	Innovation	Super AI / Theory of Mind AI	9.57
KE2	Empathy	Innovation	Super AI / Theory of Mind AI	9.52
GWA11	Coordinating the Work and Activities of Others	Innovation	General AI / Limited Memory AI	9.46
KE1	Role Independence and Adaptation	Innovation	Super AI / Theory of Mind AI	9.44
GWA9	Communicating with Persons Outside Organization	Innovation	General AI / Limited Memory AI	9.31
KE3	Role Diversity	Innovation	Super AI / Theory of Mind AI	9.24

Removed: WPE2 Conflict Management, GWA3 Guiding, Directing, and Motivating Subordinates, KE4 Role Speed

VTM problems can be ill-structured, contradicting, and include high ambiguity and uncertainty. Businesses have great potential to leverage AI in these limited cognitive resource environments. Additionally, AI excels at solving pre-defined problems and offers unique capability with specific work factors that require intuition (Akinci & Sadler-Smith, 2012), simplification (Bingham & Eisenhardt, 2011), or a level of organizational problem-solving. Therefore, AI may be useful for rapid innovation in the bolded seven work factors: time management, computer fundamentals, getting information, oral communication, customer service, attention to detail, and communicating with supervisors, peers, and subordinates. These problems likely require innovations using narrow AI, reactive AI, or limited memory AI.

However, in some cases, the business problems rationality is bounded in a greater context that requires unique knowledge, contextualization, and cognition that may be difficult for AI to operate in (Marcus & Davis, 2020). Current AI struggles with identifying, categorizing, and eliminating new organizational problems (Verganti, Vendraminelli, & Iansiti, 2020). These problems likely require general AI, super AI, Theory of Mind AI, or possibly self-awareness AI. The process followed by this study suggests that 19 work factors with ODI scores above 10.0 fall into this AI innovation category. These factors represent highly recommended areas of research for AI and business developers.

Table 53 - Rank-Ordered Index of AI Superteams Investment in 5-Year Spans

Factor	O*NET GWA or WPE Factor Name	Gartner Hype Cycle	AI-Type	HFVTM ODI Opportunity Score	Rank Ordered Index Using 5-Year Spans
WPE9	Time Management	Peak	Narrow AI / Reactive AI	10.98	Now
WPE4	Learning Orientation	Innovation	General AI / Limited Memory AI	10.83	5 Years
WPE7	Stress Management	Innovation	General AI / Limited Memory AI	10.83	5 Years
WPE1	Computer Fundamentals	Peak	Narrow AI / Reactive AI	10.71	Now
GWA1	Getting Information	Peak	Narrow AI / Reactive AI	10.57	Now
WPE5	Multi-tasking	Innovation	General AI / Limited MemoryAI	10.53	5 Years
WPE23	Leadership	Innovation	Super AI / Theory of Mind AI	10.52	10+ Years
GWA12	Developing and Building Teams	Innovation	Super AI / Theory of Mind AI	10.43	10+ Years
WPE13	Planning	Innovation	General AI / Limited Memory AI	10.42	5 Years
WPE12	Decision Making	Innovation	Super AI / Theory of Mind AI	10.41	10+ Years
WPE11	Critical Thinking	Innovation	Super AI / Theory of Mind AI	10.38	10+ Years
WPE24	Oral Communication	Peak	Narrow AI / Reactive AI	10.37	Now
WPE3	Customer Service	Peak	Narrow AI / Reactive AI	10.36	Now
WPE17	Attention to Detail	Peak	Narrow AI / Reactive AI	10.36	Now
WPE8	Teamwork	Innovation	Super AI / Theory of Mind AI	10.34	10+ Years
GWA3	Making Decisions & Solving Problems	Innovation	General AI / Limited Memory AI	10.32	5 Years
WPE16	Adaptability	Innovation	General AI / Limited Memory AI	10.31	5 Years
GWA6	Organizing, Planning, & Prioritizing Work	Innovation	General AI / Limited Memory AI	10.25	5 Years
WPE20	Perseverance	Innovation	General AI / Limited Memory AI	10.23	5 Years
GWA5	Developing Objectives and Strategies	Innovation	Super AI / Theory of Mind AI	10.23	10+ Years
WPE10	Work Ethic	Innovation	General AI / Limited Memory AI	10.22	5 Years
WPE22	Integrity	Innovation	General AI / Limited Memory AI	10.15	5 Years
WPE6	Organization	Innovation	General AI / Limited Memory AI	10.14	5 Years
WPE19	Interpersonal Skills	Innovation	General AI / Limited Memory AI	10.10	5 Years
GWA8	Communicating with Supervisors, Peers, & Subordinates	Peak	Narrow AI / Reactive AI	10.10	Now
WPE14	Relationship Building	Innovation	General AI / Limited Memory AI	10.00	5 Years
GWA4	Updating & Using Relevant Knowledge	Peak	Narrow AI / Reactive AI	9.98	Now
WPE25	Pride in Work	Innovation	General AI / Limited Memory AI	9.95	5 Years
GWA10	Establishing and Maintaining Interpersonal Relationships	Innovation	Super AI / Theory of Mind AI	9.88	10+ Years
GWA2	Processing Information	Trough	Narrow AI / Reactive AI	9.77	Now
WPE18	Initiative	Innovation	General AI / Limited Memory AI	9.73	5 Years
WPE15	Written Communication	Slope	Narrow AI / Reactive AI	9.71	Now
WPE26	Technology and Tool Usage	Innovation	General AI / Limited Memory AI	9.70	5 Years
GWA7	Interacting with Computers	Slope	Narrow AI / Reactive AI	9.62	Now
WPE21	Creativity	Innovation	Super AI / Theory of Mind AI	9.57	10+ Years
KE2	Empathy	Innovation	Super AI / Theory of Mind AI	9.52	10+ Years
GWA11	Coordinating the Work and Activities of Others	Innovation	General AI / Limited Memory AI	9.46	5 Years
KE1	Role Independence and Adaptation	Innovation	Super AI / Theory of Mind AI	9.44	10+ Years
GWA9	Communicating with Persons Outside Organization	Innovation	General AI / Limited Memory AI	9.31	5 Years
KE3	Role Diversity	Innovation	Super AI / Theory of Mind AI	9.24	10+ Years

Removed: WPE2 Conflict Management, GWA3 Guiding, Directing, and Motivating Subordinates, KE4 Role Speed

Using this scholarly understanding of AI, a five-year investment roadmap can be determined using three, five-year categories (Figure 17).

Figure 17 - Superteams Creation Hype Cycle & Investment Plan

Main Study Summary

The main study summary demonstrates that statistically significant O*NET factors exist that increase low-, moderate-, and high-performing VTM performance (P1a, P1b). The ODI opportunity algorithm and landscape analysis demonstrate 27 varying O*NET GWA and WPE factors available for AI innovation. In addition, the analysis expresses support for statistically significant O*NET factors that exist to increase the performance of HFVTMs creating superteams (P2). The O*NET GWA, WPE, and novel factors linked to performance improvement using ODI analysis and linear regression include learning orientation, multi-tasking, oral communication, attention to detail, making decisions and solving problems, and finally, organizing, planning, and prioritizing work. Linear regression analysis suggests that multi-tasking is a universal O*NET factor available for AI innovation for low-performing VTMs, moderate-performing VTMs, and HFVTMs.

Next, a definable O*NET-SOC profile consisting of 41 legacy factors is created to define AI-augmented HFVTMs (P3a). Further, a definable O*NET-SOC profile consisting of new factors, including KE1, KE2, and KE3, was created to define artificial intelligence superteams (P3b). Finally, an ODI rank-ordered O*NET-SOC profile index exists to guide AI superteams' creation, investment, and research (P4). In summary, this study's exploratory sequential mixed methods analysis supported P1a, P1b, P2, P3a, P3b, and P4. One additional note, the researcher acknowledges propositions are by definition not testable. Because this study met the scholarly definition of a supported proposition, the researcher reports the propositions as supported (Creswell, 2014).

Synthesis and Summary of Data

All five phases of this study were critical to the conclusions reached in this research study. Next, a review of the qualitative interview and quantitative data findings will take place concerning this study's research questions and propositions.

Qualitative Interview and Quantitative Findings

Each of the five stages of this exploratory sequential mixed method study was essential to the conclusions established in this research. The researcher began by developing an O*NET expert team, including two seminal experts with over 20 years of experience. This O*NET panel is used throughout the study to provide face validity and expert advice. Next, the researcher interviewed a panel of seven AI and VTM experts, leaders, and practitioners during the pilot study phase of the qualitative portion of this research to establish this study's interview process and questions. The researcher performed a total of 30 qualitative semi-structured tandem interviews to produce a quantitative survey, establish face validity, pragmatically investigate impacts on human-machine teaming, and add face validity to test this study's propositions. To test the quantitative pilot study survey instrument, the researcher used 20 respondents to test them to substantiate survey validity and reliability and establish the statistical evidence required to analyze this study's propositions. This study's primary quantitative study resulted in 393 viable VTM survey responses that met the research thresholds required to test the propositions. Below are the results of each proposition test:

- Proposition 0 – No O*NET-SOC profile components are significantly desirable for artificial intelligence augmentation and therefore do not play a significant role in virtual team member performance improvement. **Not Supported**
- Proposition 1a – There are statistically significant O*NET-SOC profile components desirable for artificial intelligence augmentation that leads to low-level virtual team member performance improvements. **Supported**
- Proposition 1b – There are statistically significant O*NET-SOC profile components desirable for artificial intelligence augmentation that leads to moderate-level virtual team member performance improvements. **Supported**
- Proposition 2 – There are statistically significant O*NET-SOC profile components desirable for artificial intelligence augmentation that leads to high-functioning virtual team member performance improvements creating superteams. **Supported**
- Proposition 3a – A definable O*NET-SOC profile consisting of legacy factors (WPEs and GWAs) can be created to define artificial intelligence augmented high-functioning virtual team members. **Supported**

- Proposition 3b – A definable O*NET-SOC profile consisting of new factors (WPEs and GWAs) can be created to define artificial intelligence superteams. **Supported**
- Proposition 4 – An outcome driven innovation rank-ordered O*NET-SOC profile index exists to guide the creation, investment, and research of AI superteams. **Supported**

Chapter 5

Discussion, Implications, & Recommendations

Overview and Summary of Research Results

This research provides the definition, proxy, analysis process, and insights on how to define the roles AI will perform as it becomes an autonomous teammate, integrated with humans, and contributing to business ROI. AI will continue to play a critical role in the future of all employees, businesses, and consumers. Because of the promise of performance and ROI increases, scholars and business leaders need to define AI's distinct roles and functions in superteams and HMTs. Businesses require enhancing organizational capabilities using AI to identify, analyze, and resolve complex problems efficiently and effectively, and superteams, HMTs, and AI-augmented VTMs offer a promising potential to increase performance capabilities that will likely outperform wholesale employee replacement with AI.

It is recommended that the innovation needs-based approach to superteaming and AI augmentation, developed by this research, be used by companies and governments to determine what to integrate with an AI lens. For example, the current explosion of ChatGPT opens multiple areas of dedicated AI use. Matching the capability of ChatGPT to areas of firm and VTM performance could be performed rapidly, giving those businesses and governments a head start on AI adoption, increasing ROI, and improving VTM performance.

This study explores factors that impact human-machine teaming, VTM augmentation, the creation of superteams, and AI ROI. As Ransbotham et al. (2019) demonstrated, 70 percent of businesses do not see positive ROI from AI, with 40 percent of businesses investing significant funds not realizing increased ROI (Ransbotham et al., 2019). However, as demonstrated by the information technology productivity paradox, although ROI is mixed, businesses cannot forgo

AI investment without risking being left behind (Brynjolfsson, 1993). This research provides a path for businesses to increase the ROI of AI. The ability of this research to demonstrate and examine how AI and humans should work together to solve O*NET-defined work activities is critical in an environment where everything is capable of AI augmentation with proper resources, data, and time over the short and long-term horizon (Revell, 2017; Lee & Qiufan, 2022).

The academic literature on human-machine teaming lacks a proxy for scholarly analysis because none have been researched, tested, and proposed. This research provides a proxy for scholarly HMT analysis. The literature on superteams lacked a definition and method for research. This research provides a definition of superteams and a method to research superteams. Using HFVTMs as a proxy for superteaming, human-machine teaming, and VTM augmentation allows this study to deepen research to explain why businesses fail to achieve the expected ROI they set out to create with AI. The concept of superteams provides the capacity to augment AI investment and VTMs and define a future area of research built on investment-driven analysis. This study's research set out on an exploration to answer these questions and completed the analysis.

Innovation Needs-Based Approach to Superteaming and AI Augmentation

The establishment of HFVTMs as a proxy for scholarly and business research into superteams, HMTs, and VTM augmentation is a critical scholarly contribution. Further, developing a scholarly and statistically validated process for establishing and ranking the work factors required to increase VTMP and create superteams is essential. This innovation needs-based approach to superteaming and AI augmentation, driven by ODI analysis and the HFVTM proxy, is a significant contribution. Proxy analysis of modern and future work involving AI allows leaders to solve critical business problems and a method to augment low-, moderate-, and high-performing VTMs with AI. Furthermore, the ability of this research to scholarly define superteams at a fundamental O*NET-SOC profile level to include WPEs and GWAs allows for fundamental analysis of this future HMT and superteams environment.

Furthermore, this paper suggests the consideration of VTM augmentation using AI and the new construct of superteams as DC and SCA at the individual team member level. Applying these unique resources at the individual level and the definition of the AI-able HFVTM WPEs and GWAs required to create superteams and augment underperforming teams is an essential takeaway. This study proposes an AI investable index, construct, and proxy built using O*NET, allowing businesses to invest with increasing certainty to reach higher levels of ROI. This study also provides O*NET with the natural beginnings of a new AI-able column to describe bespoke AI work, such as roll speed. In addition, this study provides O*NET with AI-augmentable WPEs and GWAs that provide a construct to rate the AI-ability of human work. This novel AI O*NET-SOC profile opens multiple scholarly avenues to examine work and HMTs.

Ultimately, the researcher answered this study's research questions through an exploratory sequential mixed method study of 30 qualitative interviewees and 393 VTM quantitative survey responses from various industries and backgrounds in the U.S., Australia, Canada, and Europe. The extensive set, collected through a survey of VTMs, and analyzed using JASP, provides future researchers with paths to examine VTMP, QWL, ODI, and other statistically significant measures. The remainder of chapter five discusses the research results and the implications for academic theory, O*NET, and business practitioners. Additionally, the study's limitations are discussed before a thorough discussion of future research opportunities in VTM augmentation, human-machine teaming, and superteams.

Discussion of Results

In RQ1, the study seeks to understand what effect AI augmentation has on low-performing VTMP. The test for P1a demonstrated statistically significant O*NET-SOC profile components desirable for AI augmentation that leads to low-level VTMP improvements. These profile components include multi-tasking, learning orientation, and organizing, planning, and prioritizing work. This outcome was theorized and expected because low-performing VTMs require unique needs.

Similar to the first research question, RQ2 sought to understand the effect AI augmentation has on moderate-performing VTMP. The test for P1b demonstrated there are statistically significant O*NET-SOC profile components desirable for artificial intelligence augmentation that leads to moderate-level VTMP improvements. These statistically significant O*NET-SOC profile components, including multi-tasking, oral communications, and making decisions and solving problems, are bespoke to moderate-performing VTMs. These work factors collectively differ from those of a low- and high-performing VTM in the following manner.

In RQ3, the researcher seeks to understand the effect of AI on HFVTM performance. The test for P2 demonstrates statistically significant O*NET-SOC profile components desirable for AI augmentation that leads to HFVTM performance improvements creating superteams. The top work factor for HFVTM AI augmentation is multi-tasking.

Bespoke to this study's analysis of VTM augmentation, superteams, and human-machine teaming in relation to O*NET, RQ4 sought to understand which HFVTM O*NET-SOC profile factors have the highest outcome-driven innovation opportunity score for AI augmentation desirability. The analysis of RQ4 occurs across three propositions focusing on defining an O*NET-SOC profile consisting of legacy factors that can be determined to define artificial intelligence-augmented HFVTMs (P3a), defining an O*NET-SOC profile consisting of new factors that can be determined to define superteams (P3b), and the existence of an outcome-driven innovation rank-ordered O*NET-SOC profile index to guide the creation, investment, and research of AI superteams (P4).

Beyond the statistical differences related to VTM augmentation, superteams, human-machine teaming, and O*NET discussed above, this paper will now address the combined qualitative, quantitative, research process conclusions, and research takeaways determined during this research. First, this study demonstrates that O*NET job factors required for AI augmentation differ for each performance level. While the ODI opportunity algorithm and landscape analysis demonstrate 27 varying work factors, out of the original 79 legacy and new GWAs and WPEs, are recommended for AI augmentation to increase VTMP and ROI, the factors differ by performance level. For example, low-level VTM performers require help with multi-tasking, learning orientation, and organizing, planning, and prioritizing work. In essence, the data suggests that these low-performers require help from AI to understand what to do, how to do it, how to plan it, and how to balance work.

Moderate-level VTM performers require AI help to increase performance from a different set of O*NET job factors. Moderate performers require a different set of innovative AI augmentation products. These performers require help with making decisions and solving problems, orally communicating their work, and allowing them to take on more through multi-tasking. High-performing VTMs require additional needs, such as attention to detail. As the performers take on more, they require newly learned skills to increase performance, and the ability to provide the required details as they perform increased and more complex problems.

This research suggests that these work factors have the most significant opportunity to increase performance and ROI.

Finally, HFVTMs require AI augmentation to multi-task at a superteam level. This study takeaway is calculated by combining the individual O*NET ODI scores for HFVTMs and linear regression analysis of HFVTM performance versus ODI opportunity scores. The data suggest that WPE5, multi-tasking is the primary statistically significant O*NET-SOC profile component desirable for AI augmentation that leads to the creation of superteams. AI focusing on multi-tasking, or the ability to handle or switch between multiple tasks and assignments by setting priorities and managing workflow under varying deadlines, is a significant activity for HFVTMs.

In summary, this research accomplished many relevant goals set out at the beginning of this research. This study achieved many noteworthy outcomes, from novel constructs such as superteams and using HFVTMs as a proxy for human-machine teaming analysis to an innovative analysis of VTM augmentation and O*NET factors. Before discussing each of these contributions to applied science, literature, and O*NET, a summary of relevant takeaways is presented below in Table 54.

Table 54 – Contributions to Applied Science, Literature and O*NET

- HFVTMs are a proxy for superteam research.
- HFVTMs are a proxy for team augmentation and HMT research.
- AI superteams and team augmentation can be considered a dynamic capability
- AI superteams and team augmentation can be considered an sustained competitive advantage (RBV)
- O*NET-SOC Profile for Superteams (Legacy & New factors)
- Rank ordered investment of AI
- AI Investment Process
- Advise how humans and AI can work together
- Improved business ROI path

Multi-tasking AI leading to Superteams and Increased ROI

Interestingly, this study suggests the creation of HMT superteams are created using AI to team with humans at the multi-tasking level. The ability of AI to team with humans in rapid swapping, switching gears, juggling, or multi-tasking to free up the brains of our highest functioning VTMs may be critical areas of research to increase performance, increase AI ROI, and create the superteams of tomorrow. The ability of AI to free up the human partner's brain power allows these human virtual teammates to focus on critical activities knowing that AI will not let a critical work component come crashing down, maybe the future of work. Finally, multi-tasking is critical to performance increases in low-performing VTMs, moderate-performing VTMs, as well as HFVTMs.

Contributions of the Study

This research aimed to define the construct and academic definition of superteams. In addition, this study aimed to establish HFVTMs as a suitable proxy for superteams, VTM augmentation, and human-machine teaming research. This study adds to the research on superteams by creating its first academic definition. The ability of this paper to demonstrate that superteams exist and that VTM augmentation can occur across numerous industries provides ample opportunities for further research. This research adds to the AI and HMT body of knowledge by creating a definition for superteams and a model that explains how it may be researched, examined, and used to increase ROI.

Further, this study adds to the research surrounding business strategy and the use of AI by demonstrating that superteams and VTM augmentation can be considered a DC and a sustained competitive advantage using the literature surrounding the RBV. This study demonstrates the possibility that AI-augmentable VTMs and superteams may allow firms to create and sustain heterogeneous resources that are long-lived and difficult to reproduce. The ability of this paper to deliver an avenue for academic researchers to advise how humans and AI can work together more proficiently is a critical and novel construct. Finally, this study provides a basis for investigating AI-enabled subgroup formation and extending the theory of subgroups to include AI-enabled technologies like robots and their moderating effects on team performance and quality (You & Robert, 2022). Finally, this demonstrates the significant ability of tandem interviewing as a research tool in exploratory research.

Contribution to Applied Practice

This study first offers a rank-ordered investment plan built from the outcome-driven innovation scores for businesses and leaders seeking to maximize, transform, and improve AI ROI through augmented VTMs, human-machine teaming, and AI investment. These frequency, satisfaction, and importance scores provide a path for leaders and firms to apply a simple AI investment process to improve ROI and guide AI investment bespoke to their teams and industries. Firms must seek to manage and invest in AI technologies to maximize AI ROI, augment VTs, and create superteams where possible. Investments focusing on using narrow AI, reactive AI, or limited memory AI to meet the time management, computer fundamentals, getting information, oral communication, customer service, attention to detail, and communicating with supervisors, peers, and subordinates work factors should be investigated now.

Second, by developing a method, process, and proxy to research this study's novel challenges, the research provides an avenue to advise how humans and AI can work together to improve firm ROI. Further, this study demonstrates how impactful human-machine teaming and team augmentation can be, suggesting that the very nature of work will change. Organizations must prepare for a new work environment where humans and AI work together in a HAT environment. Firms can implement investments and changes to establish successful human and AI superteams. Lastly, this research suggests that firms cannot give the same AI tools, solutions, and capabilities to all workers and expect consistent ROI and positive results. AI solutions must be fit-for-purpose for the business and employee requirement. For example, low-performers require different help from AI teammates with respect to high-performers regarding stress management. For instance, while low performers need assistance from AI on what to do, how to do it, and how to balance work. However, high performers require AI that reduces stress loads from taking on greater amounts of work and increased their capacity to multi-task.

Contributions to O*NET

This study's contribution to O*NET is extensive. First, the study developed which O*NET-SOC GWAs and WPEs are critical for AI augmentation of VTMs through HMTs. The O*NET GWA, WPE, and novel factors linked to performance improvement using ODI analysis and statistical analysis include learning orientation, multi-tasking, oral communication, attention to detail, making decisions and solving problems, and finally, organizing, planning, and prioritizing work.

Second, the study developed the first-ever O*NET-SOC profile of AI-Able WPE and GWA legacy factors. Third, this study developed the first AI O*NET novel factors bespoke to AI. Fourth, this study recommends the creation of a new O*NET-SOC column consisting of GWA and WPE factors critical to AI. Fifth, this study demonstrated that O*NET might require AI-specific work factors such as role speed (KE4) that only AI can perform. Additional AI-related items, such as AI automation, should be explored by future researchers. Finally, the KSACs related to superteams and the highest level ODI score work factors are likely valuable areas of research. These related KSACs, especially those surrounding multi-tasking, must be explored for AI augmentation.

Contributions to AI and Human-Machine Teaming

This study's contributions to AI and HMTs are equally as impressive. Set in the backdrop of the Gartner Hype Cycle, developing the most critical areas of AI-able work-related requirements on three five-year running cycles is instrumental for research, development, and implementation to maximize usability and ROI. Creating work factor constructs for AI, bespoke to this dissertation research, is unique. For example, businesses and researchers can now innovate using AI with increased confidence that the product will be adopted and implemented.

Because this research demonstrates that there are statistically significant work factors desirable for augmentation to increase performance the researcher argues VTs and superteams, consisting of HFVTMs in combination with AI, will be the two predominant team types in the next phase of humanity Further, AI and HMTs in business will consistently increase and become ubiquitous due to their ability to increase the performance levels of all VTMs. Finally, due to the possible performance increases from AI at the VTM level, AI will likely be preferred by the next generation of workers who see anything less as a waste of effort.

Limitations

The primary limitation of this research is the extent the study delimited and controlled for certain response types and VTM participation. For example, this study delimited the complete list of 75 O*NET-SOC GWAs and WPEs to a focused and testable list of 43 legacy and novel factors. Moreover, within the taxonomy of O*NET, only GWAs and WPEs were examined and tested.

Further, this study delimited the effect of AI technology acceptance in VTMs. To what degree VTMs, superteams, and HMTs will accept AI solutions in these areas rely on the ability of the AI products to deliver an ROI greater than 20 percent, as described in the literature surrounding ODI. Additionally, this study does not examine AI trust and reliability because these effects are widely known to impact AI performance.

Finally, this study controlled for VTM experience only during survey data collection. Other control variables, including VT tenure, VT size, and VT type, were not controlled for in this study. The effect of other control variables must be investigated to ensure the impact on VTMP, VTM QWL, and VTM subgroup formation (Carton & Cummings, 2012; 2013) would not negatively impact the results.

Recommendations and Future Research

This research only begins to explore the scholarly link between AI, HMTs, VTs, and VTM augmentation. There are numerous O*NET, scholarly, AI, and applied science opportunities to conduct additional research in relation to human-machine teaming, VTM augmentation, and superteams. First, this study developed multiple research streams bespoke to specific industries, leadership levels, generational needs, VTM types, and many more. Future research should examine this data unique to these areas to prescribe specific AI augmentation solutions more granularly. Additionally, future research should use this study's proxy, definitions, VTM augmentation analysis, superteams analysis, and AI-augmentation ranking process and examine specific VTMs and fields such as cyber, electronic warfare, telecommunications, finance, medical, defense, military, and other fields. It is likely this study's process can extend to all fields with the desire to use AI to increase ROI, improve worker productivity, and create superteams in their fields.

Empathy in humans working with AI is a critical area of research, evident from the scholarly research presented here and within CASA. Empathy's role in HMTs, superteams, and AI-augmented VTMs are recommended for future scholarly research. Additionally, researchers must examine VTM, organization, and industry desire for AI augmentation and how to manage the negative desire to increase ROI opportunities. Tangentially related to empathy, future researchers should examine whether AI can create new positive faultlines and take advantage of these positive faultlines to solve work-related activities beneficial to the firm and VTM. Additionally, can AI help form informal VTs based on positive faultlines that, in turn, create positive performing subgroups? If AI can directly influence team performance, future researchers should look to establish a link to VTM outcomes and successes. Moreover, future researchers should continue to examine teaming intelligence and CASA with respect to HMTs and superteams.

Future research should also focus on how AI, superteaming, and team augmentation may impact VTM's well-being and QWL. Because this research uses the VTM as the unit of analysis, future researchers should examine AI's role in increasing VT subgroup well-being, QWL, and health. The study of the team and opportunities to impact work factors unique to the team is suggested. Furthermore, during the tandem interviews, Nicole expressed interest in AI tools assisting HFVTMs in innovating during their downtime versus being micromanaged. This novel use of AI should be explored more by future researchers. Additionally, it is recommended that scholars use a JTBD matrix to develop five strategies for AI augmentation and superteaming. These strategies should include differentiated, dominant, disruptive, discrete, and sustaining strategies.

Within O*NET, multiple areas of future research exist. Because this study began by addressing the uppermost portion of the O*NET taxonomy with GWAs and related WPEs to define a process for establishing HFVTM factors for this study and future research, future scholars should seek to explore proxy analysis, superteams, VTM augmentation, and HMTs at the lower levels of the O*NET-SOC to include DWAs, IWAs and KSACs. Additionally, possible novel O*NET job factors specific to AI, such as roll speed and automation, should be explored to add additional clarity within O*NET to the jobs to be done by AI in the current and future workforce. O*NET must not be a human-only taxonomy; AI and VTM work factors must be accounted for and researched.

Concerning superteams, future researchers should examine the effects of high- and low-level task differences in VTM augmentation and superteaming. For example, exploring individual industries and jobs, including those surveyed in this research, may unveil other areas of augmentation and human-machine teaming suited ideally to AI augmentation and teaming. Understanding which industries and jobs may or may not be best suited for AI augmentation may reveal different threads related to increasing firm AI ROI. Additionally, future research should refine the definition of superteams to evolve from the descriptive definition demonstrated in this research to a prescriptive definition. This paper evolved the definition of superteams from a trade literature term to a scholarly definition. Future research is required to refine this definition into the components firms and leaders require to develop a superteam. Further, this research measures HFVTMs using equal weighted QWL and VTMP scores. Future researcher should refine this measure to more precisely measure the percentages of these instruments that make up the final HFVTM score.

Moreover, future research should perform this study's analysis on non-western country VTMs. The relevant differences in culture and work attitudes may extend or confirm this study's conclusions. Likewise, future research must examine ethical AI implications in superteams and HMTs, including the explainability, robustness, validation, underlining bias, and security of AI teammates and superteaming tools. The above ethical AI-related factors are likely to impact the competitiveness of the AI teammate heavily. This study delimited trust in AI; however, future analysis should explore AI trust within HMTs and superteams, define trust and AI ethical-related O*NET GWA and WPE work factors, and seek to understand the metrics and measures of trust in HMTs and AI superteams. Finally, as this research demonstrates that the study's propositions are testable and meet the criteria of hypothesis testing (Creswell, 2014) using the HFVTM proxy and processes created by the researcher, future scholars should create hypothesis-driven research to expand analysis into the foundations of future work and evolve these tools, processes, concepts, and definitions.

References

Adamovic, M. (2017). An employee-focused human resource management perspective for the management of Global Virtual Teams. *The International Journal of Human Resource Management*, *29*(14), 2159–2187. https://doi.org/10.1080/09585192.2017.1323227

Akinci, C., & Sadler-Smith, E. (2012). Intuition in management research: A historical review. *International Journal of Management Reviews*, *14*(1), 104-122.

Alaiad, A., Alnsour, Y., & Alsharo, M. (2019). Virtual teams: Thematic taxonomy, constructs model, and future research directions. *IEEE Transactions on Professional Communication*, *62*(3), 211–238. https://doi.org/10.1109/tpc.2019.2929370

Andersson, D., Rankin, A., & Diptee, D. (2017). Approaches to team performance assessment: A comparison of self-assessment reports and Behavioral Observer Scales. *Cognition, Technology & Work*, *19*(2-3), 517–528. https://doi.org/10.1007/s10111-017-0428-0

Andres, H. P. (2012). Technology-mediated collaboration, shared mental model and task performance. Journal of Organizational and End User Computing, 24(1), 64–81.

Andrews, K R. (1971). The concept of corporate strategy. Homewood, Ill. Dow Jones-Irwin.

Annunzio, S. L. (2005). High performing workgroups . Consulting to Management , 16 (1), 12-15.

Ansoff, H. L. (1965). *Corporate Strategy*. McGraw-Hill.

Arksey, H., & Knight, P. (1999). *Interviewing for social scientists: An introductory resource with examples*. Sage Publications.

Ashforth, B. E., & Mael, F. (1989). Social Identity Theory and the organization. *Academy of Management Review*, *14*(1), 20–39. https://doi.org/10.5465/amr.1989.4278999

Ashley, M., & Sahota, N. (2019). *Own the A.I. Revolution: Unlock Your Artificial Intelligence Strategy to disrupt your competition*. The McGraw-Hill Companies, Inc.

Athanasou, J. A., & Perera, H. N. (2020). *International Handbook of Career Guidance*. Springer.

Au, Y., & Marks, A. 2012. Virtual teams are literally and metaphorically invisible: Forging identity in culturally diverse virtual teams. Employee Relations, 34: 271-287.

Awang, Z. (2014). A Handbook on SEM for Academics and Practitioners. Retrieved February 26, 2023.

Azarbouyeh, A., & Jalali Naini, S. G. (2014). A study on the effect of teleworking on quality of work life. *Management Science Letters*, *4*(6), 1063–1068. https://doi.org/10.5267/j.msl.2014.5.027

Bakker, A. B. (2011). An evidence-based model of work engagement. *Current Directions in Psychological Science*, *20*(4), 265–269. https://doi.org/10.1177/0963721411414534

Banalieva, E. R., & Dhanaraj, C. (2019). Internalization theory for the digital economy. Journal of International Business Studies, 50(8), 1372–1387. https://doi.org/10.1057/s41267-019-00243-7

Barlett, J. E., Kotrlik, J., & Higgins, C. (2001). Organizational Research: Determining Appropriate Sample Size in Survey Research. *Information Technology, Learning, and Performance Journal*.

Barney, J. (1991). Firm Resources and sustained competitive advantage. *Journal of Management*, *17*(1), 99–120. https://doi.org/10.1177/014920639101700108

Barney, J. (1991). Firm Resources and sustained competitive advantage. *Journal of Management*, *17*(1), 99–120. https://doi.org/10.1177/014920639101700108

Barney, J. B. (1986). Strategic Factor Markets: Expectations, Luck, and Business Strategy. *Management Science*, *32*(10), 1231–1241. https://doi.org/10.1287/mnsc.32.10.1231

Bélanger, F., Watson-Manheim, M. B., & Swan, B. R. (2013). A multi-level socio-technical systems telecommuting framework. *Behaviour & Information Technology*, *32*(12), 1257–1279. https://doi.org/10.1080/0144929x.2012.705894

Bettencourt, L., & Ulwick, A. (2008, May 16). *The customer-centered innovation map*. Harvard Business Review. Retrieved March 28, 2022, from https://hbr.org/2008/05/the-customer-centered-innovation-map

Bezrukova, K., Jehn, K. A., Zanutto, E. L., & Thatcher, S. M. (2009). Do workgroup faultlines help or hurt? A moderated model of faultlines, team identification, and group performance. *Organization Science*, *20*(1), 35–50. https://doi.org/10.1287/orsc.1080.0379

Bezrukova, K., Jehn, K. A., Zanutto, E. L., & Thatcher, S. M. B. (2009). Do workgroup faultlines help or hurt? A moderated model of faultlines, team identification, and group performance. *Organization Science, 20*(1), 35–50. http://dx.doi.org/10.1287/orsc.1080.0379.

Bingham, C. & Eisenhardt, K. (2011). Rational Heuristics: The 'Simple Rules' that Strategists Learn from Process Experience. Strategic Management Journal 32(13):1437 – 1464. https://doi.org/10.1002/smj.965

Bingham, C. B., & Eisenhardt, K. M. (2011). Rational heuristics: the 'simple rules' that strategists learn from process experience. *Strategic management journal*, *32*(13), 1437-1464.

Bini, S. A. (2018). Artificial Intelligence, machine learning, Deep Learning, and cognitive computing: What do these terms mean and how will they impact health care? *The Journal of Arthroplasty*, *33*(8), 2358–2361. https://doi.org/10.1016/j.arth.2018.02.067

Biswal, A. (2022, February 11). *7 types of artificial intelligence that you should know in 2022*. Simplilearn.com. Retrieved April 23, 2022, from https://www.simplilearn.com/tutorials/artificial-intelligence-tutorial/types-of-artificial-intelligence

Blee, K. M., & Taylor, V. (2002). Semi-structured interviewing in social movement research. In *Methods of Social Movement Research* (pp. 92–117). essay, University of Minnesota Press.

Bogers, M., Chesbrough, H., Heaton, S., & Teece, D. J. (2019). Strategic management of open innovation: A dynamic capabilities perspective. *California Management Review*, *62*(1), 77–94. https://doi.org/10.1177/0008125619885150

Bougie, R., & Sekaran, U. (2020). *Research methods for business: A skill-building approach*. Wiley.

Bourgault, M., Drouin, N., & Hamel, E. 2008. Decision making within distributed project teams: An exploration of formalization and autonomy as determinants of success. Project Management Journal, 39: S97-S110.

Bradley, B. H., Baur, J. E., Banford, C. G., & Postlethwaite, B. E. (2013). Team players and collective performance: How agreeableness affects team performance over time. Small Group Research, 44(6), 680–711. http://dx.doi.org/10.1177/1046496413507609

Breu, K., & Hemingway, C. J. 2004. Making organisations virtual: The hidden cost of distributed teams. Journal of Information Technology, 19: 191-202.

Brown, T. (2003). The effect of verbal self-guidance training on collective efficacy and team performance. Personnel Psychology, 13, 935-964.

Brueller, P., & Carmeli, A. (2011). Linking capacities of high quality relationship to team learning and performance in service organisations. Human Resource Management, 50 (4), 455-477.

Bryant, F. B., & Yarnold, P. R. (1995). Principal-components analysis and exploratory and confirmatory factor analysis. In L. G. Grimm & P. R. Yarnold (Eds.), *Reading and understanding multivariate statistics* (pp. 99–136). American Psychological Association.

Bryant, S. M., Albring, S. M., & Murthy, U. 2009. The effects of reward structure, media richness and gender on virtual teams. International Journal of Accounting Information Systems, 10: 190-213.

Brynjolfsson, E. (1993). The productivity paradox of information technology. Communications of the ACM, 36(12), 66-77.

Bunderson, J. S., & Boumgarden, P. (2010). Structure and learning in self-managed teams: Why “bureaucratic” teams can be better learners. *Organization Science*, *21*(3), 609–624. https://doi.org/10.1287/orsc.1090.0483

Burrus, J., Jackson, T., Xi, N., & Steinberg, J. (2013). Identifying the most important 21st century workforce competencies: An analysis of the Occupational Information Network (o*net). *ETS Research Report Series*, *2013*(2), i-55. https://doi.org/10.1002/j.2333-8504.2013.tb02328.x

Campion, M. A., Morgeson, F. P., & Mayfield, M. S. (1999). O*NET’s theoretical contributions to job analysis research. In N.G. Peterson, & M.D. Mumford (Eds.), An occupational information system for the 21st century: The development of O*NET (pp. 297-304). Washington, DC, US: American Psychological Association.

Carless, S. A., & Wintle, J. (2007). Applicant attraction: The role of recruiter function, work–life balance policies and career salience. *International Journal of Selection and Assessment*, *15*(4), 394–404. https://doi.org/10.1111/j.1468-2389.2007.00398.x

Carton, A. M. (2011). *A theory, measure, and empirical test of subgroups in work teams* (dissertation).

Carton, A. M., & Cummings, J. N. (2012). A theory of subgroups in work teams. *Academy of Management Review*, *37*(3), 441–470. https://doi.org/10.5465/amr.2009.0322

Carton, A. M., & Cummings, J. N. (2013). The impact of subgroup type and subgroup configurational properties on work team performance. *Journal of Applied Psychology*, *98*(5), 732–758. https://doi.org/10.1037/a0033593

Carton, A., & Cummings, J. (2009). A faultline-based model of team leadership. *Academy of Management Proceedings*, *2009*(1), 1–6. https://doi.org/10.5465/ambpp.2009.44257605

Cattell, R. B. (1979). *The scientific use of factor analysis in Behavioral and Life Sciences*. Plenum press.

Chadwick, B. A., Bahr, H. M., & Albrecht, S. L. (1984). *Social Science Research Methods*. Prentice-Hall.

Champagne (2017, September 16). Using humor to increase survey engagement - doc champagne. Matthew Champagne, Ph.D. - Surveys Expert. Retrieved December 18, 2022

Chang, S.-J., van Witteloostuijn, A., & Eden, L. (2010). From the editors: Common method variance in International Business Research. *Journal of International Business Studies*, *41*(2), 178–184. https://doi.org/10.1057/jibs.2009.88

Chi, O. H., Jia, S., Li, Y., & Gursoy, D. (2021). Developing a formative scale to measure consumers' trust toward interaction with artificially intelligent (AI) Social Robots in Service delivery. *Computers in Human Behavior*, *118*, 106700. https://doi.org/10.1016/j.chb.2021.106700

Chi, S.-P., Chang, Y.-Y., & Tsou, C.-M. 2012. The effect of team characteristics and communication environment to the virtual team performance. International Journal of Networking and Virtual Organisations, 10: 137-152.

Choi, J. N., & Sy, T. (2009). Group-level organizational citizenship behavior: Effects of demographic faultlines and conflict in small work groups. *Journal of Organizational Behavior*. https://doi.org/10.1002/job.661

Chong, E. (2007). Role balance and team development: A study of team role characteristics underlying high and low performing teams. Institute of Behavioural and Applied Management, 202-217.

Chrobot-Mason, D., Ruderman, M. N., Weber, T. J., & Ernst, C. (2009). The challenge of leading on unstable ground: Triggers that activate social identity faultlines. *Human Relations, 62*(11), 1763–1794. http://dx.doi.org/10.1177/0018726709346376.

Cochran, W. G. (1977). *Sampling techniques*. John Whiley & Sons.

Cohen, J. (1988). *Statistical Power Analysis for the behavioral sciences*. L. Erlbaum Associates.

Cohen, L., Manion, L. & Morrison, K. (2000). Research methods in education (5th ed.). London: Routledge/Falmer.

Cohen, P., West, S. G., & Aiken, L. S. (2014). *Applied multiple regression/correlation analysis for the behavioral sciences*. Psychology press.

Comrey, A. L., & Lee, H. B. (1992). Interpretation and application of factor analytic results. *Comrey AL, Lee HB. A first course in factor analysis*, *2*, 1992.

Connaughton, S. L., & Shuffler, M. (2007). Multinational multicultural distributed teams: A review and future agenda. *Small Group Research, 38*(3), 387–412. https://doi.org/10.1177/1046496407301970

Cooper, D. R., & Schindler, P. S. (2006). *Business Methods Research* (11th ed.). McGraw-Hill.

Costello, A. B., & Osborne, J. (2005). Best practices in exploratory factor analysis: Four recommendations for getting the most from your analysis. *Practical assessment, research, and evaluation*, *10*(1), 7.

Costello, A. B., & Osborne, J. (2005). Best practices in exploratory factor analysis: Four recommendations for getting the most from your analysis. *Practical assessment, research, and evaluation*, *10*(1), 7.

Couper, M. (2000) Review: Web Surveys: A Review of Issues and Approaches, Public Opinion Quarterly, Volume 64, Issue 4, February 2000, Pages 464–494, https://doi.org/10.1086/318641

Couper, M. P., Kapteyn, A., Schonlau, M., & Winter, J. (2007). Noncoverage and nonresponse in an Internet survey. Social Science Research, 36(1), 131–148. https://doi.org/10.1016/j.ssresearch.2005.10.002

Cramton, C. D., & Hinds, P. J. (2005). Subgroup dynamics in internationally distributed teams: Ethnocentrism or cross-national learning? *Research in Organizational Behavior*, *26*, 231–263. https://doi.org/10.1016/s0191-3085(04)26006-3

Craven, D. E., & Rivkin, D. (2020). Using o*net to identify and design career pathways. *Career Pathways*, 299–322. https://doi.org/10.1093/oso/9780190907785.003.0017

Crawford, S., McCabe, S. E., & Pope, D. (2005). Applying web-based survey design standards. *Journal of Prevention & Intervention in the Community*, *29*(1-2), 43–66. https://doi.org/10.1300/j005v29n01_04

Creswell, J. (2014). *Research design: qualitative, quantitative, and mixed methods approaches* (4th ed.). Sage Publications.

Creswell, J. W., & Poth, C. N. (2017). *Qualitative inquiry and research design: Choosing among five approaches*. SAGE Publications.

Crisp, C. B., & Jarvenpaa, S. L. (2013). Swift trust in Global Virtual Teams. *Journal of Personnel Psychology*, *12*(1), 45–56. https://doi.org/10.1027/1866-5888/a000075

Cummings, J. N., Espinosa, J. A., & Pickering, C. K. 2009. Crossing spatial and temporal boundaries in globally distributed projects: A relational model of coordination delay. Information Systems Research, 20: 420-439.

D'Aveni, R. A., Dagnino, G. B., & Smith, K. G. (2010). The age of temporary advantage. *Strategic Management Journal*, *31*(13), 1371–1385. https://doi.org/10.1002/smj.897

Daim, T. U., Ha, A., Reutiman, S., Hughes, B., Pathak, U., Bynum,W., & Bhatla, A. (2012). Exploring the communication breakdown in global virtual teams. International Journal of Project Management, 30(2), 199–212.

Dambrin, C. (2004). How does telework influence the manager-employee relationship? *International Journal of Human Resources Development and Management*, *4*(4), 358. https://doi.org/10.1504/ijhrdm.2004.005044

Danna, K., & Griffin, R. W. (1999). Health and well-being in the workplace: A review and synthesis of the literature. *Journal of Management*, *25*(3), 357–384.

Deci, E. L. (1972). Intrinsic motivation, extrinsic reinforcement, and inequity. Journal of Personality and Social Psychology, 22(1) 112-120.

DeCoster, J. (1998). Overview of factor analysis.

Dekker, S. W., & Woods, D. D. (2002). Maba-Maba or Abracadabra? progress on human-automation co-ordination. *Cognition, Technology & Work*, *4*(4), 240–244. https://doi.org/10.1007/s101110200022

Deloitte. (2021, March 8). *Using AI to turn your teams into superteams*. Harvard Business Review. Retrieved March 28, 2022, from https://hbr.org/sponsored/2021/03/using-ai-to-turn-your-teams-into-superteams

Demerouti, E., Bakker, A. B., de Jonge, J., Janssen, P. P. M., & Schaufeli, W. B. (2001). Burnout and engagement at work as a function of demands and control. *Scandinavian Journal of Work, Environment & Health*, *27*(4), 279–286. https://doi.org/10.5271/sjweh.615

Demerouti, E., Derks, D., ten Brummelhuis, L. L., & Bakker, A. B. (2014). New ways of working: Impact on working conditions, work–family balance, and well-being. *The Impact of ICT on Quality of Working Life*, 123–141. https://doi.org/10.1007/978-94-017-8854-0_8

Deming, W. E. (2000). *Out of the crisis*. The MIT Press.

Deming, W.E. (1993) Total Quality Management in Higher Education. *Management Services, 35*, 18-20.

Deterding, S., Dixon, D., Khaled, R., & Nacke, L. (2011). From game design elements to gamefulness. *Proceedings of the 15th International Academic MindTrek Conference on*

Envisioning Future Media Environments - MindTrek '11, 9–15. https://doi.org/10.1145/2181037.2181040

DeVellis, R. F., & Thorpe, C. T. (2021). *Scale development: Theory and applications*. Sage publications.

Díaz-Fernández, M. C., González- Rodríguez, M. R., & Simonetti, B. (2020). Top management team diversity and high performance: An integrative approach based on upper echelons and complexity theory. *European Management Journal*, *38*(1), 157–168. https://doi.org/10.1016/j.emj.2019.06.006

Dina, F. (2010). Factors that define high performing virtual teams.

Dochtermann, N. A., & Jenkins, S. H. (2011). Developing multiple hypotheses in behavioral ecology. *Behavioral Ecology and Sociobiology, 65*(1), 37–45. http://www.jstor.org/stable/41413995

Droege, R. C. (2010). Department of Labor job analysis methodology. In S. Gael (Eds.), *The job analysis handbook for business, industry, and government* (pp. 993–1018). New York: Wiley.

Drucker, P. F. (2002). *The discipline of innovation*. Harvard business review, 80(8), 95-102.

Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2019). Artificial intelligence for decision making in the era of Big Data–evolution, challenges and research agenda. *International journal of information management*, *48*, 63-71.

Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2019). Artificial intelligence for decision making in the era of Big Data–evolution, challenges and research agenda. International journal of information management, 48, 63-71.

Dubes, R., & Jain, A. K. (1980). Clustering methodologies in exploratory data analysis. Advances in computers, 19, 113-228.

Efraty, D., & Sirgy, M. J. (1990). The effects of quality of working life (QWL) on employee behavioral responses. *Social Indicators Research, 22*(1), 31–47.

Efraty, D., Sirgy, M. J., & Claiborne, C. B. (1991). The effects of personal alienation on organizational identification: a quality-of-work-life model. *Journal of Business and Psychology, 6*(1), 57–78.

Examining Associations Between Job Characteristics and Health: Linking Data From the Occupational Information Network (O*NET) to Two U.S. National Health Surveys Author(s): Toni Alterman, James Grosch, Xiao Chen, David Chrislip, Martin Petersen, Edward Krieg Jr, Haejoo Chung and Carles Muntaner. Source: Journal of Occupational and Environmental Medicine, Vol. 50, No. 12 (December 2008), pp. 1401-1413 Published by: Lippincott Williams & Wilkins Stable URL: https://www.jstor.org/stable/44997746 Accessed: 17-02-2022 23:30 UTC

Fabrigar, L. R., Wegener, D. T., MacCallum, R. C., & Strahan, E. J. (1999). Evaluating the use of exploratory factor analysis in psychological research. *Psychological methods*, *4*(3), 272.

Faul, F., Erdfelder, E., Lang, A.-G., & Buchner, A. (2007). G*Power 3: A flexible statistical power analysis program for the social, Behavioral, and Biomedical Sciences. *Behavior Research Methods*, *39*(2), 175–191. https://doi.org/10.3758/bf03193146

Felstead, A., Jewson, N., Phizacklea, A., & Walters, S. (2002). Opportunities to work at home in the context of work-life balance. *Human Resource Management Journal*, *12*(1), 54–76. https://doi.org/10.1111/j.1748-8583.2002.tb00057.x

Fitts, P. M. (1951). Engineering psychology and equipment design.

Fjermestad, J. (2004). An analysis of communication mode in group Support Systems Research. *Decision Support Systems*, *37*(2), 239–263. https://doi.org/10.1016/s0167-9236(03)00021-6

Fonner, K. L., & Roloff, M. E. (2010). Why teleworkers are more satisfied with their jobs than are office-based workers: When less contact is beneficial. *Journal of Applied Communication Research*, *38*(4), 336–361. https://doi.org/10.1080/00909882.2010.513998

Ford, T. C., Woods, W., & Crewther, D. P. (2017). Spatio-temporal source cluster analysis reveals Fronto-temporal auditory change processing differences within a shared autistic and schizotypal trait phenotype. *NeuroImage: Clinical*, *16*, 383–389. https://doi.org/10.1016/j.nicl.2017.04.022

Galbraith, J. R. (1974). Organization design: An information processing view. *Interfaces*, *4*(3), 28–36. https://doi.org/10.1287/inte.4.3.28

Gartner. (2021, September 22). *The 4 trends that prevail on the gartner hype cycle for AI, 202*. Gartner. Retrieved April 19, 2022, from https://www.gartner.com/en/articles/the-4-trends-that-prevail-on-the-gartner-hype-cycle-for-ai-2021

George, D., & Mallery, P. (2019). *Ibm Spss statistics 26 step by step: A simple guide and reference*. Routledge.

Gibbs, J. L., Boyraz, M., Sivunen, A., & Nordbäck, E. (2020). Exploring the discursive construction of subgroups in global virtual teams. *Journal of Applied Communication Research*, *49*(1), 86–108. https://doi.org/10.1080/00909882.2020.1851745

Gibbs, J. L., Sivunen, A., & Boyraz, M. (2017). Investigating the impacts of team type and design on Virtual Team Processes. Human Resource Management Review, 27(4), 590–603. https://doi.org/10.1016/j.hrmr.2016.12.006

Gibson, C. B., & Gibbs, J. L. (2006). Unpacking the concept of virtuality: The effects of geographic dispersion, electronic dependence, dynamic structure, and national diversity on Team Innovation. *Administrative Science Quarterly*, *51*(3), 451–495. https://doi.org/10.2189/asqu.51.3.451

Gibson, C., & Vermeulen, F. (2003). A healthy divide: Subgroups as a stimulus for team learning behavior. *Administrative Science Quarterly, 48*, 202–239. https://doi.org/10.2307/3556657

Gilson, L. L., Maynard, M. T., Jones Young, N. C., Vartiainen, M., & Hakonen, M. (2014). Virtual Teams Research: 10 Years, 10 Themes, and 10 Opportunities. *Journal of Management*, *41*(5), 1313–1337. https://doi.org/10.1177/0149206314559946

Glas, D. F., Kanda, T., Ishiguro, H., & Hagita, N. (2012). Temporal awareness in teleoperation of conversational robots. IEEE Transactions on Systems, Man and Cybernetics, Part A: Systems and Humans, 42, 905–919.

Goksel Canbek, N., & Mutlu, M. E. (2016). On the track of Artificial Intelligence: Learning with Intelligent Personal assistants. *International Journal of Human Sciences*, *13*(1), 592. https://doi.org/10.14687/ijhs.v13i1.3549

Golden, T. D., & Raghuram, S. 2010. Teleworker knowledge sharing and the role of altered relational and technological interactions. Journal of Organizational Behavior, 31: 1061-1085.

Gordon, J. R. (1990). Management and organizational behavior. Newton, Mass. Allyn & Bacon.

Gorman, P., Nelson, T., & Glassman, A. (2004). The millennial generation: A strategic opportunity. *Organizational Analysis*, *12*(3), 255–270.

Gorsuch, R. L. (1983). Three methods for analyzing limited time-series (N of 1) data. *Behavioral Assessment*.

Gorusch, R. L. (1983). *Factor analysis* (2nd ed.). Lawrence Erlbaum Associates.

Grant, C. A., Wallace, L. M., & Spurgeon, P. C. (2013). An exploration of the psychological factors affecting remote e-worker's Job Effectiveness, well-being and work-life balance. *Employee Relations*, *35*(5), 527–546. https://doi.org/10.1108/er-08-2012-0059

Green, S. B., Lissitz, R. W., & Mulaik, S. A. (1977). Limitations of coefficient alpha as an index of test unidimensionality1. *Educational and Psychological Measurement*, *37*(4), 827-838.

Greenhaus, J. H., & Kossek, E. E. (2014). The contemporary career: A work–home perspective. *Annual Review of Organizational Psychology and Organizational Behavior*, *1*(1), 361–388. https://doi.org/10.1146/annurev-orgpsych-031413-091324

Greenhaus, J. H., Bedeian, A. G., & Mossholder, K. W. (1987). Work experiences, job performance, and feelings of personal and family well-being. *Journal of Vocational Behavior*, *31*(2), 200–215. https://doi.org/10.1016/0001-8791(87)90057-1

Grote, G., & Guest, D. (2016). The case for reinvigorating quality of working life research. Human Relations, 70, 149–167.

Groves, R. M., & Peytcheva, E. (2008). The impact of nonresponse rates on nonresponse bias: A meta-analysis. *Public Opinion Quarterly*, *72*(2), 167–189. https://doi.org/10.1093/poq/nfn011

Guadagnoli, E., & Velicer, W. F. (1988). Relation of sample size to the stability of component patterns. *Psychological bulletin*, *103*(2), 265.

Gully, S. M., Incalcaterra, K. A., Hoshi, A., & Beaublen, J. M. (2002). A meta-analysis of team-efficacy, potency, and performance: Interdependence and level of analysis as moderators of observed relationships. Journal of Applied Psychology, 87, 819-832.

Guttman, H. M. (2011). Collaborating for high performance. American Management Association.

Guzzo, R. A., & Dickson, M. W. (1996). Teams in organizations: Recent research on performance and effectiveness. *Annual Review of Psychology*, *47*(1), 307–338. https://doi.org/10.1146/annurev.psych.47.1.307

Hackman, J. R. (1987). The design of work teams. *Handbook of Organizational Behavior*, 315–342.

Hackman, J. R. (2002). *Leading Teams: Setting the Stage for Great Performances - The Five Keys to Successful Teams*. Harvard Business School Press.

Hair, J. H. (2010). *Multivariate Data Analysis: A global perspective*. Pearson.

Hauswald, J., Laurenzano, M. A., Zhang, Y., Li, C., Rovinski, A., Khurana, A., Dreslinski, R. G., Mudge, T., Petrucci, V., Tang, L., & Mars, J. (2015). Sirius. *ACM SIGPLAN Notices*, *50*(4), 223–238. https://doi.org/10.1145/2775054.2694347

Heerwegh, D., Vanhove, T., Matthijs, K., & Loosveldt, G. (2005). The effect of personalization on response rates and data quality in web surveys. *International Journal of Social Research Methodology*, *8*(2), 85–99. https://doi.org/10.1080/1364557042000203107

Helfat, C. E., & Martin, J. A. (2014). Dynamic managerial capabilities. *Journal of Management*, *41*(5), 1281–1312. https://doi.org/10.1177/0149206314561301

Hershatter, A., & Epstein, M. 2010. Millennials and the world of work: An organization and management perspective. Journal of Business and Psychology, 25: 211-223.

Hill, K. A. (2023). High Functioning Virtual Team Members & Health: A Mixed Methods Analysis of Subgroups, Performance, and Standard Occupational Classification Factors (dissertation proposal).

Hill, R. (1998). What sample size is "enough" in internet survey research? *Interpersonal Computing and Technology: An Electronic Journal for the 21st Century*, *6*(3-4).

Hinds, P. J., Neeley, T. B., & Cramton, C. D. (2014). Language as a lightning rod: Power contests, Emotion Regulation, and subgroup dynamics in Global Teams. *Journal of International Business Studies*, *45*(5), 536–561. https://doi.org/10.1057/jibs.2013.62

Hoch, J. E., & Kozlowski, S. W. J. (2012). Leading virtual teams: Hierarchical leadership, structural supports, and shared team leadership. Journal of Applied Psychology, 99: 390-403.

Hoelzle, J. B., & Meyer, G. J. (2013). Exploratory factor analysis: Basics and beyond.

Hofer, C. W., & Schendel, D. (1978). Strategy formulation: Analytical Concepts. St. Paul: West Pub. Co.

Hofer, M. A. (1978). Hidden Regulatory Processes in early social relationships. *Social Behavior*, 135–166. https://doi.org/10.1007/978-1-4684-2901-5_7

Hogg, M. A., & Terry, D. J. (2000). Social identity and self-categorization processes in organizational contexts. *The Academy of Management Review*, *25*(1), 121. https://doi.org/10.2307/259266

Holmes, T. A. (2005). Ten characteristics of a high performance work team. In ASTD, & M. Silberman (Ed.), The 2005 ASTD Team and Organisational Development Sourcebook (pp. 179-182). Alexandria: ASTD Press.

Holton, J. A. (2001). Building Trust and collaboration in a virtual team. *Team Performance Management: An International Journal*, *7*(3/4), 36–47.https://doi.org/10.1108/13527590110395621

Homan, A. C., van Knippenberg, D., Van Kleef, G. A., & De Dreu, C. K. (2007). Interacting dimensions of diversity: Cross-categorization and the functioning of diverse work groups. *Group Dynamics: Theory, Research, and Practice*, *11*(2), 79–94. https://doi.org/10.1037/1089-2699.11.2.79

Hong, M., Benjamin, J.J., & Müller-Birn. C. (2018). Coordinating Agents: Promoting Shared Situational Awareness in Collaborative Sensemaking. In Companion of the 2018 ACM Conference on Computer Supported Cooperative Work and Social Computing. 217–220.

Huang, J. L., Bowling, N. A., Liu, M., & Li, Y. (2015). Detecting insufficient effort responding with an infrequency scale: Evaluating validity and participant reactions. *Journal of Business and Psychology*, *30*(2), 299-311.

Iansiti, M., & Lakhani, K. (2014). Digital Ubiquity: How connections, sensors, and data are revolutionizing business. *Harvard Business Review*, *1*(11), 90–99. https://doi.org/10.2469/dig.v45.n2.8

Ilgen, D. R., Hollenbeck, J. R., Johnson, M., & Jundt, D. (2005). Teams in organizations: From input-process-output models to IMOI models. *Annual Review of Psychology*, *56*(1), 517–543. https://doi.org/10.1146/annurev.psych.56.091103.070250

Imperva. (2022). Imperva: The State of security within eCommerce. *Computer Fraud & Security*, *2022*(1). https://doi.org/10.12968/s1361-3723(22)70003-6

Isaac, S., & Michael, W. B. (1995). Handbook in research and evaluation. San Diego, CA: Educational and Industrial Testing Services.

Israel, G. D. (1992). Determining sample size.

Israel, G. D. (1992). *Sampling the evidence of extension program impact*. Gainesville, FL: University of Florida Cooperative Extension Service, Institute of Food and Agriculture Sciences, EDIS.

Jackson, B., & Madsen, S. (2005). In *Common factors of high performance teams*. Utah; SelectedWorks.

Jarman, R. (2005). When success isn't everything – case studies of two virtual teams. *Group Decision and Negotiation*, *14*(4), 333–354. https://doi.org/10.1007/s10726-005-0318-3

Jeanneret, P. R., Borman, W. C., Kubisiak, U. C., & Hanson, M. A. (1999). Generalized work activities. An Occupational Information System for the 21st Century: The Development of O*NET., 105–125. https://doi.org/10.1037/10313-007

Jeanneret, P. R., Borman, W. C., Kubisiak, U. C., & Hanson, M. A. (1999). Generalized work activities. *An Occupational Information System for the 21st Century: The Development of O*NET.*, 105–125. https://doi.org/10.1037/10313-007

Jehn, K. A., & Bezrukova, K. (2010). The faultline activation process and the effects of activated faultlines on coalition formation, conflict, and group outcomes. *Organizational Behavior and Human Decision Processes*, *112*(1), 24–42. https://doi.org/10.1016/j.obhdp.2009.11.008

Jehn, K. A., & Chatman, J. A. (2000). The influence of proportional and perceptual conflict composition on Team Performance. *International Journal of Conflict Management*, *11*(1), 56–73. https://doi.org/10.1108/eb022835

Jehn, K. A., & Mannix, E. A. (2001). The dynamic nature of conflict: A longitudinal study of intragroup conflict and group performance. Academy of Management Journal, 44(2), 238-251.

John, O. P., & Soto, C. J. (2007). The importance of being valid: Reliability and the process of construct validation. In R. W. Robins, R. C. Fraley, & R. F. Krueger (Eds.), *Handbook of research methods in personality psychology* (pp. 461–494). The Guilford Press.

Johnson, M., & Vera, A. (2019). No ai is an island: The case for teaming intelligence. *AI Magazine*, *40*(1), 16–28. https://doi.org/10.1609/aimag.v40i1.2842

Jones, G. R., & George, J. M. (1998). The experience and evolution of trust: Implications for cooperation and teamwork. *Academy of Management Review*, *23*(3), 531–546. https://doi.org/10.5465/amr.1998.926625

Judge, T. A., Thoresen, C. J., Bono, J. E., & Patton, G. K. (2001). The job satisfaction–job performance relationship: A qualitative and Quantitative Review. *Psychological Bulletin*, *127*(3), 376–407. https://doi.org/10.1037/0033-2909.127.3.376

Julious, S. A. (2005). Sample size of 12 per group rule of thumb for a pilot study. *Pharmaceutical Statistics*, *4*(4), 287–291. https://doi.org/10.1002/pst.185

Juran, J. M. (1967). The QC circle phenomenon. *Industrial Quality Control*, *23*(7), 25-34.

Juran, J. M. (1970). Consumerism and product quality. *Quality Progress*, *3*(7), 18-27.

Juran, J. M. (1994). The upcoming century of quality. *Quality progress*, *27*(8), 29.

Kaber, D. B., Perry, C. M., Segall, N., McClernon, C. K., & Prinzel, L. J., III. (2006). Situation awareness implications of adaptive automation for information processing in an air traffic control related task. International Journal of Industrial Ergonomics, 36, 447–462.

Kafner, R. (1990). Motivation theory and industrial and organizational psychology. In *Handbook of industrial and organizational psychology* (pp. 75–170). Consulting Psychologists Press.

Kankanhalli, A., Tan, B. C. Y., &Wei, K. -K. (2007). Conflict and performance in global virtual teams. *Journal of Management Information Systems, 23*(3), 237–274. http://dx.doi.org/10.2753/MIS0742–1222230309.

Kaplan, A., & Haenlein, M. (2019). Siri, Siri, in my hand: Who's the fairest in the land? on the interpretations, illustrations, and implications of Artificial Intelligence. *Business Horizons*, *62*(1), 15–25. https://doi.org/10.1016/j.bushor.2018.08.004

Katzenbach, J. R., & Smith D. K. (1993). The wisdom of teams: Creating the high-performance organization. New York, Harper Business.

Katzenbach, J. R., & Smith, D. (1993). *The wisdom of teams*. Harvard Business School Press.

Katzenbach, J. R., & Smith, D. K. (1993). The discipline of teams. Harvard Business Review, 111-120.

Katzenbach, J. R., & Smith, D. K. (1999). *The wisdom of teams: Creating the high-performance organisation*. Harper Collins Publishers.

Kaur, W. H., & Lasecki, W. S. (2019). *Building shared mental models between humans and AI for ...* Retrieved March 29, 2022, from http://www-personal.umich.edu/~harmank/Papers/CHI2019_MentalModels_HAI.pdf

Kemerling, K. R. (2002). *The effects of telecommuting on employee productivity: A perspective from managers, office co-workers and telecommuters* (dissertation).

Kiesler, D. J. (1983). The 1982 interpersonal circle: A taxonomy for complementarity in human transactions. *Psychological Review*, *90*(3), 185–214. https://doi.org/10.1037/0033-295x.90.3.185

Kirkman, B. L., & Rosen, B (2000). Powering up teams. Organizational Dynamics, 23(3), 48-66.

Kline, P. (1979). *Psychometrics and psychology*. Academic Press.

Klitmøller, A., & Lauring, J. (2013). When global virtual teams share knowledge: Media richness, cultural difference and language commonality. Journal of World Business, 48(3), 398–406.

Knight, D., Durham, C. & Locke, E. (2001). The relationship of team goals, incentives, and efficacy to strategic risk, tactical implementation, and performance. Academy of Management Journal, 44(2), 326-338.

Koutsabasis, P., Vosinakis, S., Malisova, K., & Paparounas, N. 2012. On the value of virtual worlds for collaborative design. Design Studies, 33: 357-390.

Kozlowski, S. W., & Bell, B. S. (2003). Work groups and teams in organizations. *Handbook of Psychology*. https://doi.org/10.1002/0471264385.wei1214

Kozlowski, S. W., & Ilgen, D. R. (2006). Enhancing the effectiveness of work groups and teams. Association for Psychological Science, 77-124.

Kraaijenbrink, J. (2011). Human capital in the resource-based view. *Oxford Handbooks Online*. https://doi.org/10.1093/oxfordhb/9780199532162.003.0009

Krejcie, R. V., & Morgan, D. W. (1970). Determining sample size for research activities. *Educational and Psychological Measurement*, *30*(3), 607–610. https://doi.org/10.1177/001316447003000308

Kutner, M., Nachtsheim, C., & Neter, J. (2004). Applied Linear Regression Models (Fourth ed.). McGraw Hill, NY.

Kwon, Y., & Lee, J. (2020). Demographic faultlines in groups: The curvilinearly moderating effects of task interdependence. *The Journal of Asian Finance, Economics, and Business, 7*, 311–322. https://doi.org/10.13106/jafeb.2020.vol7.no3.311

Larson, L., & DeChurch, L. (2020). Leading Teams in the Digital Age: Four Perspectives on Technology and What They Mean for Leading Teams. The leadership quarterly, 31(1), 101377. https://doi.org/10.1016/j.leaqua.2019.101377

Larson, C. E., Larson, C., & LaFasto, F. M. (1989). *Teamwork: What must go right/what can go wrong* (Vol. 10). Sage.

Lau, D. C., & Murnighan, J. K. (1998). Demographic diversity and faultlines: The compositional dynamics of Organizational Groups. *Academy of Management Review*, *23*(2), 325–340. https://doi.org/10.5465/amr.1998.533229

Lau, D. C., & Murnighan, J. K. (2005). Interactions within groups and subgroups: The effects of demographic faultlines. *Academy of Management Journal, 48*, 645–659. http://dx.doi.org/10.5465/AMJ.2005.17843943.

Lawshe, C. H. (1975). A quantitative approach to content validity. *Personnel Psychology*, *28*(4), 563–575. https://doi.org/10.1111/j.1744-6570.1975.tb01393.x

Lee, C. S., & Watson-Manheim, M. B. (2014). Perceived risks and ICT use. Journal of Computer Information Systems, 54(2), 16–24.

Lee, D.-J., Singhapakdi, A., & Sirgy, M. J. (2007). Further validation of a need-based quality-of-work-life (QWL) measure: Evidence from marketing practitioners. *Applied Research in Quality of Life*, *2*(4), 273–287. https://doi.org/10.1007/s11482-008-9042-x

Lee, J. D., & See, K. A. (2004). Trust in automation: Designing for appropriate reliance. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *46*(1), 50–80. https://doi.org/10.1518/hfes.46.1.50.30392

Lee, K.-F., & Qiufan, C. (2022, January 19). *What AI Cannot Do*. Big Think. Retrieved April 13, 2022, from https://bigthink.com/the-future/what-ai-cannot-do/

Levin, S., Federico, C. M., Sidanius, J., & Rabinowitz, J. L. (2002). Social dominance orientation and intergroup bias: The legitimation of favoritism for high-status groups. *Personality and Social Psychology Bulletin*, *28*(2), 144–157. https://doi.org/10.1177/0146167202282002

Li, J., & Hambrick, D. C. (2005). Factional groups: A new vantage on demographic faultlines, conflict, and disintegration in work teams. *Academy of Management Journal*, *48*(5), 794–813. https://doi.org/10.5465/amj.2005.18803923

Liu, M., & Wronski, L. (2017). Examining completion rates in web surveys via over 25,000 real-world surveys. *Social Science Computer Review*, *36*(1), 116–124. https://doi.org/10.1177/0894439317695581

Liu, Y. C., & Li, F. C. 2012. Exploration of social capital and knowledge sharing: An empirical study on student virtual teams. International Journal of Distance Education Technologies, 10: 17-38.

Lloret, S., Ferreres, A., Hernández, A., & Tomás, I. (2017). The exploratory factor analysis of items: guided analysis based on empirical data and software. *Anales de psicología*, *33*(2), 417-432.

Locke, E. A., Latham, G. P., & Smith, K. J. (1990). A theory of goal setting & task performance. Prentice Hall.

Low, T. A., White, E. D., Koschnick, C. M., & Elshaw, J. J. (2022). Sum-Based Scoring for Dichotomous and Likert-scale Questions. arXiv preprint arXiv:2212.13533.

Lund, S., Madgavkar, A., Manyika, J., & Smit, S. (2020). What's next for remote work: An analysis of 2,000 tasks, 800 jobs, and nine countries. *McKinsey Global Institute*, 1-13.

Lyons, J. B., Sycara, K., Lewis, M., & Capiola, A. (2021). Human–Autonomy Teaming: Definitions, debates, and directions. *Frontiers in Psychology*, *12*. https://doi.org/10.3389/fpsyg.2021.589585

Maccoby, E. E., & Maccoby, N. A. (1954). The interview: a tool of social science. *Handbook of Social Psychology*.

Madhulatha, T. S. (2012). An overview on clustering methods. arXiv preprint arXiv:1205.1117.

Majchrzak, A., Rice, R. E., Malhotra, A., King, N., & Ba, S. (2000). Technology adaptation: The case of a computer-supported inter-organizational virtual team. MIS Quarterly, 24(4), 569–600.

Malhotra, A., Majchrzak, A., & Rosen, B. (2007). Leading virtual teams. *Academy of Management Perspectives*, *21*(1), 60–70. https://doi.org/10.5465/amp.2007.24286164

Mallon, D., Durme, Y. V., & Hauptmann, M. (2022, March 21). *Superteams*. Deloitte Insights. Retrieved March 28, 2022, from https://www2.deloitte.com/us/en/insights/focus/human-capital-trends/2020/human-ai-collaboration.html

Mann, P. H. (1985). *Methods of social investigation*. Blackwell.

March, J. G., & Stinchcombe, A. (1965). Social structure and organizations. In *Handbook of organizations* (pp. 142–193). essay, Rand McNally.

Marcus, G. & Davis, E. (2020). *Rebooting AI: Building artificial intelligence we can trust*, Vintage.

Marcus, G., & Davis, E. (2020). GPT-3, Bloviator: Open AI's language generator has no idea what it's talking about. MIT Technology Review. Accessed February 23, 2023. https://www.technologyreview.com/2020/08/22/1007539/gpt3-openai-language-generator-artificial-intelligence-ai-opinion/

Marjanovic, Z., Struthers, C. W., Cribbie, R., & Greenglass, E. R. (2014). The Conscientious Responders Scale: A new tool for discriminating between conscientious and random responders. *Sage Open*, *4*(3), 2158244014545964.

Martel, J.-P., & Dupuis, G. (2006). Quality of work life: Theoretical and methodological problems, and presentation of a new model and measuring instrument. *Social Indicators Research*, *77*(2), 333–368. https://doi.org/10.1007/s11205-004-5368-4

Martins, L. L., Gilson, L. L., & Maynard, M. T. (2004). Virtual teams: What do we know and where do we go from here? Journal of Management, 30: 805-835.

Mason, J., Classen, S., Wersal, J., & Sisiopiku, V. (2021). Construct validity and test–retest reliability of the Automated Vehicle User Perception Survey. *Frontiers in Psychology*, *12*. https://doi.org/10.3389/fpsyg.2021.626791

Matteson, S. M., & Lincoln, Y. S. (2009). Using Multiple Interviewers in Qualitative Research Studies: The Influence of Ethic of Care Behaviors in Research Interview Settings. Qualitative Inquiry, 15(4), 659–674. https://doi.org/10.1177/1077800408330233

MAXQDA. (2022, March 25). *All-in-one qualitative & mixed methods data analysis tool*. MAXQDA. Retrieved March 26, 2022, from https://www.maxqda.com/

Maxwell, J. A. (2013). *Qualitative research design an interactive approach*. SAGE Publications.

Maznevski, M. L., & Chudoba, K. M. (2000). Bridging space over time: Global virtual team dynamics and effectiveness. Organization Science, 11(5), 473–492.

McIntosh, M. J., & Morse, J. M. (2015). Situating and constructing diversity in semi-structured interviews. *Global Qualitative Nursing Research*, *2*, 233339361559767. https://doi.org/10.1177/2333393615597674

McIntosh, M. J., & Morse, J. M. (2015). Situating and constructing diversity in semi-structured interviews. *Global Qualitative Nursing Research*, *2*, 233339361559767. https://doi.org/10.1177/2333393615597674

McNeese, N. J., Demir, M., Cooke, N. J., & Myers, C. (2017). Teaming with a synthetic teammate: Insights into human-autonomy teaming. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *60*(2), 262–273. https://doi.org/10.1177/0018720817743223

Meister, A., Thatcher, S. M. B., Park, J., & Maltarich, M. (2019). Toward a temporal theory of faultlines and subgroup entrenchment. Journal of Management Studies, 57(8), 1473–1501. https://doi.org/10.1111/joms.12538

Metiu, A. (2006). Owning the code: Status closure in distributed groups. Organization Science, 17, 418–435.

Meyer, B., Glenz, A., Antino, M., Rico, R., & González-Romá, V. (2014). Faultlines and Subgroups. *Small Group Research*, *45*(6), 633–670. https://doi.org/10.1177/1046496414552195

Minas, R. K., Potter, R. F., Dennis, A. R., Bartelt, V., & Bae, S. (2014). Putting on the thinking cap: Using neuroIS to understand information processing biases in virtual teams. Journal of Management Information Systems, 30(4), 49–82.

Mohammed, S., & Dumville, B. C. (2001). Team mental models in a team knowledge framework: Expanding theory and measurement across disciplinary boundaries. Journal of Organizational Behavior, 22, 89–106.

Molines, M., Sanséau, P.-Y., & Adamovic, M. (2017). How organizational stressors affect collective organizational citizenship behaviors in the French police. *International Journal of Public Sector Management*, *30*(1), 48–66. https://doi.org/10.1108/ijpsm-02-2016-0043

Molleman, E. (2005). Diversity in demographic characteristics, abilities and personality traits: Do faultlines affect team functioning? *Group Decision and Negotiation*, *14*(3), 173–193. https://doi.org/10.1007/s10726-005-6490-7

Monforte, J. & Úbeda-Colomer, J. (2021). Tinkering with the two-to-one interview: Reflections on the use of two interviewers in qualitative constructionist inquiry, Methods in

Psychology, Volume 5, 2021, 100082, ISSN 2590-2601, https://doi.org/10.1016/j.metip.2021.100082

Montoya-Weiss, M. M., Massey, A. P., & Song, M. (2001). Getting it together: Temporal coordination and conflict management in global virtual teams. Academy of Management Journal, 44(6), 1251–1262.

Moon, B. M., Hoffman, R., Novak, J., & Canas, A. (2011). 2. In *Applied concept mapping: Capturing, analyzing, and organizing knowledge* (pp. 24–46). essay, CRC Press.

Morris, M. G., & Venkatesh, V. (2000). Age differences in technology adoption decisions: Implications for a changing work force. *Personnel Psychology*, *53*(2), 375–403. https://doi.org/10.1111/j.1744-6570.2000.tb00206.x

Morrison-Smith, S., & Ruiz, J. (2020). Challenges and barriers in virtual teams: A literature review. *SN Applied Sciences*, *2*(6). https://doi.org/10.1007/s42452-020-2801-5

Morse, J. M., & Niehaus, L. (2009). *Mixed method design: Principles and procedures*. Left Coast Press.

Morse, J. M., & Niehaus, L. (2009). *Mixed method design: Principles and procedures*. Left Coast Press.

Mullen, B., & Cooper, C. (1994). The relation between group cohesiveness and performance: An integration. Psychological Bulletin , 115, 210-227.

Mumford, M. D., & Peterson, N. G. (1999). The o*net content model: Structural considerations in describing jobs. *An Occupational Information System for the 21st Century: The Development of O*NET.*, 21–30. https://doi.org/10.1037/10313-002

Mumford, M. D., Peterson, N. G., & Childs, R. A. (1999). Basic and cross-functional skills. In N.G. Peterson, & M.D. Mumford (Eds.), An occupational information system for the 21st century: The development of O*NET (pp. 46-69). Washington, DC, US: American Psychological Association.

Myers, K. K., & Sadaghiani, K. 2010. Millennials in the workplace: A communication perspective on millennials' organizational relationships and performance. Journal of Business and Psychology, 25: 225-238.

NAICS. (2022, January 1). *NASIC US Business Firmographics – Company Size*. NAICS Association. Retrieved April 16, 2022, from https://www.naics.com/business-lists/counts-by-company-size/

Nakata, C., & Im, S. (2010). Spurring cross-functional integration for higher new product performance: A group effectiveness perspective. Journal of Product Innovation Management, 27, 554-571.

Nass, C., & Moon, Y. (2002). Machines and mindlessness: social responses to computers. J Soc Issues 56(1):81–103

Nass, C., Steuer, J., & Tauber, E. R. (1994). Computers are social actors. *Conference Companion on Human Factors in Computing Systems - CHI '94*. https://doi.org/10.1145/259963.260288

National Center for O*NET Development. (2010). *O*NET data collection program*: *Office of management and budget clearance package. Part A: Justification*. Raleigh: Author.

Nelson, B. (1997). Does one reward fit all?. Workforce, 76 (2), 67.

Nelson, B. (2010). Top-performing team traits: Productivity and morale, keys to team success. Healthcare Registration, 3-4.

Nohe, C., Michel, A., & Sonntag, K. (2014). Family-work conflict and job performance: A diary study of boundary conditions and mechanisms. *Journal of Organizational Behavior*, *35*(3), 339–357. https://doi.org/10.1002/job.1878

Norris, M., & Lecavalier, L. (2010). Evaluating the use of exploratory factor analysis in developmental disability psychological research. *Journal of autism and developmental disorders*, *40*, 8-20.

Novak, B. (2022, March 8). *How companies stay on budget when relocating employees*. River Journal Online News for Tarrytown Sleepy Hollow Irvington Ossining Briarcliff Manor CrotononHudson Cortlandt and Peekskill. Retrieved April 22, 2023, from https://riverjournalonline.com/business/how-companies-stay-on-budget-when-relocating-employees/30032/

Nurmi, N. (2011). Coping with coping strategies: How distributed teams and their members deal with the stress of distance, time zones and culture. *Stress and Health*, *27*(2), 123–143. https://doi.org/10.1002/smi.1327

O'Leary, M. B., & Mortensen, M. (2010). Go (con)figure: Subgroups, imbalance, and isolates in geographically dispersed teams. *Organization Science*, *21*(1), 115–131. https://doi.org/10.1287/orsc.1090.0434

O*NET. (2022). *O*Net resource center*. O*NET Resource Center. Retrieved March 27, 2022, from https://www.onetcenter.org/

Office of Management and Budget. (2000). Standard Occupational Classification (SOC) System.

Office of Management and Budget. (2010). Standard Occupational Classification (SOC) System.

Parasuraman, R., Cosenzo, K. A., & De Visser, E. (2009). Adaptive automation for human supervision of multiple uninhabited vehicles: Effects on change detection, situation awareness, and mental workload. Military Psychology, 21, 270.

Paul, R., Drake, J. R., & Liang, H. (2016). Global Virtual Team Performance: The Effect of Coordination Effectiveness, Trust, and Team Cohesion. IEEE Transactions on Professional Communication, Professional Communication, IEEE Transactions on, IEEE Trans. Profess. Commun, 59(3), 186–202

Pauleen, D. J., & Yoong, P. (2001). Relationship building and the use of ICT in boundary-crossing virtual teams: a facilitator's perspective. Journal of Information Technology, 16(4), 205–220.

Pearsall, M. J., Ellis, A. P. J., & Evans, J. M. (2008). Unlocking the effects of gender faultlines on team creativity: Is activation the key? *Journal of Applied Psychology, 93*, 225–234. https://doi.org/10.1037/0021-9010.93.1.225

Penarroja, V., Orengo, V., Zornoza, A., & Hernandez, A. 2013. The effects of virtuality level on task-related collaborative behaviors: The mediating role of team trust. Computers in Human Behavior, 29: 967-974.

Penrose, L. S., & Penrose, R. (1958). Impossible objects: A special type of visual illusion. *British Journal of Psychology*, *49*(1), 31–33. https://doi.org/10.1111/j.2044-8295.1958.tb00634.x

Peters, T., & Waterman, R. H. (1982). In search of excellence. New York, Harper & Row Publishers.

Peterson, N. G., & Sager, C. E. (2010). The dictionary of occupational titles and the occupational information network. In J. L. Farr & N. T. Tippins (Eds.), *Handbook of employee selection* (pp. 887–908). New York: Routledge/Taylor & Francis Group.

Pfeffer, J. (1998). The human equation. Cambridge: Harvard Business School Press.

Pinegar, J. S. (2005). What customers want: Using outcome-driven innovation to create breakthrough products and services by Anthony W. Ulwick. *Journal of Product Innovation Management*, *23*(5), 464–466. https://doi.org/10.1111/j.1540-5885.2006.00217.x

Pinjani, P., & Palvia, P. 2013. Trust and knowledge sharing in diverse global virtual teams. Information & Management, 50: 144-153.

Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, *88*(5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879

Polzer, J., Crisp, C., Jarvenpaa, S. L., & Kim, J.W. (2006). Extending the faultline model to geographically dispersed teams: How collocated subgroups can impair group functioning. Academy of Management Journal, 49(4), 679–692.

Porter, M. E., & Heppelmann, J. (2015). How Smart, Connected Products Are Transforming Companies. Harvard Business Review. https://hbr.org/2015/10/how-smart-connected-products-are-transforming-companies.

Porter, M. E. (1980). *Competitive strategy*. The Free Press.

Porter, M. E. (1996). What is strategy? *Harvard Business Review,* 37–54.

Porter, M. E., & Heppelmann, J. (2014). How Smart, Connected Products Are Transforming Competition. Harvard Business Review. https://hbr.org/2014/11/how-smart-connected-products-are-transforming-competition.

Porter, S. R., & Whitcomb, M. E. (2005). Non-response in student surveys: The role of demographics, engagement and personality. *Research in Higher Education*, *46*(2), 127–152. https://doi.org/10.1007/s11162-004-1597-2

Powell, A., Piccoli, G., & Ives, B. (2004). Virtual teams. *ACM SIGMIS Database: the DATABASE for Advances in Information Systems,* 35(1), 6–36. https://doi.org/10.1145/968464.968467 ‘

Powell, A., Piccoli, G., & Ives, B. (2004). Virtual teams. *ACM SIGMIS Database: the DATABASE for Advances in Information Systems*, *35*(1), 6–36. https://doi.org/10.1145/968464.968467

Prinzel, L. J., Freeman, F. G., Scerbo, M. W., Mikulka, P. J., & Pope, A. T. (2000). A closed-loop system for examining psychophysiological measures for adaptive task allocation. International Journal of Aviation Psychology, 10, 393–410.

Przybilla, L. (2020). Investigating social phenomena in IT project teams as dynamic entities. *Proceedings of the 2020 on Computers and People Research Conference*, 167–168. https://doi.org/10.1145/3378539.3393853

Quader, M. R., & Quader, M. S. (2008). A Critical Analysis of High Performing Teams: A Case Study Based on the British Telecommunication (Bt) Plc. *Journal of Services Research*, *8*(2), 175–216.

Quigley, N. R., Tesluk, P. E., Locke, E. A., & Bartol, K. M. 2007. A multilevel investigation of the motivational mechanisms underlying knowledge sharing and performance. Organization Science, 18: 71-88.

Raghuram, S., & Wiesenfeld, B. (2004). Work-nonwork conflict and job stress among virtual workers. *Human Resource Management*, *43*(2-3), 259–277. https://doi.org/10.1002/hrm.20019

Ragu-Nathan, T. S., Tarafdar, M., Ragu-Nathan, B. S., and Tu, Q. (2008). The consequences of technostress for end users in organization: Conceptual development and empirical validation. Information Systems Research, 19, 417–433. [Online]. Available: https://doi.org/10.1287/isre.1070.0165

Rainey, H. G. (1991). Understanding and managing public organizations. San Francisco: Jossey-Bass.

Raisamo, R., Rakkolainen, I., Majaranta, P., Salminen, K., Rantala, J., & Farooq, A. (2019). Human augmentation: Past, present and future. International Journal of Human-Computer Studies, 131, 131-143.

Rammert, W. (2008). *Where the Action is. Distributed Agency between Humans, Machines, and Programs* (pp. 62-91). transcript.

Ransbotham, S., Khodabandeh, S., Fehling, R., LaFountaine, B., & Kiron, D. (2019, October 15). *Winning with AI*. MIT Sloan Management Review. Retrieved April 13, 2022, from https://sloanreview.mit.edu/projects/winning-with-ai/

Rebaccal, A., Mahesh D., & Venkatesan D., (2019). A study on quality of worklife with reference of kerala feeds pvt ltd. Scholar: *National School of Leadership, 8*(1.5).

Reeves, B., & Nass, C. I. (1998). *The media equation: How people treat computers, television and new media like real people and places*. Centre for the Study of Language & Info.

Regan, M. D. (1999). The journey to teams: A practical step-by-step implementation plan. New York, Holden Press.

Reiter-Palmon, R., Brown, M., Sandall, D. L., Buboltz, C. B., & Nimps, T. (2006). Development of an o*net web-based job analysis and its implementation in the U. S. Navy: Lessons learned. *Human Resource Management Review*, *16*(3), 294–309. https://doi.org/10.1016/j.hrmr.2006.05.003

Revilla, M., & Höhne, J. K. (2020). How long do respondents think online surveys should be? new evidence from two online panels in Germany. International Journal of Market Research, 62(5), 538–545.

Rico, R., Molleman, E., Sanchez-Manzanares, M., & Van der Vegt, G. S. (2007). The effects of diversity faultlines and team task autonomy on decision quality and social integration. *Journal of Management, 33*, 111–132.

Robinson, W. S. (2009). Ecological correlations and the behavior of individuals. *International Journal of Epidemiology*, *38*(2), 337–341. https://doi.org/10.1093/ije/dyn357

Rubin, H. J., & Rubin, I. S. (1995). *Qualitative interviewing: The Art of Hearing Data*. Sage.

Ruppel, C. P., Gong, B., & Tworoger, L. C. (2013). Using communication choices as a boundary-management strategy. *Journal of Business and Technical Communication*, *27*(4), 436–471. https://doi.org/10.1177/1050651913490941

Russell, S. J., & Norvig, P. (2020). Artificial intelligence: A modern approach. Boston: Pearson.

Saad, L. & Wigert, B. (2022, March 21). *Remote work persisting and trending permanent*. Gallup.com. Retrieved March 28, 2022, from https://news.gallup.com/poll/355907/remote-work-persisting-trending-permanent.aspx

Sah, L., Singh, D. R., & Sah, R. K. (2020). Conducting qualitative interviews using virtual communication tools amid COVID-19 pandemic: A learning opportunity for future research. *Journal of Nepal Medical Association*, *58*(232). https://doi.org/10.31729/jnma.5738

Salas, E., Burke, C. S., & Cannon-Bowers, J. A. (2000). Teamwork: Emerging principles. International Journal of Management Review, 2 (4), 339-356.

Sampson, V., & Clark, D. B. (2011). A comparison of the collaborative scientific argumentation practices of two high and two low performing groups. Research in Science Education, 41, 63-97.

Sanches, S. A., Swildens, W. E., van Busschbach, J. T., & van Weeghel, J. (2019). Identifying social participation subgroups of individuals with severe mental illnesses: A latent class analysis. *Social Psychiatry and Psychiatric Epidemiology*, *54*(9), 1067–1077. https://doi.org/10.1007/s00127-019-01704-y

Sandall (2023) defines *Workplace Essential Skills* as an employee's foundational skills required by individuals to be successful irrespective of the job they are performing or are required for successful performance within a job, irrespective of the person doing the job.

Sandall, D. (2023). Operational Definitions and Rules. SkillsEngine. Retrieved February 23, 2023, from https://www.skillsengine.com/

Sax, H. C. (2012). Building high performance teams in the operating room. Surgical Clinics of North America, 15-19.

Scase, R. (2003). Employment relations in small firms. *Industrial relations: Theory and practice*, *1*, 470.

Shahedul Quader, M., & Rashedul Quader, M. (2008). A critical analysis of high performing teams: A case study based on the British telecommunications. Journal of Services Research, 8 (2), 175-216.

Shaikh, S. J., & Cruz, I. F. (2022). Ai in human teams: Effects on technology use, members' interactions, and creative performance under time scarcity. *AI & SOCIETY*. https://doi.org/10.1007/s00146-021-01335-5

Shih, T.-H., & Fan, X. (2008). Missing data in growth-curve modeling: A Monte Carlo Study. *PsycEXTRA Dataset*. https://doi.org/10.1037/e517522008-001

Shulman, A. D. (1996). Putting group information technology in its place: communication and good work group performance (pp. 257-361). Handbook of organization studies. S. R. Clegg, C. Hardy and W. R. Nord. London, Sage Publications.

Sirgy, M. J. (1991). Quality-of-life studies in marketing and management: An overview. *Journal of Business and Psychology*, 3–7.

Sirgy, M. J., Efraty, D., Siegel, P., & Lee, D.-J. (2001). A New Measure of Quality of Work Life (QWL) Based on Need Satisfaction and Spillover Theories. *Social Indicators Research*, *55*(3), 241–302. https://doi.org/10.1023/a:1010986923468

Sirgy, M. J., Reilly, N. P., Wu, J., & Efraty, D. (2008). A work-life identity model of well-being: Towards a research agenda linking quality-of-work-life (QWL) programs with quality of life (QOL). *Applied Research in Quality of Life*, *3*(3), 181–202. https://doi.org/10.1007/s11482-008-9054-6

Sirmon, D. G., Hitt, M. A., Arregle, J.-L., & Campbell, J. T. (2010). The dynamic interplay of capability strengths and weaknesses: Investigating the bases of temporary competitive advantage. *Strategic Management Journal*, *31*(13), 1386–1409. https://doi.org/10.1002/smj.893

SkillsEngine. (2022). Standards-Based Skills Taxonomy. SkillsEngine. Retrieved February 22, 2023, from https://www.skillsengine.com/skills-taxonomy

Smith, B., Sparkes, A.C., 2016. Qualitative interviewing in the sport and exercise sciences. In: Smith, B., Sparkes, A. (Eds.), Routledge Handbook of Qualitative Research in Sport and Exercise. Routledge, London, pp. 103–123.

Sodhi, M. M. S., Seyedghorban, Z., Tahernejad, H., & Samson, D. (2022). Why emerging supply chain technologies initially disappoint: Blockchain, IOT, and ai. *Production and Operations Management*. https://doi.org/10.1111/poms.13694

Stahl, G. K., Maznevski, M. L., Voigt, A., & Jonsen, K. (2009). Unraveling the effects of cultural diversity in teams: A meta-analysis of research on multicultural work groups. *Journal of International Business Studies*, *41*(4), 690–709. https://doi.org/10.1057/jibs.2009.85

Steers, R. M., Mowday, R. T., & Shapiro, D. T. (2004). The future of work motivation theory. Academy of Management Review, 29(3): 379-287.

Stevens, J.P. (1992). Applied Multivariate Statistics for the Social Sciences (2nd edition). Hillsdale, NJ: Erlbaum.

Storozuk, A., Ashley, M., Delage, V., & Maloney, E. A. (2020). Got bots? practical recommendations to protect online survey data from BOT attacks. *The Quantitative Methods for Psychology*, *16*(5), 472–481. https://doi.org/10.20982/tqmp.16.5.p472

Stowers, K., Brady, L. L., MacLellan, C., Wohleber, R., & Salas, E. (2021). Improving teamwork competencies in human-machine teams: Perspectives from team science. *Frontiers in Psychology*, *12*. https://doi.org/10.3389/fpsyg.2021.590290

Stowers, K., Oglesby, J., Sonesh, S., Leyva, K., Iwig, C., & Salas, E. (2017). A framework to guide the assessment of Human–Machine Systems. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *59*(2), 172–188. https://doi.org/10.1177/0018720817695077

Suh, A., & Shin, K. S. (2010). Exploring the effects of online social ties on knowledge sharing: A comparative analysis of collocated vs dispersed teams. Journal of Information Science, 36: 443-463.

Sukthankar G., Shumaker R., Lewis M. (2012). "Intelligent agents as teammates," in Theories of Team Cognition: Cross-Disciplinary Perspectives. eds. Salas E., Fiore S. M., Letsky M. P. (New York, NY: Routledge), 313–343.

Sullivan, C. (2006). Work at home and the work-family. In S. Lewis (Ed.), *Managing the work-home interface: a psychological perspective* (pp. 143–162). chapter, Psychology Press.

Sundstrom, E., DeMeuse, K. E., & Futrell, D. (1990). Work teams: Applications and effectiveness. American Psychological Association, 45 (2), 120-133.

Tabachnick, B. G., & Fidell, L. S. (2007). *Experimental designs using ANOVA* (Vol. 724). Belmont, CA: Thomson/Brooks/Cole.

Tajfel, H. (1974). Social identity and intergroup behaviour. *Social Science Information*, *13*(2), 65–93. https://doi.org/10.1177/053901847401300204

Tajfel, H., Turner, J. C., (1986). The social identity theory of intergroup behavior. In Worchel, S., & Austin, W. G. (Eds.), *Psychology of intergroup relations* (2nd ed., pp. 7–24). chapter, Nelson-Hall.

Tavakol, M., & Wetzel, A. (2020). Factor analysis: A means for theory and instrument development in support of construct validity. *International Journal of Medical Education*, *11*, 245–247. https://doi.org/10.5116/ijme.5f96.0f4a

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal*, *18*(7), 509–533. https://doi.org/10.1002/(sici)1097-0266(199708)18:7<509::aid-smj882>3.0.co;2-z

Teitcher, J. E., Bockting, W. O., Bauermeister, J. A., Hoefer, C. J., Miner, M. H., & Klitzman, R. L. (2015). Detecting, preventing, and responding to "fraudsters" in internet research: Ethics and tradeoffs. *Journal of Law, Medicine & Ethics*, *43*(1), 116–133. https://doi.org/10.1111/jlme.12200

Thatcher, S. M. B., & Patel, P. C. (2011). Demographic faultlines: A meta-analysis of the literature. Journal of Applied Psychology, 96, 1119–1139. http://dx.doi.org/10.1037/a0024167

Thompson, N. (2003). *Communication and language: A handbook of theory and practice*. Palgrave Macmillan.

Thunberg, S., Arnell, L., 2021. Pioneering the use of technologies in qualitative research: a research review of the use of digital interviews. Int. J. Soc. Res. Methodol. https://doi.org/10.1080/13645579.2021.1935565.

Treece, E. W., & Treece, J. W. (1982). *Elements of research in nursing*. Mosby.

Tuckman, B. W. (1965). Developmental sequence in small groups. Psychological Bulletin, 63(6), 384-399.

U.S. Department of Labor. (1991). *Dictionary of occupational titles* (4th Ed.) Washington, DC: U.S. Government Printing Office.

UCLA. (2022). *A Practical Introduction to Factor Analysis: Exploratory Factor Analysis*. OARC Stats. Retrieved March 26, 2022, from https://stats.oarc.ucla.edu/spss/seminars/introduction-to-factor-analysis/a-practical-introduction-to-factor-analysis/

Ulwick, A. (2002). *Turn customer input into Innovation*. Harvard Business Review. Retrieved March 28, 2022, from https://hbr.org/2002/01/turn-customer-input-into-innovation

Ulwick, A. & Bettencourt, L. (2008). *The customer-centered innovation map*. Harvard Business Review. Retrieved March 28, 2022, from https://hbr.org/2008/05/the-customer-centered-innovation-map

Ulwick, A., & Bettencourt, L. (2008, April 1). *Giving customers a fair hearing*. MIT Sloan Management Review. Retrieved March 28, 2022, from https://sloanreview.mit.edu/article/giving-customers-a-fair-hearing/

Ulwick, A., & Hamilton, P. (2019). *The jobs-to-be-done growth strategy matrix - strategyn*. The Jobs-to-be-Done Growth Strategy Matrix. Retrieved April 27, 2022, from https://strategyn.com/wp-content/uploads/2019/11/The-Jobs-to-be-Done-Growth-Strategy-Matrix-Strategyn-1.pdf

van Belle, G. (2002). *Statistical rules of thumb*. John Wiley.

van Knippenberg, D., De Dreu, C. K., & Homan, A. C. (2004). Work group diversity and group performance: An integrative model and research agenda. *Journal of Applied Psychology*, *89*(6), 1008–1022. https://doi.org/10.1037/0021-9010.89.6.1008 van Mierlo, H., Vermunt, J. K., & Rutte, C. G. (2008). Composing group-level constructs from individual-level survey data. *Organizational Research Methods*, *12*(2), 368–392. https://doi.org/10.1177/1094428107309322

van Rijmenam, M., & Logue, D. (2020). Revising the ‘science of the organisation’: Theorising AI agency and actorhood. *Innovation*, *23*(1), 127-144.

Venkatesh, V., & Windeler, J. B. (2012). Hype or help? A longitudinal field study of virtual world use for team collaboration. Journal of the Association for Information Systems, 13(10), 735–771.

Verganti, R., Vendraminelli, L., & Iansiti, M. (2020). Innovation and Design in the Age of Artificial Intelligence. Journal of Product Innovation Management, 37(3), 212–227. https://doi.org/10.1111/jpim.12523

Versta Research, Inc. (2011, December). *How to estimate the length of a survey*. Versta Research. Retrieved December 18, 2022, from https://verstaresearch.com/newsletters/how-to-estimate-the-length-of-a-survey/#:~:text=Research%20shows%20that%20data%20quality,or%2020%20minutes%20to%20complete

Wall, L. D. (2018). Some financial regulatory implications of Artificial Intelligence. *Journal of Economics and Business*, *100*, 55–63. https://doi.org/10.1016/j.jeconbus.2018.05.003

Walliser, J. C., de Visser, E. J., Wiese, E., & Shaw, T. H. (2019). Team structure and team building improve human–machine teaming with Autonomous Agents. *Journal of Cognitive*

Engineering and Decision Making, *13*(4), 258–278. https://doi.org/10.1177/1555343419867563

Walton, R. E. (1976). Criteria for quality of work life. In L. E. Davis & A. B. Cherns (Eds.), Quality of working life: Problems, projects and the state of the art (pp. 91–104). New York, NY: Macmillian.

Wang, H. C., & Barney, J. B. (2006). Employee incentives to make firm-specific investments: Implications for resource-based theories of corporate diversification. *Academy of Management Review*, *31*(2), 466–476. https://doi.org/10.5465/amr.2006.20208691

Watkins, M. W. (2018). Exploratory factor analysis: A guide to best practice. *Journal of Black Psychology*, *44*(3), 219–246. https://doi.org/10.1177/0095798418771807

Weiss, W. H. (2002). Organizing for quality, productivity and job satisfaction. SuperVision, 63(2), 13.

What is organizational climate and why should you warm up to it? (2009 1-September). Retrieved 2012 30-July from Where great workplaces start: http://greatworkplace.wordpress.com/2009/09/01/what-is-organizational-climate-and-why-should-you-warm-up-to-it/

Wheatley, D. (2012). Good to be home? time-use and satisfaction levels among home-based teleworkers. *New Technology, Work and Employment*, *27*(3), 224–241. https://doi.org/10.1111/j.1468-005x.2012.00289.x

Whitley, K. M. (2002). Analysis of Scifinder scholar and web of science citation searches. *Journal of the American Society for Information Science and Technology*, *53*(14), 1210–1215. https://doi.org/10.1002/asi.10192

Wigert, B. & Agrawal, S. (2022, August 31). *Returning to the office: The Current, Preferred, and Future State of Remote Work.* Gallup.com. Retrieved February 27, 2023, from https://www.gallup.com/workplace/397751/returning-office-current-preferred-future-state-remote-work.aspx

Wildman, J. L., & Griffith, R. L. (2015). Leading global teams means dealing with different. *Leading global teams: Translating multidisciplinary science to practice*, 1-10.

Williams, L. J., Hartman, N., & Cavazotte, F. (2010). Method variance and marker variables: A review and comprehensive CFA marker technique. *Organizational Research Methods*, *13*(3), 477–514. https://doi.org/10.1177/1094428110366036

Wilson, J. M., Marin, P. J., Rhea, M. R., Wilson, S. M. C., Loenneke, J. P., & Anderson, J. C. (2012). Concurrent training. *Journal of Strength and Conditioning Research*, *26*(8), 2293–2307. https://doi.org/10.1519/jsc.0b013e31823a3e2d

Wilson, J., & Daugherty, P. R. (2019, November 19). *How humans and ai are working together in 1,500 companies*. Harvard Business Review. Retrieved March 29, 2022, from https://hbr.org/2018/07/collaborative-intelligence-humans-and-ai-are-joining-forces

Wilson, M., & Greenhill, A. (2004). Gender and teleworking identities in the risk society: A research agenda. *New Technology, Work and Employment*, *19*(3), 207–221. https://doi.org/10.1111/j.1468-005x.2004.00138.x

Winter, S. G. (2003). Understanding dynamic capabilities. *Strategic Management Journal*, *24*(10), 991–995. https://doi.org/10.1002/smj.318

World Economic Forum, *The Global Competitiveness Report 2017-2018*, 2018

Yamane, T. (1967). *Statistics: An introductory analysis* (2nd ed.). Harper and Row.

Ye, Q., Wang, D., & Guo, W. (2019). Inclusive leadership and team innovation: The role of team voice and performance pressure. European Management Journal, 37, 468e480. https://doi.org/10.1016/j.emj.2019.01.006

Yin, M., Wortman Vaughan, J., & Wallach, H. (2019). Understanding the effect of accuracy on trust in Machine Learning Models. *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*. https://doi.org/10.1145/3290605.3300509

Yong, A. G., & Pearce, S. (2013). A beginner's guide to factor analysis: Focusing on exploratory factor analysis. *Tutorials in quantitative methods for psychology*, *9*(2), 79-94.

You, S., & Robert, L. (2022). Subgroup formation in human-robot teams: A multi-study mixed method approach with implications for theory and Practice. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4018366

Zhang, Z., Zhu, S., Mink, J., Xiong, A., Song, L., & Wang, G. (2022). Beyond bot detection: Combating fraudulent online survey takers. *Proceedings of the ACM Web Conference 2022*. https://doi.org/10.1145/3485447.3512230

Appendix A – IRB Approval / Non-Human Subjects Research Determination

Florida Institute of Technology
Institutional Review Board

Notice of Exempt Review Status
Certificate of Clearance for Human Participants Research

Principal Investigator:	Eric Demirjian
Date:	May 17, 2022
IRB Number:	22-051
Study Title:	AI Superteaming Exploratory Sequential Mixed Methods Dissertation

Your research protocol was reviewed and approved by the IRB Chairperson. Per federal regulations, 45 CFR 46.101, your study has been determined to be minimal risk for human subjects and exempt from 45 CFR46 federal regulations. The Exempt determination is valid indefinitely. Substantive changes to the approved exempt research must be requested and approved prior to their initiation. Investigators may request proposed changes by submitting a Revision Request form found on the IRB website.

Acceptance of this study is based on your agreement to abide by the policies and procedures of Florida Institute of Technology's Human Research Protection Program (http://web2.fit.edu/crm/irb/) and does not replace any other approvals that may be required.

All data, which may include signed consent form documents, must be retained in a secure location for a minimum of three years (six if HIPAA applies) past the completion of this research. Any links to the identification of participants should be maintained on a password-protected computer if electronic information is used. Access to data is limited to authorized individuals listed as key study personnel.

The category for which exempt status has been determined for this protocol is as follows:

2. Research that only includes interactions involving educational tests (cognitive, diagnostic, aptitude, achievement), survey procedures, interview procedures, or observation of public behavior (including visual or auditory recording) if at least one of the following criteria is met:

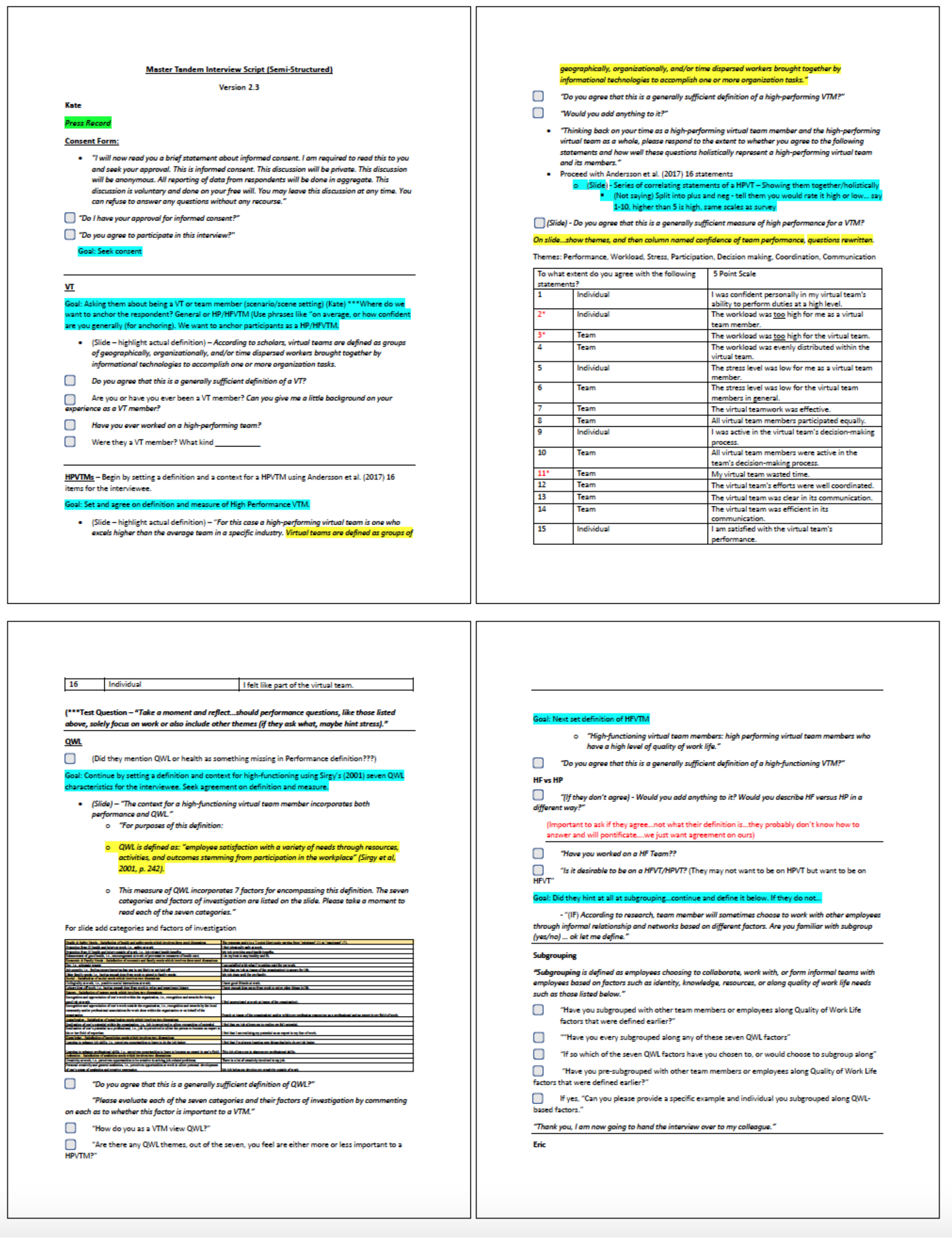
    a. The information obtained is recorded by the investigator in such a manner that the identity of the human subjects cannot readily be ascertained, directly or through identifiers linked to the subjects; or

    b. Any disclosure of the human subjects' responses outside the research would not reasonably place the subjects at risk of criminal or civil liability or be damaging to the subjects' financial standing, employability, educational advancement, or reputation; or

    c. The information obtained is recorded by the investigator in such a manner that the identity of the human subjects can readily be ascertained, directly or through identifiers linked to the subjects, and IRB can determine if there are adequate provisions in place to protect the privacy of the subjects and confidentiality of the data.

Appendix B – Qualitative Tandem Interview Script and Questions

The tandem interview script and questions, formulated from job statements (Ulwick & Bettencourt, 2008) and concept mapping (Moon, 2011) are listed in Appendix B, Figure 14.



Master Tandem Interview Script (Semi-Structured)

Version 2.3

Kate

Press Record

Consent Form:

- *"I will now read you a brief statement about informed consent. I am required to read this to you and seek your approval. This is informed consent. This discussion will be private. This discussion will be anonymous. All reporting of data from respondents will be done in aggregate. This discussion is voluntary and done on your free will. You may leave this discussion at any time. You can refuse to answer any questions without any recourse."*

☐ *"Do I have your approval for informed consent?"*

☐ *"Do you agree to participate in this interview?"*

Goal: Seek consent

VT

Goal: Asking them about being a VT or team member (scenario/scene setting) (Kate) ***Where do we want to anchor the respondent? General or HP/HFVTM (Use phrases like "on average, or how confident are you generally (for anchoring). We want to anchor participants as a HP/HFVTM.

- (Slide – highlight actual definition) – *According to scholars, virtual teams are defined as groups of geographically, organizationally, and/or time dispersed workers brought together by informational technologies to accomplish one or more organization tasks.*

☐ *Do you agree that this is a generally sufficient definition of a VT?*

☐ Are you or have you ever been a VT member? *Can you give me a little background on your experience as a VT member?*

☐ *Have you ever worked on a high-performing team?*

☐ Were they a VT member? What kind ____________

HPVTMs – Begin by setting a definition and a context for a HPVTM using Andersson et al. (2017) 16 items for the interviewee.

Goal: Set and agree on definition and measure of High Performance VTM.

- (Slide – highlight actual definition) – *"For this case a high-performing virtual team is one who excels higher than the average team in a specific industry. Virtual teams are defined as groups of geographically, organizationally, and/or time dispersed workers brought together by informational technologies to accomplish one or more organization tasks."*

☐ *"Do you agree that this is a generally sufficient definition of a high-performing VTM?"*

☐ *"Would you add anything to it?"*

- *"Thinking back on your time as a high-performing virtual team member and the high-performing virtual team as a whole, please respond to the extent to whether you agree to the following statements and how well these questions holistically represent a high-performing virtual team and its members."*
- Proceed with Andersson et al. (2017) 16 statements
    - (Slide) - Series of correlating statements of a HPVT – Showing them together/holistically
        - (Not saying) Split into plus and neg - tell them you would rate it high or low… say 1-10, higher than 5 is high, same scales as survey

☐ *(Slide) - Do you agree that this is a generally sufficient measure of high performance for a VTM?*

On slide…show themes, and then column named confidence of team performance, questions rewritten.

Themes: Performance, Workload, Stress, Participation, Decision making, Coordination, Communication

To what extent do you agree with the following statements?		5 Point Scale
1	Individual	I was confident personally in my virtual team's ability to perform duties at a high level.
2*	Individual	The workload was too high for me as a virtual team member.
3*	Team	The workload was too high for the virtual team.
4	Team	The workload was evenly distributed within the virtual team.
5	Individual	The stress level was low for me as a virtual team member.
6	Team	The stress level was low for the virtual team members in general.
7	Team	The virtual teamwork was effective.
8	Team	All virtual team members participated equally.
9	Individual	I was active in the virtual team's decision-making process.
10	Team	All virtual team members were active in the team's decision-making process.
11*	Team	My virtual team wasted time.
12	Team	The virtual team's efforts were well coordinated.
13	Team	The virtual team was clear in its communication.
14	Team	The virtual team was efficient in its communication.
15	Individual	I am satisfied with the virtual team's performance.
16	Individual	I felt like part of the virtual team.

(*Test Question – *"Take a moment and reflect…should performance questions, like those listed above, solely focus on work or also include other themes (if they ask what, maybe hint stress)."***

QWL

☐ (Did they mention QWL or health as something missing in Performance definition???)

Goal: Continue by setting a definition and context for high-functioning using Sirgy's (2001) seven QWL characteristics for the interviewee. Seek agreement on definition and measure.

- *(Slide) – "The context for a high-functioning virtual team member incorporates both performance and QWL."*
    - *"For purposes of this definition:*
    - *QWL is defined as: "employee satisfaction with a variety of needs through resources, activities, and outcomes stemming from participation in the workplace" (Sirgy et al, 2001, p. 242).*
    - *This measure of QWL incorporates 7 factors for encompassing this definition. The seven categories and factors of investigation are listed on the slide. Please take a moment to read each of the seven categories."*

For slide add categories and factors of investigation

☐ *"Do you agree that this is a generally sufficient definition of QWL?"*

"Please evaluate each of the seven categories and their factors of investigation by commenting on each as to whether this factor is important to a VTM."

☐ "How do you as a VTM view QWL?"

☐ "Are there any QWL themes, out of the seven, you feel are either more or less important to a HPVTM?"

Goal: Next set definition of HFVTM

- *"High-functioning virtual team members: high performing virtual team members who have a high level of quality of work life."*

☐ *"Do you agree that this is a generally sufficient definition of a high-functioning VTM?"*

HF vs HP

☐ *"(If they don't agree) - Would you add anything to it? Would you describe HF versus HP in a different way?"*

(Important to ask if they agree…not what their definition is…they probably don't know how to answer and will pontificate….we just want agreement on ours)

☐ *"Have you worked on a HF Team??*

☐ *"Is it desirable to be on a HFVT/HPVT?* (They may not want to be on HPVT but want to be on HFVT"

Goal: Did they hint at all at subgrouping…continue and define it below. If they do not…

- "(IF) *According to research, team member will sometimes choose to work with other employees through informal relationship and networks based on different factors. Are you familiar with subgroup (yes/no) … ok let me define."*

Subgrouping

*"**Subgrouping** is defined as employees choosing to collaborate, work with, or form informal teams with employees based on factors such as identity, knowledge, resources, or along quality of work life needs such as those listed below."*

☐ "Have you subgrouped with other team members or employees along Quality of Work Life factors that were defined earlier?"

☐ ""Have you every subgrouped along any of these seven QWL factors"

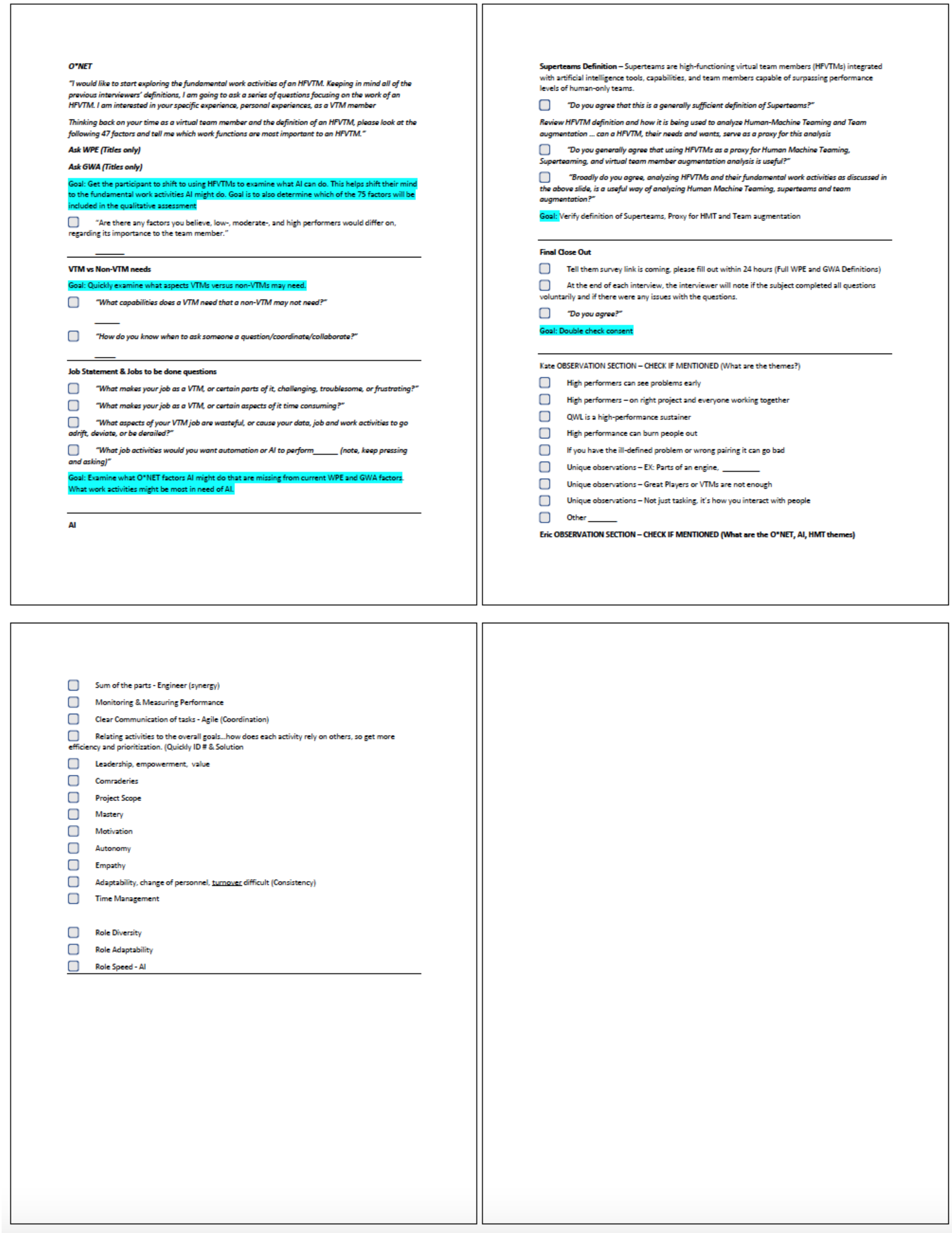
☐ "If so which of the seven QWL factors have you chosen to, or would choose to subgroup along"

☐ "Have you pre-subgrouped with other team members or employees along Quality of Work Life factors that were defined earlier?"

☐ If yes, "Can you please provide a specific example and individual you subgrouped along QWL-based factors."

"Thank you, I am now going to hand the interview over to my colleague."

Eric



O*NET

"I would like to start exploring the fundamental work activities of an HFVTM. Keeping in mind all of the previous interviewers' definitions, I am going to ask a series of questions focusing on the work of an HFVTM. I am interested in your specific experience, personal experiences, as a VTM member

Thinking back on your time as a virtual team member and the definition of an HFVTM, please look at the following 47 factors and tell me which work functions are most important to an HFVTM."

Ask WPE (Titles only)

Ask GWA (Titles only)

Goal: Get the participant to shift to using HFVTMs to examine what AI can do. This helps shift their mind to the fundamental work activities AI might do. Goal is to also determine which of the 75 factors will be included in the qualitative assessment

☐ "Are there any factors you believe, low-, moderate-, and high performers would differ on, regarding its importance to the team member."

______

VTM vs Non-VTM needs

Goal: Quickly examine what aspects VTMs versus non-VTMs may need.

☐ *"What capabilities does a VTM need that a non-VTM may not need?"*

______

☐ *"How do you know when to ask someone a question/coordinate/collaborate?"*

______

Job Statement & Jobs to be done questions

☐ *"What makes your job as a VTM, or certain parts of it, challenging, troublesome, or frustrating?"*

☐ *"What makes your job as a VTM, or certain aspects of it time consuming?"*

☐ *"What aspects of your VTM job are wasteful, or cause your data, job and work activities to go adrift, deviate, or be derailed?"*

☐ *"What job activities would you want automation or AI to perform______ (note, keep pressing and asking)"*

Goal: Examine what O*NET factors AI might do that are missing from current WPE and GWA factors. What work activities might be most in need of AI.

AI

Superteams Definition – Superteams are high-functioning virtual team members (HFVTMs) integrated with artificial intelligence tools, capabilities, and team members capable of surpassing performance levels of human-only teams.

☐ *"Do you agree that this is a generally sufficient definition of Superteams?"*

Review HFVTM definition and how it is being used to analyze Human-Machine Teaming and Team augmentation … can a HFVTM, their needs and wants, serve as a proxy for this analysis

☐ *"Do you generally agree that using HFVTMs as a proxy for Human Machine Teaming, Superteaming, and virtual team member augmentation analysis is useful?"*

☐ *"Broadly do you agree, analyzing HFVTMs and their fundamental work activities as discussed in the above slide, is a useful way of analyzing Human Machine Teaming, superteams and team augmentation?"*

Goal: Verify definition of Superteams, Proxy for HMT and Team augmentation

Final Close Out

☐ Tell them survey link is coming, please fill out within 24 hours (Full WPE and GWA Definitions)

☐ At the end of each interview, the interviewer will note if the subject completed all questions voluntarily and if there were any issues with the questions.

☐ *"Do you agree?"*

Goal: Double check consent

Kate OBSERVATION SECTION – CHECK IF MENTIONED (What are the themes?)

☐ High performers can see problems early

☐ High performers – on right project and everyone working together

☐ QWL is a high-performance sustainer

☐ High performance can burn people out

☐ If you have the ill-defined problem or wrong pairing it can go bad

☐ Unique observations – EX: Parts of an engine, ________

☐ Unique observations – Great Players or VTMs are not enough

☐ Unique observations – Not just tasking, it's how you interact with people

☐ Other ______

Eric OBSERVATION SECTION – CHECK IF MENTIONED (What are the O*NET, AI, HMT themes)

☐ Sum of the parts - Engineer (synergy)

☐ Monitoring & Measuring Performance

☐ Clear Communication of tasks - Agile (Coordination)

☐ Relating activities to the overall goals…how does each activity rely on others, so get more efficiency and prioritization. (Quickly ID # & Solution

☐ Leadership, empowerment, value

☐ Comraderies

☐ Project Scope

☐ Mastery

☐ Motivation

☐ Autonomy

☐ Empathy

☐ Adaptability, change of personnel, turnover difficult (Consistency)

☐ Time Management

☐ Role Diversity

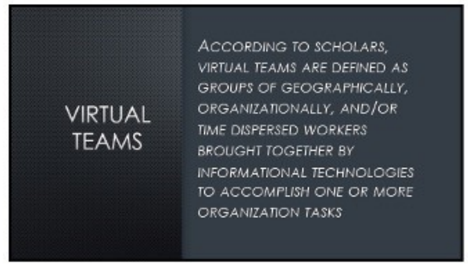
☐ Role Adaptability

☐ Role Speed - AI

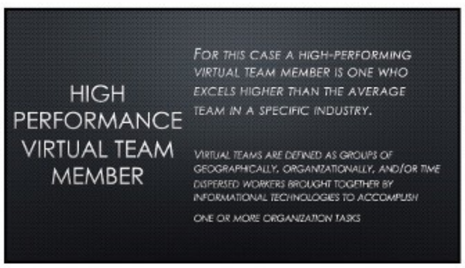
Figure 18 - Qualitative Tandem Interview Question Example


SURVEY
Thank you for your participation
Consent
This is informed consent. This discussion will be private. This discussion will be anonymous. All reporting of data from respondents will be done in aggregate. This discussion is voluntary and done on your free will. You may leave this discussion at any time. You can refuse to answer any questions without any recourse."
"Do I have your approval for informed consent?"
"Do you agree to participate in this interview?"

1


VIRTUAL TEAMS
According to scholars, virtual teams are defined as groups of geographically, organizationally, and/or time dispersed workers brought together by informational technologies to accomplish one or more organization tasks

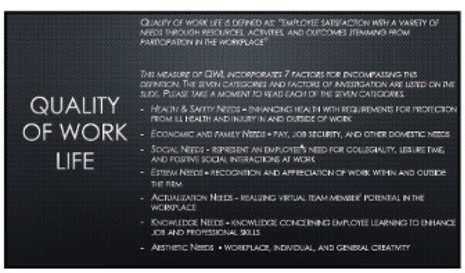
2


HIGH PERFORMANCE VIRTUAL TEAM MEMBER
For this case a high-performing virtual team member is one who excels higher than the average team in a specific industry.
Virtual teams are defined as groups of geographically, organizationally, and/or time dispersed workers brought together by informational technologies to accompush
one or more organization tasks

3


VIRTUAL TEAM MEMBER PERFORMANCE
ANDERSSON

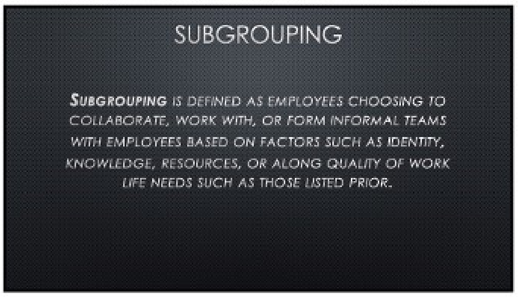
4


QUALITY OF WORK LIFE
Quality of work life is defined as: "Employee satisfaction with a variety of needs through resources, activities, and outcomes stemming from participation in the workplace"
This measure of QWL incorporates 7 factors for encompassing this definition. The seven categories and factors of investigation are listed on the slide. Please take a moment to read each of the seven categories.
- Health & Safety Needs – enhancing health with requirements for protection from ill health and injury in and outside of work
- Economic and Family Needs – pay, job security, and other domestic needs
- Social Needs - represent an employee's need for collegiality, leisure time, and positive social interactions at work
- Esteem Needs – recognition and appreciation of work within and outside the firm
- Actualization Needs - realizing virtual team member' potential in the workplace
- Knowledge Needs – knowledge concerning employee learning to enhance job and professional skills
- Aesthetic Needs – workplace, individual, and general creativity

5


HIGH FUNCTIONING VIRTUAL TEAMS
High performing virtual team members who have a high level of quality of work life.

6



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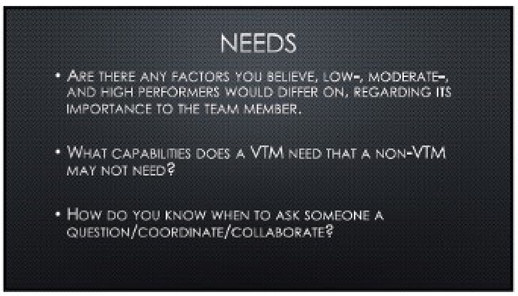
8



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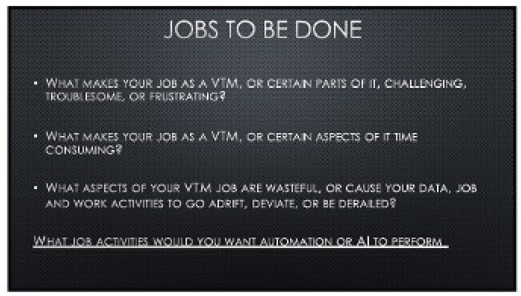

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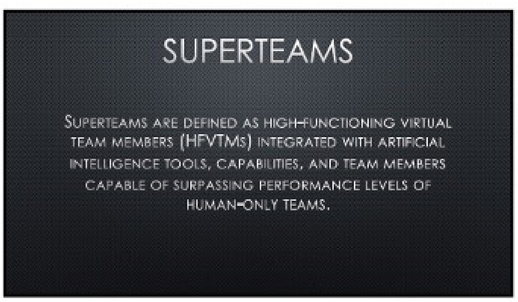

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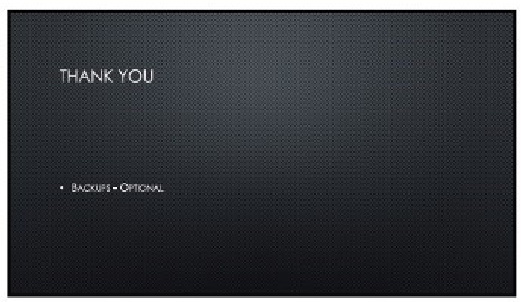

12

Figure 19 - Qualitative Tandem Interview Final PowerPoint

Appendix C – Email to Potential Survey Participants

Hello,

Besides being a virtual team member and leader I am currently pursuing a Doctorate in Business Administration with a focus on human machine teaming. I have moved into the dissertation phase of the program. This research is focused on understanding virtual team member augmentation through artificial intelligence, Superteams, and defining an O*NET profile for AI.

In order to collect the data needed for the research, I have developed a short survey that I would greatly appreciate a small amount of your time to complete. Based on test runs of the survey, it should take you less than 15 minutes to complete. All responses are confidential, and no IP addresses are collected by the survey tool. If you would like a copy of the final results, I would be happy to send them to you, even if you decide not to respond. Email me at edemirji2005@my.fit.edu and I will send you the results late this year. Thank you for your assistance. It is greatly appreciated!

Regards, Eric Demirjian

Appendix D1 – Proposed Self-Administered VTM Performance 16 Question Survey (Andersson et al., 2017)

Figure 20 – Virtual Team Member Performance Original Survey

	Question Focus for analysis	Original Wording as Surveyed	Likert Scale
1	Team	How confident are you personally in your team's diagnosis/treatment?	1 to 11
To what extent do you agree with the following statements		All remaining are 5-point Likert Scale	
2	Individual	The workload was high for [me indiviudally/the subject]	1 to 5
3	Team	The workload was high for the team	1 to 5
4	Team	The workload was evenly distributed within the team	1 to 5
5	Individual	The stress level was low for [me as an individual/the subject]	1 to 5
6	Team	The stress level was low for the team members in general	1 to 5
7	Team	The teamwork was effective	1 to 5
8	Team	All team members participated equally	1 to 5
9	Individual	[I/The subject} was active in the team's decision-making process	1 to 5
10	Team	All team members were active in the team's decision-making process	1 to 5
11	Team	[My/The] team was wasting time	1 to 5
12	Team	The team's efforts were well coordinated	1 to 5
13	Team	The team was clear in its communication	1 to 5
14	Team	The team was efficient in its communication	1 to 5
15	Team	I am satisifed with the team's performance	1 to 5
16	Individual	I felt part of the team	1 to 5

Appendix D2 – Modified Self-Administered Virtual Team Performance 16 Question Survey

Figure 21 – Virtual Team Member Performance Final Survey with Changes

SAR	Question Focus for analysis	Wording as surveyed	Likert Scale
1	Individual	I was confident personally in my virtual team's ability to perform duties at a high level?	1 to 5
To what extent do you agree with the following statements		All remaining are 5-point Likert Scale	
2	Individual	The workload was <u>too</u> high for me as a virtual team member.	1 to 5
3	Team	The workload was <u>too</u> high for the virtual team.	1 to 5
4	Team	The workload was evenly distributed within the virtual team.	1 to 5
5	Individual	The stress level was low for me as a virtual team member.	1 to 5
6	Team	The stress level was low for the virtual team members in general.	1 to 5
7	Team	The virtual teamwork was effective.	1 to 5
8	Team	All team members participated equally.	1 to 5
9	Individual	I was active in the virtual team's decision-making process.	1 to 5
10	Team	All virtual team members were active in the team's decision-making process.	1 to 5
11	Team	My virtual team was wasting time.	1 to 5
12	Team	The virtual team's efforts were well coordinated.	1 to 5
13	Team	The virtual team was clear in its communication.	1 to 5
14	Team	The virtual team was efficient in its communication.	1 to 5
15	Individual	I am satisfied with the virtual team's performance.	1 to 5
16	Individual	I felt like part of the virtual team.	1 to 5

Appendix E – Example Importance, Frequency, and Satisfaction (ODI) Survey Questions

AI-VTMA	Importance vs Frequency	O*NET WPE			
			Question Focus for analysis	Wording as surveyed	Scale
	Importance	17	Individual	WPE 1	1 to 10
	Frequency	18	Individual	WPE 1	1 to 10
	Importance	20	Individual	WPE 2	1 to 10
	Frequency	21	Individual	WPE 2	1 to 10
AIA-VTMP	ODI Satisfaction	O*NET WPE			
			Question Focus for analysis	Wording as surveyed	Scale
	Satisfaction	19	Individual	WPE 1	1 to 10
	Satisfaction	22	Individual	WPE 2	1 to 10

Appendix F – Informed Consent Statement

I will now read you a brief statement about informed consent. I am required to read this to you and seek your approval. This is informed consent. This discussion will be private. This discussion will be anonymous. All reporting of data from respondents will be done in aggregate. This discussion is voluntary and done on your free will. You may leave this discussion at any time. You can refuse to answer any questions without any recourse. Do I have your approval for informed consent? Do you agree to participate in this interview?

Appendix G – Master Study Statistical Reliability

Table 55 - Master Study VTM Performance Reliability

Estimate	McDonald's ω	Cronbach's α
Point estimate	0.929	0.927
95% CI lower bound	0.918	0.916
95% CI upper bound	0.939	0.937

VTM Performance Item	McDonald's ω	Cronbach's α
Performance Item_1	0.925	0.924
Reverse Performance Item 2	0.93	0.928
Reverse Performance Item 3	0.928	0.926
Performance Item_4	0.925	0.923
Performance Item_5	0.928	0.926
Performance Item_6	0.928	0.926
Performance Item_7	0.92	0.919
Performance Item_8	0.922	0.921
Performance Item_9	0.928	0.927
Performance Item_10	0.924	0.923
Reverse Performance Item 11	0.924	0.923
Performance Item_12	0.922	0.921
Performance Item_13	0.92	0.919
Performance Item_14	0.921	0.92
Performance Item_15	0.921	0.919
Performance Item_16	0.923	0.922
Performance Item_17	0.925	0.924
Performance Item_18	0.925	0.924

QWL Question Estimate	McDonald's ω	Cronbach's α
Point estimate	0.869	0.87
95% CI lower bound	0.85	0.851
95% CI upper bound	0.888	0.888

Table 56 - Master Study VTM QWL Reliability

QWL Question	McDonald's ω	Cronbach's α
QWL Question_1	0.871	0.873
QWL Question_2	0.873	0.873
QWL Question_3	0.87	0.872
QWL Question_4	0.862	0.862
QWL Question_5	0.873	0.872
QWL Question_6	0.861	0.862
QWL Question_7	0.865	0.867
QWL Question_8	0.871	0.87
QWL Question_9	0.858	0.86
QWL Question_10	0.86	0.862
QWL Question_11	0.849	0.852
QWL Question_12	0.854	0.855
QWL Question_13	0.857	0.859
QWL Question_14	0.854	0.857
QWL Question_15	0.857	0.86
QWL Question_16	0.863	0.865
QWL Question_17	0.857	0.859
QWL Question_18	0.859	0.861

Appendix H – MANOVA & ANOVA High, Moderate, Low VTMP vs O*NET Importance

MANOVA: Pillai Test VTMP High, Moderate, Low Groups vs O*NET Importance					
Cases	df	Approx. F	$Trace_{Pillai}$	Num df	p
(Intercept)	1	2415.869	0.997	43	< .001
VTMP_H_M_L	2	1.727	0.351	86	< .001
Residuals	390				

ANOVA: WPE1_Importance					
Cases	f Squares	df	Mean Square	F	p
(Intercept)	35212.2	1	35212.214	44796.039	< .001
VTMP_H_M_L	15.224	2	7.612	9.684	< .001
Residuals	306.562	390	0.786		
ANOVA: WPE2_Importance					
(Intercept)	30303.8	1	30303.819	11135.463	< .001
VTMP_H_M_L	1.843	2	0.921	0.339	0.713
Residuals	1061.34	390	2.721		
ANOVA: WPE3_Importance					
(Intercept)	34365.5	1	34365.458	27538.879	< .001
VTMP_H_M_L	32.865	2	16.433	13.168	< .001
Residuals	486.677	390	1.248		
ANOVA: WPE4_Importance					
(Intercept)	32538.9	1	32538.87	15686.264	< .001
VTMP_H_M_L	24.132	2	12.066	5.817	0.003
Residuals	808.998	390	2.074		
ANOVA: WPE5_Importance					
(Intercept)	30903.9	1	30903.88	11062.236	< .001
VTMP_H_M_L	43.601	2	21.8	7.804	< .001
Residuals	1089.52	390	2.794		
ANOVA: WPE6_Importance					
(Intercept)	30550.2	1	30550.191	12618.283	< .001
VTMP_H_M_L	56.578	2	28.289	11.684	< .001
Residuals	944.231	390	2.421		
ANOVA: WPE7_Importance					
(Intercept)	32648.2	1	32648.153	14388.368	< .001
VTMP_H_M_L	18.912	2	9.456	4.167	0.016
Residuals	884.936	390	2.269		
ANOVA: WPE8_Importance					
(Intercept)	34346.8	1	34346.758	22582.101	< .001
VTMP_H_M_L	24.062	2	12.031	7.91	< .001
Residuals	593.179	390	1.521		
ANOVA: WPE9_Importance					
(Intercept)	33992.4	1	33992.43	26812.886	< .001
VTMP_H_M_L	18.142	2	9.071	7.155	< .001
Residuals	494.428	390	1.268		
ANOVA: WPE10_Importance					
(Intercept)	35325.9	1	35325.893	34494.991	< .001
VTMP_H_M_L	14.713	2	7.356	7.183	< .001
Residuals	399.394	390	1.024		
ANOVA: WPE11_Importance					
(Intercept)	34197.3	1	34197.344	30571.342	< .001
VTMP_H_M_L	16.399	2	8.2	7.33	< .001
Residuals	436.257	390	1.119		
ANOVA: WPE12_Importance					
(Intercept)	33602.9	1	33602.941	21667.518	< .001
VTMP_H_M_L	10.229	2	5.115	3.298	0.038
Residuals	604.829	390	1.551		
ANOVA: WPE13_Importance					
(Intercept)	33068.8	1	33068.766	20516.488	< .001
VTMP_H_M_L	31.627	2	15.813	9.811	< .001
Residuals	628.608	390	1.612		
ANOVA: WPE14_Importance					
(Intercept)	31545.7	1	31545.651	14882.842	< .001
VTMP_H_M_L	10.705	2	5.353	2.525	0.081
Residuals	826.643	390	2.12		
ANOVA: WPE15_Importance					
(Intercept)	31797	1	31797.01	17056.717	< .001
VTMP_H_M_L	56.955	2	28.477	15.276	< .001
Residuals	727.035	390	1.864		
ANOVA: WPE16_Importance					
(Intercept)	31797	1	31797.01	17337.669	< .001
VTMP_H_M_L	58.736	2	29.368	16.013	< .001
Residuals	715.254	390	1.834		
ANOVA: WPE17_Importance					
(Intercept)	32739.4	1	32739.361	22114.094	< .001
VTMP_H_M_L	44.253	2	22.127	14.946	< .001
Residuals	577.385	390	1.48		
ANOVA: WPE18_Importance					
(Intercept)	31456.1	1	31456.122	16229.265	< .001
VTMP_H_M_L	29.966	2	14.983	7.73	< .001
Residuals	755.911	390	1.938		
ANOVA: WPE19_Importance					
(Intercept)	33197.3	1	33197.313	21949.429	< .001
VTMP_H_M_L	38.833	2	19.417	12.838	< .001
Residuals	589.854	390	1.512		
ANOVA: WPE20_Importance					
(Intercept)	31348.9	1	31348.855	15695.456	< .001
VTMP_H_M_L	28.19	2	14.095	7.057	< .001
Residuals	778.955	390	1.997		
ANOVA: WPE21_Importance					
(Intercept)	25990.9	1	25990.88	7171.005	< .001
VTMP_H_M_L	73.588	2	36.794	10.152	< .001
Residuals	1413.53	390	3.624		
ANOVA: WPE22_Importance					
(Intercept)	36588.5	1	36588.458	37467.832	< .001
VTMP_H_M_L	12.695	2	6.348	6.5	0.002
Residuals	380.847	390	0.977		
ANOVA: WPE23_Importance					
(Intercept)	32684.6	1	32684.621	17340.147	< .001
VTMP_H_M_L	36.264	2	18.132	9.62	< .001
Residuals	735.115	390	1.885		
ANOVA: WPE24_Importance					
(Intercept)	33289.3	1	33289.285	25371.407	< .001
VTMP_H_M_L	28.004	2	14.002	10.672	< .001
Residuals	511.711	390	1.312		
ANOVA: WPE25_Importance					
(Intercept)	31295.3	1	31295.29	15341.242	< .001
VTMP_H_M_L	80.131	2	40.066	19.641	< .001
Residuals	795.579	390	2.04		
ANOVA: WPE26_Importance					
(Intercept)	28590.1	1	28590.087	6708.747	< .001
VTMP_H_M_L	23.884	2	11.942	2.802	0.062
Residuals	1662.03	390	4.262		
ANOVA: GWA1_Importance					
(Intercept)	32302.7	1	32302.72	20562.014	< .001
VTMP_H_M_L	43.594	2	21.797	13.875	< .001
Residuals	612.686	390	1.571		
ANOVA: GWA2_Importance					
(Intercept)	29035.3	1	29035.328	10079.541	< .001
VTMP_H_M_L	35.23	2	17.615	6.115	0.002
Residuals	1123.44	390	2.881		
ANOVA: GWA3_Importance					
(Intercept)	33399.8	1	33399.819	22984.687	< .001
VTMP_H_M_L	28.459	2	14.229	9.792	< .001
Residuals	566.722	390	1.453		
ANOVA: GWA4_Importance					
(Intercept)	31563.6	1	31563.573	20209.848	< .001
VTMP_H_M_L	53.329	2	26.664	17.073	< .001
Residuals	609.099	390	1.562		
ANOVA: GWA5 _Importance					
(Intercept)	28812.3	1	28812.277	9354.308	< .001
VTMP_H_M_L	39.481	2	19.74	6.409	0.002
Residuals	1201.24	390	3.08		
ANOVA: GWA6_Importance					
(Intercept)	32049.4	1	32049.366	17598.279	< .001
VTMP_H_M_L	41.379	2	20.69	11.361	< .001
Residuals	710.254	390	1.821		
ANOVA: GWA7_Importance					
(Intercept)	28743.8	1	28743.819	6157.895	< .001
VTMP_H_M_L	8.739	2	4.369	0.936	0.393
Residuals	1820.44	390	4.668		
ANOVA: GWA8_Importance					
(Intercept)	33123.8	1	33123.827	20842.086	< .001
VTMP_H_M_L	46.355	2	23.178	14.584	< .001
Residuals	619.818	390	1.589		
ANOVA: GWA9_Importance					
(Intercept)	27878.1	1	27878.117	6189.211	< .001
VTMP_H_M_L	27.203	2	13.601	3.02	0.05
Residuals	1756.68	390	4.504		
ANOVA: GWA10_Importance					
(Intercept)	31295.3	1	31295.29	13792.853	< .001
VTMP_H_M_L	28.82	2	14.41	6.351	0.002
Residuals	884.89	390	2.269		
ANOVA: GWA11_Importance					
(Intercept)	28013	1	28013.038	6660.556	< .001
VTMP_H_M_L	40.696	2	20.348	4.838	0.008
Residuals	1640.27	390	4.206		
ANOVA: GWA12_Importance					
(Intercept)	31152.7	1	31152.674	12566.638	< .001
VTMP_H_M_L	51.516	2	25.758	10.391	< .001
Residuals	966.809	390	2.479		
ANOVA: GWA13_Importance					
(Intercept)	26170.1	1	26170.099	4509.212	< .001
VTMP_H_M_L	13.459	2	6.73	1.16	0.315
Residuals	2263.44	390	5.804		
ANOVA: KE1 _Importance					
(Intercept)	28658.4	1	28658.361	8847.068	< .001
VTMP_H_M_L	44.309	2	22.155	6.839	0.001
Residuals	1263.33	390	3.239		
ANOVA: KE2_Importance					
(Intercept)	28829.4	1	28829.405	10016.707	< .001
VTMP_H_M_L	64.124	2	32.062	11.14	< .001
Residuals	1122.47	390	2.878		
ANOVA: KE3_Importance					
(Intercept)	25473	1	25473.018	5675.379	< .001
VTMP_H_M_L	114.53	2	57.265	12.759	< .001
Residuals	1750.45	390	4.488		
ANOVA: KE4_Importance					
(Intercept)	22083.8	1	22083.756	3196.398	< .001
VTMP_H_M_L	53.754	2	26.877	3.89	0.021
Residuals	2694.49	390	6.909		

Appendix I – MANOVA & ANOVA High, Moderate, Low VTMP vs O*NET Satisfaction

MANOVA: Pillai Test VTMP High, Moderate, Low Groups vs O*NET Satisfaction					
Cases	**df**	**Approx. F**	**$\text{Trace}_{\text{Pillai}}$**	**Num df**	**p**
(Intercept)	1	716.496	0.989	43	< .001
VTMP_H_M_L	2	2.437	0.462	86	< .001
Residuals	390				

ANOVA: WPE1_Satisfaction					
Cases	**f Squares**	**df**	**Mean Square**	**F**	**p**
(Intercept)	25424.7	1	25424.735	7468.449	< .001
VTMP_H_M_L	98.593	2	49.297	14.481	< .001
Residuals	1327.67	390	3.404		
ANOVA: WPE2_Satisfaction					
(Intercept)	21017.5	1	21017.496	4271.917	< .001
VTMP_H_M_L	157.734	2	78.867	16.03	< .001
Residuals	1918.77	390	4.92		
ANOVA: WPE3_Satisfaction					
(Intercept)	25408.7	1	25408.651	7122.815	< .001
VTMP_H_M_L	164.133	2	82.066	23.006	< .001
Residuals	1391.22	390	3.567		
ANOVA: WPE4_Satisfaction					
(Intercept)	21399.5	1	21399.491	4103.763	< .001
VTMP_H_M_L	130.814	2	65.407	12.543	< .001
Residuals	2033.7	390	5.215		
ANOVA: WPE5_Satisfaction					
(Intercept)	21591.8	1	21591.779	3839.217	< .001
VTMP_H_M_L	163.859	2	81.929	14.568	< .001
Residuals	2193.36	390	5.624		
ANOVA: WPE6_Satisfaction					
(Intercept)	20813.2	1	20813.232	4534.793	< .001
VTMP_H_M_L	206.795	2	103.397	22.528	< .001
Residuals	1789.97	390	4.59		
ANOVA: WPE7_Satisfaction					
(Intercept)	20827.8	1	20827.789	3974.746	< .001
VTMP_H_M_L	75.599	2	37.8	7.214	< .001
Residuals	2043.61	390	5.24		
ANOVA: WPE8_Satisfaction					
(Intercept)	26546.8	1	26546.819	8417.897	< .001
VTMP_H_M_L	185.27	2	92.635	29.374	< .001
Residuals	1229.91	390	3.154		
ANOVA: WPE9_Satisfaction					
(Intercept)	21919.1	1	21919.148	4648.963	< .001
VTMP_H_M_L	163.062	2	81.531	17.292	< .001
Residuals	1838.79	390	4.715		
ANOVA: WPE10_Satisfaction					
(Intercept)	29814.1	1	29814.069	11759.217	< .001
VTMP_H_M_L	86.134	2	43.067	16.986	< .001
Residuals	988.798	390	2.535		
ANOVA: WPE11_Satisfaction					
(Intercept)	27291.7	1	27291.667	9899.267	< .001
VTMP_H_M_L	52.127	2	26.064	9.454	< .001
Residuals	1075.21	390	2.757		
ANOVA: WPE12_Satisfaction					
(Intercept)	25104	1	25104.023	7384.647	< .001
VTMP_H_M_L	63.176	2	31.588	9.292	< .001
Residuals	1325.8	390	3.399		
ANOVA: WPE13_Satisfaction					
(Intercept)	22733.1	1	22733.132	4989.805	< .001
VTMP_H_M_L	143.061	2	71.53	15.701	< .001
Residuals	1776.81	390	4.556		
ANOVA: WPE14_Satisfaction					
(Intercept)	23253.3	1	23253.254	5078.202	< .001
VTMP_H_M_L	119.923	2	59.961	13.095	< .001
Residuals	1785.82	390	4.579		
ANOVA: WPE15_Satisfaction					
(Intercept)	26727.9	1	26727.941	8754.456	< .001
VTMP_H_M_L	122.362	2	61.181	20.039	< .001
Residuals	1190.7	390	3.053		
ANOVA: WPE16_Satisfaction					
(Intercept)	25040.1	1	25040.125	7663.787	< .001
VTMP_H_M_L	154.616	2	77.308	23.661	< .001
Residuals	1274.26	390	3.267		
ANOVA: WPE17_Satisfaction					
(Intercept)	25248.1	1	25248.092	7256.268	< .001
VTMP_H_M_L	132.908	2	66.454	19.099	< .001
Residuals	1357	390	3.479		
ANOVA: WPE18_Satisfaction					
(Intercept)	26431.9	1	26431.88	8603.207	< .001
VTMP_H_M_L	88.911	2	44.456	14.47	< .001
Residuals	1198.21	390	3.072		
ANOVA: WPE19_Satisfaction					
(Intercept)	26992.5	1	26992.491	8800.796	< .001
VTMP_H_M_L	154.359	2	77.179	25.164	< .001
Residuals	1196.15	390	3.067		
ANOVA: WPE20_Satisfaction					
(Intercept)	23655	1	23654.964	5906.423	< .001
VTMP_H_M_L	88.103	2	44.051	10.999	< .001
Residuals	1561.93	390	4.005		
ANOVA: WPE21_Satisfaction					
(Intercept)	20091.9	1	20091.858	3886.611	< .001
VTMP_H_M_L	98.035	2	49.018	9.482	< .001
Residuals	2016.11	390	5.17		
ANOVA: WPE22_Satisfaction					
(Intercept)	33178.9	1	33178.934	19255.047	< .001
VTMP_H_M_L	62.046	2	31.023	18.004	< .001
Residuals	672.02	390	1.723		
ANOVA: WPE23_Satisfaction					
(Intercept)	24437.2	1	24437.153	5874.733	< .001
VTMP_H_M_L	135.563	2	67.781	16.295	< .001
Residuals	1622.29	390	4.16		
ANOVA: WPE24_Satisfaction					
(Intercept)	25489.1	1	25489.122	7741.995	< .001
VTMP_H_M_L	115.873	2	57.937	17.597	< .001
Residuals	1284.01	390	3.292		
ANOVA: WPE25_Satisfaction					
(Intercept)	25828.5	1	25828.489	7396.39	< .001
VTMP_H_M_L	159.616	2	79.808	22.854	< .001
Residuals	1361.9	390	3.492		
ANOVA: WPE26_Satisfaction					
(Intercept)	21710.5	1	21710.537	4145.819	< .001
VTMP_H_M_L	68.138	2	34.069	6.506	0.002
Residuals	2042.33	390	5.237		
ANOVA: GWA1_Satisfaction					
(Intercept)	21784.9	1	21784.926	6337.153	< .001
VTMP_H_M_L	204.39	2	102.195	29.728	< .001
Residuals	1340.68	390	3.438		
ANOVA: GWA2_Satisfaction					
(Intercept)	22158.8	1	22158.781	6338.839	< .001
VTMP_H_M_L	162.89	2	81.445	23.298	< .001
Residuals	1363.33	390	3.496		
ANOVA: GWA3_Satisfaction					
(Intercept)	25682.8	1	25682.771	8533.279	< .001
VTMP_H_M_L	152.439	2	76.219	25.324	< .001
Residuals	1173.79	390	3.01		
ANOVA: GWA4_Satisfaction					
(Intercept)	23686	1	23686.008	6737.951	< .001
VTMP_H_M_L	220.02	2	110.01	31.295	< .001
Residuals	1370.97	390	3.515		
ANOVA: GWA5 _Satisfaction					
(Intercept)	19750.1	1	19750.117	4178.167	< .001
VTMP_H_M_L	176.36	2	88.18	18.655	< .001
Residuals	1843.52	390	4.727		
ANOVA: GWA6_Satisfaction					
(Intercept)	23950.7	1	23950.697	6466.772	< .001
VTMP_H_M_L	242.877	2	121.439	32.789	< .001
Residuals	1444.43	390	3.704		
ANOVA: GWA7_Satisfaction					
(Intercept)	22143.8	1	22143.766	4103.001	< .001
VTMP_H_M_L	79.417	2	39.708	7.358	< .001
Residuals	2104.82	390	5.397		
ANOVA: GWA8_Satisfaction					
(Intercept)	26317.2	1	26317.191	8567.734	< .001
VTMP_H_M_L	206.861	2	103.43	33.672	< .001
Residuals	1197.95	390	3.072		
ANOVA: GWA9_Satisfaction					
(Intercept)	22855	1	22854.985	5049.213	< .001
VTMP_H_M_L	122.702	2	61.351	13.554	< .001
Residuals	1765.31	390	4.526		
ANOVA: GWA10_Satisfaction					
(Intercept)	25618.1	1	25618.14	7437.707	< .001
VTMP_H_M_L	191.56	2	95.78	27.808	< .001
Residuals	1343.3	390	3.444		
ANOVA: GWA11_Satisfaction					
(Intercept)	22158.8	1	22158.781	5288.964	< .001
VTMP_H_M_L	192.265	2	96.132	22.945	< .001
Residuals	1633.95	390	4.19		
ANOVA: GWA12_Satisfaction					
(Intercept)	23469.1	1	23469.132	6176.743	< .001
VTMP_H_M_L	238.025	2	119.013	31.322	< .001
Residuals	1481.84	390	3.8		
ANOVA: GWA13_Satisfaction					
(Intercept)	19145.2	1	19145.163	3185.913	< .001
VTMP_H_M_L	114.204	2	57.102	9.502	< .001
Residuals	2343.63	390	6.009		
ANOVA: KE1 _Satisfaction					
(Intercept)	24690.1	1	24690.14	7241.879	< .001
VTMP_H_M_L	241.211	2	120.606	35.375	< .001
Residuals	1329.65	390	3.409		
ANOVA: KE2_Satisfaction					
(Intercept)	23826	1	23825.954	6229.87	< .001
VTMP_H_M_L	296.502	2	148.251	38.764	< .001
Residuals	1491.54	390	3.824		
ANOVA: KE3_Satisfaction					
(Intercept)	21695.7	1	21695.674	4919.494	< .001
VTMP_H_M_L	334.37	2	167.185	37.909	< .001
Residuals	1719.96	390	4.41		
ANOVA: KE4_Satisfaction					
(Intercept)	15763.7	1	15763.667	2369.107	< .001
VTMP_H_M_L	116.335	2	58.167	8.742	< .001
Residuals	2595	390	6.654		