



**THE INFLUENCE OF EDUCATION AND EXPERIENCE UPON CONTEXTUAL
AND TASK PERFORMANCE**

DISSERTATION

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AFIT-ENS-DS-16-S-073

**DEPARTMENT OF THE AIR FORCE
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DISSERTATION

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Abstract

Supply chain workers make observable, preventable errors while completing their assigned tasks in the shipping process. Previous research has indicated that individuals with a greater grasp of their work and better system-knowledge are less likely to commit interpretation errors. A worker's task performance and contextual performance may, likewise, be affected by an individual's knowledge of why and where they fit into a larger system—defined as mission clarity. Mission clarity is comprised of education, experience and subject characteristics. This research conducts a controlled experiment with 100 workers in the Air Force supply career field assessing the relationships of mission clarity elements and job performance. The results show that mission clarity affects pick and pack job performance in controlled warehouse order fulfillment tasks. Results also reveal that participants who received the experience portion of mission clarity committed fewer errors, resulting in increased task performance.

I am grateful for the loving support of my wife and children. They have been a blessing and source of encouragement throughout this research. To God belongs the glory for all great things.

Thank you Mom and Dad, for encouraging me to seek answers instead of accepting the unknown as status quo.

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Allen R. Miller

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I. Introduction

Problem Context

Human errors, inventory record inaccuracies, and organizational learning can cause and result from shipping errors (Argote, 2013; DeHoratius and Raman, 2008; Embrey and Lane, 1990). As an example, consider an incident from 2005-2008 that occurred involving Minuteman III nuclear missile components. In March of 2005 missile nose cones with fuses, but no nuclear material, were sent from F.E. Warren Air Force Base (AFB) to Hill AFB for storage. The items were mislabeled on the outside of the box as helicopter batteries and were placed on a pallet with other helicopter batteries. In August of 2006, Taiwan ordered helicopter batteries and the order was fulfilled from the Hill AFB storage facility. In March of 2008, Taiwan service members attempted to install the batteries and noticed they were the wrong part. They started the process for reimbursement and U.S. authorities realized the mistake and recovered the parts. The box was closed in March of 2005 and not opened until August 2008; all this time it was mislabeled and improperly accounted for and stored incorrectly (White, 2008).

The incident led to a public relations firestorm. There were 15 senior officers disciplined, extended media coverage and assessments throughout the Department of Defense (DOD). This inventory record inaccuracy, coupled with human error led to a significant shipping error. Afterwards, numerous root-cause studies were conducted and organizational changes were implemented, including standing up a new operational command structure called “Global Strike Command.” The goal of the changes and new command was to affect organizational change, facilitate learning and develop a culture of safety (Amaani, 2009). This example shows the interplay of human errors, the

importance of record accuracy, and the impact organization learning (or the lack there of) can have on shipping performance.

Errors in supply chain management can also be abundant and costly. In 2010, about 750,000 warehouses worldwide distributed approximately 1 trillion US dollars in goods. Warehouses represent approximately 20% of the logistics costs for many businesses, and order picking accounts for 55% to 65% of the total operational costs of a warehouse (De Koster et al., 2007). The large cost associated with warehouse operations generates the need for efficient and effective operations. The operations within a warehouse can be decomposed into individual tasks. Each task is affected by a number of known and unknown influences. Managers seek out practical methods to improve task performance, thereby increasing warehouse, firm and supply chain performance.

There are many processes in a warehouse, see Figure 1. However, they can be crudely categorized into four basic areas: 1) to receive the goods from a source, 2) to store the goods until they are required, 3) to pick the goods when they are required, and 4) to ship the goods to the appropriate user. Of these four areas, order picking is the most fertile process for productivity improvements since it is the most labor-intensive operation in warehouses with manual systems, and a very capital-intensive operation in warehouses with automated systems (Li et al., 2012). Being labor-intensive and the most expensive warehouse activity, errors in order picking can lead to increased inventory record inaccuracies (IRI) (Thiel et al., 2010) and higher costs for the entire supply chain (De Koster et al., 2007).

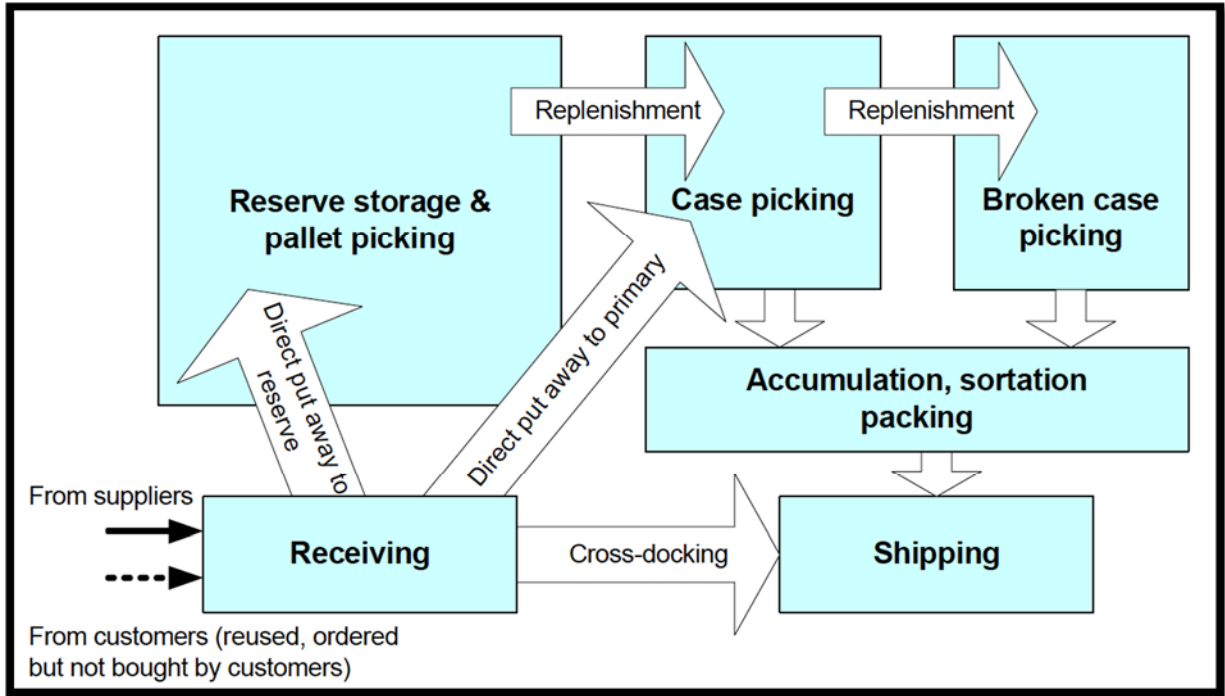


Figure 1: Typical Warehouse Functions and Flows (Tompkins, 2003)

Order picking is the term for all the sub-tasks required to gather items from an assorted inventory in preparation for shipment or internal movement; it is a fundamental activity performed in warehouses (Baumann et al., 2012). Often, the items are located in bins placed on shelves or large racking. Accompanying the task of order picking is the process of packing the picked items in preparation for shipment to the customer. In some warehouses, individuals are now capable of attaining 1000 picks per hour (De Koster et al., 2007). Such a vast number of actions creates significant potential for errors. Errors in the shipping process come from a variety of sources such as picking the wrong item, wrong amount, breakage, and confusion (De Koster et al., 2007). Another common source of errors arises from the necessity for workers to enter data into an information system. These errors frequently generate inaccurate inventory records that can propagate

to picking errors, resulting in increased order-return costs, create negative publicity, and can even pose safety hazards, such as when critical items do not arrive when and where needed (d'Hont, 2004).

Research into human task provides the most insight when the task elements are understood and assessed individually (Swain, 1990). Early task analysis efforts by Taylor (1911) and Gilbreth (1909) showed that a higher-level task could be broken down into its constituent parts (Diaper and Stanton, 2003). The process to assign each action a unique probability of error originated in 1952 with mathematician Herman Williams and electronics engineer Purdy Meigs at Sandia National Laboratories (Swain, 1990), who wanted to find ways to reduce the risk associated with working on nuclear weapons. The work of these early researchers has evolved into the field of human reliability analysis (HRA) (Swain, 1990). A key element of HRA is that each task performed by workers can be analyzed and assigned a probability of error based upon how often workers fail to complete the task in an acceptable manner. Furthermore, if a desired final error-rate is desired, managers can look at sub-tasks to find where improvements will have the most impact on overall performance (Bedny and Karwowski, 2003).

In supply chain management, human errors have been addressed peripherally; an exception is found in the Toyota Production System (TPS) and Lean initiatives, which have emphasized the impact of individual performance on overall production systems (Swamidass, 2007). TPS implements kanban structures, which are visual motivational elements to enhance performance. The kanban process makes a previously arbitrary action visible and is a constant reminder of the task at hand (Takahashi et al., 2007). Beyond TPS and Lean process movements, other aspects of the supply chain can be

affected by human errors (Galar et al., 2011). Supply chain management (SCM) literature has called for more studies assessing how individuals affect supply chain performance (Ballard, 1996; Fawcett et al., 2010).

This research addresses the phenomenon of human-errors in the supply chain in light of what has been called the Medici Effect, popularized in Frans Johansson's book "The Medici Effect" (Johansson, 2006). The Medici Effect states that discoveries often happen at the intersection of disciplines. Similarly, this research integrates key elements from human factors research, inventory management, and behavioral operations into the supply chain management (SCM) setting. Each of these disciplines contributes to understanding the phenomenon leading to errors in pick and pack operations. First, human factors research has looked at human performance in a variety of settings (Reason, 1995). Secondly, inventory management research has discovered that worker errors both contribute to and are caused by inventory record inaccuracies (IRI) (Mersereau, 2013). Thirdly, behavioral operations has shown how improvements in performance are related to individual traits including learning, both individually and how the organization learns processes and maintains cooperate knowledge (Argote, 2013; Bendoly et al., 2010). Lastly, the individual differences have been shown to impact behaviors (Jawahar and Gerald, 2011). Therefore, the current state of academic research is primed for an analysis of how individual performance affects warehouse operations, specifically picking operations. This research seeks to fill the SCM human-error gap by integrating these major areas into a model of individual job performance and conducting a controlled experiment to test the proposed model.

II. Literature Review

*We shall not cease from exploration
And the end of all our exploring
Will be to arrive where we started
And know the place for the first time.
--T.S. Eliot, Four Quartets*

Introduction

The above quote provides a poetic description of how academia and industry have viewed the relationship of training workers and performance. We know that without training, performance decreases and conversely, with more training performance increases (Fry, 1992). However, we do not often know precisely what training is most effective. How much training is enough? What amount of training provides the best return on investment? What is the most influential part of training: task training, education, or experience? How do we know the workers are actually learning what they are being taught? This research begins with these questions in light of the basic model below presented by Bruccoleri et al. (2014, p. 802).

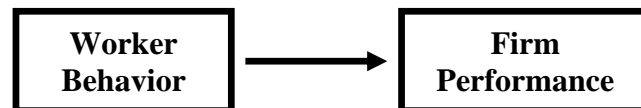


Figure 2: Worker Performance Model (Bruccoleri et al., 2014)

However, there are other factors influencing the basic relationship depicted in Figure 2. One example is that contextual performance affects job performance (Conway, 1999). This research will present results from literature to expand the conceptual model above, Figure 2, to include two additional steps, depicted in Figure 3.

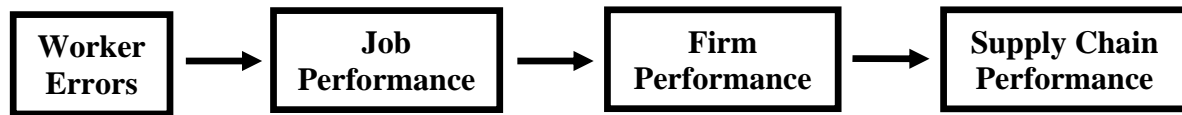


Figure 3: Errors and SCM Performance Model

This research discusses theories that help to establish a logical flow of how human error affects the SC and how organizations can and should address human error. This research begins by looking at the individual's performance in relation to learning, education, experience and training. Next, the research considers literature showing how organizations learn and how both individual and organizational learning affect performance. Performance is considered at the individual and organizational levels; this research also connects the resource-based view (RBV) and knowledge-based view (KBV) theories of the firm to firm performance. Errors are an inherent component of performance (Knoll, 2012); therefore this research will also present error theories, mitigation strategies and consequences. However, to begin this research will look at learning; first as individual, then, as an organization.

Individual Learning and Education

Learning is not a modern field of study; it has well established origins from the ancient philosophers (Jaeger, 1934) to more modern influential scholars such as John Dewey to contemporary scholars (Merriam et al., 2007). This research presents some of the overarching theories that researchers have broadly accepted and related to measureable behavioral outcomes. The behavioral outcomes include worker performance (Schunk, 2011) .

Behaviorism, cognitivism, constructivism, and transformative learning are the general learning theories most often referenced when discussing instructional settings (Siemens, 2005). Within these theories, the researchers present nuanced definitions of learning. Still, many of the definitions are quite similar; below, this research presents three definitions and discusses their common elements. First, consider Driscoll (2000), who defines learning as “a persisting change in human performance or performance potential...[which] must come about as a result of the learner’s experience and interaction with the world” (Driscoll, 2000, p. 11). A second, and widely used definition of learning is, “a relatively permanent change in behavioral potentiality that occurs as a result of reinforced practice” (Kimble, 1961, p. 6). Finally, an updated definition based on Kimble’s definition that incorporates changes in the field of learning is Olson’s (2015) definition. “Learning is a relatively permanent change in behavior or in behavioral potentiality that results from experience and cannot be attributed to temporary body states such as those induced by illness, fatigue, or drugs” (Olson, 2015, p. 6).

The above definitions all share the view that learning is relatively permanent. Furthermore, learning involves both the learner and some outside event, either *experience, practice, or interaction with the world*. The definitions also require behavioral change from the learner. Not all researchers studying learning agree that a behavioral change is necessary. Gestalt learning falls under the cognitive perspective of learning (Rock and Palmer, 1990). According to Gestalt theory, an initial failure, called *impasse*, is necessary for insight learning. An *impasse* requires the learners to forego their first solution strategy and begin the cognitive trial-and-error processes. As they

struggle through the cognitive trial-and-error process, they restructure or re-organize prior knowledge into new information, learning (Ash et al., 2012, p. 8).

Learning cannot be directly studied (Olson, 2015); therefore, researchers must utilize some observable element to act a surrogate for learning. So, even when researchers use a definition such as “learning refers to a change in behavior potentiality and performance refers to the translation of this potentiality” (Olson, 2015, p. 4), they still must develop a means to measure that potentiality. The behavioral element is a requirement for observation and measurement. Although, it is not a requirement for theory development nor introspective assessments (Ash et al., 2012). Indeed, many models of learning and cognition accept insight and knowledge before any behavioral change is exhibited (Köhler, 1959). Köhler elaborates by defining insight as, “the fact that, when we are aware of a relation, of any relation, this relation is not experienced as a fact by itself, but rather as something that follows from the characteristics of the objects under consideration” (1959, p. 729). Constructivism also includes insight as a vital element, but emphasizes the active involvement of the learner (Merriam et al., 2007). Finally, transformative learning theory includes three primary avenues of expanding consciousness: psychological, convictional, and behavioral (Mezirow, 1991). Again, we see the common elements of internal change occurring with learning, but still acknowledging that some behavioral resultant change is possible, if not apparent; therefore we would expect an experimental design looking at behavioral change to consider learning as a variable. Next, this research will cover literature that looks at the other aspect inherent to learning: education.

Education and Experience

The purpose of education according to Dewey was “to prepare the young for future responsibilities and for success in life, by means of acquisition of the organized bodies of information and prepared forms of skill which comprehend the material of instruction” (Dewey, 1938, p. 3). He viewed learners as passive recipients of their education; he did not mean it derogatory but to say that they lack the life experiences necessary to connect experience and education. He proposes an alternative method to standardized lectures of abstract thoughts that emphasizes linking experiences to the subject matter (Dewey, 1938). Dewey further suggests that progressive education will move from accepting passive learners to helping students understand the intimate and necessary relationship between education and experience. He contends that for learning to take place, it depends on the learner having the correct idea of related experiences. However, he warns against equating experience with education. In fact, an experience can be counter-productive towards learning and education. He recommends providing experiences that enable and enhance education (Dewey, 1938). Kolb expanded Dewey’s work by defining learning as, “the process whereby knowledge is created through the transformation of experience.” (Kolb, 1984). This definition deviates from the definitions presented earlier; it does not include a behavioral requirement and elevates the importance of experience. This view of education and experience is consistent with Kolb and Kolb’s experience-based learning theory (Kolb and Kolb, 2005). Experience-based learning theory is an extension of Dewey’s perspective that education should include experience in addition to traditional educational methods (Dewey, 1938).

Skinner isolated the experience concept, contending that learning occurs as the result of a repeated and reinforced stimulus (Skinner, 1953). His work has evolved into the classical behaviorism with wide-spread acceptance of the stimulus-response (S-R) phenomenon (Chance, 2007). Researchers have expanded, even replaced, Skinners S-R model (Chance, 2007; Moxley, 1998). However, the role experiences play in learning has not faded (Argote and Miron-Spektor, 2011). The goal of education in industry is to enable the worker to accomplish some new task or to accomplish an activity with better performance (Crick et al., 2013). In the military, the services send workers to technical schools ranging from a few weeks to many months based on the complexity to the career field (USAF, 2014). The goal is that the workers are able to perform the tasks for which they were trained (USAF, 2008). Therefore, managers (and academics) must assess the performance of the workers to see what was learned and how it will impact organizational performance.

Performance

Increased performance is the desired result of learning and, by extension, the goal of training, education and experience (Crick et al., 2013). Motowildo et al., build the case that job performance is comprised of task and contextual performance; they define job performance as the “aggregated value to the organization of the discrete behavioral episodes that an individual performs over a standard interval of time” (1997, p. 72). Furthermore, their theory integrates individual personality and cognitive differences to explain the variability in task and contextual performance. Motowidlo and Van Scotter conducted job performance research in an operational setting using real-world tasks and surveys. They utilized 715 Air Force mechanics ranging from the enlisted ranks of E-2 to

E-5. The subjects were graded by senior supervisors on overall performance, task performance and contextual performance. They found that experience explains more variance in task performance and personality explains more variance in contextual performance (Motowidlo and Van Scotter, 1994). This research will look at both task performance and contextual performance in more depth below.

Task Performance

“Behavior is what people do at work. Performance is behavior with an evaluative component” (Motowidlo et al., 1997, p. 73). The workers’ performance will change the condition of the organization and will either contribute to or hinder organizational goals (Motowidlo and Van Scotter, 1994). Motowidlo makes a distinction of task performance that is intuitive, but the distinction has not garnered wide acceptance (Yang et al., 2016). Motowidlo describes the first type of task performance as “activities that transform raw materials into the goods and services that are the organization’s products” (Motowidlo et al., 1997, p. 75). He defines type two as the support, administrative and logistical tasks (Motowidlo et al., 1997). Although his terminology and stark delineation has not gained wide usage, academics and practitioners continue to acknowledge a difference in *sharp-end* and *blunt-end* positions in an organization (Dekker et al., 2011; Hopkins, 2012; Reason, 2002). This difference may play a role in how well the workers perceive the impact of their daily routines. It may be that type one task, sharp-end, have a more accurate perspective of how their actions accomplish the organizations goals (Reason, 1998). If so, the type two tasks, support or blunt-end, may not have as broad a perspective of how their actions affect the primary mission of the organization. Both classes of behaviors bear a direct relation to the organization’s technical core either by

direct execution, sharp-end, or by maintenance and support, blunt-end (Motowidlo and Van Scotter, 1994; Reason, 2008).

So, how can organizations improve worker performance? Brackenreg has found that experiential learning can improve task performance (2004). She defines experiential learning as including some sort of *doing* along with traditional education. This method of teaching is focused on gaining a better understanding of the task itself. The goal is help the worker to attain a better cognitive understanding of the task to the point they are able to articulate what they are doing, connecting their experience to the principle being taught (Brackenreg, 2004). Kolb (2009; 1984) developed a conceptual model, see Figure 4, showing how the cyclical nature of experiential learning can lead to broader, and hopefully more accurate, formation of abstract concepts. Therefore, research assessing performance would expect experiences to affect the measured outcomes.

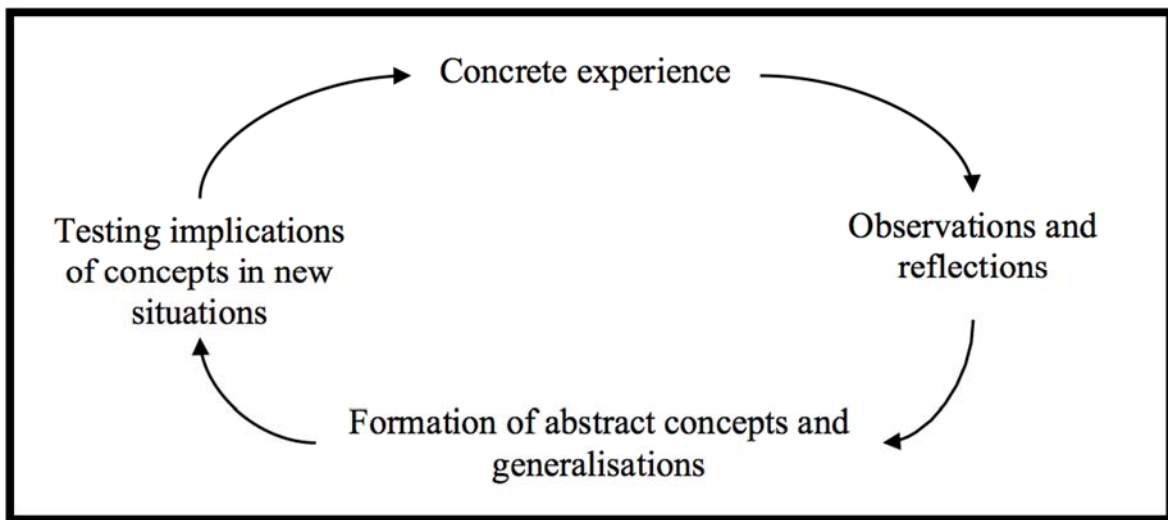


Figure 4: Lewinian Experiential Learning Model (Kolb, 1984)

In the field of human factors, researchers have been concerned with performance since its inception (Reason, 1990). Rasmussen developed a widely accepted three-level framework for understanding human performance, see Figure 5 (Rasmussen, 1983; Sheridan, 2015). “SRK provides a language in which to talk about types of behavior as a basis for system design. It provides a basis on which to clarify differences in behavior.” (Goodstein et al., 1988, p. 28).

Rasmussen’s early discussions of SRK began with skills, then rules and showed knowledge as the most advanced; later models by Rasmussen and other researchers reverse the order to show the natural progress experienced in learning (Sheridan, 2015). Knowledge-based behaviors occur in situations that are somewhat unfamiliar; considerable cognition is required to interpret, diagnose and decide upon an action (Rasmussen, 1982). Rule-based behaviors require more cognitive effort than skill-based behaviors, however they are based on previously experienced and stored (cognitively or externally) rules (Rasmussen, 1982). “The activity at the rule-based level is to coordinate and control a sequence of skilled acts, the size and complexity of which depend on the level of skill in a particular situation—one single decision to go home for dinner may be enough for driving you there, if the ride is not disturbed” (Rasmussen and Lind, 1982, p. 10). Skill-based behavior consists of stored patterns of behavior such as driving a vehicle, operating familiar machinery or performing routine tasks (Goodstein et al., 1988). Rasmussen emphasizes that the line between skill-based and rule-based behaviors can be fuzzy and depends on the experience of the individual (Rasmussen and Lind, 1982). As workers face new indicators (stimuli) they can switch between the levels of performance. Thus, when people face a new stimuli they are forced out of skill-based

routine and perform a quick search for a stored rule. If a rule-based behavior is appropriate, the worker will execute it. However, if the worker is not able to retrieve a stored rule, they will resort to knowledge-based processing (Goodstein et al., 1988). Actions at the knowledge-based level are much slower, require more cognitive resources and lead to more varied errors (Reason, 1990).

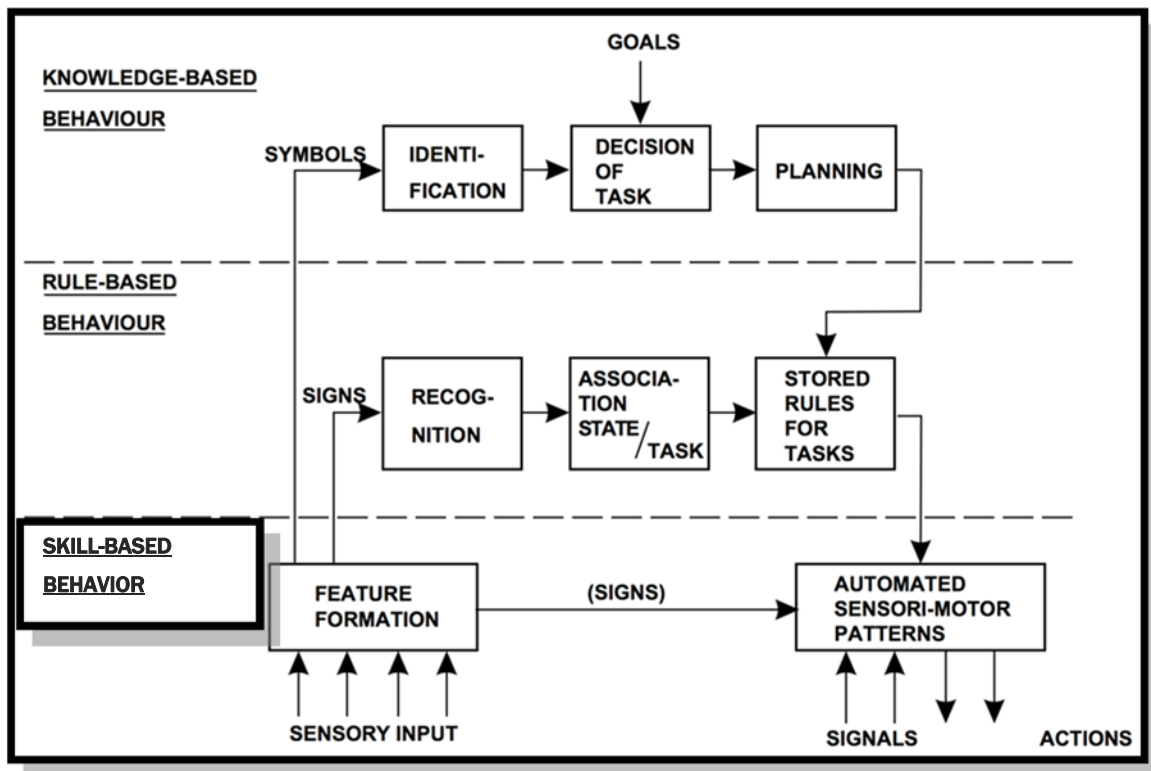


Figure 5: SRK Performance Levels (Rasmussen, 1983)

Many researchers have built upon Rasmussen's work; one common extension is Reason Generic Error Model (GEM) (Reason, 1990; Sheridan, 2015). Reason's proposed three types of errors: slips, lapses and mistakes (Reason, 1990). Reason says that the GEM relates to Rasmussen's SRK framework; "in particular it illuminates the origins of

both the commonplace departures of action from intention slips and lapses and far more subtle reasons why plans sometimes fail to achieve the desired end (mistakes)” (Reason, 1990, p. 35). Reason explains that the reason the SRK model has persisted overtime is that it intuitively matches our behavior. He states that humans are compulsive pattern-matchers (Reason, 2002). When confronted with novel challenges, our automatic reaction is to seek some off-the-shelf solution from within our stock of stored routines. Such choices are guided by two simple heuristics: (1) match like with like and (2) where there is a set of equally desirable possibilities, apply the one most used. (Goodstein et al., 1988). This research will look the GEM in more depth later in the context of human error theories. Now, the research will turn from task performance to present the other aspect of job performance, contextual performance.

Contextual Performance

Motowidlo et al. define contextual performance as:

“activities that promote the viability of the social and organizational network and enhance the psychological climate in which the technical core is embedded, activity such as helping in cooperating with others; following organizational rules and procedures even when personally inconvenient; endorsing, supporting, and defending organizational objectives; persisting with extra enthusiasm when necessary to complete successfully; in volunteering to carry on task activities that are not formally part of the job” (1997, p. 76).

Researchers have used the term contextual performance to refer to the phenomenon above; however, many researchers use the term organizational citizenship behavior (OCB) to describe similar behaviors. Organ’s original definition was:

“individual behavior that is discretionary, not directly or explicitly recognized by the formal reward system, and that in the aggregate promotes the effective functioning of the organization. By discretionary, we mean that the behavior is not an enforceable requirement of the role or the job description, that is, the clearly specifiable terms of the person’s

employment contract with the organization; the behavior is rather a matter of personal choice, such that its omission is not generally understood as punishable” (Organ, 1988, p. 4)

Organ now defines OCB as, “performance that supports the social and psychological environment in which task performance tasks place” (Organ, 1997, p. 95). The new OCB definition is more succinct; Organ even says the contextual performance and OCB are now considered synonymous. He states that the only remaining difference is that he considers OCB to be exclusive to non-rewarded task (and non-punishable for neglecting the task) whereas contextual performance might include all non-technical related tasks (Organ, 1997). In addition to being a construct, OCB is also a well-used survey measure designed to capture contextual performance (Smith et al., 1983). Therefore, for the remainder of this research, the terms are considered synonymous and the term OCB will be used to refer to the measure of contextual performance.

This researcher has presented literature that shows the dual nature of job performance, task performance and contextual performance. Before leaving the topic, this research will consider one other relevant view regarding the determinants of job performance. Motowidlo (1997) expands the work of Hunter (1983) in defining three distinct determinants of job performance: declarative knowledge, procedural knowledge and skill, and motivation. Declarative knowledge is the knowledge of facts principles and procedures; procedure knowledge is both skill and actually doing what should be done; motivation is a choice comprised of, whether to exert effort, how much effort to exert, and how long to exert effort. Motowidlo found that, “individual differences in personality, ability, and interests are presumed to combine and interact with education,

training, and experience to shape declarative knowledge and procedural knowledge and skill” (Motowidlo et al., 1997, p. 77).

Theories of the Firm

In this section, this research compares two theories of the firm. This research considers the resource-based view (RBV) and the knowledge-based view (KBV) theories of the firm due to their interconnectedness of ideas with performance, human factors and organizational learning. The prevalent theories that researchers use in the SCM field often only address human errors only peripherally, if at all (Williams and Tokar, 2008). These two theories integrate the human component to varying degrees and will be useful for applying our research to the SCM field.

Most academics contend Wernerfelt (1984) formalized the RBV theory, although some cite Penrose (1959) as the progenitor of RBV (Conner, 1991). Wernerfelt (1984) proposed that firms should consider the resource side of their operations to the extent that most firms analyze the production side. He does not use the terms upstream and downstream resources, but that is how some have described RBV more recently (Rungtusanatham et al., 2003; Zhu et al., 2004). He defined firm resources as “assets which are tied semi-permanently to the firm” (Wernerfelt, 1984, p. 172). He offers an even broader definition by saying resources can be viewed as the strength or weakness of a firm: such as, brand names, in-house knowledge, employee skills, contacts, equipment, and procedures. The RBV looks at both tangible and intangible assets. Therefore, it has been used in a broad spectrum of applications (Kraaijenbrink et al., 2010).

Some have argued that RBV is not a true theory of the firm (Foss, 1996). The widely accepted standard for a theory of the firm is that it must answer two questions: first, why

does the firm exist, and what is the firm's scope (Coase and Coase, 1937; Conner, 1991; Demsetz, 1988)? The argument against RBV as a theory of the firm contends that it explains how a firm operates and competes (scope), but it does not explain why the firm exists. Without addressing the firm's purpose for being, some cannot accept it as a valid theory of the firm (Kraaijenbrink et al., 2010). Nonetheless, there are many who consider it to be an adequate theory of the firm (Barney, 1994; Conner, 1991; Foss, 1996). Another perspective is to pair the RBV with the KBV to create a viable theory of the firm (Dosi et al., 2008; Grant, 1996).

As with all theories, they are refined and advanced by others, even morphing significantly over time. RBV is no exception. The following quote is from Wernerfelt written as ten-year follow-up to his original article. "The original paper is very terse and abstract, hiding both the practicality and the generality of the ideas. In my view, the paper was not influential because of my own later work, but because a number of others chose to build on it" (Wernerfelt, 1995, p. 171). A good example of how it has evolved is found in Barney's (1994) explanation of a firm's sustained competitive advantage (SCA). If a firm desires to obtain a SCA it needs to procure and fully exploit valuable, rare, inimitable, and non-substitutable resources. As firms compete, under the RBV, the firm that has the best resources and can fully exploit them will outperform other firms. Therefore, the firms should develop the resources that give them the best advantage (Wernerfelt, 1984). A worker's effectiveness is considered a resource (Peteraf, 1993); the more effective workforce will commit fewer errors (Reason, 2000). Consequently, the firm with the more effective workforce will have a more valuable human capital resource, which is a factor in their SCA.

The KBV faces many of the same criticisms and hurdles as the RBV; however, when they are viewed in tandem, more researchers are willing to accept them as a theory of the firm (Foss, 1996; Takeuchi', 2013). The RBV includes knowledge as a resource; however, KBV elevates knowledge above other sources. Researchers give knowledge preeminence over other resources due to its difficulty to develop, synergistic effects, and strategic importance (Purser and Montuori, 1995). Knowledge is also unique when firms seek to procure it as a resource. Spender (1996) shows that knowledge procurement is inherently different from other resources. Spender's arguments are similar to the concept presented below, see Figure 6, showing that knowledge can reside in an organization even if all the people in the organization are exchanged. The RBV originated out of economic literature as an alternative to transaction based economics (Penrose, 1959; Wernerfelt, 1984). Whereas, the KBV originated from strategic management efforts (Phelan and Lewin, 2000); the literature supporting a KBV of the firm has a stronger psychology and management background (Huber, 1991). The KBV, as a theory of the firm, requires the foundational theory of organizational learning.

Organizational Learning

Organizational learning (OL) has been defined as a construct, field, and theory. OL, has changed significantly in the literature in recent decades. Therefore, this research uses the historical evolutionary perspective (Shah and Ward, 2007) to first look at the past development of OL and its early use in the social sciences, progressing to how supply chain (SC) managers presently view it. Next, the research will present recommendations from literature for better use of OL, and show how OL relates to other valuable theories employed in SCM.

OL is a competence that all organizations should actively develop, given that it has been shown that the better organizations learn, the more likely they are to detect errors, correct them, innovate and even assess what errors they cannot detect (Argyris, 1999). Research involving OL has evolved through many definitions and applications to arrive at where it is today. OL was first presented as a formal theory when Weber (1922) identified the ability of bureaucracies to learn from experiences. As time progressed, researchers developed finer analyses of what it meant to learn as an organization. An extant work by Bavelas (1950), identified that not only do organizations have individuals that learn in them...the organizations themselves take on a progressive capacity to perform differently, essentially, they can learn. He developed a simple exercise to prove his concept. He formed two groups of five members each and had them perform a task, which required them to share information that is given to the members individually. The first group's members were identified as A1, A2, A3, A4, and A5. The second group was comprised of individuals identified as B1, B2, B3, B4, and B5. Group A was arranged in a hub and spoke pattern and the B's in a loop pattern, see Figure 6. After the participants were thoroughly trained in the task, they began communicating; Group A via the member in the middle and Group B via the person next to them going around the circle. After a number of additional trials, A1 and B1 were interchanged. The groups continued to use their respective patterns. After a few more trials, A2 and B2 were switched, then A3 with B3, and so on until the original hub and spoke group was populated by B1 through B5, and the original circle group with A1 through A5. In the end, the original A's and B's switched how they communicated as they switched organizations. It demonstrated an

emergent (at that time) property of an organization—a persistence of pattern that survives a complete replacement of the individuals in a group or organization (Simon, 1991).

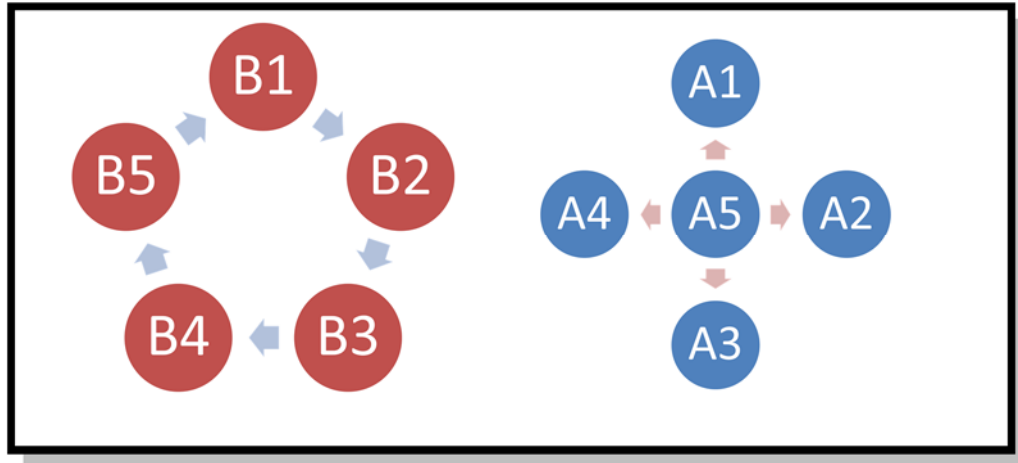


Figure 6: OL Experiment (Bavelas, 1950)

The above example supports the view that the diffusion of information comes not only via formal manuals, training, and other explicit modes, but also from the informal efforts to function as productive member in the organization (Lave and Wenger, 2001). In the experiment, the newcomers modified their previous training to match their surroundings. Learning can be abstract learning, or the practice of the actual work performed by members of an organization (Brown and Duguid, 1991). Some authors suggest that the informal methods of discussing organizational norms, practices and asking, “how are things done around here” from perceived organizational experts are more influential on OL than formal efforts (Brown and Duguid, 1991). OL becomes a relatively intangible strategic resource in the SCM process, as such, it can help to develop a competitive advantage for the company (Biotto et al., 2012; Flint et al., 2008; Panayides, 2007). The competitive advantage is realized by members responding to

changes in the internal and external environment, specifically correcting or elevating errors in the firm's functions (Esper et al., 2007). This perspective brings OL in close contact, and in fact supporting, the KBV and RBV of the firm (Manuj Ayman Yazdanparast, Atefeh, 2013).

The above findings frame an important question that has permeated the area of OL since its inception. Where does learning and knowledge reside in a firm (Epple et al., 1991)? If it resides completely in the physical aspects of the firm (training manuals, equipment, technology, etc.) then every shift at a production plant should perform very similar regardless of the workers. Conversely, if the elements of the firm can change or be removed, and the firm continues to function well, then knowledge appears to reside in the individuals. However, there is likely a combination of the two locations (Epple et al., 1991). Others have proposed that knowledge resides solely in the individual (Simon, 1991). He proposes that OL only occurs in one of two ways: either by the learning of its members or by incorporating new members with new knowledge. However, he contends that although the learning is solely by the members, it is what those members know in common that is manifested as OL. In other words, OL is the social aspect of individual learning (Simon, 1991). His view is contrasted by the Bavelas two-group example above and current perspectives that attribute the collective knowledge to the actual organization (Esper et al., 2007). Multiple researchers have proposed models to identify how individual knowledge relates to OL (Cohen, 1991; March, 1991). One proposed model suggests that there are four progressive constructs that facilitate the integration of individual knowledge into knowledge possessed by the organization (Crossan et al., 1999). Their proposition is that individuals obtain knowledge through the methods

previously discussed and achieve the ability to intuitively “know” how to act. Next, they interpret various situations and determine how to act upon their intuitions. Then, the individuals know how their knowledge and actions affect their tasks; they integrate their knowledge. The final step is for processes to become permanent through formal and informal transfers to other members to achieve institutionalization. Thus, OL occurs via *intuiting, interpreting, integrating, and institutionalization* (Crossan et al., 1999). If we accept this model or similar models that show a progression from individual learning to OL, then the goal would be to facilitate and speed the transition from individual to organization (Esper et al., 2007).

Some organizations have evolved from a group of individuals with collective knowledge into synergistic functioning entities, as seen in the world of manufacturing as it became more diverse, intertwined, and expansive (Langley, 1986). Weick (1991) researched how well manufacturing operations were able to learn, when learning was defined, in the traditional manner, as performing a task differently when presented with the same stimulus. Weick proposed that firms also learn to produce the same response when presented with different stimuli. He explains that a company that is able to produce goods at a steady rate when a supply disruption occurs is an example of different stimulus, but same response. This reversal of same-different to different-same presented a conceptually new way to perceive and study OL. “The goal is to construct a theoretical representation of the sequence of events that occurs while stimulus information is transformed by perceptual and cognitive operations into the encoded forms that are preserved in organized memory” (Estes, 1988, p. 362). This definition of learning for individuals has increasingly been applied to both individuals in an organization and the

organization itself (Weick, 1991). If one is to accept that an organization can learn, then there should be research measuring the rate at which an organization learns. Yelle (1979) proposed that organizations have learning curves; he tested his hypothesis in manufacturing settings and found that OL is related to performance and can be measured similar to individual learning curves. Other research called the phenomenon an “experience curve” or “progress curve” (Argote, 2013); yet, the concept is similar to Yelle’s (1979) findings. With the concept of a SC as an entity or organization itself gaining acceptance (Cooper et al., 1997), the concept of OL has further extended to the collaborative environment necessary for the SC to function (Biotto et al., 2012). Therefore, literature has identified knowledge and learning as occurring at both the individual and organizational levels.

The trend of OL literature indicates that it is becoming more widely accepted and more broadly applied in business settings, including SCM. Furthermore, more universities are offering OL as a course in undergraduate and graduate business fields of study (Argote, 2013). The concept of OL has a solid foundation, established in multiple disciplines; the future of OL looks to be of immense value to multiple fields, including reducing errors in the shipping process.

Organizational Learning as a Theory

In the SCM literature, researchers have been calling for a greater focus on how OL affects SC performance (Richey et al., 2010; Schmenner et al., 2009). Authors tend to focus either on organizational learning as the actual organization learning (such as corporate knowledge), or the authors focus on the individual learning. SCM addresses OL much like it addresses human error: it is perceived as strategically important, but not

well understood (Lee et al., 2013). Managers using the Toyota Production System attest that individual learning and performance has a great impact on the overall production system (López et al., 2005). Despite the lack of SCM literature focusing on OL, it has found acceptance as a theory in some literature (Argyris and Schon, 1996; Fiol and Lyles, 1985). Its growth into a theory is due to the importance it has on firm performance, in concert with an ever-increasing focus of academic research on the impact of OL (Miner and Mezias, 1996). Specifically, OL as a theory is important in SCM due to the impact it has, not only on firm performance, but how it affects overall SC performance (Hult et al., 2003).

Despite the logically deduced theoretical link that organizational resources such as OL can improve customer relationships and give rise to higher service quality (Hult et al., 2000), relatively few SC studies have been devoted to empirically testing the effects of organizational learning (Hult et al., 2003). The acknowledgement of how important OL is as a strategy for competitive advantage has been accepted in the marketing field longer than in SCM (Panayides, 2007). Thus, a review of OL literature finds more support in marketing and organizational behavior literature than in SCM literature. SC managers are still seeking for more conclusive answers of how OL influences their SC specific organizations (Hult et al., 2007; Yu et al., 2013).

As more firms shift from employee task-training to knowledge-based learning, the importance of OL theory will likely grow (Bowersox et al., 2000). With task-training, the employee knows how to perform their assigned task regardless of the upstream or downstream processes. Conversely, knowledge-based learning in SCM settings, requires a more holistic approach to learning, such as teaching via multiple mediums (Hine and

Goul, 1998). As we expand the concept of a learning organization, we can see that the concept logically applies across entire supply chains. Therefore, additional benefits could be realized from learning across the broader entity of the supply chain. The result of the learning organization is that firm performance improves by developing learning skills and harnessing the knowledge of its employees. However, according to Mangan and Christopher's (2005) assessment, logistics organizations may not be the best examples of learning organizations. They state that SCM has placed far less of an emphasis on the growth and development of personnel than on operational efficiency and improving customer relations. A better use of OL by SCM would be to conduct research applicable to practitioners that also solidifies OL theory as an integral part of SC performance. Other fields that contain a social element have invested more in OL theory; the work achieved in related fields serves to bolster the position that SCM performance could be improved through a better understanding of how individuals and organizations learn.

In its current state, OL is inherently part of a multi-theoretical lens. Depending on which field is studying OL, it has been related to organizational behavior (Cyert and March, 1963), RBV (Olavarrieta and Ellinger, 1997), KBV (Chiva and Alegre, 2005). Authors who present OL as a theory identify its applicability both managers and academia. Theoretical implications for OL relate to how an idea of performance can be impacted by who, what, when, where, why, and how we learn as individuals and as organizations. OL theory has gained ground as conceptual models have permeated the literature. The proliferation and acceptance of common models not only benefits the theory, but aids practitioners who want to know how all this actually affects their

organization. Managerial implications for OL are growing as the theory helps practitioners gain understanding of how they can disseminate information and integrate knowledge in their organization.

Human Error Theories

The types of errors that a person can make vary based on settings and activity (Gel et al., 2010). Therefore, researchers have developed and employ varied models and theories with unique characteristics making them more fitting for specific settings. Numerous methods have been developed for assessing system reliability in regards to human error. The technique for human error rate prediction (THERP), systemic human error reduction and prediction approach (SHERPA), task analysis for error identification (TAFEI), human cognitive reliability (HCR), a technique for human error analysis (ATHENA) and the cognitive reliability and error analysis method (CREAM) are just a few of the methods for determining how human error-rates affect overall system reliability (Swain, 1990). This research does not compare each method; rather, the intention is to highlight current literature showing how the field addresses human reliability.

The Normal Accident Theory developed by Charles Perrow proposes two related dimensions, interactive complexity and loose/tight coupling (Perrow, 1983). He explains that these two items determine a system's susceptibility to accidents. Interactive complexity is the presence of unfamiliar, unplanned, and/or unexpected of events. These events are often not visible or at least not readily perceived. He defines a tightly coupled system as being highly interdependent and having each part of the system linked to many other parts. This relationship means that a change in one part of the system will potentially affect all of the system. Thus a tightly coupled system would respond quickly

to errors, while a loosely coupled or decoupled systems would be able to absorb errors without destabilization (Perrow, 1983). System accidents that occur in systems with both interactive complexity and tight coupling will likely not be resolved before causing system-wide consequences. Like Reason, he concludes that accidents are inevitable in systems, yet he does provide suggestions for improved safety (Reason, 1990). The basic goal is to reduce the degree to which a system is tightly coupled (Marais et al., 2004). He is advocating measures to increase system resiliency.

Bedny and Karwowski looked at the warehouse operations of “picking and packing” orders (Bedny and Karwowski, 2003). They assigned a probability of error based upon how often workers fail to complete the task-element in an acceptable manner. The original efforts up through the work by Bedny and Karwowski show that managers can look at sub-tasks to find where improvements will have the most impact the overall error-rate. This ability to assess the overall probability of error continues to be researched to see how it can foster a culture of safety (Galar et al., 2011). However, there are limitations to these human reliability analyses HRAs; some even call them counterproductive to increasing safety (Leveson, 2011; Marais et al., 2004). Other research has used empirical measures to develop error-rates for a given task (Berger and Ludwig, 2007). While researching the impact of auditory feedback devices, Berger and Ludwig found that pickers had an error rate of about 2.44 errors per 1,000 cases picked (Berger and Ludwig, 2007).

Swain presents a detailed analysis of how HRA can be used by organizations. The article presents the needs for HRA, types of HRA, and limitations of HRA. He contends that the main use of HRA is to facilitate the broader probabilistic risk assessment (PRA)

of a system. In particular, he states that “as equipment becomes more reliable, human errors contribute relatively more to system problems” (Swain, 1990). For example, in nuclear power plants human error has been estimated to account for over 90% of the estimated probability for accident scenarios. When seeking to understand human reliability, Swain proposes that the analysis has both qualitative and quantitative components. The qualitative components relate to proposing potential means in which an error can occur. Much of this analysis takes place before the system is built in order to design a more resilient. The quantitative component is comprised of measurements of human error probabilities (HEPs). The HEPs are calculated based on a detailed task analysis and provide a rate of errors over a given period of time or number of occurrences. Although the PRA, and consequently, HRA, are still conducted and provide a valuable tool for system design and operations, they do have limitations. First, the HRA could be calculated with less-than-adequate data. This problem leads to the use of stop-gap models and subject-matter experts (SMEs) to provide estimates. Also, standardized measurements, such as psychosocial instruments, have to be calibrated for given settings and systems. The estimates can be used for simulations, but if the parameters were incorrect, the variance is propagated further through the simulation. There is also a lack of validated models that have taken proposed HRAs and then compared the calculated rates to the finished operating system’s rates. As with all estimates, there is also a limitation from the assumptions made in order to complete the analysis. Finally, there is a limitation of performance shaping factors such as attitudes, cultural differences and irrational behavior. All of these limitations are commonly accounted for by increased estimate variances and higher HEPs (Swain, 1990). Swain

provides suggestions for increasing system reliability in the presence of less-than-adequate data; his proposals are presented in the final section of this paper along with other mitigation strategies.

The above research lead to the creation of a widely accepted model of human-error, the generic error-modeling system (GEMS). This is the model adopted by this research. Its ubiquitous nature in human factors, psychology and management fields means that it has influenced much research by its structures, even if not explicitly stated. The GEMS has its foundations in the work of Rasmussen and Rouses in the early 1980s, but was synthesized and popularized by James Reason and Donald Norman throughout the 1980s and 1990s (Rasmussen, 1987; Reason, 1990; Rouse, 1983). The GEMS proposes three types of errors based on three types of performance. The *execution* stage of cognitive processing is where most actions occur and functions at the skill-based level. The errors at this stage are manifested as slips and lapses. Slips and lapses are errors due to failures in execution and/or storage of an action sequence (Reason, 1990). The next type of error occurs at the rule-based level of performance. Errors at this level are classified as rule-based mistakes. They are based on faulty rules for execution and associated with *storage* cognitive processes. A faulty rule will lead to a “strong-but-wrong” response. These types of error are often harder to detect as rapidly as skill-based errors. In fact, if there are not subsequent checks, the mistake may never be found (Stewart and Chase, 1999). Finally, the third level of performance is the knowledge-based level and invokes *planning* cognitive processes. Here, mistakes require feedback because the individual is consciously aware of the problem and recognizes the need for problem solving (Reason,

1990). These three levels of performance provided the foundation for Reason's proposal of the "Swiss Cheese" model, see Figure 7.

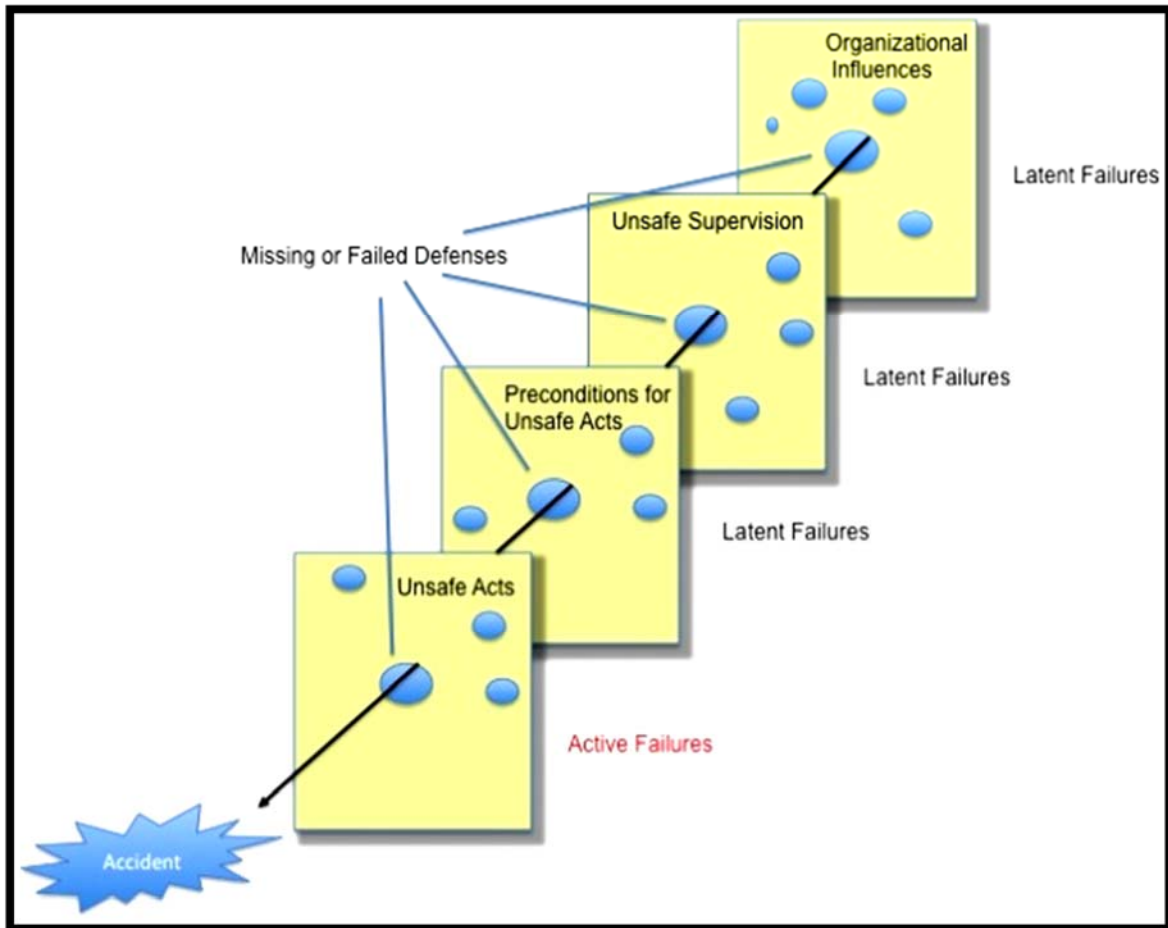


Figure 7: Accident Causal Model; aka "Swiss Cheese Model" (Reason, 1990)

The fundamental concept of his model is that accidents are rarely, if ever, the result of a single error. Normally, a single error is detected at a subsequent step and remedied before the initial error results in an accident. However, sometimes the subsequent fail-safes also fail. The series of errors was compared to slices of Swiss cheese that all happen to have holes lined up in such a fashion that an error flows through multiple

checks. Reason further proposes that each slice of cheese represents specific aspects of the accident environment. Figure 7 shows how Reason proposes organizational influences, unsafe supervision, and preconditions for unsafe acts all facilitate conditions for latent failures. These hazards lead to an environment where active failures flow through expected checks to cause a mishap. The weaknesses of the latent layers are not necessarily active failures but may manifest when they should catch an unsafe act; for example, fatigue or complacency (Jennings, 2008). Shappell and Wiegmann modified Reason's model by including 19 specific causal categories and called it the human factors analysis and classification system (HFACS) (Shappell and Wiegmann, 2004). The categories are subordinate definitions for four main domains that mirror Reason's model as can be seen in Figure 8 (Jennings, 2008). An analysis of each category is beyond the scope of this comparison; but as an example, consider the modifications to the unsafe acts segment. Shappell and Wiegmann added errors as subordinate to unsafe acts and as a peer to violations. Errors can be classified further into decision errors based on procedural errors, poor choices, or problem solving errors. Skill-based errors are technique based or "stick and rudder" errors. Perceptual errors are related to decision and skill-based errors, but are based on some faulty perception, often due to a degraded operating environment. The other category for unsafe acts is violations. Violations can be routine, such as driving 5 mph over the posted speed limit. Violations can also be exceptional, such as flying an airplane under a bridge (Shappell and Wiegmann, 2004). The GEMS model provided the basis for the Department of Defense (DOD) version of the HFACS.

The DOD-HFACS, see Figure 9, was developed in 2003 in response to a mandate by Secretary of Defense, Donald Rumsfeld, to reduce the number of accidents in the DOD. He proposed the goal of a 50% reduction over two years (Jennings, 2008). To facilitate this endeavor, he proposed a revamp of how we look at accidents. The intent was to develop a single structure to analyze the role human factors play in aviation, ground, weapons, afloat, space and off-duty mishaps.

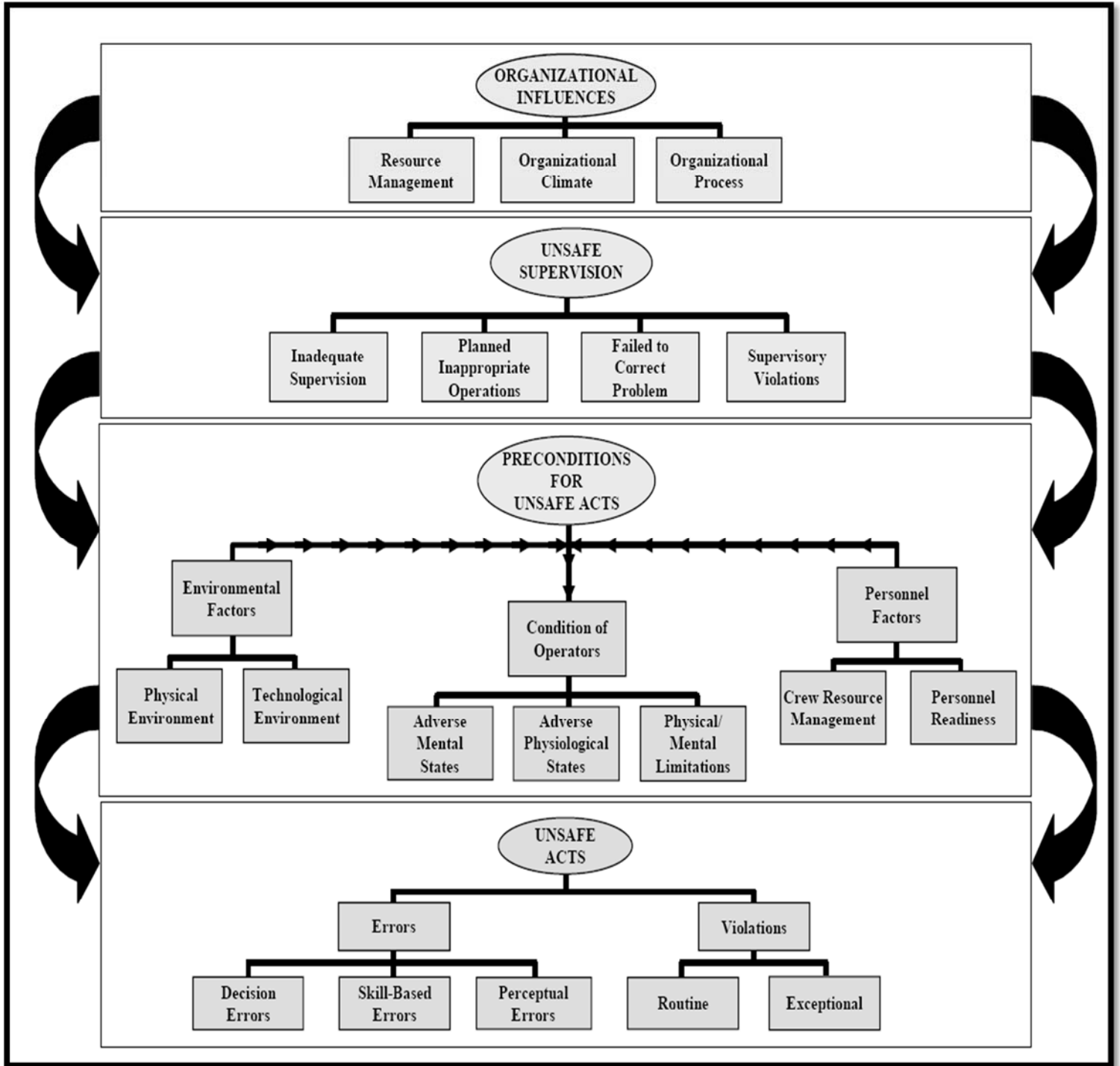


Figure 8: HFACS (Jennings, 2008)

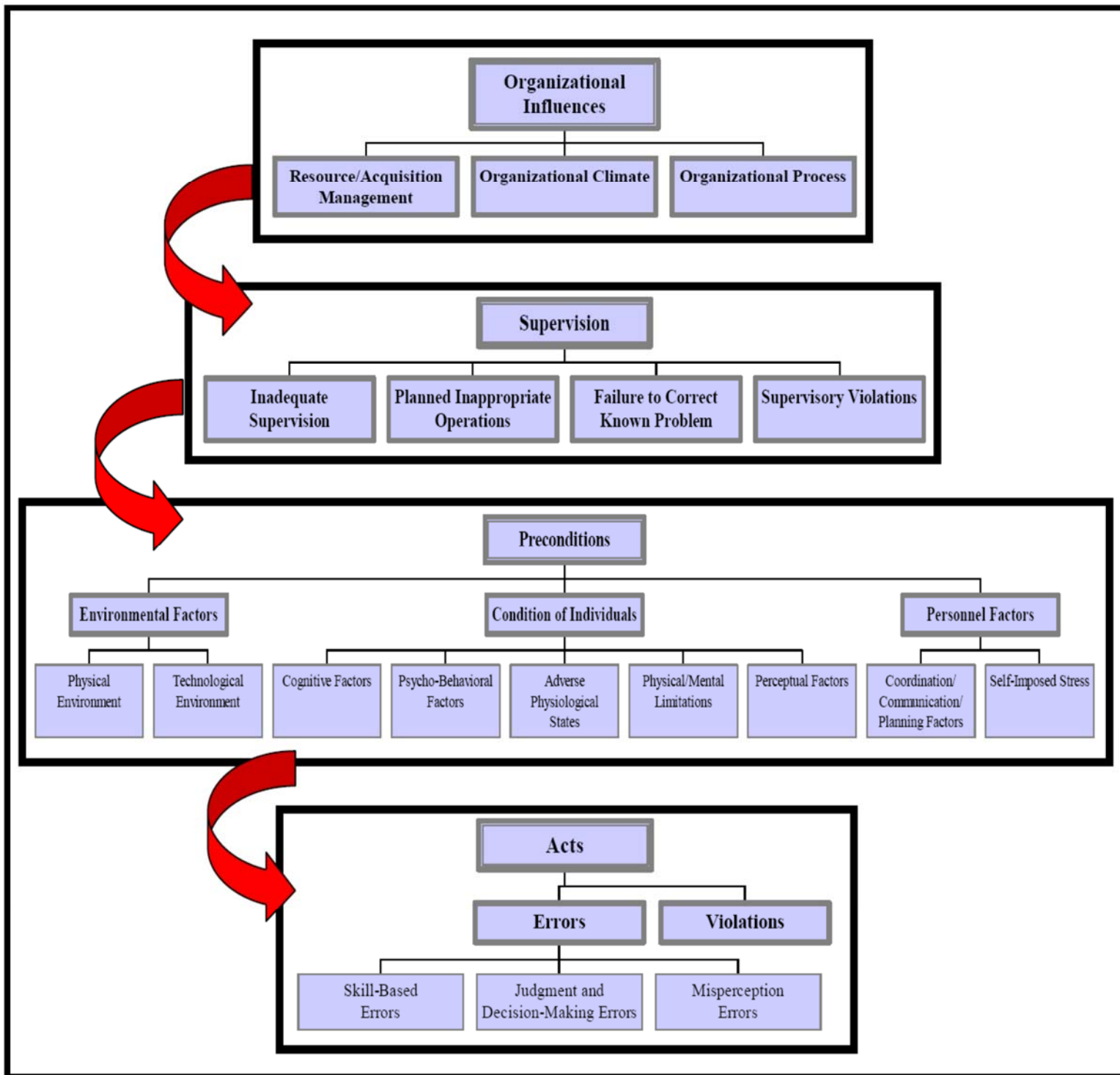


Figure 9: DOD-HFACS (Jennings, 2008)

The existing HFACS was designed based on aviation accidents. The DOD wanted a structure that would work for all types of military accidents. In 2005, all branches and agencies of the DOD agreed to use the DOD-HFACS to investigate accidents (O'Connor, 2008). The DOD-HFACS is very similar to the existing HFACS with the following exceptions, identified by O'Connor, that make it more applicable to non-flying situations as well.

- 'routine violations' and 'exceptional violations' were dropped as categories of 'violations'
- 'adverse mental state' was dropped as a category of 'conditions of the individual'
- 'cognitive factors', 'psycho-behavioral factors', and 'perceptual factors' were added as 'conditions of the individual'
- 'crew resource management' and 'personal readiness' were dropped as categories in 'personnel factors'
- 'coordination/communication/ planning factors' and 'self-imposed stress' were added as categories in 'personnel factors'

The resulting DOD-HFACS diagram is very similar to the original HFACS diagram as can be seen by comparing Figure 8 and Figure 9. The DOD-HFACS includes lower levels of analysis for each of the categories visible in Figure 9. The additional categories provide analysts guidance as they use the system for assessing root causes of accidents. A case study of the system was conducted by an Army safety officer, (Jennings, 2008) showing how the DOD-HFACS has been used to assess high mobility multipurpose wheeled vehicle (HMMWV) rollovers. He attributes the high number of rollovers in 2004 to the technical modifications made to "up-armor" a vehicle. The added protection changed the vehicles' center of gravity and made them more top-heavy and consequently

more likely to rollover. Jennings walks through the use of the DOD-HFACS for an individual rollover, noting how the aggregate analyses of numerous rollovers lead to changes in training and standard operating procedures. While there are many factors affecting rollover rates, Figure 10 is an example of a successful accident-remediation.

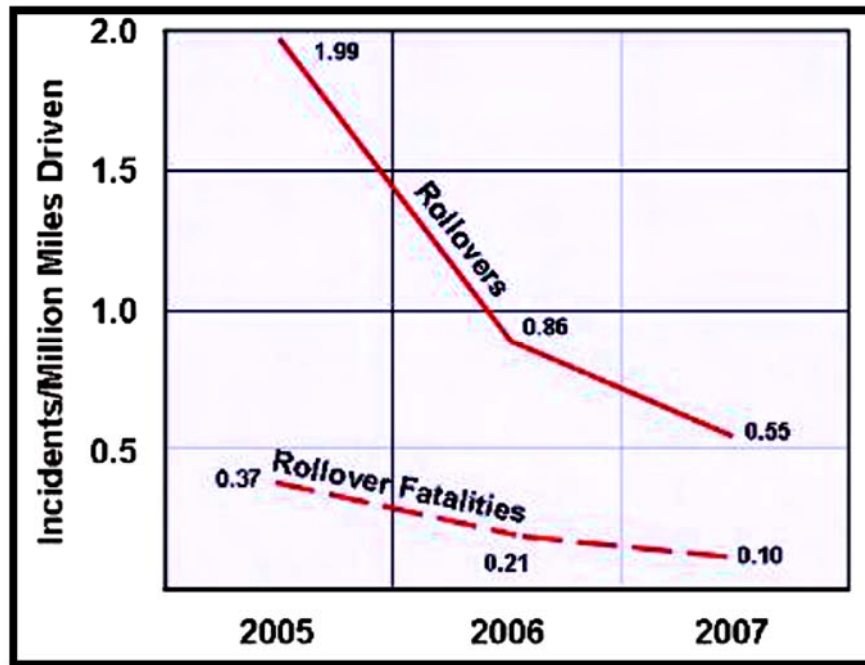


Figure 10: Rollover Assessment, DOD-HFACS (Jennings, 2008)

One last system for assessing errors and understanding system safety will be presented because it contrast the basics of the previous systems and seeks to replace them (Leveson, 2011). Leveson developed a system based on her unsatisfied experiences with previous models. Her proposal is that previous models are insufficient for accessing failures given today's technology. She contends that previous models are based on analogue technology that behaves very differently than the digital systems in use today.

Modern systems are built with such complexity that “they are beyond our ability to intellectually manage” (Leveson, 2011, p. 4). The premise of her proposed system is built upon challenging existing assumptions and proposing seven new assumptions. The first assumption she challenges states that previous models operate on the assumption that safety can be calculated like reliability rates. That is, if we make each component less prone to error (higher reliability rates), then the entire system will be less likely to fail. She challenges this assumption by saying that a system can be highly reliable and highly unsafe at the same time.

A system can fail even when none of the components fail; this phenomenon attests to the complexity of our systems (Dekker et al., 2011). For example, the Mars Polar Lander crash-landed due to an unforeseen interaction between systems that were individually highly reliable (and worked as programmed). The reverse thrusters received a signal that the landing leg system had deployed. Although the landing legs deployed properly, when programmed, the thrusters were programmed to accept this signal as an indication that the landing sequence was complete. Therefore, the system thought the landing sequence was complete and shut down the thrusters while still airborne. Another example occurred in a batch chemical reactor in England. The system was programmed to hold all variables constant when an anomaly was detected. An anomaly was detected just as a needed cooling-valve was opening. The system halted the change of any variables, preventing the valve from fully opening to provide the cooling water. The reactor overheated releasing contaminated steam into the atmosphere (Leveson, 2011). Occurrences such as these lead to the new assumption that systems with high levels of reliability are neither

necessary nor sufficient for the system to be safe. The remaining six assumption replacements are provided in Table 1.

Table 1: STAMP Assumptions (Leveson, 2011)

Old Assumption	New Assumption
Safety is increased by increasing system or component reliability; if components do not fail, then accidents will not occur.	High reliability is neither necessary nor sufficient for safety.
Accidents are caused by chains of directly related events. We can understand accidents and assess risk by looking at the chains of events leading to the loss.	Accidents are complex processes involving the entire sociotechnical system. Traditional event-chain models cannot describe this process adequately
Probabilistic risk analysis based on event chains is the best way to assess and communicate safety and risk information.	Risk and safety may be best understood and communicated in ways other than probabilistic risk analysis.
Most accidents are caused by operator error. Rewarding safe behavior and punishing unsafe behavior will eliminate or reduce accidents significantly.	Operator error is a product of the environment in which it occurs. To reduce operator "error" we must change the environment in which the operator works.
Highly reliable software is safe.	Highly reliable software is not necessarily safe. Increasing software reliability will have only minimal impact on safety.
Major accidents occur from the chance simultaneous occurrence of random events.	Systems will tend to migrate toward states of higher risk. Such migration is predictable and can be prevented by appropriate system design or detected during operations using leading indicators of increasing risk.
Assigning blame is necessary to learn from and prevent accidents or incidents.	Blame is the enemy of safety. Focus should be on understanding how the system behavior as a whole contributed to the loss and not on who or what to blame for it.

In relation to human errors, Leveson suggests changing how we design systems to compliment the human ability to control the system. Currently, many systems have humans doing tasks that are better fit for automation and have automated decisions that could be made better by humans. An example is to design systems with incremental algorithms that require human interaction along the path to the desired outcome. This is based upon the idea that in simple systems, the errors are normally errors of commission. For example, the operator incorrectly actuated the wrong control. Conversely, in

complex systems, most errors are errors of omission. The system is working in an automated fashion and the operator fails to conduct a step needed in the middle of the automated process. The occurrence of omission errors can be reduced by maintaining the operators' vigilance throughout automated processes. A simple example is found in our computers as we try to delete a file. If we hit the delete key, the system could completely erase the file and all records of its existence (to a degree not retrievable by the average user). However, the process is broken into segments requiring user interaction when the file is deleted, confirmed, when deleted from recycle bin, and again confirmed. Such process changes will decrease the likelihood of an unintended outcome (Leveson, 2011).

The above assumptions and observations are all integrated into the Systems-Theoretic Accident Model and Processes (STAMP). The goal of STAMP is to integrate safety into the system design from the beginning. The author states that too often safety analyses occur after an incident or late in the product use stage. Conversely, when using STAMP, engineering a safer system requires designing the safety-control structure and controls into the system as an inherent part of the system. However, the Air Force already has supply systems (among many other systems with varying levels of interaction with primary supply systems) in existence. Leveson suggests redesigning the system as appropriate to obtain the benefits of a STAMP-based design. The STAMP is a relatively new method and does not have the broad implementation of the HFACS. None-the-less, the premise of integrating safety in the entire system design as proven to be effective for reducing errors in varied systems (Khan et al., 2012; Lewis, 2013; Marais et al., 2004). Some systems can be quite complex and the consequences for errors significant. Next,

this research considers literature of these organizations, which require high levels of reliability in operations.

Errors in High-reliability Organizations (HROs)

This research is concerned with errors in HROs due to the impact an error can have upon the organization and society at large. There is a wide-range of organizations that have been analyzed as HROs; researchers most often associated with HROs are Todd La Porte, Gene Rochlin, Karlene Roberts, Karl Weick, and Paula Consolini (Marais et al., 2004). HROs are enterprises with “missions involving processes that require extraordinary measures to maintain low risk in the presence of disruptions that could result in catastrophic events or fatalities” (Lewis, 2013). An HRO has also been described as a social system that has developed a cultural sensitivity to social, organizational, cognitive, and technical challenges; it accepts the challenges and transforms them into opportunities for safety improvements (Bagnara et al., 2010). The concept of six sigma states that in many circumstances 99% accuracy is not satisfactory. Rather, through continued improvement error-rates can drop to less than 1 in 1,000,000. This rate is referred to as six sigma because it is near the sixth standard deviation of normally distributed data (Kwak and Anbari, 2006). An internet search will reveal a number of motivating statistics about why 99.9% is not acceptable. For example, 99.9% accuracy in maternity wards would result in twelve newborns going to the wrong parents daily (Quinley, 2013).

Society accepts the need to have some systems extremely reliable, such as nuclear power plants and commercial aircraft; however, less obvious processes also can have far-reaching implications for those involved. For example, a sausage factory that distributes

tainted meat can have deleterious effects for a large population. To effectively operate at high levels of reliability, individual tasks must be completed with high accuracy, or have redundant systems to increase reliability (Roberts et al., 2001). Bierly and Spender state that HROs become increasingly complex and often experience more noticeable accidents than other organizations (Bierly and Spender, 1995). Therefore, high-risk organizations transform into HROs based on the sensitivity they often develop in response to the isolated events that could trigger larger accidents. They look at the single enterprise of nuclear submarines. Roberts, et al. conversely, state that peer organizations can have very different levels of reliability based on managerial decisions (Roberts et al., 2001).

Roberts et al. propose three keys to enhancing reliability in complex organizations. First, the organization will aggressively seek to know what it does not already know. The quest to reduce the “unknown” will empower their employees by spending more on training, exercises, and process changes than other organizations. The result is employees who are able to detect unusual or unexpected problems. The second proposed key is to balance efficiency with reliability. “Firms that have reduced numbers of accidents are fully aware of the simple truth that what gets measured gets managed” (Roberts et al., 2001). To obtain high levels of reliability, the authors contend that organizations must obtain feedback via surveys, focus groups, and interviews to ensure that the real goals of the organization are the same as what management believes them to be. For reliability and efficiency to be fully balanced, incentive systems must reflect this balance. They recommend instituting an accounting system to capture the costs of having and preventing exercises. The third and final key they propose is to communicate the organizational big picture to everyone.

Organizations must also empower individual workers to understand their impact on the overall system. Roberts et al. (2001) provide the example of the *Herald of Free Enterprise* passenger ferry. In 1987, it was transporting 460 passengers and 80 crewmembers in addition to vehicles. The helmsman was responsible for checking the open door indicator light. He failed to check the light and the ferry started across the channel with the door open. Water inundated the ferry and it sank, resulting in 188 deaths (Roberts et al., 2001); his error impacted much more than his localized duty. An organization that necessitates high levels of reliability should ensure that all workers understand how their tasks affect the larger operations (Roberts et al., 2001).

The DOD can be analyzed as an HRO; at a lower level, even individual mission sets within the Air Force share characteristics of an HRO (Alonso et al., 2006; Baker et al., 2006). As HROs, the units within the DOD can be improved by many of the same measures that aid other HROs; however, there are unique attributes that both hinder and help military units increase their reliability (Bagnara et al., 2010). The military is accustomed to conducting exercises and developing robust contingency plans. Yet, the military has not traditionally considered it vital that members know how their assigned tasks fit into the larger mission. We are often content to provide virtually all members tactical knowledge, but reserve operational and strategic information that reveals how each component works together. While the nature of warfare dictates an element of secrecy, some tasks may benefit from informing the operators of how they support the entire mission.

Error mitigation strategies

Swain (1990) states that better implementation of human factor considerations will reduce the likelihood of an error going unnoticed. He provides five examples where most systems are currently underutilizing human factor resources and can be improved. The first area of improvement is to realize that 99% error-free is often unacceptable in high-risk systems such as discussed above. The current mode of operation is to rely on difficult-to-follow written procedures; an alternative would be to make relatively minor changes in processes or system structures to better mitigate the impact a single error will have on the system (Reason, 2004).

Another area for improvement is to implement a system of unannounced emergency exercises with “table-top” walkthroughs. It appears that managers have heeded his recommendation. Currently, the Department of Homeland Security exercises civilian organizations that have the potential for catastrophic emergencies...such as a nuclear power plant. Individual plants also have implemented measures akin to Swain’s recommendations. The Diablo Canyon nuclear power plant has it workers conduct normal operations for three weeks, then has one week of training and exercises (Roberts et al., 2001). He also states that checklists for normal operating procedures are commonly used during emergencies. A better practice would be to develop emergency operating procedures that can be accessed based on symptoms. This would be similar to pilots having normal procedural checklists in written format in addition to memorized “bold-face” checklists for specific emergencies.

Finally, he states that displays and controls should be organized to aid the creation of accurate mental models when there is an error (Swain, 1990). A personal example was

observed in the C-17 aircraft. Its fuel system controls are laid out in the shape of the aircraft. To transfer fuel from one tank to another, the pilots active a switch that is located graphically on the panel between the tanks. When there is a problem in a given location of the fuel system, the location blinks. Additional initiatives to mitigate errors have been popularized by the Lean initiatives and the TPS (Takahashi et al., 2007).

For example, organizations following TPS often implement the kanban procedures for scheduling the movement of inventory (Nolan, 2000). A simple kanban example may function as a three bin system where one bin resides on the production floor and contains one type of part needed for assembly. When the bin is empty, the kanban card is displayed. Then, a worker takes the bin to the local inventory store and switches it for a full bin and new kanban card. The inventory store continues the exchange with the supplier, filling the third bin. The process cycles and, when working as designed, the worker will not accidentally run out of inventory nor will there be an excess of inventory at the production center (Takahashi et al., 2007).

A more error-prevention focused example from TPS is the use of poka-yokes. Poka-yoke is a Japanese term meaning “fool-proof” or “mistake-proof.” The poka-yoke principle is to design a system so that it cannot be accomplished incorrectly under normal circumstances (Nolan, 2000). An example is electrical plug-ins; if a device requires a specific polarity, one prong will be wider than the other preventing users from inserting the plug upside down. Other applications certainly advocate the concept of poka-yoke designs apart from TPS. Nolan proposes that processes can be designed to reduce the error-rate of humans using the process. The example he provides is receiving cash from an ATM. Since the objective is receiving cash, some customers will walk away before

the transaction is finalized and the card returned. However, if the process is changed so that the cash is not dispensed until the very end (after the receipt and card are dispensed) then fewer people will forget their card in the ATM. He states that the same concepts could be initiated in hospitals to reduce errors (Nolan, 2000). For example, manufacturers could make anesthetic connections for different applications in such a way that they cannot be hooked together incorrectly. A process change example would be to not stock easily confused items in the same areas (Reason, 2004).

The DOD has employed some of the above suggestions to reduce accidents and error-rates. The DOD changed how it managed the storage of nuclear weapon related material (NWRM) after two highly publicized events when NWRM was mistaken for other inventory (Snyder et al., 2013). The Air Force and Navy implemented the recommendation to store critical items that are easily confused in separate locations. Now, all NWRM is stored in a physically separate part of the warehouse. An ongoing area of improvement is new training methods (Kwak and Anbari, 2006). Roberts et al. state that formal training can be effective for improving workers' ability to recognize when they commit an error. However, in the most reliable organizations, the formal training is accompanied by strong cultures that recognize that the system is not perfect and that improvements can be noticed at all levels (Roberts et al., 2001). The DOD is still formulating how it can foster a culture of safety when our profession inherently participates in high-risk activities. We cannot eliminate all dangers or human errors. Reason suggests the goal is to understand that processes involving humans will have human error; however, creating a culture of safety will enable the mission to continue even in the presence of infrequent errors (Reason, 1998).

Error Theories in the Air Force

The models presented above have provided varying levels of utility for the Air Force. They all have something to offer, not the least of which is to get us thinking about how human factors have affected other organizations. Additionally, they have guided this research to know what type of errors should be expected in a HRO and in a supply setting. While the above models are quite different in some regards, they have elements that can have been integrated into an Air Force initiatives to improve supply chain performance. System design efforts seek to reduce error in a system by changing the fundamental system structure and its workings (Daouk and Leveson, 2001). This is the hallmark of the Leveson's Theoretic Accident Model and Processes (STAMP) model. Leveson suggests that a system can be designed from the ground up in such a fashion that it will preemptively reduce the opportunities for error. She also states that if a system is already in place, then it must be redesigned using the STAMP model to gain the most benefit (Leveson, 2011). The Air Force supply structure is already in place, and has many processes that are deeply rooted across the entire federal government.

The Air Force is constrained by international agreements, Environmental Protection Agency requirements, DOD requirements, and our own publications. Leveson's model provides insight into how both existing and revamped automated processes can best operate with users. Her model suggests that improvements can be made to both the physical structure and the processes. An example of a partial redesign occurred with the implementation of a new Air Force supply transportation protective services checklist, see Figure 11. This process was redesigned to synthesize guidance from multiple agencies. Part of the process is automated and part of it requires user input and

interactions. While the checklist was developed before Leveson's 2011 book, the new process incorporated the concept of involving the user at key steps in the process. This same checklist also included elements from the GEMS.

Although the Air Force integrated some newer methods found in human error literature, it continues to use DOD-HFACS as the primary human error analysis tool. The DOD-HFACS can be implemented by users with significantly less training and provide more consistent results than a systems-approach that varies more frequently (Jennings, 2008). Even though the DOD-HFACS has a defined structure, it is not static; it can be modified by adjusting pertinent factors in each subsection. The DOD-HFACS is most applicable to large-scale errors or accidents; whereas, the GEMS can provide a means of remediation for less complex errors. While there can be many consequences of error depending on the organization and system (Marais et al., 2004), errors that affect inventory records are particularly egregious in the supply chain management (Kök and Shang, 2004).

OUTBOUND TRANSPORTATION PROTECTIVE SERVICE MATERIEL WORKSHEET		
Shipping Arms Ammunition And Explosives (AA&E), Classified (Secret and Confidential), Nuclear Weapons-Related Materiel (NWRM), Sensitive and Controlled Items Worksheet		
Pack, prepare and move transportation protective service material IAW DTR 4500.9-R, MIL-STD-129, AFI 24-203, AFI 20-110, and/or applicable Technical Order. By completing this worksheet, certifiers are verifying that applicable guidance has been followed.		
I. PACKAGING/PREPARATION		
A. Shipping document: TCN#	DD FORM 1348-1A	DD FORM 1149
B. Has shipping document been thoroughly reviewed to ensure type of shipment, CIIC and SRC? Type Shipment (Circle All That Apply): AA&E SECRET CONFIDENTIAL SENSITIVE CONTROLLED CRYPTO ITEM NWRM What is the CIIC? SRC?		
C. Does serial/lot number(s) on shipping document match item serial/lot number(s)?	Serial/lot #:	
D. Is item packed IAW special packaging instructions to prevent damage while in-transit?		
E. Has packing list with appropriate documentation been placed inside Number 1 container?		
F. Are the appropriate labels/markings on the outside of the container?		
G. Has shipping document(s) been properly annotated? (Print name/sign/date/time) to show receipt.		
<u>PACKED BY:</u> PRINT NAME/SIGNATURE: DATE/TIME:		
<u>CERTIFIED BY</u> PRINT NAME/SIGNATURE: DATE/TIME:		
II. SHIPMENT DOCUMENTATION		
A. Has a DD Form 1907 or truck manifest been prepared to ensure control of the shipment?		
B. For MILAIR shipments: Has an ATCMD been properly prepared/routed? Has a DD Form 1387-2 been properly prepared and distributed?		
C. Has an appropriate movement document been prepared? Has the movement document been released in CMOS to provide advanced shipment notification, strategic ITV and, if applicable, activate DTTS?		
D. Has a REPSHIP been forwarded immediately upon carrier departure? Does REPSHIP request acknowledgement of receipt of the shipment?		
<u>DOCUMENTATION PREPARER</u> PRINT NAME/SIGNATURE: DATE/TIME:		
<u>CERTIFIED BY</u> PRINT NAME/SIGNATURE: DATE/TIME:		
III. SHIPMENT DISPOSITION/RECORDS		
A. Has receiving agency acknowledged receipt of REPSHIP?	Acknowledged by:	DATE/TIME:
B. Has REPSHIP been suspended?	RDD	Actual Delivery Date
C. Has all documentation for this shipment been filed IAW AFRIMS?		
AF FORM 4387, 20110511		

Figure 11: TPS Checklist (AF Form 4387)

Inventory Record Inaccuracies

As firms operate with, and maintain, physical inventory they also keep a record of the inventory's location. The degree to which the inventory is tracked varies greatly, from the legal minimum showing purchases and sales to total asset visibility using state-of-the-art tracking technologies such as radio frequency identification (RFID) systems (DOD, 2003; Rinehart, 1960). Occasionally, the physical inventory quantity is different from the inventory record quantity. The difference between the inventory record and the physical inventory creates an inventory record inaccuracy (IRI) (Iglehart and Morey, 1972). The vast majority of inventory management literature does not account for the differences in physical and recorded inventories (Kang and Gershwin, 2005). The exception is literature focused on IRI. For this section of the literature review, this research will look at the history of research regarding improving record accuracy. The goal of this section is to provide a source for understanding the field of inventory accuracy literature, including presenting sources of IRI, solutions for IRI and to highlight opportunities for future research.

IRI adversely impacts business activities that rely upon accuracy for demand data, forecasts, and replenishments (Thiel et al., 2010). It is estimated that companies spend about 1% percent of annual sales on automated decision support tools (Steidtmann, 1999). Inaccurate data undermines the billions of dollars spent on these automated systems. Most firms, and academic literature, have not accounted for the variance between physical inventory and data records. They are either unaware of the discrepancies or have operated on the assumption that the difference between the two is small enough that it will not impact operations (Fleisch and Tellkamp, 2005). However,

empirical and analytical research has shown that the differences can be stark and have a deleterious effect upon operations (Iglehart and Morey, 1972; Kang and Gershwin, 2005).

This research will use the historical evolutionary perspective (Shah and Ward, 2007) to first look at the past development of IRI research and its use in the supply chain management (SCM) literature from its early references, progressing to how SC managers presently view it. Then, this research will expand the review of IRI literature by first providing an overview of IRI terms, including sources and solutions from IRI literature.

IRI Background

The general definition of IRI is that it occurs when there are discrepancies between the physical quantity and the stock keeping unit (SKU) record quantity (DeHoratius and Raman, 2008). Rinehart (1960) is the first researcher to identify IRI as an obstacle to operational performance. From a case study of a federal government supply facility, Rinehart documents substantial discrepancies between recorded and actual inventory quantities. IRI also includes record discrepancies relating to location. If an item is misplaced, it is unable to fill a customer demand until found (Rekik, 2011). IRI can lead to items becoming “frozen” or “inflated.” A frozen record shows that there are sufficient items in stock to meet demand but the physical inventory is not available for purchase (Barratt et al., 2010). This phenomenon happens with automated data processing systems because the system indicates sufficient inventory (above the reordering point). The inventory level will remain static or frozen, due to the fact that no physical inventory is available for customers to initiate a demand for the automated data system. Conversely, if the system shows less inventory than is physically available, then a purchase can

prematurely generate a requisition resulting in excessive on-hand inventory (Barratt et al., 2010).

The extent of the problem has been assessed heuristically (Thompson, 1985), empirically (DeHoratius and Raman, 2008), and analytically (De Kok et al., 2008). DeHoratius & Raman (2008) conducted research with a large electronics retailer and found that out of about 370,000 SKUs, more than 65% of the inventory records did not match the physical inventory levels. Additionally, 20% of the inventory records differed from the physical stock by six or more items. Barratt et al. (2010) found that in only a ten-day period, physical inventory swung above and below the corresponding system record. The problem of IRI can be quite drastic and have a significant impact on reordering policies (Iglehart and Morey, 1972). The discrepancies can arise for a myriad of reasons, the reasons most often cited in the IRI literature include shrinkage, misplacement, random yields from suppliers, and transaction errors. Each of these causes have a human error component.

IRI Causes

Shrinkage is the term used to describe attrition of inventory over time; it is also called stock loss. The most common forms of shrinkage are thefts and accidental damage by workers and customers (Rekik and Jemai, 2009). Some have divided shrinkage into malicious and non-malicious categories (Beck and Chapman, 2003; Rekik and Sahin, 2012). Non-malicious shrinkage includes losses due to spoilage, obsolescence, demonstration wear, and accidental damage (Atali et al., 2009). Malicious shrinkage includes fraud, unauthorized consumption, and theft. However, most human error-models are focused on the actions of *well-intentioned* workers and do not address

malicious behaviors as performance errors (Reason, 1990). Shrinkage is unique from the other sources of IRI because it only results in negative discrepancies, whereas the other forms of IRI can result in a net positive or net loss. Therefore, shrinkage, especially unknown stock losses, result in overestimates of actual stock on hand (Fleisch and Tellkamp, 2005).

Misplacement errors result in inventory that is not readily accessible for use or sale. The material is in the facility somewhere, but the location is unknown to the person seeking to purchase or use the item (Kang and Gershwin, 2005). The item could have been misplaced by a customer moving it from shelf to shelf. Misplacements can also result from employee errors while handling the item at any point during receiving, storing or stocking processes (Rekik, Sahin, Jemai, et al., 2008). The items may be miscoded and routed to the wrong location, or the workers may commit a handling mistake and place the item in the incorrect location. Misplaced items appear to be a stock-out to customers and can require significant man-hours for employees to track down misplaced items. The extent of misplaced items can be large; Ton and Raman (2004) reported that, in 2002, 4% of Amazon's warehouse inventory was misplaced. Possibly related to misplacement and other human induced IRI, is the phenomenon of satisficing (Winter, 2000). Schwartz et al. state that satisficing occurs when an individual "simply encounters and evaluates goods until one is encountered that exceeds the acceptability threshold" (2002). Although this research is often applied to economic choices, it has been show to apply in other scenarios (Caplin et al., 2011).

Suppliers can also introduce IRI into the system by supplying incorrect quantities, miscoded items, or defective products (Rekik, 2011). Bensoussan, Çakanyildirim, and

Sethi (2007) found that shipments are frequently accepted and data updated in the inventory information system without physical verification of the items. This practice will lead to IRI that may not be discovered for great lengths of time, even years (Solis, 2004). Moreover, if the products delivered are counted but not inspected for usability, then inaccuracies can manifest later in the process when subpar items are discovered (Bensoussan et al., 2007).

Transaction errors normally occur at the receiving and outbound sides of the facility. A common retail transaction error results from cashier scanning procedures. For example, a customer may purchase three different flavored granola bars. They are all identically priced and look somewhat similar. To quicken the checkout process, the cashier may only scan the first bar then key in a multiplier of three. Or, they may actually swipe the same bar three times and push the rest over to be bagged. When cashiers do not scan each SKU, a transaction error occurs resulting in either an overage or shortage of actual inventory in relation to the inventory data system. On the inbound side, shipments that arrive from the suppliers have to be registered into the store information system. If the items are incorrectly processed at this point, there will be a resulting IRI (Kang and Gershwin, 2005). This error is closely related to the aforementioned discrepancies from the suppliers' shipments. It is possible for the data to be incorrect due to multiple errors. The shipment could have the wrong amount and be miscoded. Later the same items could be misplaced or stolen. All of these factors emphasize the benefits of having total asset visibility (Solis, 2004).

In addition to shrinkage, misplacement, supplier yield, and transaction errors, researchers have considered other factors, although much less frequently. Causes such as

employee turnover, RFID accuracy, and database management have all been considered (DOD, 2003; Raman et al., 2001; Sari, 2008). Of particular note, is an experiment conducted by Sheppard and Brown (1993) that considered: unit value, weigh-counting, quantity on-hand, dollar value of stock on hand, number of places that the part was used, and stockroom staff's rating of the error likelihood for a part. The authors found each of the items to significantly impact IRI. Having considered some of the sources of IRI, this research now turns to the common solutions presented in literature.

IRI Solutions

Periodic counting of all inventory on hand was the standard method of improving record accuracy for many years and continues to be used by inventory managers (Rekik and Sahin, 2012). The process involves counting all inventory on hand, then comparing the results with the inventory information system. This method can cause service interruptions by stopping manufacturing or warehouse operations during the counts; in retail environments, the counts can be conducted during non-business or non-peak business hours. In each of these circumstances, the count will incur some additional costs (Rekik and Sahin, 2012). The goal of the count is to improve data accuracy; however, the counts are conducted by fallible humans. One article estimated inventory counts to be about 95% accurate. Thus, if the inventory records were highly accurate to begin with, an inventory count may actually reduce the record accuracy (Millet, 1994). The cost of counting high-cost items is often justified, but with low-cost items, it may be more cost effective for a business to simply add more inventory and not count the items (Gumrukcu et al., 2008). For example, compare the benefit of counting engine assemblies versus counting each candy bar at every aisle in a large store. It is important

to consider that adding inventory can be counterproductive for Lean operations (Kang and Gershwin, 2005).

Cycle-counting was the first widespread alternative to periodic complete inventory verification to appear in the literature (Iglehart and Morey, 1972; Smith, 1976) and is still the most pervasive solution (Muller, 2011). Many have considered cycle-counting as the panacea for inventory inaccuracies, calling it “the most systematic method of solving inventory accuracy problems” (Gumrukcu et al., 2008). Cycle counting is the planned continuous counting of a small set of items during a period (Backes, 1980). The overall goal of cycle counting is defined as improving inventory accuracy. However, some inventory managers can add the goals of identifying causes of inventory inaccuracy and providing improvement in customer service levels by making the in-store operations more effective (Gumrukcu et al., 2008). Managers must also consider the desired accuracy of the records. A common benchmark is 95% (Muller, 2011). Cycle counting avoids some of the cost of a periodic count because a smaller area can be counted with less impact upon ongoing operations (Polakoff, 1987). A common technique of cycle counting is to enact an “ABC” hierarchy (see Table 2). “A” items would be counted more often because they are either more valuable or believed to pose more risk if unavailable (Cantwell, 1985). Graff (1987) identifies fallacies of the ABC system for a manufacturing setting. The often-overlooked “C” parts could cause production lines to stop in the same way high velocity “A” items could.

Table 2: ABC cycle counting example (Cantwell, 1985)

Class	# of Item in Class	# of Counts Per Year	Workdays Between Counts	Day Available for Counting	Average Daily Counts
A	1800	6	2 months = 40 workdays	30	60
B	4155	3	4 months = 80 workdays	60	70
C	28687	1	1 year = 240 workdays	180	160

Zones provide another method to improve inventory accuracy. Articles that tested this mitigation strategy were all manufacturing stockrooms. Nevertheless, the method could be reasonably applied in other inventory settings; such as workers being responsible for picking from certain warehouse zones (De Koster et al., 2007). Zoning is implemented by placing specific individuals over a defined area of inventory or zone. The individual is responsible for the inventory accuracy of their zone. The zoning method gives the individual more responsibility and more control over their area of operation (Sandras Jr. and Bolander, 1978).

Technology, as a means to improve inventory accuracy, is the focus of many recent IRI articles. Some contend that inventory inaccuracy issues became apparent due to the development of tracking technology (Kang and Gershwin, 2005). The barcode system is the most commonly used inventory tracking and data capture technology in practice (Sahin and Dallery, 2009). In 2001, five billion codes were scanned every day in 140 countries (Agarwal, 2001). Although the introduction of tracking systems significantly reduced inventory inaccuracies, the existence of errors in inventory records are still

commonly observed (Lee et al., 2004). For barcode systems, labels must be properly positioned in order to be detected by readers. Otherwise operators must manually scan products, increasing the opportunity for errors (Sahin and Dallery, 2009).

Another major technology available for tracking inventory is RFID systems comprised of tags located on either the item itself or on the packaging, including aggregated inventory such as a pallet. RFID has become so prevalent in many inventory operations and in the literature, that there is a plethora of articles focusing just on RFID technology (Delaunay et al., 2007). Many of the articles focusing on RFID technologies address IRI as an area that will inherently improve with the adoption of the new technology (Wang et al., 2010). The proponents of RFID systems state that it can provide an automated “zero human intervention solution to the problem” (Hardgrave et al., 2013). Others have taken a more reserved stance, citing limitations of the technology. Studies have discovered that errors such as misread and no-read occur too often; one study experienced only an eighty percent success rate in reading tags across various conditions (Rekik, Sahin and Dallery, 2008). Others have found that radio frequencies can be absorbed by liquids and reflected by metals (Uçkun et al., 2008). These limitations leave room for further analysis and improvement in inventory tracking systems.

The work by Dehoratius and Raman (2008) is unique (and frequently cited in subsequently published articles) because the authors developed a model to test the interaction of various factors that could likely impact IRI. They also work with a large data set to develop their model. They found that fast turnover items (more transactions per period for a given SKU) resulted in greater IRI (DeHoratius and Raman, 2008).

However, researchers found the opposite to be true in other studies (Barratt et al., 2010). The settings for each study are slightly different, thus the field needs more research to help delineate conflicting findings.

Nachtmann, Waller, and Rieske (2010) add explicit consideration of demand error caused by IRI. Continuing our granola bar example from above, if all three bars are scanned as one type...there will be a false demand data for all three bars. Nachtmann et al. (2010) mainly focus on the bar that shows three demands when there was actually only one. Yet, there is also incorrect data for the other two bars that show no demand but were purchased at the same rate as the first bar. They found demand error to affect the system performance (probability of a stock-out) less than inventory errors. They conclude that demand error primarily leads to problems in forecasting, which results in larger safety stock (SS) values (Nachtmann et al., 2010). The increased SS can be unnecessary and tie up capital, but does not lead to more stock-outs. Similarly, Sari (2008) found that collaborative SC structures, where a four-echelon chain shared demand data and inventory levels, experienced more disruption due to IRI than a vendor-managed structure. Sari (2008) attributed the increased disruption from IRI to the presence of less SS. Using the classic just-in-time analogy, water can be viewed as inventory covering up a whole myriad of issues. As the water level lowers (inventory levels decrease), the dangerous rocks become apparent (Wilson, 1996). One of those rocks is IRI; some the articles have shown how firm performance can be impacted more drastically by IRI in structures striving for lower inventory levels such as just-in-time, Lean and collaborative-planning-forecasting-replenishment (Sari, 2008).

IRI Solutions

Inventory record accuracy continues to challenge the Air Force, many manufacturers, warehouses, and retailers. Researchers are still working towards a consensus on how to manage IRI and adequate tools to manage IRI are still emerging (Mersereau, 2013).

Even within the area of cycle counting, managers can receive conflicting guidance. One study noticed better performance with more frequent counts (Raman et al., 2001).

Conversely, another researcher found that warehouse inventory accuracy improved with fewer cycle counts (Polakoff, 1987). Below are some of the existing solutions.

DeHoratius, Mersereau, and Schrage (2008) suggest firms have one of three options: Prevention, Correction, or Integration to reduce IRI. Current literature contains examples of each option. However, there is currently not a quantitative comparison of the efficacy of different methods; although the collective knowledge-base seems to conclude that the more you can do to address IRI, the better results you can achieve. The limitation is that some solutions are not fitting for all firms, and even if many methods are fitting, they may be cost prohibitive (De Koster et al., 2007). As the desired inventory accuracy increases, limiting factors increase exponentially (costs, time, computational power, etc.). It would be easier for company to improve from 60% to 90% accuracy than for them to improve from 90% to 95% and so on (Miller, 1997).

Prevention: Prevention includes items such as employee training, management buy-in, process changes, and supplier coordination (DeHoratius et al., 2008; Rekik and Sahin, 2012). For example, if a large source of a firm's IRI stems from point-of-sale transaction errors, then managers can focus training on this area. Referring to our earlier example of the cashier scanning three granola bars, if the cashiers have been trained to scan one item

then key in a multiplier number, retraining them to scan every SKU could prevent a portion of the firm's IRI.

Correction: The implementation of RFID technologies is an example of a prevention method and a correction method depending on how it is utilized (Hardgrave et al., 2013). If the RFID system, or any other tracking system, is used to maintain improved location of inventory, then it is primarily a correction method. The manager will know that the inventory is now in one location when the database previously showed it elsewhere; this employment is used for active reconciliation of inventory records. For any tracking system to serve as a prevention method, managers must review system reconciliations to find root causes of the needed corrections (Atali et al., 2009).

Integration: A few simulations (Bai et al., 2012; DeHoratius and Raman, 2008; K k and Shang, 2007) found that desired performance levels can be achieved with IRI, as long as there is an accurate estimate of the error. Thus, the inventory records do not necessarily need to be 100% correct. However, this solution may lead to holding more inventory to account for the IRI. Another proposed method called cycle-count policy with state-dependent base-stock levels (CCABS) is a combination of corrective actions and integration (K k and Shang, 2007). CCABS calls managers to perform an inspection only if the inventory recorded is less than a threshold level, and order up to a base-stock level that varies depending on the number of periods since the last inspection. They state that this method can reduce costs while still achieving performance goals.

Other recommendations include collaborating with the accounting department to conduct more accurate cycle counts (Backes, 1980; Kohn, 1978). Effective solutions will likely require human resource elements such as training and education (Witt, 2006). As

early as 1978, Weber conducted a controlled experiment assessing the impacts of IRI and auditors responses with the goal of improving human performance. One study stated that the most important requirement for a successful cycle counting program is top management support (Cantwell, 1985). The same is likely true for any serious effort to improve inventory records. In conclusion, IRI can cause and are caused by factors involving humans; these factors, therefore, should be studied when seeking to improve IRI.

Psychological Measures

The extent individuals can vary may be unlimited; however, most of these differences have commonalities and small deviations go largely undetected (Goldberg, 1990; Rasmussen, 1982). Goldberg (1990) provides a detailed history presenting how researchers have repeatedly shown the robustness of five common elements among as many as 18,000 descriptive terms. The five elements have evolved into what is called the *big-five factors of personality* or often just the *big-five* (John et al., 2008). Table 3 provides a comparison of the five factors, along with common traits of those who score low versus those with high scores across the five factors.

Table 3: Big Five Factors of Personality (Goldberg, 1990; John and Srivastava, 1999)

Dimension	Also Called	Description	Low Score Traits	High Score Traits
Extraversion	Surgency	an energetic and enthusiastic approach	loner, quiet, passive, reserved	joiner, talkative, assertive, ambitious, social, confident
Agreeableness		the person's level of altruism, cooperation, willingness to conform to group norms, and warmth or kindness	worried, temperamental, self-conscious, emotional	calm, even-tempered, comfortable, unemotional
Conscientiousness	Dependability	the ability to control impulses to facilitate goal-directed behavior	negligent, lazy, disorganized, late	conscientious, hard-working, well-organized, punctual
Neuroticism	Emotional Stability	contrast emotional stability with feelings of anxiety, nervousness, and depression	suspicious, critical, ruthless, irritable	trusting, lenient, soft-hearted, good-natured
Openness	Openness to experience, intellect, culture	describes the breadth of and depth of one's life, including the originality and complexity of experiences	down-to-earth, uncreative, conventional, uncurious	imaginative, creative, original, curious

Due to the ubiquity of the big-five structure, it has been used across many studies spanning decades (John et al., 2008). Even though it has been widely used, researchers have received mixed results when trying to use one dimension as a predictor of task performance or contextual performance (Organ, 1994; Tett et al., 1991). For example, conscientiousness and agreeableness are two well-supported and commonly accepted predictors of citizenship behavior (Chiaburu et al., 2011). A meta-analysis of 87 studies

found that extroversion, emotional stability (neuroticism), and openness (intellect) increase the predictive power of conscientiousness and agreeableness, but that they are not the only significant standalone predictors of contextual performance (Chiaburu et al., 2011). However, earlier studies did not find any of the factors to consistently predict contextual behavior; rather a *constellation* of factors appeared to best predict contextual behaviors (Organ, 1994). Some of the inconsistencies when using dimensions of the big-five model may arise from the exploratory employment versus confirmatory analyses. A meta-analysis of 97 studies found that confirmatory validities are more than twice as high as exploratory studies (Tett et al., 1991). Despite its often futile ability to predict behaviors via personality, the big-five provides a common framework for personality assessments; “few theoretical frameworks can compete with the impact of the five-factor model on psychological science” (Judge et al., 2013, p. 875).

NASA-Task-load Index

Research has shown a link between performance and psychosocial variables such as stress, personality traits, perceived workload and cognitive factors (Grasha and Schell, 2001; Rubio et al., 2004; Schell and Grasha, 2000). In addition to measures for various psychosocial measures, some studies include the NASA-Task-load Index (NASA-TLX) as a measure of perceived task-load (Hart and Staveland, 1988). This measure was developed for NASA to help identify an individual’s threshold of task-saturation. The measure assesses perceived task-load across five dimensions; it also assesses which dimensions are identified as having the greatest impact upon task-load. The five dimensions are summarized below in

Table 4. The assessment is contains two parts; the first has the subject indicate how well they believe they performed across the six dimensions in

Table 4. Next, the participants are presented with all the possible combinations of dimension pairs and are asked which of the two dimensions was a greater determinant of task-load for the task just completed. The pairs provide a composite score identifying which dimensions are most influential for the participant on the given tasks (Hart, Sandra, 2006). For example, a participant may find mental demand more influential in a cognitive task, while finding physical demand more influential during a task involving heavy lifting. Across multiple settings, researchers have found perceived task-load to affect performance (Grasha and Schell, 2001; Hart, Sandra, 2006; Rubio et al., 2004; Schell and Grasha, 2000).

Table 4: NASA-TLX Rating Scale Definitions

Title	Endpoints	Descriptions
MENTAL DEMAND	<i>Low/High</i>	How much mental and perceptual activity was required (e.g., thinking, deciding, calculating, remembering, looking, searching, etc.)? Was the task easy or demanding, simple or complex, exacting or forgiving?
PHYSICAL DEMAND	<i>Low/High</i>	How much physical activity was required (e.g., pushing, pulling, turning, controlling, activating, etc.)? Was the task easy or demanding, slow or brisk, slack or strenuous, restful or laborious?
TEMPORAL DEMAND	<i>Low/High</i>	How much time pressure did you feel due to the rate or pace at which the tasks or task elements occurred? Was the pace slow and leisurely or rapid and frantic?
EFFORT	<i>Low/High</i>	How hard did you have to work (mentally and physically) to accomplish your level of performance?
PERFORMANCE	<i>Good/Poor</i>	How successful do you think you were in accomplishing the goals of the task set by the experimenter (or yourself)? How satisfied were you with your performance in accomplishing these goals?
FRUSTRATION LEVEL	<i>Low/High</i>	How insecure, discouraged, irritated, stressed and annoyed versus secure, gratified, content, relaxed and complacent did you feel during the task?

An extension of job performance research considers how personality traits interact with the subject's perceived task-load (Chiorri et al., 2015; Grasha and Schell, 2001). Chiorri et al. (2015) found that higher levels of extroversion were associated with higher levels of perceived workload, while conscientiousness and emotional stability were associated with lower levels of perceived workload. They also found that higher levels of neuroticism were associated with higher scores on the frustration dimension; this finding was consistent with other research (Rose et al., 2002). Conversely, another study did not observe the same interaction of perceived workload and performance (Czaja et al., 1998). The discrepancy may be due to the nature of the task itself (Chiorri et al., 2015);

therefore, as more research is conducted utilizing the big-five model and NASA-TLX, these differences should become more reliable with replication (Tett et al., 1991).

Motivation

Motivation is not the direct focus of this research, but research considering job performance often includes motivation; motivation seems to be inherently linked to performance (Kanfer, 1990). However, the link remains elusive from a specific model that has provided practitioners with actionable guidance. “There remains a general lack of understanding regarding human motivational mechanisms as they relate to operational objectives in a variety of contexts” (Bendoly et al., 2010, p. 440). Malone and Lepper (1987) propose seven types of motivation related to performance. One type is intrinsic task interest; they found that when instructors (trainers or managers) vary instruction methods for more experienced workers, their on-task effort increases (Malone and Lepper, 1987). Managers and researchers are often seeking to increase an individual’s motivation, and consequently improve performance (Boswell, 2000; Buller and McEvoy, 2012). One suggestion has been to enact participative goal-setting procedures (Lee et al., 1989). The intention is that participative procedures will improve task performance by increasing goal commitment, acceptance and difficulty (Kanfer, 1990). *Line of sight* regarding how workers’ actions affect outcomes has been found to enhance performance (Boswell, 2000; Buller and McEvoy, 2012). “All else being equal, it is clear that information-sharing procedures that enhance an individual’s capabilities for performing a task will enhance performance” (Kanfer, 1990, p. 112). Boudreau et al. (2003) building upon Vroom’s classic 1964 work supports the belief that individual performance is a multiplicative function of ability and motivation (Boudreau et al., 2003; Vroom, 1964).

SCM Experiments

In supply chain management, human errors are often addressed tangentially with the notable exception of the Toyota Production System (TPS) and Lean initiatives mentioned earlier. TPS implements kanban structures, which are visual motivational elements to enhance performance. The kanban process makes a previously arbitrary action visible and is a constant reminder of the task at hand (Takahashi et al., 2007). Still, other aspects of the supply chain can be affected by human errors beyond TPS and Lean process movements (Galar et al., 2011). Thus, SCM literature has called for more studies assessing how individuals affect supply chain performance (Ballard, 1996; Fawcett et al., 2010); below are a couple of examples of previous SCM error-related studies.

Grasha and Schell (2001) conducted a controlled experiment and discovered how psychosocial factors can affect error-rates in simulated prescription filling tasks. Other research (Galar et al., 2011; Nolan, 2000; Reason, 2000) has found that standard error-rates fluctuate greatly based on a whole range of factors. The impact that specific factors have on error-rates is more precise for some, while others are more arbitrary and used to provide a margin of safety. For example, researchers simply doubled the expected error-rate for nuclear weapon assembly tasks completed while flying versus on the ground (Swain, 1990). More recent research has also found that stress significantly increases the error-rate for most individuals (Proctor and Van Zandt, 2011). The researchers designed an experiment to induce a level of stress on particular participants by giving them less time to complete the assigned tasks. The experiment was conducted by having participants fill prescription orders for 80 and 90 minutes. During the exercises and afterwards, the total errors were counted for each participant. The participants completed

pre- and post-surveys with 15 psychosocial measures such as stress, fatigue, anxiety, etc. They also completed the NASA-TLX to assess the level of task-saturation of each participant. The results indicated that the individuals made errors at about the same rate as observed in actual pharmacies. They also identified psychosocial measures that significantly correlated with an increased number of individual errors. Of note, is that they confirmed a higher error-rate for the participants in the groups with higher induced stress. The participants who had higher levels of steady-state stress identified in the pre-test also had higher error-rates. However, they did not test any methods for reducing the number of errors committed.

In another study (Weaver et al., 2010), the researchers assessed order-picking times when the method of pick-list was varied. Participants fulfilled orders using traditional text-based lists, graphical paper lists, audio queues, or a heads-up monocle device. The primary variable of interest was order-picking times, but the researchers did count the errors committed by each participant. They found that the heads-up display was the method that enabled the fastest and most accurate order picking by the participants. However, they did not measure correlations of individual differences. They also acknowledge the impracticality of implementing robust human-computer interaction devices at the current state of technology. Such a change would be expensive and cumbersome (Weaver et al., 2010); consequently, the need remains for further research into cost effective methods to reduce errors in the SC.

Summary

This research has presented literature to show how fewer errors can lead to increased task performance, increased firm performance, increased SCM performance.

Specifically, as individual task and contextual learning occurs, it enables organizational learning to occur; thereby improving supply accuracy. Superior skills and resources, taken together, represent the ability of a firm to surpass its competitors in the marketplace (Day and Wensley, 1988). This macro level improvement is made possible by improving the micro level components. This research propositions that mission understanding or *mission clarity* is a fertile area for assessment, because it relates to an individual's understanding of how their actions impact the macro system.

Some researchers have proposed concepts similar to mission clarity, but with different nuances. One example is *workplace awareness* (Gutwin et al., 1996). Workplace awareness is primarily associated with advances in telecommuting and organizations seeking to maintain group awareness of collaborative projects. Additionally, in a recent commentary prefacing a social work journal, the editor calls for social workers to increase their *organizational awareness* (Silverman, 2015). The editor does not present organizational awareness as a construct, but calls for broader understanding of connections between macro and micro components of social work. In another commentary, John Beck encourages practitioners to have a better understanding of the multi-faceted challenges facing healthcare organizations (such as reimbursements, rising administrative costs, risk, accounts receivables, etc.). Beck states that improved organizational awareness will improve leadership's ability to attain strategic and tactical goals via continuous improvement (Beck, 2015). Beck is addressing organizational leaders and calling for specific healthcare questions to be answered by the academic community. Finally, in an editorial assessing the impact of BOM upon various fields, the authors request researchers seek specific elements that further the understanding of how

individuals impact organizational performance (Croson et al., 2013). The authors conduct a review of trends and developing topics in operations management. They find an increase in the acceptance of an individual's response as opposed to looking at only the aggregate responses. They also call for better connections of micro-level findings to macro-level implications. Much of the above literature review has identified theories and research specific to the micro-level; e.g. worker training, education, learning, task performance, motivation, etc. Theories of the firm and organizational learning are examples of macro-level views; however, they are less abundant. Even more sparse, are studies that directly seek to connect the two (Sawhney, 2013). Therefore, this researcher proposes *mission clarity* as a construct to connect micro and macro perspectives of performance; *mission clarity* is an individual's understanding of why and where they fit into the larger system; it is comprised of their mission related education, experiences and individual characteristics.

Problem Statement

This research integrates the current needs of supply chain management regarding human errors in the order picking and packing process with principles from human factors engineering, inventory management, and psychology. Human factors research has provided a strong framework for analyzing tasks at a very detailed level to provide insight into how errors affect the larger desired outcome (Reason, 2000); one such framework is Activity Theory. Activity Theory is frequently employed when researchers are looking for insight into how an individuals' task completion is affected by all elements in the setting, including cultural, psychosocial, environmental, and organizational factors (Kuutti, 1996). In particular, recent Activity Theory applications

have focused on how workers interact with computer systems (Bedny and Karwowski, 2003; Engstrom, 2000). The research provides support for considering numerous factors when assessing the probability of an operator making an error during an activity. Models based upon Activity Theory often carefully consider factors other theories treat as peripheral to the activity. For example, Activity Theory would consider a person's culture, humidity, lighting, etc. Bedny and Karwowski, looked at the warehouse operations of "picking and packing" orders via Activity Theory (Bedny and Karwowski, 2003). They recorded the probability of error based upon how often workers failed to complete a task in an acceptable manner. The original efforts up through the work by Bedny and Karwowski confirm that if a final error-rate is desired, managers can look at sub-tasks to find where improvements will have the most impact on overall performance (Bedny and Karwowski, 2003). They also concluded, similar to Leveson, that human operations are becoming increasingly intertwined with computer systems (Leveson, 2011). Considering the above research and observed opportunities, *it is proposed that supply chain workers make observable, preventable errors while completing their assigned tasks in the shipping process.*

Research Questions

A quote by Baron von Steuben succinctly captures the essence of this research. Baron von Steuben was a Prussian officer in George Washington's Continental Army. He was responsible for training and discipline of recruits. In his memoirs he records "You can tell Prussian, German, French soldiers to do this and he does it; with the Americans I am obliged to say 'this is why you do it; then he will do it'" (Lockhart, 2008). The concept is that, at least in American culture, performance may be affected by an

individual's knowledge of why and where they fit into a larger system, called *mission clarity*. Thus, the overall research question is: What is the relationship of mission clarity to job performance?

This research combines education, experience and subject characteristics as factors that constitute mission clarity. As can be seen in Figure 12, this research includes task performance, perceived task-load, and contextual performance elements of job performance. The solid lines connecting mission clarity factors to job performance factors indicate a direct relationship, while the dashed lines indicate an interaction effect. This will expand the investigative questions into twelve specific hypotheses, presented below. The subject characteristics of interest relate to mission clarity such previous careers, years of experience, depot tours, deployments, specialty courses. It is important to consider subject characteristics because previous research suggests that a decision maker's experience with solving a particular type of problem, can impact their future performance (Mennecke et al., 2000). Moreover, other items that comprise subject characteristics are likely to vary across a wide spectrum for workers.

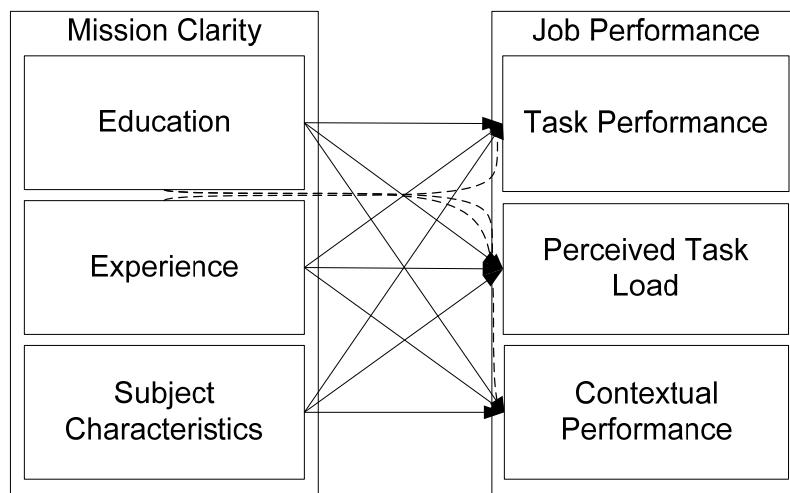


Figure 12: Proposed Research Model

Hypotheses

Task performance is enhanced by education, experience and subject characteristics. Although learning is not directly observable, researchers are able to infer learning from measureable performance behaviors. Education has been found to be a vital element for improving performance, and experience is a catalyst for making education efficacious. Nonetheless, education and experience affect individuals differently, partly due to pre-existing levels of education and experiences, called subject characteristics. Therefore, there seems to be an interaction between increased education, experience, and subject characteristics in relation to increased performance, reference hypothesis 1 below.

- H.1: There is a positive relationship between *task performance* and:
 - H.1.a: *more education*.
 - H.1.b: *more experience*.
 - H.1.c: *education* experience*.
 - H.1.d: *subject characteristics*.
 -

Education, experience and subject characteristics also influence the perception of task load. Every individual has a point at which they become task saturated, when adding another task would degrade their cumulative performance. If hypothesis 1 holds true, then it is a possible consequence that individuals would change their perception of the existing task load, reference hypothesis 2. They may have a better understanding of the task and view it as worthy of more attention, thus increasing their perceived task load, or they may gain confidence in the task to the point that it requires less attention, thus lowering their perceived task load.

- H.2: There is a significant relationship between *perceived task-load* and:
 - H.2.a: *more education*.
 - H.2.b: *more experience*.
 - H.2.c: *education* experience*.
 - H.2.d: *subject characteristics*.

Contextual performance, also called organizational citizenship behavior, is enhanced by education, experience and subject characteristics. There is an established link between increased task performance and improved contextual performance. However, the direction, strength and antecedents involved are not settled. This research is uniquely structured to assess the impact of education, experience, and subject characteristics upon contextual performance in order to elucidate the relationships, reference hypothesis 3. For example, individuals with more education and experience may be organizational experts able to interact more comfortably with other employees.

- H.3: There is a significant relationship between *organizational citizenship behavior* and:
 - H.3.a: *more education*.
 - H.3.b: *more experience*.
 - H.3.c: *education* experience*.
 - H.3.d: *subject characteristics*.

III. Methodology

Introduction

Logistics and supply chain management (SCM) are diverse fields encompassing numerous business activities; Stock and Boyer (2009) highlight the diversity of the field by analyzing 166 definitions of SCM. A critical component of many SCM activities is the individual. However, the individual's behavior is often treated as rational and not studied for its impact upon the supply chain (SC) (Williams and Tokar, 2008).

“Behavioral experiments represent a potentially valuable and currently underutilized approach for gaining insight into logistics and supply chain decision making that is commonly characterized by departures from rational thought” (Michael Knemeyer and Naylor, 2011, p. 296). Controlled experiments are by no means new to related disciplines such as economics, psychology and sociology; yet, they are a recent development in SCM (Tokar, 2010). Many researchers and journal editors have called for more research focusing on the human contribution to SC performance (Fawcett et al., 2008, 2011; Mentzer and Flint, 1997; Näslund, 2002). While there is a need for behavioral experiments to help address important SCM problems, not all research is well fitted for an experiment (Tokar, 2010). For behavioral research to yield meaningful results, it must be both well-fitting for the phenomenon and carefully conducted (Michael Knemeyer and Naylor, 2011). As discussed in the literature review above, human errors are well fitting for behavioral experiments. Therefore, this research will conduct a behavioral-based controlled experiment to determine the effect of education and experience on job performance in an Air Force pick and pack operation.

Interviews

Before developing the experiment, this researcher began by conducting 16 informal interviews with subject matter experts (SMEs) including Air Force officers, senior enlisted members, junior enlisted members, and civilian logisticians. These interviews were not formalized and most were conversational in format. The conversational-interviews were conducted from the fall of 2014 to the fall of 2015. The purpose was to determine how pick and pack operations are conducted and what factors they believe may affect worker performance. Additionally, this researcher toured two large distribution centers (one for a global retailer, one for a regional food distribution company) and two Air Force supply warehouses to discuss the organizations' pick and pack operations. Due to the varied opportunities to interact with SMEs during tours, phone calls and email correspondences, the interviews varied in format. The results from the interviews were not formalized and the collection was not standardized across SMEs. However, to gain a perspective of the organization's pick and pack operations, this researcher would ask the SMEs many of the following questions:

- Senior SMEs
 - How much training do workers receive before they are considered “ready” for their tasks?
 - What novel experiences relating to organizational scope (tours, visiting customers, job exchanges, etc.) are available?
 - Are the opportunities formalized or ad hoc?
 - What do you see as the result of these experiences?
 - What have you seen that affects supply workers' performance?
 - What steps are in place to catch and correct order errors?
 - Do you track error-rates? If so, how?

- Junior SMEs
 - How much training did you receive before being expected to know your job?
 - Did you feel like the training quantity or duration was correct?
 - What opportunities do you have to see more of the organization's operations (tours, visiting customers, job exchanges, etc.)?
 - Have you done any of these items?
 - What are your thoughts of these experiences, did they help you understand what your organization does?
 - Which experiences helped you to understand your job's importance?
 - What checks are in place in case you make a mistake?

The SMEs' comments were compiled to create common elements affecting pick and pack performance. For example, SMEs uniformly stressed the importance of stocking the pick and pack area accurately. If a worker places an incorrect bin in the pick and pack area, the error can propagate through many orders before found. Similarly, the SMEs identified the importance of inventory record accuracy throughout the warehouse in order to conduct a successful pick and pack operation. Another item of concern related to the unit of issue for the order. Some items are packaged and issued together, whereas others are issued individually. For example shoes come in *pairs*, pencils may come in *packages* with a quantity of ten, and batteries may be issued as *each*.

Based on the SMEs input, this researcher developed a small preliminary experiment using six volunteer master and doctoral students. The experiment was used to refine the proposed methodology. For example, during the preliminary experiment, some participants were allowed to fill the orders with no time limit to determine about how long each order would take to complete. One participant said, "This is not like regular

picking; I would never have as much time as I wanted to fill an order. We are always rushed to get everything done.” This anecdotal statement supported the literature, that most picking operations are rushed activities (De Koster et al., 2007). During the timed trials, no participants were able to complete all the orders. In the trials without a time limit, the participants still made errors. Next, this researcher conducted the primary experiment based on the culmination of the literature, interviews, preliminary experiment.

Primary Experiment

This study utilized 103 active duty enlisted Air Force supply workers from one Supply Squadron and two Air Force Supply Chain Operations Groups (SCOG). The study utilized this sample population because it is the largest concentration of Air Force supply workers in the Air Force. The Supply Squadron and one SCOG were located at Langley Air Force Base (AFB); the other SCOG was at Scott AFB. The experiment was offered to the first 6 enlisted grades (E-1 through E-6). However, none of the participants were E-1s, see Figure 13. The majority of subjects were E-4s and were normally distributed among E-2 to E-6 participants. The participants reported age on a 7-point Likert scale; the majority of participants were 24-26 years old and skewed towards younger participants, see Figure 14. Finally, as an incentive, the participants at both locations were entered into a drawing for a one-day pass. This military incentive was given by the commander and entitled the recipient(s) to one day of excused absence from work.

The sample is representative of the target population across demographic assessments performed. Four of the 12 demographic measurements were compared to known Air

Force supply workers population values. These population data are collected and maintained by the Air Force Personnel Center (AFPC). AFPC publishes the data via a searchable web-based utility. However, eight demographic items were collected to explore demographic traits associated with experiences that theory suggested may influence performance. These items were tested to ensure random assignments were not biased among the groups. The exploratory items were not significantly more present in any one group.

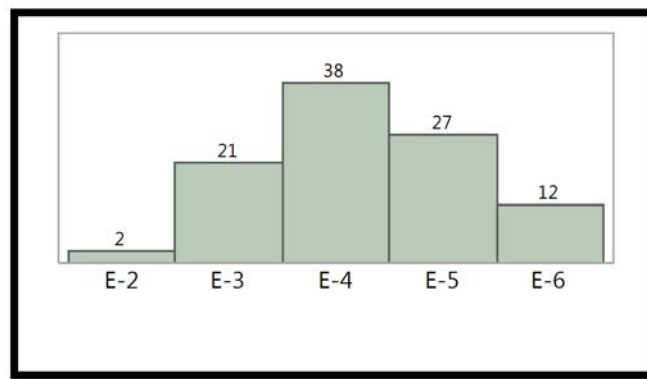


Figure 13: Enlisted Grade Distribution

Three subjects were excluded. The first subject was excluded because the subject was on crutches, although the subject was able to hobble through the experiment without his crutches, he was not considered to be a representative sample of the normal population. The second subject was excluded due to an incomplete experiment. This subject seemed disorientated and was the only subject to not complete the computer-based inventories necessary for including the subjects' scores. The third subject was excluded due to errors in administering the experiment. Subjects were allowed to ask

questions throughout the experiment, and they were given standard responses to the extent possible. For example, if the participant asked if it was okay to perform the task in a certain way, they were told to use their discretion. However, if they explicitly asked a direct question, they were given a direct answer. Refer to the statements below as examples.

- Excerpt of direction given: “Once you have made the shipping label, place it in the plastic tub. Then, use the picklist to select the items needed to fill the order and place them in the tub with the corresponding label.”
- Participant A question: “Can I put the label in the tub now?”
- Researcher’s response: “It is up to you.”
- Participant B question: “I forgot, what did you say we were supposed to do with the labels once they are printed?”
- Researcher’s response: “The labels are to be placed in the plastic tubs corresponding to each order.”

The third excluded subject asked a question differently than other subjects. This researcher tried to respond in such a way as to allow her freedom to make a decision about the tasks without unfairly giving her more guidance than other subjects. See the conversation below; it occurred about a third of the way through the primary task.

- Participant: “So, I want to make sure I am doing this correctly. This column [pointing to the picklist] refers to the item, this column is the quantity needed for the order, and this is the unit of issue.”
- She was correct; the researcher responded with a nod and said, “That is correct.”
- She then asked: “So I am picking the quantity [pointing] for the order; what’s the unit of issue mean?”
- Researcher’s response: “The unit of issue is a designation that indicates the count, measurement, or form of the item ordered. It will let you know if the item has multiple items, for example, in a package, or if each item counts as an ordered item.”
- Participant: “Oh, okay; thanks.”

The researcher's response mirrored the AFH 23-123v2pt1 description of unit of issue. Instead of clarifying the worker's actions, the response actually confused her. Prior to asking the question, she was picking each line item correctly. Afterwards, she switched and picked only one item for each line item, based on the unit of issue instead of the needed quantity. Therefore, this case was removed due to receiving unclear guidance causing her misunderstand the tasks. After removing these three cases, the number of included cases was 100.

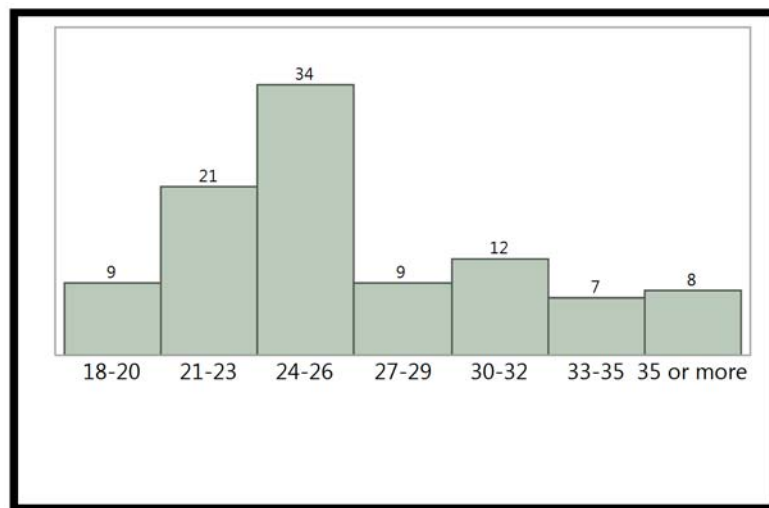


Figure 14: Participant Age Distribution

Treatments

Regardless of group, all participants received the same initial training for the experiment tasks. This researcher selected three predictors for job performance as components of an individual's mission clarity. This research defines mission clarity as an individual's knowledge of why and where they fit into a larger system; comprised of

education, experience and *subject characteristics*. There are many ways organizations can choose to educate their workers (Schunk, 2011). Based on SME input and current Air Force methods of education (USAF, 2014), this study operationalized the *education* treatment using traditional education methods. Specifically, the subjects received a verbal explanation of the items' use via a 1-minute computer-based presentation. The participants heard a recorded narrative while viewing a PowerPoint presentation with a building slide, see Appendix B.

Literature has shown that experience is an integral part of learning (Argote and Miron-Spektor, 2011). However, the literature is focused on experience related directly to the task (Crick et al., 2013). Our hypothesis expands the current perception of experience to include experiences not directly related to the tasks. Rather, the experience is designed to provide perspective to the overall mission; the intent is to provide the participant with greater context as to *why* they are completing a task. Therefore, *experience* was operationalized as a novel experience related to the mission, but not necessarily to the tasks. Subjects met an end user of the supplies who has flown medical evacuation missions. The confederate was a pilot and fellow student who volunteered to support this research. He was an active duty Air Force lieutenant colonel C-130 and KC-135 pilot. He met with participants for about 6 minutes and relayed two *war stories*. The interaction with the confederate was the experience treatment. The confederate told the same stories to all participants; however, they were delivered in-person in a conversational format. The confederate stated the importance of carrying the needed medical items and the necessity to not carry too many items due to lower flying-altitudes and higher fuel consumption rates. *Subject characteristics* is the third component

affecting mission clarity. Participants completed the Big Five Inventory (BFI) personality assessment (John and Srivastava, 1999; John et al., 2008) The BFI has been widely used to assess individuals personality tendencies for job screening, performance prediction and correlations to other phenomena (Fossati et al., 2011; Goldberg, 1990; O'Connor and Cohn, 2009). O'Connor and Cohn (2009) found that the BFI has predictive value, especially the subcomponents of conscientiousness and neuroticism in relation to aviator performance.

Performance Measures

Job performance was measured using three primary measures: task performance, perceived task-load, and contextual performance. A score of *performance*, instead of using raw error scores, was chosen to accurately capture picking and packing task-performance. As can be seen in Equation 1, the denominator includes the percent complete added to the percent of time remaining. The numerator includes the errors committed and a constant of one. The constant is necessary to accurately compare two individuals who commit no errors but have different percent complete and percent of time remaining values; otherwise both individuals would have a score of zero.

$$\frac{Errors + 1}{\% complete + \% time remaining} = Performance$$

Equation 1: Performance Response Variable Formulation

Consider the five notional subjects presented in Table 5. Imagine that subjects 1-3 committed ten errors each; if we only compared errors, they would all receive the same score even though they performed the assigned task to a different level of completion.

Once percent complete and time remaining are considered, we can see their relative performance. The comparison of the five notional subjects also shows how lower response scores indicate better task performance. Each subject utilized the full amount of time unless they completed all picks. Therefore, if a subject completed the task with no errors and did not finish early, their score would be one as can be seen with Subject 4 in Table 5. If the subject is able to complete the entire task with no errors and time remaining, their score would be less than one as can be seen with Subject 5 in Table 5. If a subject makes one or more error, their score will be greater than one as can be seen in Subjects 1, 2, and 3.

Table 5: Comparison of Performance Variable

	Errors	% lines complete	% time remaining	Formulation	$Y_{\text{performance}}$
Participant 1	10	100%	50%	$\frac{10 + 1}{1 + .5}$	7.33
Participant 2	10	100%	0%	$\frac{10 + 1}{1 + 0}$	11
Participant 3	10	50%	0%	$\frac{10 + 1}{.5 + 0}$	22
<i>Participant 4</i>	<i>0</i>	<i>100%</i>	<i>50%</i>	$\frac{0 + 1}{1 + .5}$	<i>0.67</i>
<i>Participant 5</i>	<i>0</i>	<i>100%</i>	<i>0%</i>	$\frac{0 + 1}{1 + 0}$	<i>1</i>

To measure task errors, the study used a paper-based error tally sheet, see Appendix C. The tally sheet could capture task duration, skill-based errors, rule-based errors,

knowledge based error, and notes. Additionally, it could track other items of interest for future studies, such as how many questions the subjects asked throughout the experiment.

Perceived task-load was measured with the NASA-TLX (Hart and Staveland, 1988) and by counting the number of completed lines. The 20-item version of the Organizational Citizenship Behavior Checklist (Fox et al., 2012), was used to measure contextual performance (Organ, 1997; Smith et al., 1983). The above predictors and performance measures comprise the elements needed to answer the research hypotheses and are depicted in Figure 15. The solid lines connecting the mission clarity factors indicate a proposed direct relationship, while the dashed lines indicate an interaction effect between education and experience upon job performance.

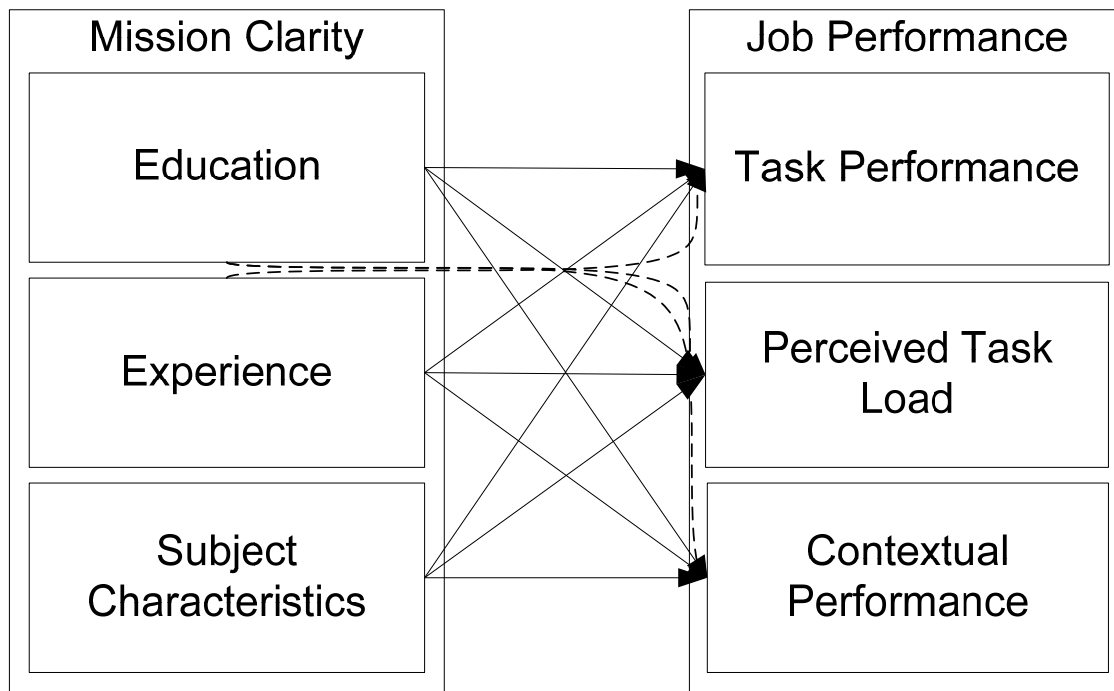


Figure 15: Research Model

Procedure

The following experiment received internal review board (IRB) exemption approval (Appendix D). The experiment was conducted over the course of four weeks at Langley AFB and 1 week at Scott AFB, to include 74 trials at Langley AFB and 28 trials at Scott AFB (the three excluded subjects occurred at Scott AFB). The subjects volunteered to participate in the experiment after being notified via a standardized email briefly describing the study; the email was written by the researcher and sent via their organization's leadership. Subjects were randomly assigned to one of four groups to conduct a mixed-design experiment; the design included a 2 x 2 factorial component and a within-subject baseline component (Van Breukelen, 2006). The first factor was education with the two levels being education treatment and no education treatment. The second factor was experience, also with two levels of experience treatment and no experience treatment, see Table 6. The control group received no education treatment and no experience treatment. The group identified as *Edu* received only the education treatment. The group identified as *Exp* only received the experience treatment and the group identified as *Edu & Exp* received both the education and experience treatments.

Table 6: 2x2 Factorial Design

All Participants trained	No Experience	Experience
No Education	1: Control n=27	2: Exp n=24
Education	3: Edu n=25	4: Edu & Exp n=24

The experimental design included a mix of within-subject components and between-subject comparisons. However, to understand the phenomenon and properly account for individual differences, the study also conducted an analysis of covariance (ANCOVA). This method allows the baseline residuals to be used as a covariate in the model containing the treatments (Van Breukelen, 2006). The covariate accounts for the individual differences inherent to each subject. Some people are more error prone than others (Reason, 1990). The covariate captures the individuals' differences in performance from the mean. Therefore, if an individual scores much lower than the mean, we would expect them score much lower in subsequent assessments; that is, it provides a baseline of performance for an individual.

The participants signed up for time slots of 90 minutes starting at 0700, running through 1700. We utilized three primary areas for the experiment. The first was a welcoming area that consisted of two chairs and a table. For all participants, the experiment started by welcoming the volunteer, providing necessary disclosure and consent forms, instructions, and answering any questions. The task was thoroughly explained and participants could ask questions throughout; participants were shown an

example pick list and label. After the introductory phase, which lasted about 8 minutes, the participants were led to the task area, which contained a mock supply area.

The task area consisted of two supply racks with a total of 60 positions filled with varied items used for fulfilling the mock orders. To match inventory management literature, the supply area contained about 5% erroneous stock. The error types were held constant for all participants. For example, participants needed to pick 3 bandages with 2 safety pins. The bandages were in small bags in the bin. The bin contained 5 bags; only three contained two safety pins. The two bags without the safety pins were always placed on top of the three correct bags. Therefore, participants who did not check the bags would grab the incorrect bags. The task also contained two serialized items. The items were placed so that if they grabbed the first two, the first would be correct and the second would have the wrong serial number. To pick the serialized items correctly, the participants had to verify the pick list notes and the physical item. The varied possibilities of errors enabled me to divide the errors into generic error modeling system (GEMS) model using the skill, rule, knowledge (S-R-K) structure (Embrey and Lane, 1990; Reason, 2000). The task area also contained the label maker and large plastic tubs for filling each order. The participants could see a tablet with a timer showing the remaining time for the given task. The third area was a separate cubicle area with a laptop used to complete the post-experiment measures.

To account for individual differences associated with picking performance, a baseline was established for each individual, see Table 7. The participant was directed to complete a shipping label then fill one order based on a laminated pick list that contained all needed information for the label and picking 16 line items, see Appendix E.

Participants were timed during the label making process, but there was no time limit and the tablet-timer was not active. After they completed the label and indicated they were ready to begin picking, they were instructed to begin and 5-minute timer was started. Once they completed the order or exhausted the available time, they stopped and the researcher set the order (plastic tub) to the side. Next, the treatment was administered. The control group participants began the second task without any treatment. Participants in the education only treatment group were shown the pre-recorded PowerPoint presentation on a laptop in the experiment area. Participants in the experience only group were escorted a short distance to a neighboring cubicle area to meet the confederate. Participants receiving both treatments were first shown the presentation in the experiment area and then escorted to the experience area. These two operationalizations of education and experience are consistent with Kolb and Kolb's experience-based learning theory (Kolb and Kolb, 2005).

Table 7: Establishing Participant Baseline

All Participants will be trained	1st Run <8 min	2nd Run <24 minutes
1: Control	baseline	Control
2: Education	baseline	Ed
3: Experience	baseline	Exp
4: Edu & Exp	baseline	Edu & Exp

After the treatment was administered, participants returned to the experiment area for the second task. They were given a laminated sheet with three separate orders, see Appendix F. Each order required an associated shipping label, contained 16 line items, and utilized a separate plastic tub. The participants were directed to complete the labels for all three orders before picking any of the items for an order. This was a logistical accommodation because there was no time limit for making the labels, but matches some operation warehouses that will print picking lists and shipping labels in batches. After participants completed the shipping labels, they began picking the orders. They were instructed to pick the first order before moving to the second. Each order contained 16 line-items varying from two to twenty-three items needed to fill the order. The orders were balanced so that they would not be too large to fit into the provided plastic tubs. Once the participants completed the orders or exhausted the 15-minute timer, they were told, “Good job.”

Lastly, they were escorted to the other cubicle area to complete the computer-based inventories. This was the same location as the experience treatment area, where they met the confederate, but he was not in the area while they completed the computer-based inventories. Using a laptop, participants completed the NASA-TLX, Big-Five Inventory, Organizational Citizenship Behavior Inventory, mission knowledge assessment and demographic questionnaire. The NASA-TLX was completed online, with a stand-alone version as a backup. Even with the backup version, the data transfer from the online assessment was not seamless; nine participants’ data were not saved. The remaining items were completed using Google Forms; all but one participant successfully completed and saved the data using Google Forms. Once the participants completed the

computer-based inventories, they were thanked again and instructed them to sign-up for the one-day pass drawing. The total experiment duration averaged 67 minutes with standard deviation of 14 minutes and 45 seconds. After a participant left the experiment area, the task was reset for the next participant.

While the participants were completing the task, they were watched and the researcher recorded specific behaviors on an assessment sheet; the sheet is provided in Appendix B. The assessment sheet was also used to make notes specific to a participant, including relevant comments that provided qualitative context to the experiment. After the participants left the experiment area, the assessment sheet was used to record any errors with the orders. The same procedure was used to count errors and reset the experiment for each participant. All items were double counted as they were returned to the bins; all deviations were annotated. After all errors were tabulated, the task area was straightened and readied for the next participant. All data was transcribed into Excel. Data entry was verified using formulas to check for errors and anomalies. Additionally, 10% of the entries were re-entered to assess the accuracy of the data. When compared, the data entry was found to be accurate, although the process did reveal an incorrect formula. Finally, the data of interest to the quantitative analysis were imported in the JMP Statistical software for analysis (“JMP®”, n.d.). The following analysis uses a statistical significance of .05 throughout.

IV. Results

Manipulation Check

A manipulation check was conducted for the education treatment to determine if the treatment worked as intended. Participants completed eight questions regarding the information presented in the educational treatment; the questions are listed in

Table 8. However, question #6 was rejected due to poor wording. The question asks, “How many line-items did you pack during the task?” The confusion arose from whether the participants were putting the number of items they were supposed to pick or the number they actually picked; that is, did they remember that each order contained 16 items. Additionally, participants could have included the pretest line items along with the task items. Therefore, the question was not included in the analysis. The inter-item reliability was calculated using JMP and reported as a Cronbach’s alpha (“JMP®”, n.d.). The Cronbach alpha score for the measurement was .65. Ideally, a higher score would be preferred. However, the lower value is not uncommon in first measurements associated with intelligence measures (Loewenthal, 2001a).

Table 8: Mission Knowledge Questions

Mission Knowledge 1	What types of items were primarily shipped during the task?
Mission Knowledge 2	Who was the intended recipient of the orders filled during your task?
Mission Knowledge 3	Where did the items come from that were shipped?
Mission Knowledge 4	Who will be delivering the items?
Mission Knowledge 5	According to the task description, how often does the Air Force send routing shipments like the ones you filled during the task?

Mission Knowledge 6	How many line-items did you pack during the task? (<i>Not included in analysis.</i>)
Mission Knowledge 7	To how many countries were the orders sent?
Mission Knowledge 8	What country was on at least one of the orders?

The manipulation check indicates that the treatment worked as expected. As can be seen in Table 9, the ANOVA between the treatment groups (including the control) shows that one of them is significantly different from another treatment group ($F=3.19, p=.03$). Further analysis using Tukey-Kramer honestly significant differences (HSD) showed the ordered differences and revealed that the experience and education group scored significantly higher than the control and experience group. However, the experience and education group did not score significantly higher than the education group, as can be seen in

Table 10. Additionally, a least squares analysis of the treatment effect that isolates the effect of each treatment reveals that it is *education* that is significantly affecting the change in mission knowledge scores ($F=6.76$, $p=0.01$), as can be seen in Table 11. These findings verify that participants who received the education treatment did, in fact, represent a new population, representative of increased knowledge regarding the task.

Table 9: Manipulation Check ANOVA

Source	DF	Sum of Squares	Mean Square	F Ratio	Prob > F
Model	3.00	0.18	0.06	3.19	0.03
Error	95.00	1.79	0.02		
C. Total	98.00	1.97			

Table 10: Tukey-Kramer HSD Ordered Differences

Level of Comparison		Difference	Std Err Diff	Lower CL	Upper CL	p-Value
Exp & Edu	Control	0.11	0.04	0.03	0.18	0.01
Exp & Edu	Exp	0.10	0.04	0.02	0.18	0.01
Exp & Edu	Edu	0.06	0.04	-0.01	0.14	0.10
Edu	Control	0.04	0.04	-0.03	0.12	0.28
Edu	Exp	0.04	0.04	-0.04	0.12	0.33
Exp	Control	0.00	0.04	-0.07	0.08	0.93

Table 11: Manipulation Check Least Squares by Treatment Effect

Source	Sum of Squares	F Ratio	Prob > F
Education	0.13	6.76	0.01
Experience	0.03	1.51	0.22
Education*Experience	0.02	1.23	0.27

Models

Each major hypothesis is comprised of four components; to assess the twelve hypotheses, this research includes 6 models shown in Table 12. The results of the models and hypotheses are presented first; then, post-hoc analyses are discussed. Model 1 and 4 were formulated to test hypotheses with task performance as the response variable. As an ANCOVA analysis, Model 1 included the baseline performance residuals as a covariate. The covariate accounts for the individual differences inherent to each subject and captures the individuals' differences in performance from the mean. Therefore, if an individual scores much lower than the mean, we would expect them score much lower in subsequent assessments; that is, it provides a baseline of performance for an individual. Models 2, 3, 4, 5, and 6 are testing subject characteristics not manipulated by treatment

and do not include the baseline residuals as a covariate. The interaction variable was included in Models 1, 2, and 3 based on the literature showing the interconnectedness of education and experience (Dewey, 1938; Schunk, 2011). The models are discussed in greater detail, individually, below.

Table 12: Research Models and Associated Hypotheses

Model Identifier	Hypotheses Tested	Model
M1	H.1.a H.1.b H.1.c	$y_{performance} = \beta_0 + \beta_1 x_{\log baseline} + \beta_2 x_{ed} + \beta_3 x_{ex} + \beta_4 x_{ed} x_{ex}$
M2	H.2.a H.2.b H.2.c	$y_{percieved\ task\ load} = \beta_0 + \beta_1 x_{ed} + \beta_2 x_{ex} + \beta_3 x_{ed} x_{ex}$
M3	H.3.a H.3.b H.3.c	$y_{OCB} = \beta_0 + \beta_1 x_{ed} + \beta_2 x_{ex} + \beta_3 x_{ed} x_{ex}$
M4	H.1.d	$y_{performance} = \beta_0 + \beta_1 x_{supply\ ed} + \beta_2 x_{supply\ ex} + \beta_3 x_{extraversion} + \beta_4 x_{agreeableness} + \beta_5 x_{conscientiousness} + \beta_6 x_{neuroticism} + \beta_7 x_{openess}$
M5	H.2.d	$y_{percieved\ task\ load} = \beta_0 + \beta_1 x_{supply\ ed} + \beta_2 x_{supply\ ex} + \beta_3 x_{extraversion} + \beta_4 x_{agreeableness} + \beta_5 x_{conscientiousness} + \beta_6 x_{neuroticism} + \beta_7 x_{openess}$
M6	H.3.d	$y_{OCB} = \beta_0 + \beta_1 x_{supply\ ed} + \beta_2 x_{supply\ ex} + \beta_3 x_{extraversion} + \beta_4 x_{agreeableness} + \beta_5 x_{conscientiousness} + \beta_6 x_{neuroticism} + \beta_7 x_{openess}$

Model Assumptions

To meet the required assumption of normality, the residuals should not be distributed significantly different than the normal distribution. This can be assessed visually and via statistical tests; both were performed upon the data. Normality was assessed visually by looking at the normal quantile plot of residuals against predicted residuals. The residuals of the baseline treatments showed significant deviations from normality, as can be seen where the values exceed the normal threshold (indicated by red dashed lines in Figure 16). This was expected due to the fact that the job performance measures have a fixed level for maximum performance, but allow individuals to make virtually any number of errors. Similarly, participants can only work so fast, but can vary greatly in how slow they can perform.

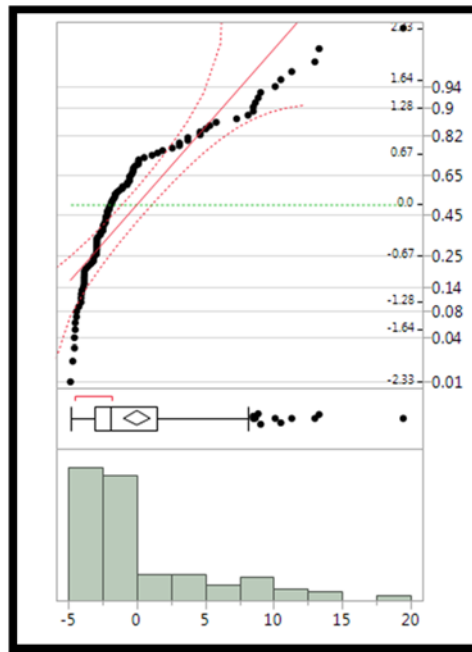


Figure 16: Residual Normal Quantile Plot

The response variable was transformed exponentially using a log transformation. This transformation resulted in residuals that were normally distributed as can be seen in Figure 17. This figure shows that the values fall much closer to the expected values (the straight red line). The distribution follows the normal distribution much more closely, as indicated by comparing the green histogram bars. Additionally, the Shapiro-Wilks test was also used to test the residuals from the transformed variable for normality. Given that $p = .45$ was greater than $.05$, we did not reject the null hypothesis that normality was violated and accepted the distribution as normal.

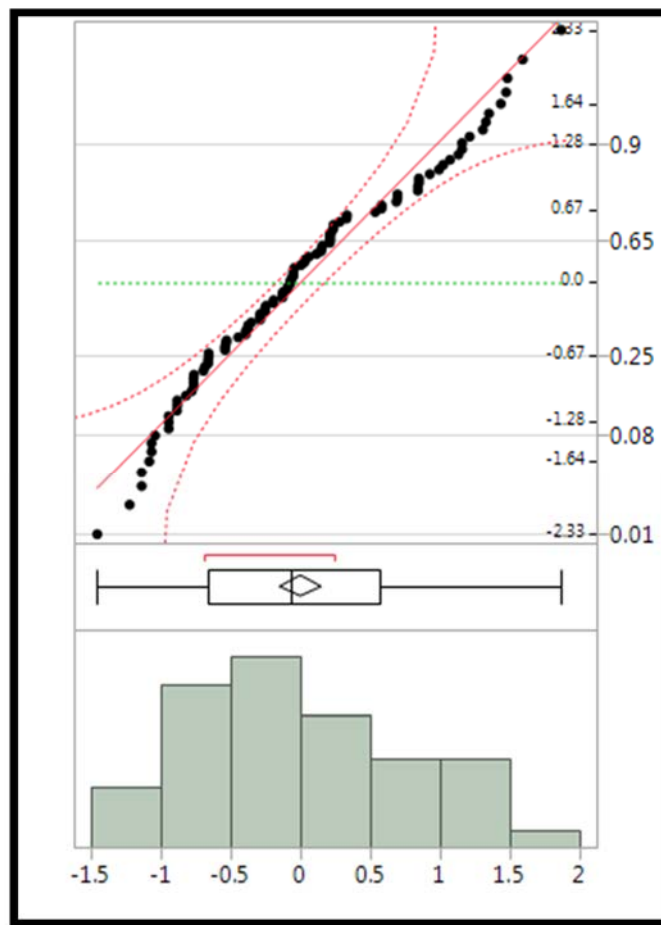


Figure 17: Transformed Residual Normal Quantile Plot

This analysis also considered the impact of time-of-day upon the variance of the response variable scores. As can be seen in Figure 18, the scores show reasonable homoscedasticity. When the variance across predictors for the baseline scores are compared, they did not show significant heteroscedasticity, see Table 13. The O'Brien and Brown-Forsythe tests were used and supported the assumption of homoscedasticity. The same tests were also completed upon the predictors and the treatment performance scores. While the test are not significant at the .05 level, they are close with $p=.06$. Given that they were so close, further investigation was completed and is discussed further in the post-hoc analysis section.

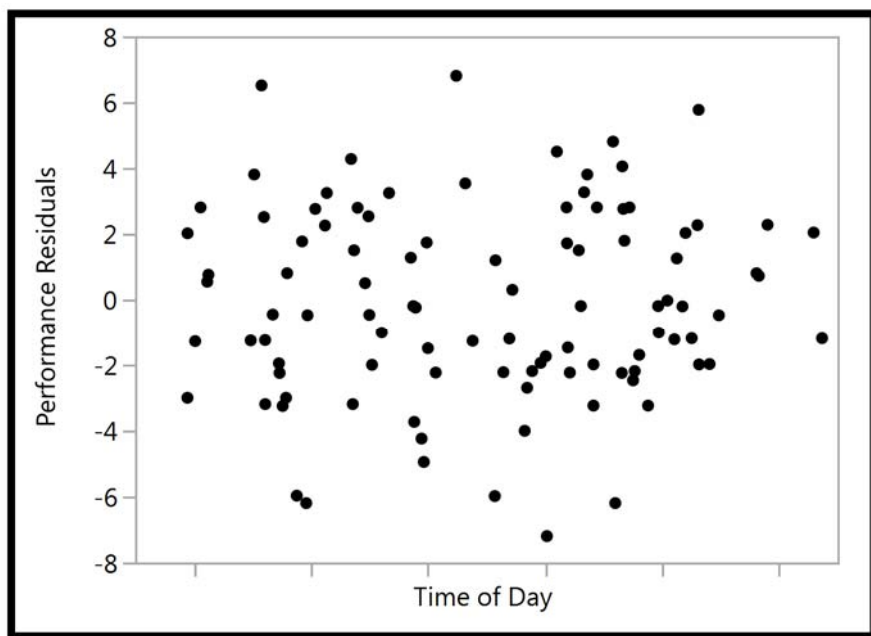


Figure 18: Time of Day Variance

Table 13: Tests of Constant Variance

Treatment Level	Count	Std Dev	Mean AbsDif to Mean	Mean AbsDif to Median	Test	F Ratio	DF Num	DF Den	Prob > F
Control	27	14.15	11.16	8.72	O'Brien [.5]	1.83	3	96	0.15
Edu	25	14.26	8.94	8.22	Brown-Forsythe	0.65	3	96	0.59
Exp	24	4.37	3.62	3.61					
Exp & Edu	24	4.32	3.59	3.59					
Baseline Level									
Control	27	6.49	4.79	3.64	O'Brien [.5]	2.49	3	96	0.06
Edu	25	4.53	3.83	3.43	Brown-Forsythe	2.49	3	96	0.06
Exp	24	4.95	3.69	3.43					
Exp & Edu	24	3.03	2.25	2.17					

Baseline Performance

To analyze the complex dataset, the researcher began by looking at the baseline performance of the four groups (lower performance scores indicate fewer errors and more desired performance). The experimental design should have resulted in baseline groups that were representative of the target population; therefore, one would expect the groups to not vary significantly. The groups did not exhibit significantly different levels of performance $p=.56$; consequently it is concluded that participants were adequately random samples from the target population. Figure 19 shows a visual comparison of the mean performance score of the four treatment groups.

Even though the treatment group means were not significantly different, the participants exhibited expected variances in performance; some people were more error-prone than others. This variance is attributed to unexplained individual differences. Looking forward to scores after receiving the treatment, the individual scores will contain the main effect from the treatment, error related to the treatment condition and error due to the individual's abilities. To eliminate the error associated with individual performance, this analysis used the baseline residuals from the baseline performance as a covariate in the model containing the treatments. This analysis of covariance (ANCOVA) allowed for the baseline performance results to account for a portion of the unexplained variance between individuals. The baseline covariate is included in the models related to performance, education and experience (H.1.a, H.1.b, H.1.c, and H.1.d). The other two response variables (perceived task-load (NASA-TLX) and organizational citizenship behavior (OCB)), were only measured once at the conclusion of the primary tasks. Therefore, they do not include the performance baseline covariate and the analysis of variance (ANOVA) methodology is used.

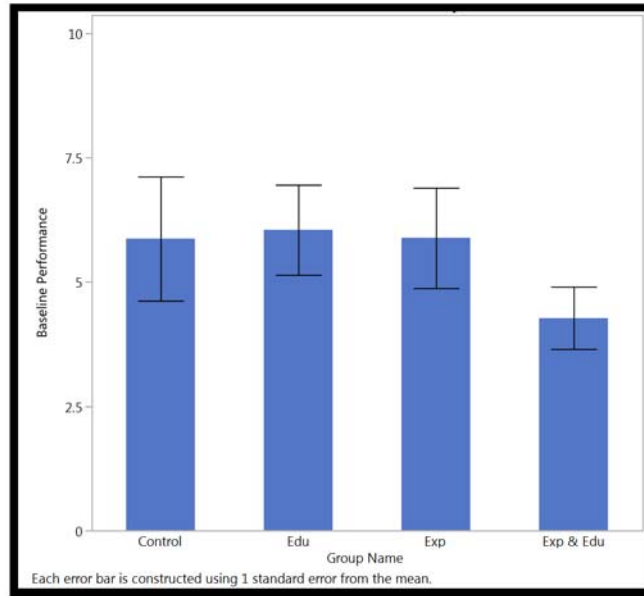


Figure 19: Baseline Groups' Performance Means

Overall Group Differences

An individual's performance was measured using three primary measures: task performance, perceived task-load, and contextual performance. A score of *performance*, instead of using raw error scores, was chosen to accurately capture picking and packing task-performance. As can be seen in Equation 1, the denominator includes the percent complete added to the percent of time remaining. The numerator includes the errors committed and a constant of one. The constant is necessary to accurately compare two individuals who commit no errors but have different percent complete and percent of time remaining values; otherwise both individuals would have a score of zero. More errors will lead to a larger numerator while greater task completion and more time remaining will result in a larger denominator; thus, lower scores indicate better performance.

Initial analyses showed that the four groups' performance means were not significantly different at baseline, see Figure 19. Next, it was found that at least one of the performance means from the treatment groups was significantly different from another, $p=.02$, see Table 14. Figure 20 shows the group means with standard error bars. Not only are the means significantly lower in groups that received the experience treatment, they also have reduced variability. The differences of variability are emphasized in Figure 21. This figure shows a graphical representation of the response concentrations. The shapes indicate that the majority of scores are centered with performance scores clustered around a score of 10. The control and education groups have a few scores with very high scores indicating more errors and degraded performance. Those who received the experience treatment did not commit the gross rule-based errors committed by the control and education only groups.

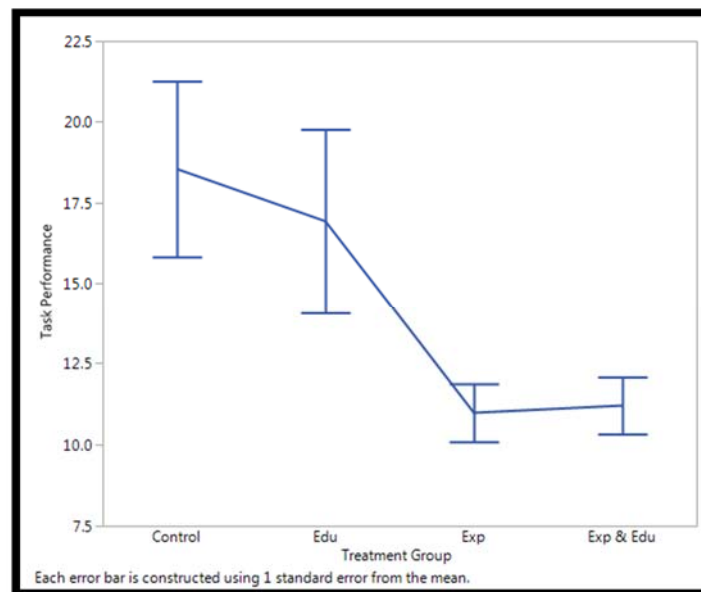


Figure 20: Treatment Group Means with Standard Error Bars

Table 14: Initial ANOVA of Treatment Groups

Source	DF	Sum of Squares	Mean Square	F Ratio	Prob > F
Model	3.00	1147.49	382.50	3.35	0.02
Error	96.00	10951.84	114.08		
C. Total	99.00	12099.33			

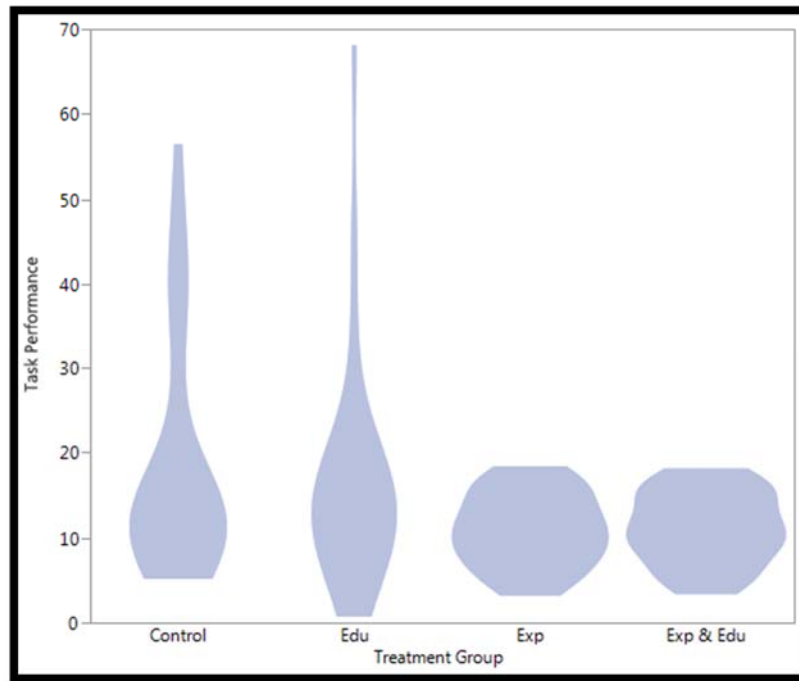


Figure 21: Treatment Group Response Concentrations

Model 1: H.1.a, H.1.b, and H.1.c

$$M1: y_{performance} = \beta_0 + \beta_1 x_{\log baseline} + \beta_2 x_{ed} + \beta_3 x_{ex} + \beta_4 x_{ed} x_{ex}$$

Equation 2: Model 1 for H.1.a, H.1.b, and H.1.c

Model 1 was formulated to test Hypothesis H.1.a, H.1.b and H.1.c. H.1.c was conducted first to assess the interaction of education and experience; it is shown in Figure 22. The results show that there is an interaction between education and experience. However, this interaction was not found to be significant ($F = 0.24$ $p = 0.62$), see Table 16. Nonetheless, the interaction is present and means that education and experience cannot be analyzed in isolation without accounting for this interaction. In the models are presented below, comparisons are made using the leverage plots in the JMP software package. The leverage plots compare the residuals from the included predictors to assess the influence exerted upon the variable of interest (“JMP®”, n.d.). The comparison allows us to understand the influence of education from the two groups that received an education treatment versus those that did not, labeled control. The two groups that did not receive the education treatment were the control group and the experience only group. Similarly, it also allows us to see the influence of experience in the two groups that received an experience treatment versus the control of those that did not receive experience, that is, those in the control group and education only group.

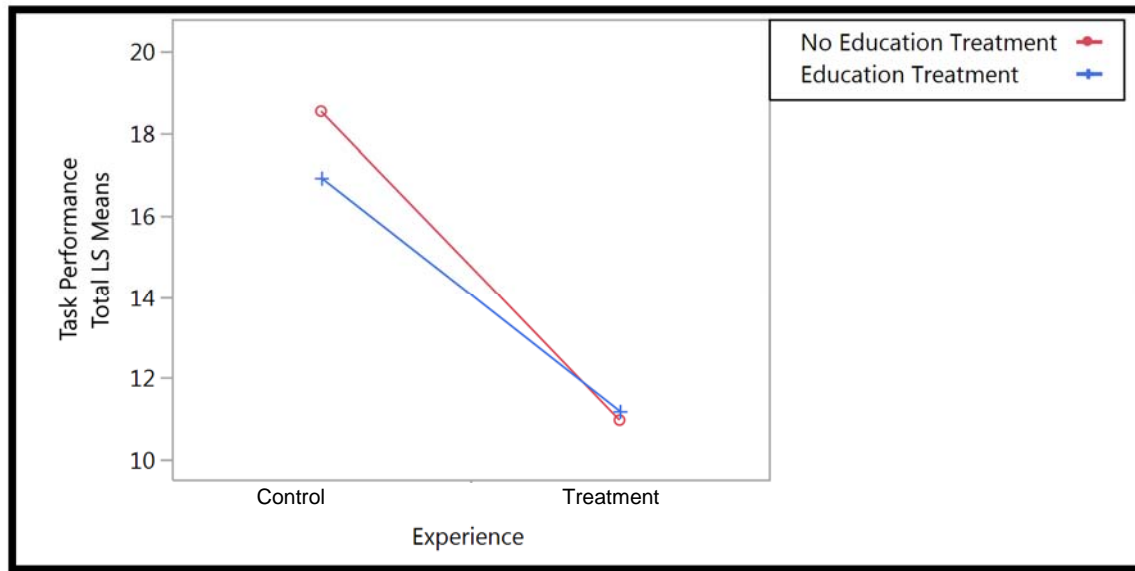


Figure 22: Education and Experience Interaction Performance Effect

Model 1 also includes H.1.a and H.1.b, both of which have performance as the response variable. As an ANCOVA analysis, it includes the baseline performance residuals. It also includes education, experience and the interaction of between education and experience. The results show that Hypothesis H.1.a was not supported; education was not found to significantly affect task performance ($F = .14, p = .71$). Figure 23 shows least squares means for the model. The least squares means (LSM) are values predicted by the model given the presence or absence of the treatment. This method allowed comparing the effect of one dependent variable, while holding other effects constant and is necessary given the interaction effects indicated in Figure 22. The LSM plots and tables below indicate which treatment condition is held constant in the labeled x axis. The LSM can differ from simple means;

Table 15 shows slight differences in the raw means and the LSMs. Often, the LSM values can be closer together than the sample means based on the predicted values and other model factors.

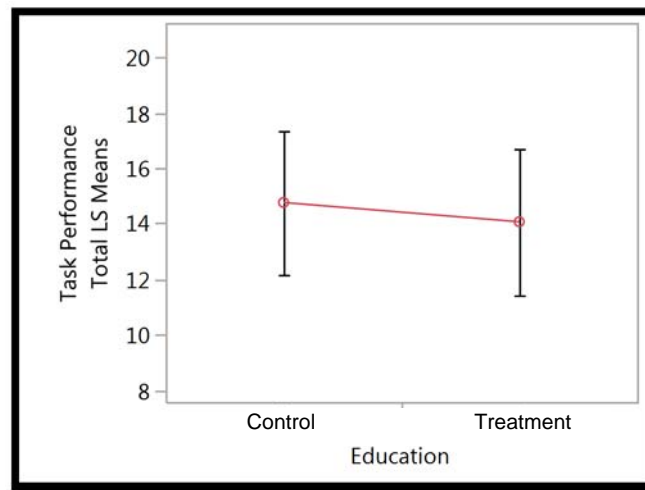


Figure 23: Education Treatment Performance LSM Plot

Table 15: Education Treatment Performance LSM Values

Level	Least Sq Mean	Std Error	Raw Mean
No Education Treatment	14.75	1.30	14.98
Education Treatment	14.06	1.33	14.12

Hypothesis H.1.b was supported; experience was found to significantly affect task performance ($F = 12.76, p < .001$). The pronounced difference between those who did not receive the experience treatment and those who did seems to be the result of correcting larger numbers of errors by some individuals. Figure 24 shows the leverage plots of the responses' residuals on a chart. This is an analysis that compares the residuals of the treatments while holding other treatments constant. The left hand

contains the relative scores for those who did not receive the experience treatment (the control group and the education only group). The right hand show those who received the experience treatment (experience only group or education and experience group). One can clearly see that the side that received the experience treatment does not contain participants with very high scores. The p-value provided in the x axis indicates that individuals who received the experience treatment, either by itself or accompanied with education, performed significantly better than the control group, $p < .01$.

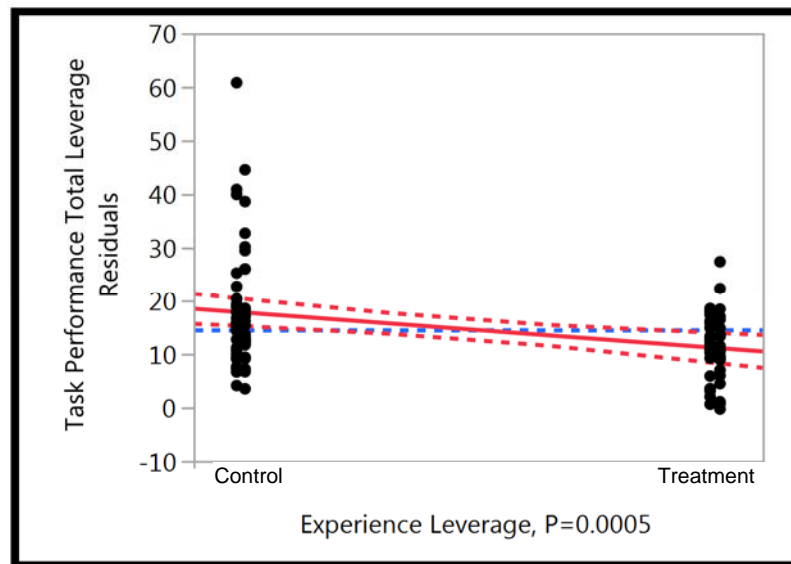


Figure 24: Experience Treatment Effect and Responses

Figure 25 shows the LSM effect of experience; when the LSM from education effect and LSM from experience are compared, one can see that experience has a much greater impact upon performance. This finding is confirmed by the complete model analysis, shown in Table 16.

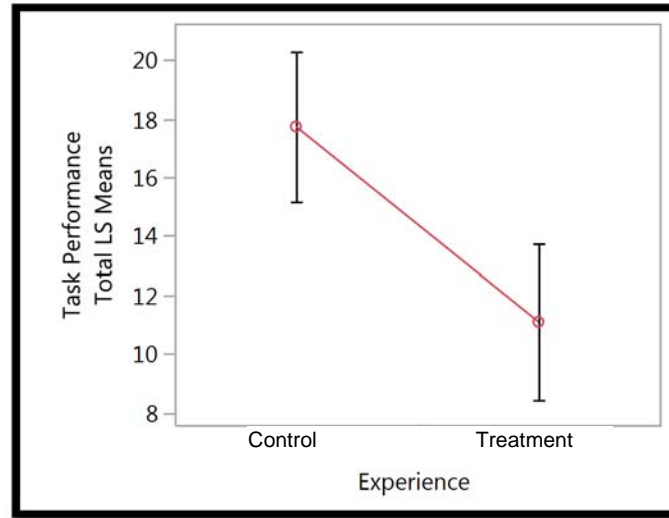


Figure 25: Experience Treatment Performance LSM Plot

Table 16: Treatment Effects upon Performance

Source	Nparm	DF	Sum of Squares	F Ratio	Prob > F
Education	1	1	12.10	0.14	0.71
Experience	1	1	1101.83	12.76	<0.001
Education*Experience	1	1	21.13	0.24	0.62
Baseline Residuals	1	1	2746.96	31.81	<.0001

Model 2: H.2.a and H.2.b

$$M2: y_{perceived\ task\ load} = \beta_0 + \beta_1 x_{ed} + \beta_2 x_{ex} + \beta_3 x_{ed} x_{ex}$$

Equation 3: Model 2 for H.2.a, H.2.b, and H.2.c

Model 2 employs the above equation to test the influence of education and experience on a participant's perceived task-load. Hypotheses H.2.a and H.2.b were not supported. Education alone was not found to significantly affect perceived task-load ($F = .90, p = .346$). Figure 26 shows that those in the education alone and experience alone group

actually indicated slightly lower perceived task-loads (although the differences are still within the margin of error). Likewise, experience alone was not found to significantly affect perceived task-load ($F = .89, p = .347$). However, there was a significant interaction effect between education and experience ($F = 5.27, p = .024$). This finding supports H.2.c. Figure 26 shows that participants in the education and experience treatment group indicated much higher task-loads than those in other groups, see Table 17.

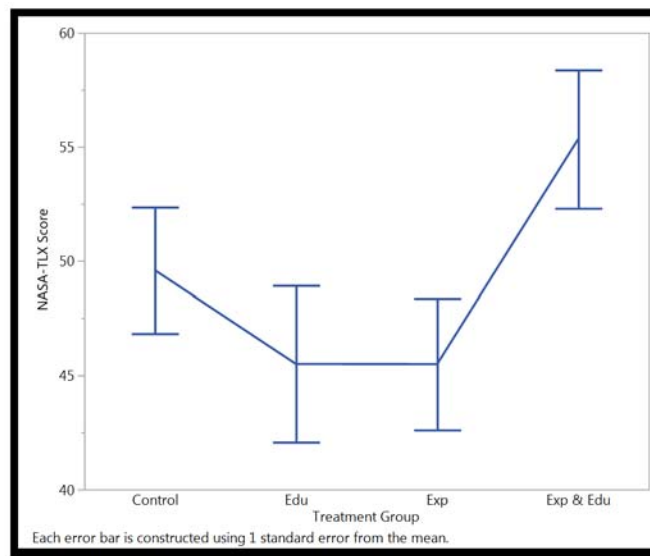


Figure 26: NASA-TLX Group Means with Standard Error Bars

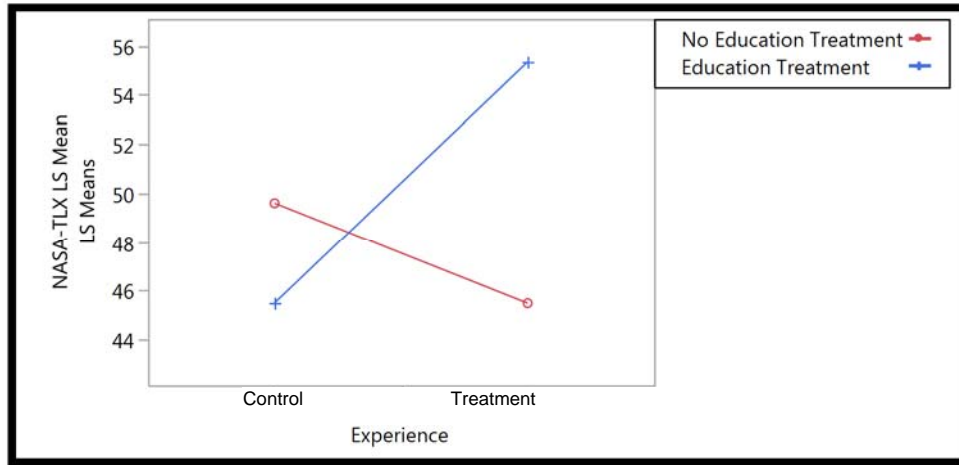


Figure 27: NASA-TLX Interaction Effect

Table 17: NASA-TLX Interaction Effect Values

Source	Nparm	DF	Sum of Squares	F Ratio	Prob > F
Education	1.00	1.00	206.48	0.90	0.35
Experience	1.00	1.00	205.03	0.89	0.35
Education*Experience	1.00	1.00	1212.11	5.27	0.02

Model 3: H.3.a and H.3.b

$$M3: y_{OCB} = \beta_0 + \beta_1 x_{ed} + \beta_2 x_{ex} + \beta_3 x_{ed} x_{ex}$$

Equation 4: Model 3 for H.3.a H.3.b, and H.3.c

Model 3 test the influence of education and experience upon the contextual performance measure of organizational citizenship behavior (OCB). Education was found to significantly affect organizational citizenship behavior ($F = 4.42, p = .038$). Therefore hypothesis H.3.a was supported. Figure 28 shows the raw scores and one can see that those who received the education treatment, either education alone or as part of the education and experience score higher. Figure 29 shows graphically that those who

received the education treatment scored significantly higher than those who did not receive the education treatment.

Table 18 provides the interaction results and confirms that education significantly affected the participants' OCB scores. Hypothesis H.3.b was not supported; experience was not found to significantly affect OCB ($F = 12.76, p = .001$), as can be seen in Figure 30. Likewise, H.3.c was not supported because no interaction effect of education and experience upon OCB was observed ($F = .03, p = .85$), see Table 18.

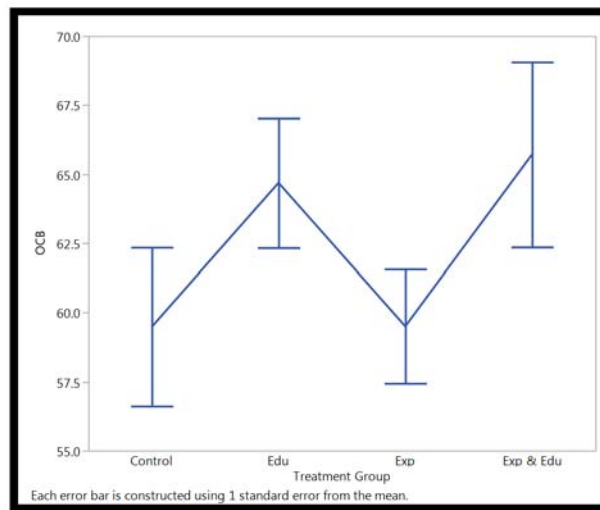


Figure 28: OCB Group Means with Standard Error Bars

Table 18: OCB Interaction Effect Values

Source	Nparm	DF	Sum of Squares	F Ratio	Prob > F
Education	1.00	1.00	811.35	4.42	0.04
Experience	1.00	1.00	6.83	0.04	0.85
Education*Experience	1.00	1.00	6.36	0.03	0.85

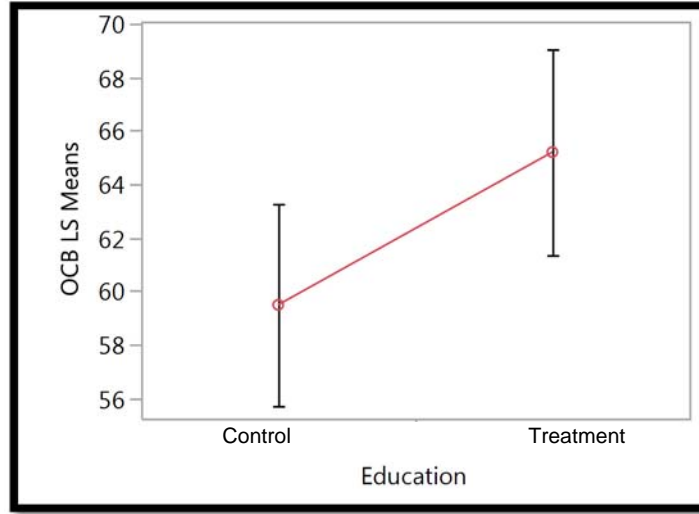


Figure 29: Education Treatment OCB LSM Plot

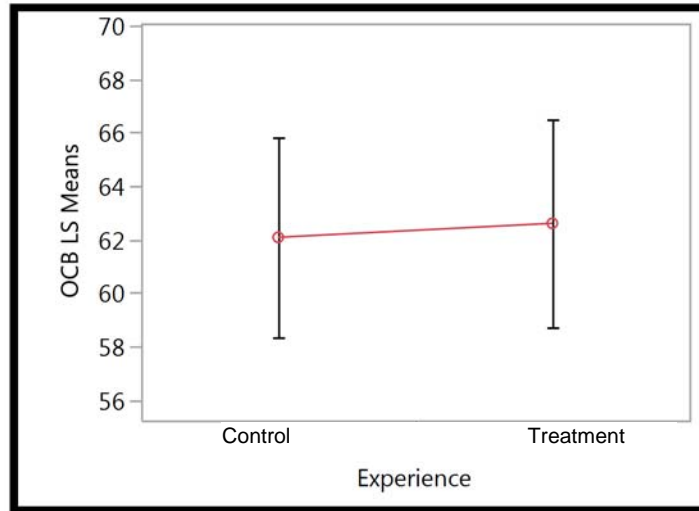


Figure 30: Experience Treatment OCB LSM Plot

Model 4: H.1.d

$$\begin{aligned}
 M4: y_{performance} &= \beta_0 + \beta_1 x_{supply\ ed} + \beta_2 x_{supply\ ex} + \beta_3 x_{extraversion} \\
 &+ \beta_4 x_{agreeableness} + \beta_5 x_{conscientiousness} + \beta_6 x_{neuroticism} \\
 &+ \beta_7 x_{openness}
 \end{aligned}$$

Equation 5: Model 4 for H.1.d

Models 4, 5, and 6 all used the same subject characteristics to test their influence upon performance, perceived task-load and OCB respectively. The subject characteristics employed were selected based upon their theoretical relationship to the research model. The models use previous supply experience, previous supply experience, and the individual dimensions of the Big-Five personality assessment: extraversion, agreeableness, conscientiousness, neuroticism and openness (John and Srivastava, 1999). Model 4 was formulated to test the influence subject characteristics upon performance. Hypothesis H.1.d was not supported; measured subject characteristics were not found to significantly affect task performance ($F = .77, p = .688$), see Table 19 and Table 20.

Table 19: Effect of Subject Characteristics upon Performance

Source	DF	Sum of Squares	Mean Square	F Ratio	Prob > F
Model	13.00	1263.12	97.16	0.77	0.69
Error	86.00	10836.21	126.00		
C. Total	99.00	12099.33			

Table 20: Effect of Subject Characteristics upon Performance Values

Source	Nparm	DF	Sum of Squares	F Ratio	Prob > F
Baseline Residuals	1.00	1.00	2278.29	22.63	<.0001
Extraversion	1.00	1.00	44.42	0.44	0.51
Agreeableness	1.00	1.00	0.94	0.01	0.92
Conscientiousness	1.00	1.00	1.24	0.01	0.91
Neuroticism	1.00	1.00	71.44	0.71	0.40
Openness	1.00	1.00	0.02	0.00	0.99

Previous Supply Exp	5.00	5.00	383.43	0.76	0.58
Previous Supply Edu	3.00	3.00	106.01	0.35	0.79

Model 5: H.2.d

$$\begin{aligned}
 M5: y_{\text{perceived task load}} &= \beta_0 + \beta_1 x_{\text{supply ed}} + \beta_2 x_{\text{supply ex}} + \beta_3 x_{\text{extraversion}} + \beta_4 x_{\text{agreeableness}} \\
 &+ \beta_5 x_{\text{conscientiousness}} + \beta_6 x_{\text{neuroticism}} + \beta_7 x_{\text{openess}}
 \end{aligned}$$

Equation 6: Model 5 for H.2.d

Model 5 was formulated to assess the influence of subject characteristics upon perceived task-load. Hypothesis H.2.d was not supported; measured subject characteristics were not found to significantly affect perceived task-load ($F = .96, p = .501$), see Table 21 and Table 22.

Table 21: Effect of Subject Characteristics upon Perceived Task-load Index

Source	DF	Sum of Squares	Mean Square	F Ratio	Prob > F
Model	13.00	2984.68	229.59	0.96	0.50
Error	86.00	20663.59	240.27		
C. Total	99.00	23648.27			

Table 22: Effect of Subject Characteristics upon Perceived Task-load Values

Source	Nparm	DF	Sum of Squares	F Ratio	Prob > F
Extraversion	1.00	1.00	56.17	0.23	0.63
Agreeableness	1.00	1.00	313.96	1.31	0.26
Conscientiousness	1.00	1.00	135.81	0.57	0.45
Neuroticism	1.00	1.00	33.84	0.14	0.71
Openness	1.00	1.00	265.09	1.10	0.30

Previous Supply Exp	5.00	5.00	2016.10	1.68	0.15
Previous Supply Edu	3.00	3.00	22.75	0.03	0.99

Model 6: H.3.d

$$M6: y_{OCB} = \beta_0 + \beta_1 x_{supply\ ed} + \beta_2 x_{supply\ ex} + \beta_3 x_{extraversion} + \beta_4 x_{agreeableness} + \beta_5 x_{conscientiousness} + \beta_6 x_{neuroticism} + \beta_7 x_{openness}$$

Equation 7: Model 6 for H.3.d

The final model was designed to assess the influence of subject characteristics upon the contextual performance measure of OCB. Hypothesis H.3.d was supported; some measured subject characteristics were found to significantly affect OCB ($F=4.74$, $p = .000$), see and

Table 23. Both extroversion and supply experience were found to significantly increase individuals' OCB, see

Table 24. Further analysis of the supply experience variable shows the strong linear relationship between increased experience and increased OCB scores, see Figure 31. The finding indicates that as supply workers acquire more experience, their levels of contextual performance improve.

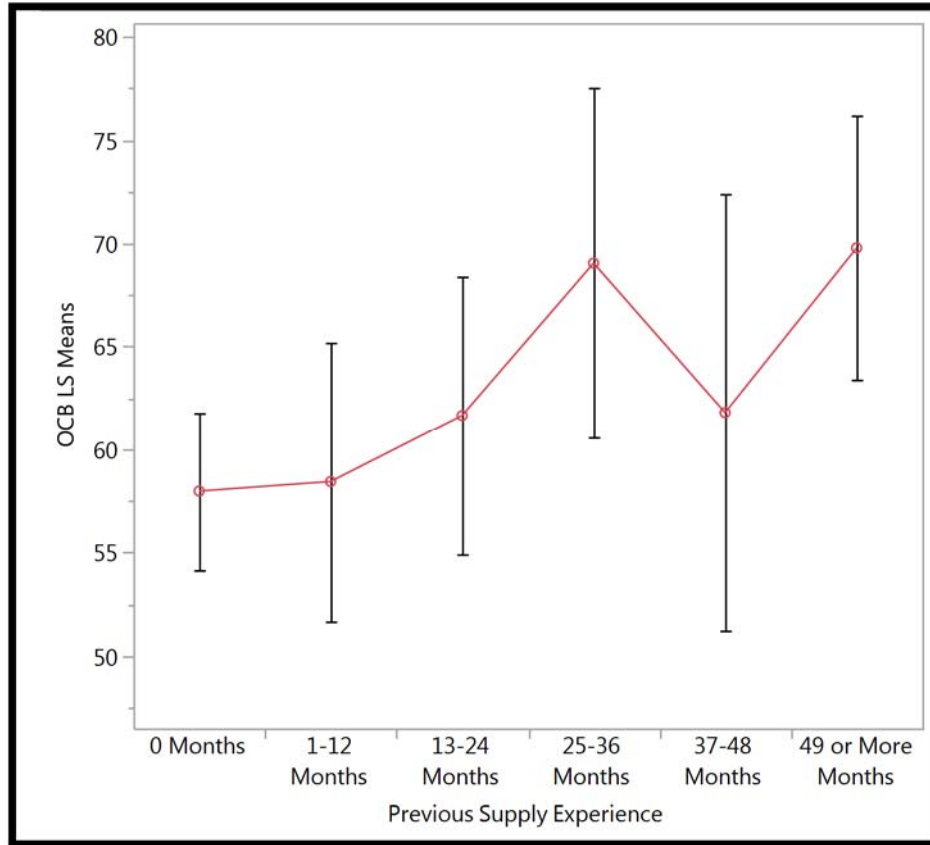


Figure 31: Previous Supply Experience Levels and OCB Scores

Table 23: Effect of Subject Characteristics upon OCB

Source	DF	Sum of Squares	Mean Square	F Ratio	Prob > F
Model	13.00	7695.71	591.98	4.73	<.0001
Error	86.00	10754.45	125.05		
C. Total	99.00	18450.16			

Table 24: Effect of Subject Characteristics upon OCB Values

Source	Nparm	DF	Sum of Squares	F Ratio	Prob > F
Extraversion	1.00	1.00	1881.82	15.05	<0.00
Agreeableness	1.00	1.00	21.68	0.17	0.68
Conscientiousness	1.00	1.00	419.98	3.36	0.07
Neuroticism	1.00	1.00	9.25	0.07	0.79
Openess	1.00	1.00	413.30	3.31	0.07
Previous Supply Exp	5.00	5.00	1632.10	2.61	0.03
Previous Supply Edu	3.00	3.00	229.12	0.61	0.61

Post-hoc Analyses

Some participants completed all line items, but made some errors. Conversely, some participants made no errors, but ran out of time before completing the task. However, no participants were able to complete all lines and commit no errors. This was taken as verification that the difficulty of the task was appropriate. Moreover, all lines were successfully picked by some participants...except one. One of the line items included two individually packaged surgical gloves that came in boxes with a quantity of ten per box; the bin location contained four boxes of gloves. The pick list identified the unit of issue as “1 each”, a unit instead of a box. All participants picked two boxes instead of opening the box and selecting two packaged gloves. Had the boxes been full, the customer would have received 20 gloves instead of two. This scenario is a realistic occurrence in Air Force warehouses. During a tour of an Air Force warehouse, this researcher noticed some boxes had yellow stickers with permanent marker writings such as “8 left in box.” Could such a prompt remedy the surgical glove picking error?

After the planned trials were completed, two additional volunteers arrived expecting to participate. This research used the opportunity to modify the mock supply area by

adding sticky notes to the end of each box with the current number of glove packages inside. The two additional participants successfully opened the boxes and picked two gloves instead of two boxes. While this ad-hoc assessment included only two participants, it certainly warrants further investigation.

There appears to be trade-off decision made by the participants between speed and accuracy. Previous research had identified changes in performance when a deadline was varied (Grasha and Schell, 2001). However, this research discovered that the individuals were making the decision to work faster and less accurate or slower and more accurate with the same time parameter (15 minutes). Figure 32 shows the results of Table 25 graphically. The results show a significant ($F = 53.70, p = <.001$) relationship between working faster and committing more errors.

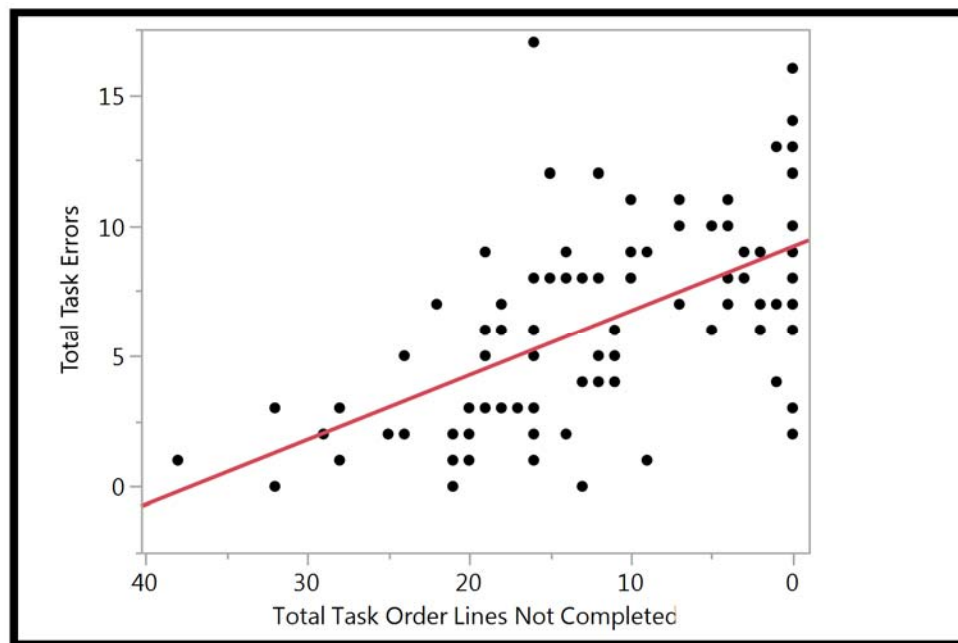


Figure 32: Speed and Errors

Table 25: Speed and Error Values

Source	DF	Sum of Squares	Mean Square	F Ratio	Prob > F
Model	1.00	532.08	532.08	53.70	<.0001
Error	98.00	970.96	9.91		
C. Total	99.00	1503.04			

Additionally, those in the experience group were slower on average, as can be seen in Figure 33. The chart shows the number of lines not completed for the picking task. While the differences seem stark, the groups are not significantly different due to the large within-group variance of lines completed. The large variances can easily be seen in Figure 34. The fanning out of the scores is indicative of unequal variance. However, when separated into block and analyzed for unequal variances, the unequal variances are not significant, as can be seen in Table 26. Although the variances are not significant at the .05 level, they are close. This is representative of a design that bottoms out at zero, but allows for a virtually infinite number of errors. Some individuals from each group completed all lines, but the means show that more total lines were completed by those in the control group; that is, they were moving faster and making more errors than the groups that received the education and experience treatments.

Table 26: Speed and Errors Test of Unequal Variance

Test	F Ratio	DFNum	DFDen	Prob > F
O'Brien[.5]	2.54	2.00	97.00	0.08
Brown-Forsythe	2.83	2.00	97.00	0.06

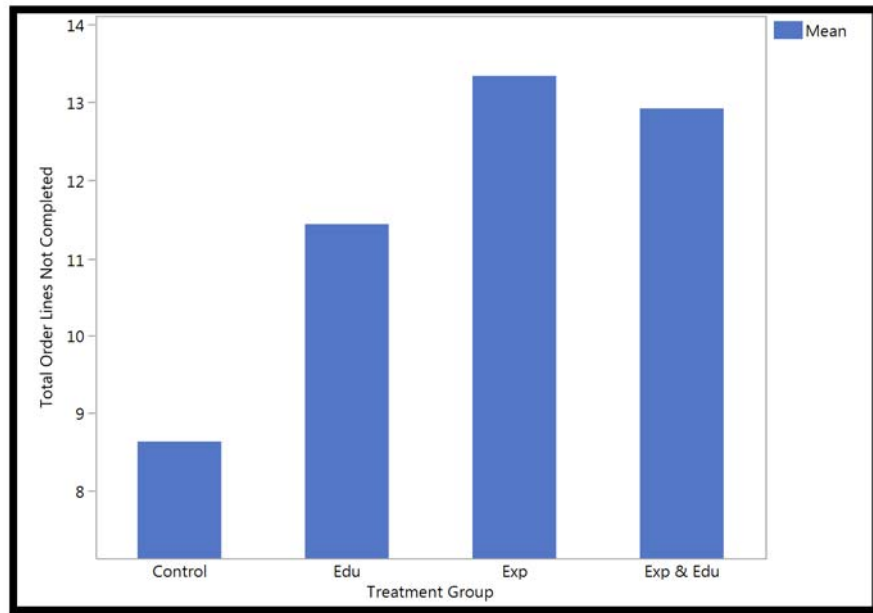


Figure 33: Lines Not Completed by Group

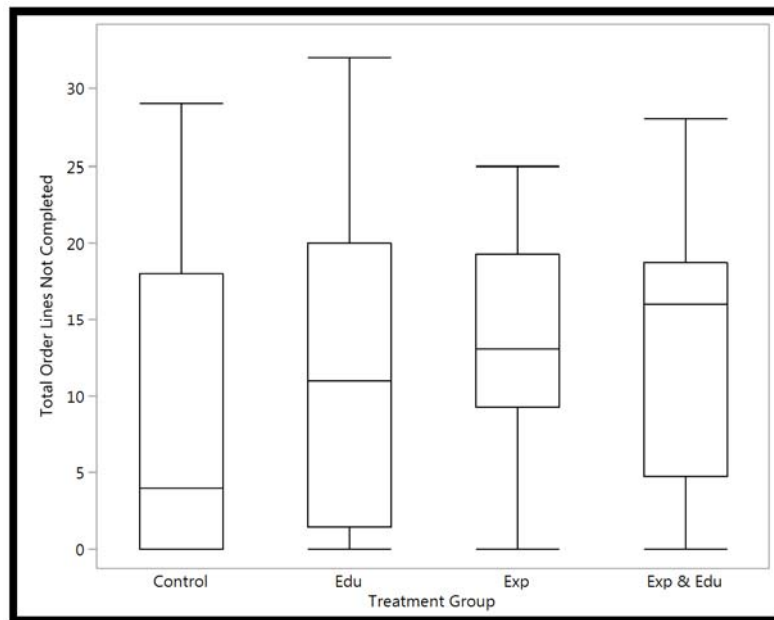


Figure 34: Variance of Lines Not Completed by Group

V. Discussion

The research model included 12 connections of mission clarity to job performance as shown in Figure 35. This research has helped identify which elements of mission clarity provide the strongest relationship to job performance. Experience was the most influential determinant of task performance. The interaction of education and experience was the most influential factor of perceived task-load. Both education and subject characteristics influenced contextual performance. The results of all the hypotheses are summarized in

Table 27.

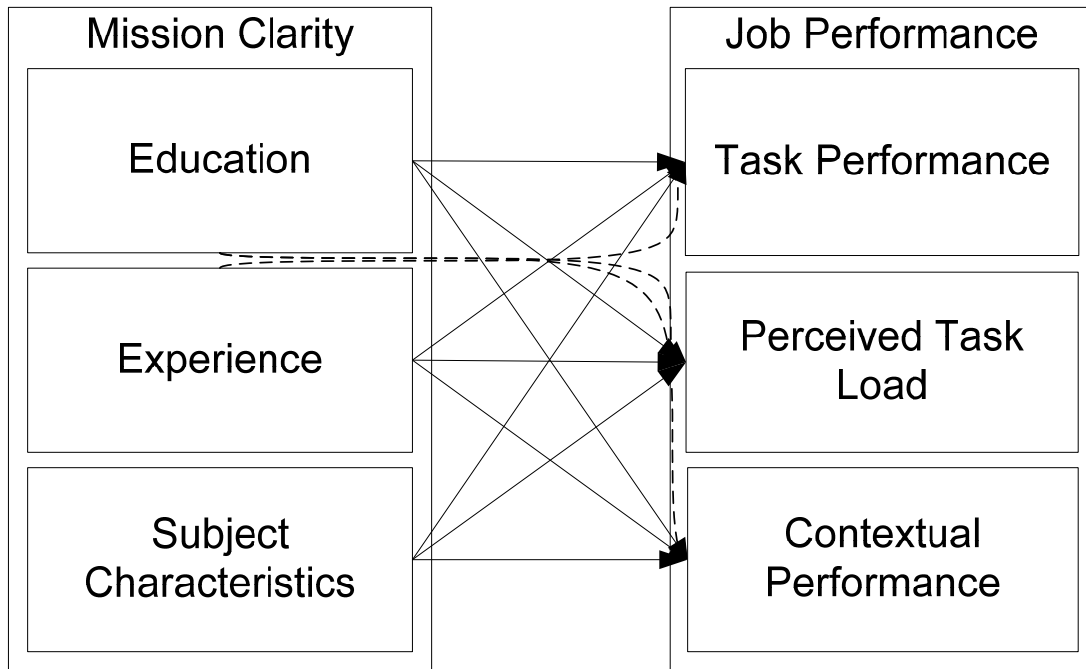


Figure 35: Research Model

Table 27: Summary of Hypotheses

	Independent Variable	Dependent Variable	Hypotheses	Outcome
H.1.a	Education	Task performance	Positive relationship	Not supported
H.1.b	Experience	Task performance	Positive relationship	Supported
H.1.c	Education*Experience	Task performance	Positive relationship	Not supported
H.1.d	Subject Characteristics	Task performance	Positive relationship	Not supported
H.2.a	Education	Task-load	Significant relationship	Not supported
H.2.b	Experience	Task-load	Significant relationship	Not supported
H.2.c	Education*Experience	Task-load	Significant relationship	Supported
H.2.d	Subject Characteristics	Task-load	Significant relationship	Not supported
H.3.a	Education	OCB	Significant relationship	Supported
H.3.b	Experience	OCB	Significant relationship	Not supported
H.3.c	Education*Experience	OCB	Significant relationship	Not supported
H.3.d	Subject Characteristics	OCB	Significant relationship	Supported

Theoretical Implications

This research included education as a component of mission clarity. The results showed that education administered via traditional learning methods has limited effects upon changing performance. This finding supports the learning literature that identifies experience as a necessary component to produce enduring changes in behavior, learning (Crick et al., 2013; Olson, 2015). The experience component provided more context to the workers' task. Increased mission clarity was shown to improve performance. Based on organizational learning literature, we expect the learning to diffuse throughout the organization (Argote, 2013). Given that experience impacts performance, then future models of mission clarity should retain experience as a key element. Subject characteristics may need to be included as control variables rather than modeled as

predictors of performance. Finally, the type and quality of education varies greatly from organization to organization. Education may need to be refined to fit the organization of interest. For example, if an organization uses only on-the-job training to educate employees, it should be operationalized differently than for organizations that rely on computer-based training. Matching the type of education to actual settings will ensure that any findings will provide meaningful conclusions.

This research buttressed human error literature regarding the types of errors workers can make. Although there are competing models of human error (Rasmussen, 1983), the generic error modeling system (GEMS) proved well-fitted for this research. Supply workers frequently face errors that can be classified as skill-based, rule-based, and knowledge-based. The participants in this study committed skill-based errors by miscounting items, dropping items, and skipping line items. They committed rule-based mistakes by failing to follow unit of issue guidance on the picking lists, incorrectly picking based on provided notes, and mislabeling orders. Finally, the opportunities for knowledge-based mistakes were not as abundant, but provided the greatest opportunity for severe errors (Reason, 2000). Participants were faced with potential knowledge-based errors when completing tasks differently than standard Air Force procedures. For example, due to logistical timing, the experiment guided participants to complete all three shipping labels before picking all three orders. In an operational Air Force warehouse, the normal procedure is to complete one order at a time and print the shipping label after picking all the needed items. However, some commercial facilities will have pickers working on more than one order at time. One facility we toured was designed for pickers to fill four orders at one time. When faced with novel problems, which exhausted their

normal operating rules, the workers would ask for guidance or guess about what they should do. Although, participants were repeatedly told they could ask questions throughout, many did not. To reduce the number of knowledge-based mistakes, workers should be empowered to seek additional information as needed in novel situations (Hopkins, 2012).

This study provided support for theoretical causes of inventory record inaccuracy (IRI). One of the contributors to IRI is the warehouse worker via misplacement (Kang and Gershwin, 2005; Rekik, Sahin, Jemai, et al., 2008). During the experimental tasks, the participants contributed to IRI with a variety of actions. Some participants would bring the order box (plastic tub) to the supply rack. Others would leave the tub on the table and walk back and forth with the items. Moreover, some would grab an excess of items, count them on the walk to the tub and return the excess to the storage rack. Some of the items were stored in smaller containers that were easily carried back and forth. However, sometimes, when returning the item to the storage rack, the participants would put them in the wrong location.

We also found evidence of satisficing. Participants were instructed to verify notes relating to the items. Participants displayed varied levels of thoroughness to achieve a satisfactory outcome. When individuals deem a choice as valid before ensuring the accuracy of that choice to the appropriate level, they are satisficing (Schwartz et al., 2002). The research revealed three main plateaus of item verification. For example, consider the information shown in the line item for an auto-suture device, see Table 28. The pickers should have proceeded to bin “R1C” and picked seven 45-4.8 auto-suture devices and ensured all packages were still sealed. Some participants would do this as

expected and correctly pick the items. Other participants would display satisficing by proceeding to the bin and assume integrity of the bins, not accounting for IRI. They would pick seven packages and not read the nomenclature or notes. In this particular bin, there was also a 45-2.5 auto-suture package. The package was roughly the same size and the device looked similar; although they were labeled differently and trimmed with different colors, see Figure 36. Lastly, some participants displayed an intermediary level of satisficing. They would proceed to the correct bin and verify the nomenclature and notes of the first item picked. Having received sufficient information to be comfortable with their decision (Caplin et al., 2011; Shi et al., 2011), they displayed satisficing by assuming the other items must also be accurate.

Table 28: Auto-Suture Line Item Example

NSN	Location	Qty	Nomenclature	Unit of Issue, Notes
5762-34-757-7178	R1C	7	45-4.8 AUTOSUTURE	1 EA, SEALED



Figure 36: Example of Visual Differences of Auto-Sutures

The research failed to reject the null hypothesis that subject characteristics affect task performance. This result seems to indicate that previous Air Force supply experience did not either help or hinder participants in the simulated task. This is understandable, given that the task was designed to be accessible for all participants regardless of experience level. The task was designed as an amalgamation of supply practices and did not conform to only Air Force operating procedures. For example, the participants used a generic pick list, see Appendix F, instead of the organization's actual forms, see Appendices G and H. Consequently, the lack of subject characteristics interacting with the performance measure increases the external validity of the study. Since subject characteristics did not significantly relate to performance, the generic tasks in the experiment could have been completed by non-supply participants.

Application to Operational Settings

This research was conducted in a controlled field setting, with operationally related elements. Therefore, the results should be externally valid to operational pick and pack operations. The practical recommendations discovered in the process of this research can apply to the Air Force as well as other organizations with pick and pack operations.

This research has added support and fidelity to the basic concept that worker behavior affects firm performance (Bruccoleri et al., 2014), see Figure 37. Increasing workers' mission clarity can be accomplished via numerous avenues, depending on the organization. An example of how an organization should increase their workers' mission clarity was discovered during the course of this research. An Air Force supply officer had initiated a base-level exchange program. The operational supply squadron began providing young supply airmen assigned to staff positions 6-months of warehouse

experience. Airmen in the staff positions work in an office setting and could potentially serve for years without ever actually working in a warehouse. This exchange program is an inexpensive solution that provides the Airmen greater context of their customers, thus increasing their mission clarity. Another example of how an organization should increase mission clarity was discovered at the conclusion of this research. A few months prior, this researcher spoke with a warehouse manager for a large retailer about mission clarity and how it should improve pick and pack performance. Afterwards, he decided to provide his pick and pack employees a distribution center tour after 90-days of employment. Such a activities should increase the employee's mission clarity. Finally, it appears that the work station design could greatly reduce the total error rate. Basic improvements to the process should include removing all identifiers including the letter O and number 0 along with uppercase "I", lowercase "l", or the number 1, which were confused during the picking process.

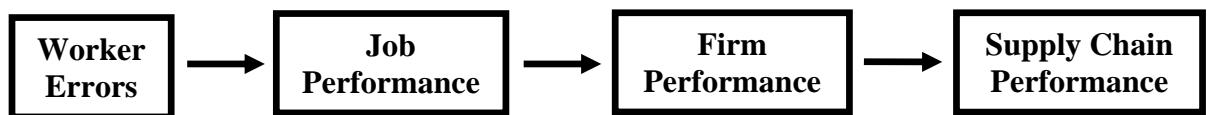


Figure 37: Conceptual Model

Organizations often desire to improve worker performance, yet improvements must be balanced with limited resources. For example, if the organization seeks to reduce the shipping error rate, they have a few options. One is to institute more checklists. Checklists can be useful for reducing skill-based errors, but increase the time needed to complete an action, thus increasing costs (Reason, 2002). Furthermore, there is a startup

cost for developing and maintaining the checklists. Other checks could be instituted such as second and third quality control reviewers. Such additions will find more errors, but also introduce potential sources of other errors, plus they rapidly increase the required manpower needed for each shipment. Another option is to invest in more augmented verifications. There is much research on technologies that can increase order accuracy (Berger and Ludwig, 2007; Hardgrave et al., 2013; Rekik, Sahin and Dallery, 2008), however they have significant startup cost. Organizations, including the Air Force, must consider what options will provide the greatest return on investment; in this case, reducing the most errors with the least disruptive and expensive option. From the research presented here, increasing worker mission clarity should provide the needed balance. Programs such as the supply exchange program referenced above are relatively inexpensive, readily carried out, and are sensible to managers.

Limitations and Call for Future Research

The target population for this research was Air Force supply workers. However, the use of active duty Air Force enlisted personnel potentially reduces the external validity to other organizations. For example, this research has shown that as supply workers acquire more experience, their level of contextual performance improves. This finding may be confounded by the correlation of supply experience to years in the Air Force. It is reasonable to expect that personnel with longer tenure in an organization would have higher levels of contextual performance. Future studies should include both supply experience and tenure with the current organization to see which variable is increasing the workers' contextual performance. However, given that the research focused on human behavior, it is reasonable to expect similar performance in similar settings. The

vice-president of Wal-Mart Logistic Services, who also had a successful career culminating as a Rear-Admiral in the U.S. Navy said, “When you get to the people aspect, you’ll find there’s not a whole lot of difference between industry and the military: people are people” (McCollum, 2016).

Some of the results included wide variances. Much of this variance could be reduced through two main approaches. The first is to increase the replications and refining the experimental procedure iteratively. The second is to reduce the phenomenon assessed in one study. For example, this experiment had participants complete both the physical task and make the shipping labels. Future research could isolate the various aspects to refine the impact of mission clarity upon the SC components. Replications could also refine the assessment of mission knowledge. The mission knowledge measurement was the only item with a Cronbach alpha below .7; it was .65. Ideally, a higher score would be preferred. Even though the lower value is not uncommon in first measurements associated with intelligence measures (Loewenthal, 2001b), future studies could increase internal reliability by refining the questions and increasing clarity. The assessment used in this research allowed some of the questions to be open ended; I recommend future assessments increase the number of questions and make them all multiple-choice. This change will eliminate the need to grade participants’ responses and should increase internal reliability.

Additionally, this research did not measure the lasting impact of organizational learning and mission clarity. Future studies could improve a portion of the organization’s mission clarity and assess the diffusion of information throughout the organization. Ideally, a study could find a large organization with multiple pick and pack locations.

The researchers could actively increase the mission clarity of workers at some sites while measuring others as a control. The results of this research indicate that the sites with greater mission clarity should perform better. If the above study is conducted, research based on the diffusion of learning could be applied to the organization to assess how many workers and to what extent organizations should increase mission clarity. It would be beneficial for an organization to know what benefits are gained from various levels of mission clarity saturation.

To reflect realistic warehouses and based on empirical findings, this research included about 5% stocking errors. The majority of errors occurred with these line items. Therefore, future research should address how organizations can effectively reduce inventory record inaccuracies. As more organizations become dependent upon complex stocking processes, record inaccuracies will affect warehouse management differently than in the past. When a warehouse is relatively open, visible inspections of racks is possible, even if tedious. However, when inventory is stocked and retrieved automatically, visually locating missing inventory can be virtually impossible.

Finally, given the exploratory relationship of mission clarity to performance, this researcher recommends future studies continue to refine the elements that comprise mission clarity and its affect upon performance. One option is to conduct a detailed task analysis to assess the human factors associated with each facet of the pick and pack procedure. The task analysis would be organizationally dependent, but would provide insight to similar operations. As the impact of mission clarity is replicated, the benefits will help organizations quantify the benefit-to-cost ratios and determine the best methods to reduce errors in picking and packing operations.

Appendix A—Big Five Inventory

Here are a number of characteristics that may or may not apply to you. For example, do you agree that you are someone who *likes to spend time with others*? Please select a number next to each statement to indicate the extent to which **you agree or disagree with that statement.**

1 Disagree Strongly	2 Disagree a little	3 Neither agree nor disagree	4 Agree a little	5 Agree strongly
---------------------------	---------------------------	------------------------------------	------------------------	------------------------

I am someone who...

- | | |
|--|--|
| <p>1. _____ Is talkative</p> <p>2. _____ Tends to find fault with others</p> <p>3. _____ Does a thorough job</p> <p>4. _____ Is depressed, blue</p> <p>5. _____ Is original, comes up with new ideas</p> <p>6. _____ Is reserved</p> <p>7. _____ Is helpful and unselfish with others</p> <p>8. _____ Can be somewhat careless</p> <p>9. _____ Is relaxed, handles stress well.</p> <p>10. _____ Is curious about many different things</p> <p>11. _____ Is full of energy</p> <p>12. _____ Starts quarrels with others</p> <p>13. _____ Is a reliable worker</p> <p>14. _____ Can be tense</p> <p>15. _____ Is ingenious, a deep thinker</p> <p>16. _____ Generates a lot of enthusiasm</p> <p>17. _____ Has a forgiving nature</p> <p>18. _____ Tends to be disorganized</p> <p>19. _____ Worries a lot</p> <p>20. _____ Has an active imagination</p> <p>21. _____ Tends to be quiet</p> <p>22. _____ Is generally trusting</p> | <p>23. _____ Tends to be lazy</p> <p>24. _____ Is emotionally stable, not easily upset</p> <p>25. _____ Is inventive</p> <p>26. _____ Has an assertive personality</p> <p>27. _____ Can be cold and aloof</p> <p>28. _____ Perseveres until the task is finished</p> <p>29. _____ Can be moody</p> <p>30. _____ Values artistic, aesthetic experiences</p> <p>31. _____ Is sometimes shy, inhibited</p> <p>32. _____ Is considerate and kind to almost everyone</p> <p>33. _____ Does things efficiently</p> <p>34. _____ Remains calm in tense situations</p> <p>35. _____ Prefers work that is routine</p> <p>36. _____ Is outgoing, sociable</p> <p>37. _____ Is sometimes rude to others</p> <p>38. _____ Makes plans and follows through with them</p> <p>39. _____ Gets nervous easily</p> <p>40. _____ Likes to reflect, play with ideas</p> <p>41. _____ Has few artistic interests</p> <p>42. _____ Likes to cooperate with others</p> <p>43. _____ Is easily distracted</p> <p>44. _____ Is sophisticated in art, music, or literature</p> |
|--|--|

Appendix B—Education Treatment Narrative and Slide

“This experiment is based on supplies needed for medical evacuation (medivac) missions facilitated by the Red Cross and local charities. The items here are a sampling of the many items that are considered surplus by the Air Force. The surplus items are transferred to the Red Cross for active medivac missions every 6 months. It is important for the orders to be filled exactly as requested, because a shortage can mean life-saving items are not available when or where they are needed. Sending the wrong items or excess items is unnecessary weight on the critical flights, potentially limiting the other resources or lives that can be flown out of hostile environments. The orders you fill today are all going to locations in the Horn of Africa area to help with field hospital construction and medical evacuations.”



Appendix C—Assessment Sheet (Front and Back)

Questions during instructions -->							Baseline		Participant ID	
Label Start		Typos	Left on	Redo			Arrival Time (wait)			
Label End							<input type="checkbox"/> Only one item per line		<input type="checkbox"/> Added Items to order	
Items Dropped							<input type="checkbox"/> Talker		<input type="checkbox"/> Cups to tubs	
? during tasks							<input type="checkbox"/> Left more messy			
Time Remaining							RED CROSS		7AZD2345X1B	
Lines not completed							AWAWA		ETHIOPIA	
Other <input type="checkbox"/> Total Order Errors							1203		1231	

Location	Skipped	Note fail	+/-	Qty	In	Nomenclature	Notes
L3B				7	11	4X7 IN CAM DRESSING FIRST AID	1 EA, PLASTIC WRAP NEEDED
L5D				2	13	PI INDICATOR UNDERGLOVE	1 EA
R6C				2	15	36 IN A.T.S. TOURNIQUET SYS	1 EA
R5B				4	10	MEDIUM BINDER CLIP	1 EA
R5C				5	12	SMALL BINDER CLIP	1 EA
R3A				7	6	LARGE RUBBER BAND	1 EA
R3B				8	9	THIN RUBBER BAND	1 EA
R3F				11	8	CARD HOLDER	1 EA
R3H				3	7	MEDIUM SAFETY PIN	1 EA
R3E				11	16	PAPER CLIP	1 EA
R3K				7	14	METAL THUMB TACK	1 EA
R3I				5	5	BRASS BRAD	1 EA
R3L				6	4	PLASTIC THUMB TACK	1 EA, CLEAR
R2D				13	3	NON-STERILE COTTON BUD	1 EA, ANY COLOR
R3J				5	2	T-TACK	1 EA
R5D				3	1	LARGE BINDER CLIP	1 EA

Label 1 Start	1 End	2 End	3 End	Left on	Order 1					
					<input type="checkbox"/> Only one item per line					
Redo					<input type="checkbox"/> Added Items to order					
Typos										
Items Dropped										
? during tasks										
Time Remaining										
Lines not completed										
Other <input type="checkbox"/> Total Order Errors										
					RED CROSS 7ASD2345X1Y AWAWA ETHIOPIA 1650 1231					

Location	Skipped	Notes fail	+/-	Qty	In	Nomenclature	Notes
L1F				3	1	MARK 1 KIT	2 PC & CASE, NEEDS INSTRUCTIONS
R1C				7	3	45-4.8 AUTOSUTURE	SEALED green right
L6A				2	5	SURGICAL HAND SCRUB	1 EA
R5A				3	8	SELF STICK WRAP	1 ROLL
R2F				3	11	40X40X56 NON-STERILE BANDAGE	INCLUDES TWO SAFETY PINS
L1B				5	2	2 IN ADHESIVE BANDAGE	1 EA
L1E				4	15	ATA TRAINING KIT	NEEDS INSTRUCTIONS
L1Aa				5	14	3IN ADHESIVE BANDAGE	1 EA
L5A				4	13	HI-LINE XS DISP CRANIOTOME	GE620SU, short, left, one GE432
R5D				13	10	LARGE BINDER CLIP	1 EA
L6C				2	16	PSI-TEC TUBING	PT4254
L1C				3	6	LARGE ADHESIVE BANDAGE	1 EA
R2A				5	7	STERILE ADHESIVE BANDAGE	1 EA
R5C				12	12	SMALL BINDER CLIP	1 EA
R3G				3	9	LARGE SAFETY PIN	1 EA
R3K				14	4	METAL THUMB TACK	1 EA

Order 2						Participant ID	
Items Dropped						__ Only one item per line	
? during tasks						__ Added Items to order	
Time Remaining						WORLD HEALTH ORG	
Lines not completed						7ASD3274Y2X	
Other __ Total Order Errors						PALS	
						SOMALIA	
						5220	
						5706	

Location	Skipped	Notes fail	+/-	Qty	In	Nomenclature	Notes
L3B				11	1	4X7 IN CAM DRESSING FIRST AID	PLASTIC WRAP NEEDED
R6B				3	2	HEMORRAGE CONTROL DRESSING	RESEALED OKAY
L2A				2	6	White box	11X35 MM BIOCOMP INT SCREW
R6A				2	8	ANTHREX ACP KIT SERIES I	1 EA
L5C				2	11	VIAL DECANTER	1 EA
R4B				3	9	ULTRASOUND TRANSMISSION GEL	1 EA
R6C				9	12	36 IN A.T.S. TOURNIQUET SYS	1 EA
R2E				3	13	4.5 IN X 4.1 YD STERILE ROLL	VACUUM SEALED
L6B				2	15	OXYGEN HIGH FLOW SAMPLER	SN: 112-138 & 112-137
L5B				3	16	HI-LINE XS DISP TWIST DRILL	GE432SU longer, right all 432s
L1D				2	10	NON-ADHERENT PAD	1 EA
R2B				3	7	LARGE KNUCKLE BANDAGE	1 EA
R3F				15	3	CARD HOLDER	1 EA
R3L				11	4	PLASTIC THUMB TACK	1 EA, CLEAR
R3E				13	14	PAPER CLIP	1 EA
R3J				7	5	T-TACK	1 EA

Order 3						__ Only one item per line	
Items Dropped						__ Added Items to order	
? during tasks							
Time Remaining						HUMANITARIAN INTL	
Lines not completed						7ASE7234Y3X	
Other __ Total Order Errors						GIOHER	
						SOMALIA	
						2550	
						5706	

Location	Skipped	Notes fail	+/-	Qty	In	Nomenclature	Notes
L5D				6	4	PI INDICATOR UNDERGLOVE	1 EA
L4A				2	2	4.7X3 MM CURVED CUTTER	1 EA
R4A				4	7	SAM SPLINT	36 IN
R1B				5	9	45-2.5 AUTOSUTURE	SEALED red left
L7B				2	13	DUAL HOSE STER 36 IN	1 EA
L1Ab				5	5	2.5 IN ADHESIVE BANDAGE	1 EA
L3A				5	15	20X15 MM TUNGSTEN LOOP ELECT	1 EA
R2C				3	10	8 PLY 2X2 IN GAUZE SPONGE	1 EA
R3A				7	6	LARGE RUBBER BAND	1 EA
R3B				7	12	THIN RUBBER BAND	1 EA
R5B				11	8	MEDIUM BINDER CLIP	1 EA
R3C				3	11	ADHESIVE FABRIC PIN	1 EA
R3D				4	14	STAR PAPER CLIP	1 EA
R3I				6	3	BRASS BRAD	1 EA
R3H				7	16	MEDIUM SAFETY PIN	1 EA
R2D				23	1	NON-STERILE COTTON BUD	ANY COLOR, 1 EA
NASA Start			FTLC			Questions during NASA TLX	
NASA End*			--NOTES--			Questions during Survey	

Appendix D—Internal Review Board Exemption



DEPARTMENT OF THE AIR FORCE
AIR FORCE INSTITUTE OF TECHNOLOGY
WRIGHT-PATTERSON AIR FORCE BASE OHIO

24 December 2014

MEMORANDUM FOR DR JEFFREY OGDEN

FROM: William A. Cunningham, Ph.D.
AFIT IRB Research Reviewer
2950 Hobson Way
Wright-Patterson AFB, OH 45433-7765

SUBJECT: Approval for exemption request from human experimentation requirements (32 CFR 219, DoDD 3216.2 and AFI 40-402) for Research Proposal "Reducing Human Errors in an Item Picking Task by Increasing Worker's Task-Knowledge".

1. Your request was based on the Code of Federal Regulations, title 32, part 219, section 101, paragraph (b) (2) Research activities that involve the use of educational tests (cognitive, diagnostic, aptitude, achievement), survey procedures, interview procedures, or observation of public behavior unless: (i) Information obtained is recorded in such a manner that human subjects can be identified, directly or through identifiers linked to the subjects; and (ii) Any disclosure of the human subjects' responses outside the research could reasonably place the subjects at risk of criminal or civil liability or be damaging to the subjects' financial standing, employability, or reputation.
2. Your study qualifies for this exemption because you are not collecting sensitive data, which could reasonably damage the subjects' financial standing, employability, or reputation. Further, the demographic data you are utilizing and the way that you plan to report it cannot realistically be expected to map a given response to a specific subject.
3. This determination pertains only to the Federal, Department of Defense, and Air Force regulations that govern the use of human subjects in research. Further, if a subject's future response reasonably places them at risk of criminal or civil liability or is damaging to their financial standing, employability, or reputation, you are required to file an adverse event report with this office immediately.

//signed//

WILLIAM A CUNNINGHAM, PH.D.
AFIT Exempt Determination Official

Appendix E—Baseline Pick List

ORDER NUMBER	City Code	Country Code	RECIPIENT	City Name, Country Name
7AZD2345X1B	1203	1231	RED CROSS	AWAWA, ETHIOPIA
NSN	Location	Qty	Nomenclature	Unit of Issue, Notes
1205-27-438-1178	R3E	11	PAPER CLIP	1 EA
1541-47-815-2063	R6C	2	36 IN A.T.S. TOURNIQUET SYS	1 EA
1694-41-652-9174	R3K	7	METAL THUMB TACK	1 EA
2654-85-928-7506	L5D	2	PI INDICATOR UNDERGLOVE	1 EA
3038-67-287-5923	R5C	5	SMALL BINDER CLIP	1 EA
3567-71-061-5453	L3B	7	4X7 IN CAM DRESSING FIRST AID	1 EA, PLASTIC WRAP NEEDED
3955-93-306-3652	R5B	4	MEDIUM BINDER CLIP	1 EA
4237-20-473-5558	R3B	8	THIN RUBBER BAND	1 EA
5828-84-560-8603	R3F	11	CARD HOLDER	1 EA
6510-04-631-1859	R3H	3	MEDIUM SAFETY PIN	1 EA
6539-41-013-7506	R3A	7	LARGE RUBBER BAND	1 EA
8816-40-967-6082	R3I	5	BRASS BRAD	1 EA
8856-37-578-1348	R3L	6	PLASTIC THUMB TACK	1 EA, CLEAR
9203-58-022-2819	R2D	13	NON-STERILE COTTON BUD	1 EA, ANY COLOR
9412-88-589-8615	R3J	5	T-TACK	1 EA
9541-47-815-4065	R5D	3	LARGE BINDER CLIP	1 EA

Appendix F—Task Pick List

ORDER NUMBER	City Code	Country Code	RECIPIENT	City Name, Country Name
7ASD2345X1Y	1650	1231	RED CROSS	AWAWA, ETHIOPIA
NSN	Location	Qty	Nomenclature	Unit of Issue, Notes
6839-85-859-8883	L6C	2	PSI-TEC TUBING	1 EA, PT4254
6910-01-469-0457	L1E	4	ATA TRAINING KIT	1 EA, NEEDS INSTRUCTIONS
2953-71-360-4490	L1Aa	5	3IN ADHESIVE BANDAGE	1 EA
3994-60-555-4177	L5A	4	HI-LINE XS DISP CRANIOTOME	1 EA, GE620SU
3038-67-287-5923	R5C	12	SMALL BINDER CLIP	1 EA
3058-03-790-7203	R2F	3	40X40X56 NON-STERILE BANDAGE	1 EA, INCLUDES TWO SAFETY PINS
9541-47-815-4065	R5D	13	LARGE BINDER CLIP	1 EA
1261-54-778-9384	R3G	3	LARGE SAFETY PIN	1 EA
7419-97-369-8271	R5A	3	SELF STICK WRAP	1 ROLL
2100-03-176-8486	R2A	5	STERILE ADHESIVE BANDAGE	1 EA
2517-69-421-4678	L1C	3	LARGE ADHESIVE BANDAGE	1 EA
2184-99-052-2396	L6A	2	SURGICAL HAND SCRUB	1 EA
1694-41-652-9174	R3K	14	METAL THUMB TACK	1 EA
5762-34-757-7178	R1C	7	45-4.8 AUTOSUTURE	1 EA, SEALED
6292-49-323-6762	L1B	5	2 IN ADHESIVE BANDAGE	1 EA
6910-01-194-0377	L1F	3	MARK 1 KIT	2 PC & CASE, NEEDS INSTRUCTIONS
ORDER NUMBER	City Code	Country Code	RECIPIENT	City Name, Country Name
7ASD3274Y2X	5220	5706	WORLD HEALTH ORG	PALS, SOMALIA
NSN	Location	Qty	Nomenclature	Notes
4968-40-931-5327	L5B	3	HI-LINE XS DISP TWIST DRILL	1 EA, GE432SU
2863-13-115-8017	L6B	2	OXYGEN HIGH FLOW SAMPLER	1 EA, SN: 112-138 & 112-137
1205-27-438-1178	R3E	13	PAPER CLIP	1 EA
6510-01-503-2117	R2E	3	4.5 IN X 4.1 YD STERILE ROLL	1 EA, VACUUM SEALED
1541-47-815-2063	R6C	9	36 IN A.T.S. TOURNIQUET SYS	1 EA
5548-87-357-4270	L5C	2	VIAL DECANTER	1 EA
5601-06-356-2460	L1D	2	NON-ADHERENT PAD	1 EA
1321-77-665-1420	R4B	3	ULTRASOUND TRANSMISSION GEL	1 EA
6955-93-306-3657	R6A	2	ANTHREX ACP KIT SERIES I	1 EA
1772-33-745-8904	R2B	3	LARGE KNUCKLE BANDAGE	1 EA
9616-95-841-3802	L2A	2	11X35 MM BIOCOMP INT SCREW	1 EA
9412-88-589-8615	R3J	7	T-TACK	1 EA
8856-37-578-1348	R3L	11	PLASTIC THUMB TACK	1 EA, CLEAR
5828-84-560-8603	R3F	15	CARD HOLDER	1 EA
6510-01-492-2275	R6B	3	HEMORRAGE CONTROL DRESSING	1 EA, RESEALED OKAY
3567-71-061-5453	L3B	11	4X7 IN CAM DRESSING FIRST AID	1 EA, PLASTIC WRAP NEEDED
ORDER NUMBER	City Code	Country Code	RECIPIENT	City Name, Country Name
7ASE7234Y3X	2550	5706	HUMANITARIAN INTL	GIOHER, SOMALIA
NSN	Location	Qty	Nomenclature	Notes
6510-04-631-1859	R3H	7	MEDIUM SAFETY PIN	1 EA
1088-45-240-0183	L3A	5	20X15 MM TUNGSTEN LOOP ELECT	1 EA
4436-90-794-0895	R3D	4	STAR PAPER CLIP	1 EA
3868-47-166-6700	L7B	2	DUAL HOSE STER 36 IN	1 EA
4237-20-473-5558	R3B	7	THIN RUBBER BAND	1 EA
4645-27-149-2292	R3C	3	ADHESIVE FABRIC PIN	1 EA
8880-93-810-4435	R2C	3	8 PLY 2X2 IN GAUZE SPONGE	1 EA
3991-91-864-6552	R1B	5	45-2.5 AUTOSUTURE	1 EA, SEALED
3955-93-306-3652	R5B	11	MEDIUM BINDER CLIP	1 EA
4889-21-236-4958	R4A	4	SAM SPLINT	36 IN
6539-41-013-7506	R3A	7	LARGE RUBBER BAND	1 EA
1839-85-859-8803	L1Ab	5	2.5 IN ADHESIVE BANDAGE	1 EA
2654-85-928-7506	L5D	6	PI INDICATOR UNDERGLOVE	1 EA
8816-40-967-6082	R3I	6	BRASS BRAD	1 EA
4201-16-299-8628	L4A	2	4.7X3 MM CURVED CUTTER	1 EA
9203-58-022-2819	R2D	23	NON-STERILE COTTON BUD	1 EA, ANY COLOR

Appendix G: DD Form 1348

[illegible]

[illegible]

Appendix I: Organizational Citizenship Behavior Inventory

How often have you done each of the following things on your present job?	Never	Once or twice	Once or twice per month
1. Picked up meal for others at work	1	2	3 4 5
2. Took time to advise, coach, or mentor a co-worker.	1	2	3 4 5
3. Helped co-worker learn new skills or shared job knowledge.	1	2	3 4 5
4. Helped new employees get oriented to the job.	1	2	3 4 5
5. Lent a compassionate ear when someone had a work problem.	1	2	3 4 5
6. Lent a compassionate ear when someone had a personal problem.	1	2	3 4 5
7. Changed vacation schedule, work days, or shifts to accommodate co-worker's needs.	1	2	3 4 5
8. Offered suggestions to improve how work is done.	1	2	3 4 5
9. Offered suggestions for improving the work environment.	1	2	3 4 5
10. Finished something for co-worker who had to leave early.	1	2	3 4 5
11. Helped a less capable co-worker lift a heavy box or other object.	1	2	3 4 5
12. Helped a co-worker who had too much to do.	1	2	3 4 5
13. Volunteered for extra work assignments.	1	2	3 4 5
14. Took phone messages for absent or busy co-worker.	1	2	3 4 5
15. Said good things about your employer in front of others.	1	2	3 4 5
16. Gave up meal and other breaks to complete work.	1	2	3 4 5
17. Volunteered to help a co-worker deal with a difficult customer, vendor, or co-worker.	1	2	3 4 5
18. Went out of the way to give co-worker encouragement or express appreciation.	1	2	3 4 5
19. Decorated, straightened up, or otherwise beautified common work space.	1	2	3 4 5
20. Defended a co-worker who was being "put-down" or spoken ill of by other co-workers or supervisor.	1	2	3 4 5

Frustration

How insecure, discouraged, irritated, stressed, and annoyed were you?

Very Low

Very High

Appendix K: List of Abbreviations

AFB Air Force Base

GEMS Generic Error Modelling System

IRI Inventory Record Inaccuracy

LSM Least Squares Means

NASA-TLX National Air and Space Administration – Task Load Index

OB Organizational Behavior

OCB Organizational Citizenship Behavior

OL Organizational Learning

SCM Supply Chain Management

SCOG Supply Chain Operations Group

SCOW Supply Chain Operations Wing

SRK- Skills, Rules, Knowledge

TPS Toyota Production System

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14. ABSTRACT Supply chain workers make observable, preventable errors while completing their assigned tasks in the shipping process. Previous research has indicated that individuals with a greater grasp of their work and better system-knowledge are less likely to commit interpretation errors. We believe worker-performance may, likewise, be affected by an individual's knowledge of why and where they fit into a larger system—defined as mission knowledge. To assess our research objectives, we conduct a controlled experiment with 100 workers in the Air Force supply career field to discern how mission clarity, that is, education, experience and subject characteristics affect pick and pack errors in simulated warehouse order fulfillment tasks. Results indicate that participants who received the experience treatment committed fewer errors, resulting in increased task performance.					
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