EXPLORING A BROADER VIEW OF TECHNOLOGY ACCEPTANCE

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In Partial Fulfillment

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Doctor of Philosophy

by

Douglas J. Steel

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TECHNOLOGY ACCEPTANCE

APPROVED:

Original signed by Wynne W. Chin
Wynne W. Chin, C. T. Bauer Professor of
Decision and Information Sciences
Chairperson of Committee

Original signed by Norman A. Johnson
Norman A. Johnson, Associate Professor of
Decision and Information Sciences

Original signed by Lisa M. Penney
Lisa M. Penney, Assistant Professor of
Psychology

Original signed by Andrew Schwarz
Andrew Schwarz, Associate Professor of
Information Systems and Decision Sciences,
Louisiana State University

Original signed by Arthur D. Warga
Arthur D. Warga, Dean
C. T. Bauer College of Business

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ABSTRACT

The primary aim of this dissertation is to establish the generalizability of the scale items used to measure 5 psychological acceptance constructs proposed by Schwarz and Chin (2007). While an initial test of validity and reliability was established by Schwarz (2003) using covariance-based structural equation modeling, a stronger test was performed to establish the generalizability of the items through a series of multigroup invariance tests. Having used 3 new independent data sets, we present the results of the combinatorial analyses of 3 pairwise comparisons of the data sets as well as a test comparing all 3 data sets simultaneously. Both confirmatory factor models and structural models were applied to examine whether item measures are identically reliable and whether the relationships among these 5 constructs also remain the same. Structurally, two models incorporating these 5 constructs were applied to predict an overall general acceptance construct and the construct of infusion. While the nomological relationships among these acceptance constructs varied as expected, the correlations and item loadings remain invariant. Therefore, the results answer the questions: (1) Can the acceptance constructs proposed by Schwarz and Chin be captured by reliable and accurate measures? (2) Are these constructs distinct from one another? and (3) Do they act similarly in different contexts?

Finally, to provide a platform for more research on workplace outcomes, this research explores the notion of technology infusion, an important form of usage. Given

that the 5 psychological acceptance constructs have predictive value toward infusion, we establish a means for further study of the concept.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

1 INTRODUCTION

The acceptance of technology by users is an age-old business problem. When a new technology or process is developed, managers are inevitably faced with the problem of users who are resistant to using the new technology or doing things in new ways. The problem has yielded a plethora of research and several models of technology acceptance. One could argue that a paradigm has evolved around the search for predictors and moderators of acceptance (Bagozzi 2007; Straub Jr. and Burton-Jones 2007). While these predictors and moderators are of some value, they are limited to a domain with a narrow definition of acceptance. This research takes a broader view of acceptance and builds on a more-informed model of technology acceptance.

The five-dimension model used in this research has predictive value towards outcomes in the workplace that are indicative of successful implementation. This is important because, as we will show, technology acceptance in the traditional sense does not necessarily result in increased productivity or other positive outcomes. But there will be cases where management interests will dictate the need for more than technology that is used frequently. Rather, there is a need for beneficial workplace outcomes. These include infusion and routinization, which are often more indicative of a successful technology implementation and beneficial workplace outcomes than usage itself (Sundaram et al. 2007; Zmud and Apple 1992a).

Further, while there are instruments for traditional measures of acceptance, there is a need for reliable measures to tap into the broader notions of acceptance. Having a useful instrument with predictive value towards workplace outcomes would provide a platform for more research on these outcomes. For this, it is important to have a generalizable instrument that is useful in many technology settings. We will demonstrate the generalizability of the instrument across three unique technology settings. This provides more confidence that the measures will be useful in other settings.

1.1 Research Problem

Businesses continue to have a need to get users to accept information technology (IT) to reap the productivity benefits envisioned. Benefits such as time and cost savings occur when the technology is used as soon as it is implemented and made available. But benefits do not necessarily always occur just because an individual is now using the IT or even using it extensively (i.e., in terms of frequency and time).

Consider the example of implementing an enterprise resource planning (ERP) system at a university. Administrators envision the benefits of efficiency and cost savings brought about by standardized processes and shared information. But these benefits were not fully realized in four years at Stanford University despite widespread “adoption” of the technology. This is summarized in an excerpt from a practitioner news article:

> *“Starting in 2001, Stanford implemented student administration systems, PeopleSoft HR, Oracle financials and several other ancillary applications. Four years later, users still complain that they have lower productivity with the new systems than with the previous ones, which were supported by a highly customized mainframe. Users also have had difficulties in accessing critical information on a timely basis. Livingston says many transactions—such as initiating a purchase requisition or requesting a reimbursement—take longer for users to do than with the prior legacy system” (Wailgum 2005).*

At the time at Stanford, some users complained of inefficiencies with the new system. Although the system was being used, it still failed to fully yield its anticipated benefits.

While adoption could be explained for this case, we lack a clear understanding of why the system failed to deliver the supposed benefit of efficiency.

While efficiency is one example of a potential workplace outcome that results from adding information technology to a workplace, there are many outcomes that go beyond the simple notion of extent of use. Consider the notion of the correct or effective use of IT. Termed by some as infusion, this form of usage looks at whether the amount and form of usage is optimal in terms of what the IT can provide to the task at hand (Sundaram et al. 2007). A business example involves a media distribution company that failed to get its clients to fully utilize their system. In it, a technology author describes the situation:

> *"[The] software did a terrific job of solving one problem, yet was never considered as a possible solution for any other business problem. Somehow, the software's early success had branded it a useful "point solution" rather than an innovative platform for an array of apps For example, while the software was superb for both mass and custom distribution of e-mails and PDFs, it could also handle global distribution of richer media formats—streaming, for instance. But clients were not even aware of the greater capability…. Why did early success blunt enhanced adoption? Communication was part of the problem… [T]he customers didn't understand what was available…. The software had been unfairly 'niched'"* (Schrage 2006).

Here, the system was not used to its full capabilities. Although the users in the example "accepted" the technology for use in a limited capacity, they failed to take advantage of all of its capabilities. This illustrates a negative workplace outcome resulting from lack of infusion.

Together, these examples illustrate that the mere use of a technology does not necessarily yield positive results. In the ERP case, people were using the software, but it did not fully yield increased efficiency. And in the case of the media communications software, the users did not use the tool to its fullest extent and thus, they did not benefit from all it could do. With that said, it is expected that well-known models of acceptance would show in both cases that the users accepted the systems. This is because models like the Technology Acceptance Model (TAM) equate acceptance with the actual use or the extent (i.e., frequency) of use. And since the systems in the examples were being used, they would meet the TAM criteria of acceptance.

We argue that acceptance goes beyond usage or extent of use. Other factors should be considered. For example, does an individual have to research aspects of the IT in order to effectively use it? Has it reached a status of efficient or routinized use? These and other outcomes of usage highlight additional considerations needed when discussing or modeling usage; however, usage and extent of use seem to be the focus of most acceptance models. This creates a problem for research models that incorporate some form of usage as dependent variables – they neglect the workplace benefits that can result from usage.

But developing models to understand the workplace outcomes of those using a technological solution covers only one aspect of acceptance. Depending on which usage outcome you select, it likely derives from a different set of psychological concepts and processes. The most well known model, TAM, and its variants (e.g., UTAUT) primarily focus on a core set of psychological perceptions, intentions, and consequent outcomes (Venkatesh et al. 2003).

Outcomes resulting from behavioral usage or post hoc assessment of the type of usage (i.e., infusion or routinization) do not necessarily imply acceptance – especially if the context was mandatory (Agarwal and Prasad 1997; Brown et al. 2002; Hartwick and Barki 1994; Wu and Lederer 2009). Instead, while acceptance can be inferred from behavior, it can be argued that a combination of both psychological perceptions and attitudes coupled with behavior provides a better gauge of acceptance.

TAM and the Unified Theory of Acceptance and Use of Technology (UTAUT) are examples of combining both behavior and psychological concepts. Thus, acceptance is about the nomological model which depicts the psychological processes that link perceptions, attitudes, and behavior. But we argue that TAM is not the only nomological model of acceptance. In some contexts, other models are more appropriate. Consider the research by Jones and his colleagues (2002a). In it, they found that while the TAM psychological concepts predicted intention to use and extent of usage, they did not necessarily impact other types of usage such as infusion. This highlights a problem because nearly all TAM studies deal with either intention or extent of use as outcomes, but not the other forms of usage (Jeyaraj, Rottman, and Lacity 2006; Lee, Kozar, and Larsen 2003). Therefore, since the TAM psychological concepts do not predict workplace outcomes such as infusion, we need to look for other psychological concepts of acceptance to do the job.

It is important to be concerned with other forms of usage because, it has been shown that extent of use does not necessarily lead to useful organizational outcomes (Senecal, Pullins, and Buehrer 2007; Sundaram et al. 2007). In the study by Sundaram and colleagues, routinization and infusion were found to influence salesperson performance but extent of use had no significant impact on this performance. Thus, to gauge important outcomes such as performance, we must look further than traditional TAM variables.

In summary, existing models of technological acceptance focus on a narrow definition of acceptance and fail to capture the nuances of acceptance that could lead to beneficial workplace outcomes. Thus, a better model of acceptance is needed. It should contribute to our understanding of workplace outcomes such as infusion and routinization. In turn, these outcomes can impact organizational performance which underscores the importance of this model.

1.2 Contribution

The primary contribution of this research is the demonstration of a methodology for establishing the generalizability of an instrument using multiple independent data sets. This method increases our confidence in the generalizability of the instrument compared to prevalent multigroup analysis methods that break up a single dataset or utilize additional data taken from the same organization. Generalizability also helps ensure the predictive value of the instrument and gives us more confidence in the conclusions drawn from its use (Malhotra and Sharma 2008).

This research will also explore a model of acceptance which is based on a broader definition of acceptance. It will show that such a model exists and is a useful tool for predicting a workplace outcome that results from acceptance. Specifically, the predictive validity of the model towards the outcome of infusion is examined. It is expected that future research will look at other workplace outcomes besides infusion.

Thus, the value of the new model depends on the subsequent outcomes. We will find that some components of the model are better at leading to certain subsequent outcomes than others are. This adds to the richness of the model because indeed, we expect its construct weights to vary based on the particular technology acceptance scenario.

Further, there is a need to consider different notions of psychological acceptance, establish their existence, and provide generalizable instruments that researchers can use to begin to develop other technology acceptance models. Incremental incorporation of additional factors to increase the predictiveness of one specific nomological model (i.e., TAM) is of limited value (Benbasat and Barki 2007). However, a generalizable, reliable instrument provides value to researchers and practitioners. Benbasat and Zmud (1999) cited measurement as an important area of research for practice because it contributes to relevance. For researchers, the value of a generalizable, invariant instrument is tied to the conclusions that can be drawn from it. As Steenkamp and Baumgartner state: “[i]f evidence supporting a measure's invariance is lacking, conclusions based on that scale are at best ambiguous and at worst erroneous.” (Steenkamp and Baumgartner 1998, p. 78). Thus, this demonstration and support for the invariance of the instruments provide for a valuable tool that researchers may use for additional, solid research.

1.3 Summary

Many technology acceptance models predict intention to use or frequency of use. But there are other workplace outcomes such as infusion and routinization that arguably could be considered part of acceptance. An article by Jones et al. (2002a) shows that TAM, the most popular acceptance model, does not help explain these workplace outcomes. This provides support for the case that new acceptance models are needed and forms the basis for this research.

2 LITERATURE REVIEW

An important stream of research in the field of information systems seeks to understand responses to new systems in terms of whether users accept or reject a new technology. This has led to research that helps explain the influences on acceptance and to numerous empirical and theoretical studies about acceptance (Davis 1989; Lee, Kozar, and Larsen 2003; Venkatesh et al. 2003). Although several research models help explain acceptance, they are built on a loosely defined notion of "acceptance." In fact, some acceptance models, including TAM, account for acceptance but fail to define its construct (Straub Jr. and Burton-Jones 2007). Indeed, we are left with the question: What exactly does it mean when a user "accepts" a technology? Further: How do we know when a user has "accepted" a technology? While there is a reasonably solid understanding of the antecedents of technology acceptance, much less attention has been paid to the black box that is called acceptance. This review will discuss many notions of acceptance. Before doing so, it will characterize the existing technology acceptance research stream.

2.1 Technology Acceptance Models

Technology acceptance is widely studied in the field of information systems, comprising about 10% of all IS publications, according to one estimate (Lee, Kozar, and Larsen 2003). Critical to the popularity of acceptance research was the 1986 development of the Technology Acceptance Model (TAM) by Fred Davis; it spurred numerous empirical and theoretical studies of adoption (Davis 1989). TAM itself has proven to be a robust and parsimonious model that helps explain the intention to use a technology.

Arguably, the model is quite effective, but it is limited by its parsimony (Bagozzi 2007). This opened the door for researchers to propose numerous predictors, moderators and other constructs that supplement technology acceptance models to help explain the intention to use a system (King and He 2006).

In summary, technology acceptance model have been developed, refined and studied in the field of information systems since 1986 when Fred Davis first proposed TAM. The next subsection will summarize the research stream of these models.

2.1.1 Overview of TAM

Existing reviews and meta-analyses about technology acceptance and TAM help us gather a better understanding of TAM. One review by Lee and his colleagues (2003) looked at the development stages of TAM, dividing it into 4 phases. After introduction and validation stages, TAM research flowed into an stage Lee et al. called model extension (2003). During this extension stage, technology acceptance researchers focused on finding external variables that could enhance the explanatory power of TAM. They identified external variables such as gender, task characteristics and cultural characteristics as having an influence on usefulness and perceived ease of use. The additional variables help explain some of the variance related to the intention to use and frequency of use constructs (Venkatesh et al. 2003). All the while, this research stream focused on the dependent variables of behavioral intention and usage.

Following this in about the year 2000, researchers shifted toward developing new technology acceptance models in a period Lee et al. (2003) called the model elaboration period. In this period, which is ongoing, there have been numerous new models including

TAM 2 (Venkatesh and Davis 2000), UTAUT (Venkatesh et al. 2003), and TAM 3 (Venkatesh and Bala 2008).

While Lee et al. looked at TAM research in terms of periods, other researchers studied the external variables added to TAM. This includes King and He (2006), who reviewed 88 TAM studies and concluded that the ease of use construct impacts intention to use more so through an indirect path that includes perceived usefulness than it does through a direct path to intention to use. Further, their work found support for the use of student subjects when generalizing to professionals. However, they caution that students are not good representative of the “general” user (p. 751).

Another review by Wu and Lederer (2009) classified the factors influencing system adoption as either individual differences or as social influences. The authors noted that these factors were used as both independent variables and as moderators.

In addition to the aforementioned TAM research, there is acceptance research in other fields. For example, Kulviwat and his colleagues (Kulviwat et al. 2007; Nasco et al. 2008) incorporated affect into a technology acceptance model and enhanced the cognitive portions of TAM to form the consumer acceptance of technology (CAT) model. This model has more explanatory power in consumer situations where the adopter of technology not only uses the product, but also enjoys it.

There is a tremendous amount of technology acceptance research, and some of this is directed toward critiques of the research stream. These are summarized in the following subsection.

2.1.2 Critiques of TAM

A recent series of articles paints a pictures of the current state of technology acceptance research (Hirschheim 2007). In the series, Straub and Burton-Jones appropriately used the term logjam to describe the "dominate but stifling paradigm" that is TAM research (Straub Jr. and Burton-Jones 2007, p. 224). These researchers call for another meta-analysis of TAM studies to determine the moderators, antecedents and external variables that deserve the most attention in future adoption research.

The critiques also delve into generalizability issues. In an extensive meta-analysis and review of TAM studies, Lee and his colleagues found generalizability problems were an often mentioned limitation. The only limitation found more frequently in their review of TAM studies was the issue of self-reported usage. They wrote:

> *"The second most cited limitation of the studies is the tendency to examine only one information system with a homogeneous group of subjects on a single task at a single point of time, thus raising the generalization problem of any single study."* (Lee, Kozar, and Larsen 2003, p. 762).

This underscores the need for more generalizable acceptance research.

Further Brown and colleagues (2002) noted that TAM does not necessarily generalize to mandatory use settings. Here, attitudes play an important role in intention formation and the behavioral intention construct becomes more complex. With this view, some adoption researchers question the appropriateness of using behavioral intention as a proxy for actual usage (Nah, Tan, and Teh 2004).

Another issue involves the "acceptance" construct itself. In much of the classic technology acceptance literature, acceptance consists of the intention to use a system or even the frequency of system use (Lee, Kozar, and Larsen 2003). With this, intention to use a system is a proxy for the behavior of actual use and, implicitly, acceptance of the system. The intention-usage link is not alarming to researchers because studies such as Taylor et al. (Taylor and Todd Assessing it usage: The role of prior experience 1995) indicate that intention to use is a reasonable proxy for usage. But the notion of acceptance is still elusive. As Straub and Burton-Jones state in their review of TAM:

> *"Although TAM refers to 'acceptance,' the 'acceptance' construct itself has never been clearly delineated" (Straub Jr. and Burton-Jones 2007, p. 224).*

We take issue with the fact that these studies deal with the same aspects of the technology process. Yes, TAM explains substantial amounts of the variance (about 40-50%) related to intention to use and frequency of use (Taylor and Todd Understanding information technology usage: A test of competing models 1995; Venkatesh and Davis 2000). But what if the same measures only predicted 20 percent of other types of acceptance such as infusion? There is not much research effort directed toward understanding the constructs, moderators, and predictors of other notions of acceptance like infusion. And since they are not necessarily achieved through usefulness and ease of use, it is important to better understand what processes contribute to them.

2.2 Five Dimensions of Acceptance

In contrast to well-established models of acceptance such as TAM and UTAUT, there are broader notions of IT acceptance such as those expressed by Schwarz and Chin (2007). As we will discuss, the latter views IT acceptance as a mix of behaviors and psychological conditions to form a more complete view of IT acceptance.

A broader view of acceptance includes both behavioral and psychological components. One view proposed by Schwarz (2003) conceptualizes technology acceptance as an entity with five dimensions: Receive, Grasp, Assess, Be Given, and

Submit. Each of these dimensions contributes to a view of acceptance as a whole. These are summarized in table 2.1.

Table 2.1 The Five Dimensions of Acceptance
(Taken from Schwarz & Chin (2007, p. 240))

Dimension	Definition
Receive	“The psychological state of taking the technology without question”
Grasp	“The psychological state of fully comprehending the intentionality (e.g. functionality and design) of the technology”
Assess	“The psychological state of evaluating the value and desirability of the technology to me”
Be Given	“The psychological state of an individual willing to adapt his/her routines to what was required by the technology “
Submit	“The psychological state of the individual surrendering to the intentionality of the technology”

The five dimensions of acceptance help researchers understand the acceptance process. A snapshot of an acceptance process at a fixed time shows a measure of each dimension. Take for example, the case of a jogging enthusiast ordering a new, portable music player. We consider this example in the following definitions.

The first dimension, Receive, means that the individual has taken the technology. For example, the new owner simply takes possession of the device via purchase or receipt as a gift. The act of taking is a handoff from the old owner to the new one. This does not mean that the person has accepted the technology - he simply took it.

Secondly, the recipient must grasp what he has taken. That is, understand the device and what it does. In our example, the recipient can press buttons to choose from a large selection of songs.

The next dimension is to assess or evaluate the technology. To do so, the recipient would ask “is it something I want or something I value?” In our example, the recipient would start considering whether he likes the new player. Interestingly, he would not have to completely grasp the player to consider its worth. That is, one does not have to understand the technology he is evaluating. This implies that there is not necessarily a sequence or staging from Grasp to Assess – one could occur or start occurring before the other.

The fourth dimension, Be Given, implies that the recipient adapts to the technology. In our example, the jogger must set aside time occasionally to keep the device charged and filled with fresh songs. He has adapted his routine to accommodate the new technology.

The final dimension is Submit, or to identify with the technology. If the jogger submits to the highest level, he would feel that the new device is perfect. He would identify with it so much that he is proud of the item and even attempts to convince others of the item’s worth.

Note that the five dimensions are not stages of acceptance. There is no requirement for achievement of any one state before another. This is consistent with the example, where the jogger can begin evaluation of the technology before grasping its purpose. The earlier research of Schwarz (2003) labeled the 5 dimensions as stages. We argue that staging is not required. Any construct or dimension can be achieved at some level prior to another.

Arguably, there are other valid conceptualizations of IT acceptance that incorporate behavioral and psychological components. But what is important to this research is that broader views of IT acceptance exist and they can be useful in understanding the broader set of workplace outcomes that result from technology acceptance. The five dimensions of acceptance are just one of these broader conceptualizations of acceptance.

2.3 Workplace Outcomes

Taking a wider view of acceptance includes looking at some of the other aspects of acceptance such as the routinization and infusion of a technology. In total, we examine 5 workplace outcomes of acceptance. Indeed, the 5 outcomes do not form an inclusive list, but instead they are a means to illustrate that there are multiple ways to think about acceptance. For the purposes of this research the following workplace outcomes were selected for further investigation: infusion, generic acceptance, routinization, deep usage, and faithfulness of appropriation.

Some early IS implementation literature provides the foundation for understanding workplace outcomes. Kwon and Zmud (1987) developed an organizational-level model which recognized stages of implementation that go beyond simple adoption. The model was refined by Cooper and Zmud (1990) to incorporate routinization and infusion in the later stages. Together, the research established a framework for post-adoptive behaviors. Further, it shows that the processes of routinization and infusion can be valuable contributors to a successful implementation.

Cooper and Zmud argue further that the stage model may be more widely applicable if "the stages are thought of as activities, some of which may occur in parallel" (1990, p. 125). Thus, activities like routinization are not necessarily relegated to the end of the acceptance process. This is consistent with the five dimensions model of acceptance where processes do not necessarily occur in stages.

Taken together, these acceptance activities help form a broader view of the acceptance process. We look at five of these outcomes in the following subsection. The first is a view of infusion.

2.3.1 Infusion

Another workplace outcome, infusion, refers to the degree to which a technology is embedded "within an organization's operational and/or managerial work systems" (Zmud and Apple 1992b, p. 150). The extension of this concept to the individual level is to define infusion as the extent to which an individual fully utilizes the technology to enhance his or her productivity.

Interestingly, infusion can be examined with respect to time. Technology that has been implemented for a while is exposed to more opportunities for increases in its level of infusion. This is consistent with the work of Zmud and Apple (1992b), who found a relationship between early adoption and infusion. The early adopters have more time to embed the technology into their work systems, and thus, increase the level of infusion of the technology.

Researchers examining the infusion of a technology would be led to examine its levels of routinization. Zmud and Apple (1992b) studied the two notions and found that routinization "seems to be a necessary but not sufficient condition in itself for an organization to achieve an advanced infusion level regarding a technology" (p. 154). Interestingly, they noticed the speed at which routinization occurred in their study -- the level of routinization increased at a faster rate than that of infusion. Thus, in a best-case scenario, workers would first adapt to the technology by changing their work routines and what follows is that the technology becomes embedded into the work environment.

Infusion has also been studied that the individual level. Schwarz (2003) defined it as "the extent to which an individual fully utilizes the technology to enhance his/her productivity" (p. 114). This construct could be measured by observation or self assessment. The observation could be completed by researchers or the employee's manager. In his work, Schwarz measured perceived infusion by asking the employee the extent to which he or she used the technology for the aforementioned purpose.

This is related to Hsieh and Wang's notion of extended use or "using more of the technology's features to support an individual's task performance" (Hsieh and Wang 2007, p 217; Saga and Zmud 1994). These researchers adapted Schwarz's measures to tap into the construct of extended use.

2.3.2 Generic Acceptance

The notion of generic acceptance is associated with a user's satisfaction with using a technology. While traditional acceptance instruments attempt to capture the nuances of antecedents and moderators of acceptance, it is informative to determine the subject's general feelings about accepting a technology. This is accomplished by a generic acceptance construct which has items that inquire about overall levels of acceptance. Users that feel they have accepted the technology "all things considered" would have high levels of generic acceptance.

2.3.3 Routinization

Routinization of technology occurs when users adjust their work routines to account for the use of a new technology. When this occurs, the workers change their perceptions of the new technology. This is summarized by Saga and Zmud (1994) who describe routinization as “the alterations that occur within work systems to account for IT application such that these applications are no longer perceived as new or out-of the ordinary” (p. 67). Thus, work routines are altered to integrate the technology into them and in turn, this can eliminate the novelty of the recently introduced technology.

2.3.4 Deep Usage

The workplace outcome of deep usage relates to the extent that the end-user utilizes all the features of the technology that can help accomplish a task (Wang and Butler 2006). A user that is deeply using a technology is going beyond the basic operational techniques and is finding more ways in which the technology can help him or her perform well. For example, a writer could use the basic features of a word processor to create a novel; however, a writer who is using this tool deeply might discover an outlining or other organizational tool in the processor that will allow him to more easily organize his thoughts and become more productive. Thus, the deep user utilizes the features available that help him better perform a job.

While Wang and Butler (2006) look at deep usage with respect to uses that go ”beyond those envisioned by management,” other researchers narrow the scope of what constitutes deep use (p. 441). These include Burton-Jones and Straub (2006), who introduce the notion of deep structure usage. It relates to the use of features that “support the underlying structure of the task” (p. 238). Taken together, the two definitions suggest that the deep user is taking advantage of obscure features of the technology toward the goal of accomplishing his or her job.

2.3.5 *Faithfulness of Appropriation*

The outcome of faithfulness of appropriation is closely tied to how the end-user operates or utilizes the new technology. Uses consistent with the intents of the original developers would be considered most faithfully appropriated. To better understand this, we look at what it means to appropriate and then what is a 'faithful appropriation'.

Poole and DeSanctis (1989) maintained that to appropriate is to use an object constructively, "to incorporate it into one's life, for better or worse" (p. 150). However, drawing from adaptive structuration theory, they argued that appropriation carries a deeper meaning: Appropriation "is really appropriation of the rules and resources the object carries [or makes available]" (p. 152). That is, the end user is not only appropriating an object, but also its capabilities and constraints. By using it, a subject is reinforcing the "structures that enabled their use in the first place" (p. 152). For example, a carpenter can be given a hammer to frame or assemble a wall. Working in the field of carpentry, which has a series of conventions and techniques, the carpenter reinforces the conventions of framing by using the hammer to drive screws into the frame. Doing this appropriates the hammer, but not in a manner consistent with the hammer design which calls for nails, not screws. Likely, the carpenter is reinforcing the structure or metaphor of driving nails rather than constraining the use of the hammer for its designers' intended purpose of driving nails. Thus, the hammer is not faithfully appropriated by the carpenter.

The notion of faithfulness of appropriation is addressed by DeSanctis and Poole (1994). They explain that users may appropriate material faithfully or unfaithfully. Faithfully appropriated objects are appropriated "consistent with the spirit and structural feature design, whereas unfaithful appropriations are not" (p. 130). With that, structural features are the “rules and resources, or capabilities, offered by the system” and the spirit is the “general intent with regard to values and goals underlying a given set of structural features” (p. 126).

2.3.6 Summary

The workplace outcomes of infusion, generic acceptance, routinization, deep usage, and faithfulness of appropriation illustrate some of the outcomes that can result from successful technology implementations. Researchers studying acceptance of technology could consider these as well as other workplace outcomes when accessing the impacts of technology implementations. Doing so will create a more-informed view of the impacts of the implementation.

Further, in mandated use contexts, these outcomes are more appropriate for study than intention to use. This is consistent with the research of Hsieh and Wang who state that “intention to use may not be the best predictor of actual usage in the post-adoptive context” (Hsieh and Wang 2007, p. 218). Better, they argue, is a behavior such as extended use. Thus, the behavior of infusion may be more appropriate than intention to use to explain usage in a mandatory use context. However, this is not without limitations.

The researchers also note that users who are forced to regularly use a system are likely to become familiar with it and more of its features. Thus, while mandatory usage may contribute to infusion, this could be a limitation to the study.

2.4 Multigroup Invariance

This research utilizes multigroup invariance tests to analyze the performance of an instrument in different contexts. These tests determine "whether or not components of the measurement model and/or the structural model are invariant (i.e. equivalent) across particular groups" (Byrne 2001, p. 173). Importantly, these multigroup invariance tests require multiple independent data sets. This contrasts with tests that rely only on data collected at similar sites (Deng et al. 2005) or on collected data that is split into subgroups for analysis (Mao and Palvia 2008). As we will discuss in this section, the use of multiple independent data sets provides more confidence in the utility of the instrument in new settings and provides evidence of generalizability.

Indeed, we argue for the importance of multigroup invariance (MGI) testing. The outcomes of such testing would be consistent with and provide support for other research that suggests the need for invariant instruments. Along these lines, it is worth examining the value of MGI testing. That is, what value does invariance testing supply? Other researchers suggest the answers as summarized in table 2.2.

Table 2.2. Invariance Testing in the Literature

Authors	Statement	Implication
Doll, Hendrickson, and Deng (1998)	"Testing for invariance (i.e., equivalence) is a… test of an instrument's robustness" (p. 841).	Invariance is robustness; invariance is equivalence.
Malhotra, and Sharma (2008)	"In other words, can the developed scales (with measurement equivalency)… be generalized to other settings or contexts (e.g., industries or countries)?" (p. 644).	Measurement equivalence is generalizability to other settings.
	Without measurement equivalency, the "meaning and interpretation of the latent constructs and their measurement can change across groups and consequently lead to invalid conclusions" (p. 644).	Establish measurement equivalence to support the validity of conclusions.
Vandenberg and Lance (2000a)	"The particular issue that we address here is of measurement equivalence (or, alternately, “measurement invariance”) across populations" (p. 5).	Measurement equivalence is equated to invariance.
	The "demonstration of measurement equivalence is a logical prerequisite to the evaluation of substantive hypotheses regarding group differences" (p. 9).	Establish measurement equivalence before evaluating hypotheses across groups.
Lee and Kozar (2009)	"(Multi-group) [a]nalysis was conducted to examine whether the models and instruments were invariant across different subgroups" (p. 36).	Multigroup analysis is a test of invariance.
	"[M]ulti-group analysis… allows a test of the generalizability of measurement items" (p. 39).	Multigroup analysis establishes generalizability.

The table highlights some benefits of MGI testing. For example, Malhotra, and Sharma (2008) mention that without the establishment of measurement equivalence, the "meaning and interpretation of the latent constructs... [can] lead to invalid conclusions" (p. 644). And Vandenberg and Lance (2000a) believe that the "demonstration of measurement equivalence is a logical prerequisite to the evaluation of substantive hypotheses regarding group differences" (p. 9). Thus, multigroup invariance testing does have benefits for research.

However, when it comes to describing multigroup invariance and what it accomplishes, the dialog falls short. Namely, the terminology used lacks the precision and consistency needed to provide clarity. For example, Doll and his colleagues (1998) appear to equate invariance with the broad term of robustness without any further clarification of what robustness provides and whether it differs with the more narrow notion of statistical robustness of an estimating process. Next, Malhotra and Sharma (2008) state that measurement equivalence allows for generalizability, but Lee and Kozar (2009) add "multi-group" to that to claim multigroup invariance provides for generalizability (p. 39). But the exact nature of the generalizability is not spelled out in the Lee and Kozar paper.

In summary, literature on measurement invariance does not converge on a single, concise rationale for its use. While the literature suggests the importance and positive benefits of establishing measurement invariance, the exact definition of the term measurement invariance is clouded with generic terminologies that appear confusing on the surface. It does not paint a complete picture. This leads us look for other explanations of measurement invariance and its benefits.

We agree with Malhotra and Sharma (2008) that the establishment of measurement invariance benefits researchers by allowing more confidence in the conclusion drawn via an instrument (even in different settings). This could be thought of as the validity of the instrument, specifically, its external validity. This is defined by Emory and Cooper (1991) as:

> *"The external validly of research findings refers to their ability to be generalized across persons, settings, and times" (p. 180).*

The issue of generalizability therefore lies at the heart of this research. In this study we use MGI methods to establish generalizability. This is discussed further in the following section.

2.4.1 Generalizability

The notion of generalizing is "to form general notions by abstraction from particular instances" (Lee and Baskerville 2003, p. 232). But with generalization, there is a distinction between the generalization and the source of the generalization. This is explicated in the Lee and Baskerville (2003) framework that is described in this section. When measurement invariance is examined through the lens of this framework, we obtain a better understanding of why measurement invariance testing is useful to researchers.

In introducing the framework, Lee and Baskerville (2003) discuss Hume's problem of induction and its implications. The problem outlined by Hume states that researchers cannot justify generalizing their findings to new settings. Specifically, according to Lee and Baskerville: "there is only one scientifically acceptable way to establish a theory's generalizability to a new setting: It is for the theory to survive an empirical test in *that* setting [emphasis added]" (Lee and Baskerville 2003, p. 241).

Along these lines, they relay the difficulties in demonstrating generalizability. In writing about some earlier research by other authors, they state that "even if Gefen and Straub (1997) had empirically tested and confirmed their extended theory in an overwhelming number of different firms, one would be able to claim only that the theory is generalizable to these firms and no others" (Lee and Baskerville 2003, p. 239).

Nevertheless, it seems reasonable to test and show the reliability and validity of an instrument as remaining constant in as many likely future research contexts as possible. In other words, we should select settings that other researchers are likely to examine in the future. While it is not practical to test a theory in every setting to which it may be applied, we indeed gain more confidence in an instrument's applicability to other settings by challenging and successfully testing it in new settings. We do so in this research through the use of multiple data sets that spans different technology implementations at different firms. To better describe what this accomplishes, we look at it through the lens of the generalizability framework given by Lee and Baskerville. This framework follows.

To establish the framework, Lee and Baskerville first distinguish between empirical and theoretical statements. Empirical statements "can refer to data, measurements, observations, or descriptions about empirical or real-world phenomena" while theoretical statements relate to "entities and relationships that cannot be directly observed" (p. 232). The former is measured and the later could be represented with a construct or a path in a structural model. In sum, the distinction between empirical and theoretical statements forms the basis for their framework to categorize generalizability.

The authors' model is a quadrant table with one axis consisting of the source of the generalization and the other relating to what the research is generalizing. For example, one quadrant, EE, represents generalizing from an empirical statement to another empirical statement. This is shown in table 2.3, where the name we assign to each category of generalization is followed by Lee and Baskerville's designation in parentheses. An example of EE generalization occurs when a statistician describes data.

With EE generalizations, the researcher makes generalizations from the sample that has been studied.

Table 2.3. Generalizability Framework
(adapted from Lee and Baskerville (2003))

Name	**Generalize From**	**Generalize To**	**Examples**
Describe (EE)	Empirical Statement	Empirical Statement	Descriptive statistics; "describing… responses to the different items in a measurement instrument" (Lee and Baskerville 2003, p. 234).
Theorize (ET)	Empirical Statement	Theoretical Statement	Formulate theory about the unsampled portion of the sampling frame.
Apply Theory (TE)	Theoretical Statement	Empirical Statement	Empirically test a theory in a different setting.
Meta Theorize (TT)	Theoretical statement	Theoretical statement	"[F]ormulation of a theory… from a literature review" (Lee and Baskerville 2003, p. 238).

Another type of generalization, ET, occurs when one formulates theory from empirical statements. This would occur, for example, when a researcher formulates theory about the unsampled portion of the sampling frame. Specifically, ET generalizations can involve developing theories about the unsampled parts of an organization that was studied.

Consistent with the problem of induction highlighted by Lee and Baskerville, the resulting theory would be valid only for the population tied to the source of the generalization. However, with additional exposure of the theory to new areas and subjects we gain more confidence in the theory. That is, as the theory continues to hold true during attempts at falsification in new settings, we gain more confidence in its utility for other populations.

The ET generalization could describe an output of the structural equation modeling process. The structural model resulting from an initial test/analysis for a particular population sample represents a theoretical generalization of type ET. That is, assessing measurement invariance and structural invariance involves the inputs of collected data to yield measurement and structural models. Indeed, this is in the realm of structural equation modeling.

The third generalization type is called TE. In this, we empirically test a new theory or "use the theory in the new setting" (Lee and Baskerville 2003, p. 237). Researchers do this when they state what a theory suggests we would expect to find in an organization. In the structural equation modeling process, this would occur when one applies a model to a new setting or organization.

The final type of generalization is named TT. This occurs when one develops theory from other theoretical statements. Lee and Baskerville provide an example of this and it involves "the formulation of theory based on the synthesis of ideas from a literature review" (Lee and Baskerville 2003, p. 238). As such the development of a meta-theory or an extension in scope of any existing theory would be examples.

Together, the four types of generalizability help form a framework to better understand the importance of multigroup invariance testing. Within this framework falls the generalizability applicable to this research: Types ET and TE.

We suggest that much of the existing structural equation modeling (SEM) measurement model research in information systems falls in ET category. This was assessed by exploring other information systems articles that utilize multigroup invariance tests. We searched the Social Sciences Citation Index (SSCI) and the Arts & Humanities Citation Index (A&HCI) from the Web of Science database using the maximum available time span of 1984-present and the search term "measurement and invariance." From these, we selected the articles that were about information system and followed traditional multigroup invariance test procedures. Additionally, an ad hoc manual search was conducted to find more information systems articles with multigroup invariance tests. The findings are given in the following table.

Table 2.4. Multigroup Invariance Research in Information Systems

Subject	Tests	Data Characterization	Groups	Conclusions	Comments	Reference
Web Site Usability	Tests for invariance of loadings and factor correlations	176 students taking an introductory psychology or introductory e-commerce course	Data split by amount of Web usage; also split by number of Web purchases in the previous year	• One of 6 invariance hypotheses rejected. • "Considering all these tests together, the adapted EUCS generalized quite well across the different groups" (p. 355).	• Split sample – appears to be ET generalization	(Abdinnour-Helm, Chaparro, and Farmer 2005)
Cross-Cultural Analysis of End-User Computing Satisfaction	Tests for invariance of item factor loadings and structural paths	Questionnaire sent to 2 organizations in India, 136 in Saudi Arabia, 25 in Taiwan, 1 in Western Europe, and 60 U.S. firms	Data formed 5 subgroups by country or area.	• Measurement model not invariant across 5 groups. • Measurement model using 3 of the 5 groups was invariant. • Structural model with the 3 groups was invariant.	• Sent to multiple organizations in several countries; appears to be TE generalization • Tested loadings first, then tested invariance of paths	(Deng et al. 2008)
Invariance of TAM Across Applications	Tests for invariance of item factor loadings and structural paths	742 undergraduate IS students at 2 universities	Data split into groups by assignment to an office application	• Measurement model was invariant. • Structural model was not found to be invariant.	• Split sample – appears to be ET generalization • Tested invariance of measurement model first and then tested invariance of structural model	(Deng et al. 2005)

Table 2.4—Continued

Subject	Tests	Data Characterization	Groups	Conclusions	Comments	Reference
Perceived Usefulness and Ease of Use Instruments	Tests for invariance of factor loadings	Undergraduate IS students at 2 universities	Data split into groups by assignment to an application; also split by gender and prior computing experience	• Measurement model not invariant across applications for a group of 4; found to be invariant for a group of 3 • Mixed results for other tests	• Split sample – appears to be ET generalization	(Doll, Hendrickson, and Deng 1998)
Personality Inventory	Tests for invariance of the measurement model across age and gender	Participants with family history of diabetes in 5 Stockholm cities	Data split by gender; data split into 4 age groups	• Found support for the case of invariance across age and gender	• Split sample – appears to be ET generalization	(Gustavsson et al. 2008)
Technology Acceptance for Internet Banking	Tests for the invariance of constructs and of latent factor means	Business graduate students a 1 university in Hong Kong	Data split across age (above/below 35 yrs), gender, and IT competence (expert/novice)	• Found supported for factorial invariance across age and gender in the measurement model • No support for theta-delta invariance of the error terms	• Split sample – appears to be ET generalization	(Lai and Li 2005)

Table 2.4—Continued

Subject	Tests	Data Characterization	Groups	Conclusions	Comments	Reference
Web Site Usability	Tests for the invariance of structural paths and of item-factor loadings	Online purchasers – subjects were university students or part of the public responding to a notice	Data split across age (above/below 30 yrs) and gender	• Found support for measurement invariance. • Lack of support for invariance across age for 4 of 8 paths. • Lack of support for invariance across gender for 3 of 8 paths.	• Split sample – appears to be ET generalization	(Lee and Kozar 2009)
Impact of Experience on IT Usage	Tests for the invariance of structural paths	Employees of 30 companies in China	Data split by experience levels	• Partial support for invariance across levels of experience; some failure to support invariance	• Split sample – appears to be ET generalization • Only structural path invariance testing is documented	(Mao and Palvia 2008)
IS Usefulness and Usage	Tests for the invariance of structural paths	Students enrolling for courses at 1 university	Data split by gender and by experience levels	• No support for invariant paths across gender; No support for invariant paths across experience levels	• Split sample – appears to be ET generalization • Only structural path invariance testing is documented	(Saeed and Abdinnour-Helm 2008)
Cross-Cultural Study of TAM	Tests for measurement invariance and structural invariance	250 teachers in Singapore and 245 teachers in Malaysia	Singapore and Malaysia	"factor loadings appeared to be equivalent across the cultures examined" (p. 1007) No support for invariance of structural paths	• "Tests for measurement… and structural invariance were performed separately" (p. 1005).	(Teo et al. 2009)

The Groups column in the list of studies contains our assessment of the apparent source of the groupings used in the multigroup invariance tests. For example, in the Abdinnour-Helm et al. (2005) study, the sample was split by the amount of hours per week the subjects used the Web. In this, the resulting groups are part of the same underlying population rather than that which would be obtained from individually sampling each population of interest. The population used in the testing also guides the type of generalizability that results from the multigroup tests. That is, since the groups originate from the same underlying population, we are not performing the invariance tests in new settings. Thus, we categorize the generalizability obtained in the article as an ET generalizability. This is indicated in the Comments column of the table.

Most of the multigroup invariance tests we uncovered in the information systems literature formed the groups for testing by splitting a sample obtained from a single population. The splits were either based on a demographic or some other characteristic. Since the resulting groups are from the same underlying population, we categorized the generalizability as type ET.

Some studies, such as those by Doll and colleagues (1998) obtained subjects from multiple sites. Yet different sites need not imply different contextual settings. In this case, the authors sampled from what is essentially the same population – undergraduate students from two universities. Since the data from both sites was merged and then split by another criterion, it appears that the groups originate from the same population and the generalizability that results is of type ET.

On the other hand, we identified some studies as having TE generalizability. The groups used in the testing belong to different populations so the invariance tests exposed the instrument to the new settings. This is a TE generalization. In particular, Deng and colleagues (2008) sampled from multiple countries or cultures and these cultures formed the groups of study for the invariance analysis. Indeed, this is an example of TE generalizability because the instrument was subjected to new settings.

And a cross cultural study by Teo et al. (2009) sampled two populations to form the groups of interest in their multigroup invariance tests. The authors surveyed 250 teachers in Singapore and 245 teachers in Malaysia and examined measurement and structural invariance using these groups to yield TE generalizability. Although the addition of the second population adds to the generalizability of the study, we argue that there is more to generalizability than the number of populations sampled. For example, the authors attempt to determine if an "11-item measure of… TAM… is robust across cultures" yet both populations in the study are the same occupation (i.e., teachers) and neighbors geographically (p. 1000). With this, the claim of cross-cultural invariance could have been boosted if there was more contrast in the two populations sampled.

In summary, the multigroup invariance studies we identified make generalizability claims that fall into the categories of ET or TE. The stronger of the two, TE, was found in two of ten articles. This is the type of invariance aimed for in this research. It requires the invariance testing of the measurement and structural models in new settings or domains.

The examination of measurement invariance in terms of the Lee and Baskerville framework, lays a foundation for the measurement and assessment necessary (but not sufficient) for claims of generalizability. This is described in the following subsection.

2.4.2 Measurement

The generalizability discussion has implications for measurement. If our goal is demonstrating the generalizability of an instrument to different technology settings, it is important to lay out a plan regarding the measures required.

Lee and Baskerville's (2003) research reinforces Hume's problem of induction by suggesting that one can never claim generalizability beyond the sample being tested (cf., Meredith 1993). While true, we still aim to have confidence that our instruments will act the same under new conditions and settings. Their suggestion of continuing to expose the instrument to tests and the fact that it holds up to the tests enhances our confidence it will act in the same way in the future in different contexts.

This suggests a means to improve confidence in a scale by exposing it to new conditions as part of the instrument validation process. That is, by utilizing multiple, dissimilar data sets we are exposing the instrument to tests in a different settings and this increases our confidence in the instrument. Thus, compared to instruments validated with single data sets, we gain more confidence that the instrument will act the same way in additional settings.

This line of reasoning suggests a number of steps. However first and foremost is for us to assess whether the instrument appears to be valid and generalizable, before using it in research. This is because it is difficult to claim any kind of generalizability of theoretical relationships without first demonstrating the invariance of the instrument.

We note that there is a distinction between invariance tests performed on data obtained from the same organization and those done across different settings. This is what distinguishes this research. In this study, the use of multiple technology scenarios provides the new settings necessary for invariance tests that yield confidence in the instrument.

2.5 Research Objectives

The objectives of this research involve assessing the measurement invariance and utility of 5 technology acceptance constructs. The main objective of this study is to examine the generalizability of an instrument across different settings. Instruments that are shown to be generalizable provide a tool for researchers examining the same phenomenon in new and different settings. Compared to instruments for which generalizability has not been explored, researchers who use a generalizable tool can be more confident that their measures would act consistently in new settings.

To address this objective we must first establish that the 5 technology acceptance constructs are a useful way of looking at acceptance and some of the beneficial workplace outcomes that can result from technology acceptance. Thus, we must determine if the 5 constructs can be adequately captured using a set of measures that gauge an acceptance scenario. For this, the measures would need to be reliable and accurate indicators of the underlying constructs. Further, the constructs being tapped into would need to be distinct from one another and invariant in different contexts. This brings us back to our primary objective - for a measure to be truly useful it ought also to be generalizable across multiple settings; hence it must be shown to be invariant across different contexts.

To further assist the main aim of this research, we will also assess whether the 5 constructs have predictive value toward different beneficial workplace outcomes, across the different settings. First we want to know if they contribute to the explanation of some workplace outcomes. If they do, we want to determine if the construct measures perform adequately and consistently while being used to predict the outcomes. In particular, we examine the generalizability of the measures by performing multigroup invariance test using different settings data.

Given the main aim is to assess generalizability of an instrument across different settings this calls for the following research questions to guide our analysis, namely:

(1) Do the five concepts of technology acceptance form reliable and accurate measures?

(2) Are they conceptually and empirically distinct from one another?

(3) Do they act similarly in different contexts?

(4) How do they differ on predictions of workplace outcomes?

In summary, the aim of this research is to assess the generalizability of an instrument in multiple settings. In so doing, the research outcomes are also expected to provide empirical support for the underlying thesis that there are more acceptance processes than those established in the traditional research stream. In addressing the research questions, this study will therefore demonstrate the utility of a different, broader view of acceptance across multiple settings.

3 METHODOLOGY

Now that the foundation for the study has been laid out, we will describe the research implementation methodology. This section describes the research design as well at the methodological issues that relate to it. Following this is a detailed research plan.

3.1 Research Design

The main research objective of this study is to examine the generalizability of an instrument across different settings. Addressing this objective calls first for a confirmatory approach to examining the accuracy and consistency of the measures. We must therefore determine if the five constructs form reliable and accurate measures, if they are distinct and if they are invariant. This involves extensive structural equation modeling and analysis described in this chapter.

The examination of the invariance of an instrument also calls for an empirical approach. While rigorous statistical testing methods are employed in the evaluation of the instrument reliability and accuracy, there is no assurance of generalizability beyond the conditions of the test data. Thus, to help support the case for generalizability, we expose the measures to multiple technology implementation settings.

We also want to determine the impact of the five dimensions of IT acceptance on workplace outcomes. This is addressed using path analyses on theoretical models. Again, this is completed in multiple settings to enhance the case for generalizability.

3.2 Variables

The study includes five dimensions of IT acceptance and several acceptance-related workplace outcomes. These constructs must be operationalized for this study.

3.2.1 Receive

The first dimension, Receive, is defined as "[t]he psychological state of taking the technology without question" (Schwarz 2003, p. 168). This activity requires that the recipient takes the item and does not question or doubt the decision to do so. Taking the item can be readily assessed with a simple yes or no, but tapping into the questioning of the decision to do so cannot. The degree to which the user questions the decision to take the technology amounts to the degree of regret for taking the item. And in an organizational context, the dimension of Receive relates to the organization's decision to take the technology. The questioning of the decision to take the technology indicates the extent of doubt that one has about the decision or even the degree to which the user regrets the decision to take it. These are expressed as the items:

> *"I have very little to no regret about our organization going with [the technology]*
>
> *I no longer second guess the original decision of our organization to use [the technology]"* (Schwarz 2003, p. 168).

These are posed on a seven-point Likert scale anchored with the labels strongly agree/disagree on the endpoints and neither agree nor disagree as the midpoint. The points between the labels were unlabeled, but available for selection by the respondent. The items were scored as 1 for strongly disagree, 4 for neither agree nor disagree, and 7 for strongly agree. And the items in between were assigned the values 2, 3, 5 and 6 as appropriate.

3.2.2 Grasp

The dimension of Grasp is defined as "[t]he final psychological state of fully comprehending the intentionality (e.g. functionality and design) of the technology" (Schwarz 2003, p. 158). This comprises understanding the technology, the purposes behind it, and its intended role. The degree of understanding these concepts of the technology is the degree to which the user has grasped the technology. This forms the items:

> *"I fully comprehend everything [the technology] is supposed to be used for*
>
> *I totally understand the rationality for all the features of [the technology]*
>
> *I am completely aware of all of the goals of all of the features of [the technology]*
>
> *I totally grasp the role [the technology] was designed to play in my work"* (Schwarz 2003, p. 158).

3.2.3 Assess

The third acceptance construct is "Assess." This is the degree to which the recipient evaluates the technology and determines if it is of value to him or her. Formally, Assess is defined as "[t]he psychological state of evaluating the value and desirability of the technology to me" (Schwarz and Chin 2007, p. 240). With this, we must examine not only the technology's value, but also the degree to which the user desires it. We are not looking to measure the assessment itself; instead the result of having assessed the item tells us that indeed it has been assessed. Thus, the degree to which the user finds the item valuable indicates not only that the item has been assessed, but it also uncovers the result of the assessment. There are three items that tap this construct:

> *"I often find myself considering more of the positive aspects than the negative aspects that [the technology] offers to me*

> *I frequently find myself evaluating more of the value-adding ways versus the negative impacts that [the technology] has on me*
>
> *I often find myself considering more of the positive aspects than the negative aspects that [the technology] offers to my organization*
>
> *I frequently find myself evaluating more of the value-adding ways versus the negative impacts that [the technology] has on my organization"* (Schwarz 2003, p. 168-169)

3.2.4 Be Given

The next dimension, "Be Given," is defined as "the final psychological state of an individual willing to adapt his/her routines to what was required by the technology" (Schwarz 2003, p. 160). This is the degree to which the user is willing to modify his or her routines in order to include the new technology. The willingness is evident in the degree to which the user has modified his or her routine. Those who have fully adapted things to accommodate the new technology would score highly in terms of the "Be Given" construct. The measures are given below.

> *"If necessary, I am willing to substantially compromise how I do work in relation to how [the technology] requires*
>
> *If necessary, I am willing to make a dramatic change to how I do work to how [the technology] requires*
>
> *If necessary, I am willing to adapt my work to what is required by [the technology]"* (Schwarz 2003, p. 169).

3.2.5 Submit

And finally the dimension called "Submit" is defined as "[t]he psychological state of the individual surrendering to the intentionality of the technology" (Schwarz and Chin 2007). Users who have Submitted to the technology use it for all of its intended purposes and roles. They identify with the technology and begin to tell others about it. It is operationalized as examining the degree to which the user believes in the technology and its roles as well as the degree to which he or she tells others about it. This leads to these measures:

> *"I buy into everything about [the technology]*
>
> *I would describe myself as an apostle of [the technology]*
>
> *I have become evangelical about [the technology] to others"* (Schwarz 2003, p. 160).

The items for the 5-dimensional acceptance instrument were validated using a measurement model. Loadings ranged from 0.81 to 0.95, and 12 of the 16 items had loadings over 0.90 (Schwarz 2003, p. 122). All of the loadings exceed the criteria of 0.70 suggested by Hair et al. (2006). Each factor with a loading over this guideline accounts for at least half of the variance of a variable and this provides "practical significance" (Hair Jr. et al. 2006, p. 127).

3.3 Models

The accuracy and consistency of the measures were evaluated with the standard confirmatory factor model shown in figure 3.1. The model meets the necessary and sufficient conditions for identification that are specified by Kline (2005). First, there are 16 observed variables which yields a total of 16(16+1)/2 or 136 data points. There are 16 error variances, 5 factor variances, and 10 factor covariance plus 16 regression coefficients for a total of 47 parameters to be estimated. Taking out 5 path loadings which are constrained to 1 to establish a scale, leaves 42 unknown parameters (Byrne 2001). Thus, the model has 136 minus 42, or 94 degrees of freedom.

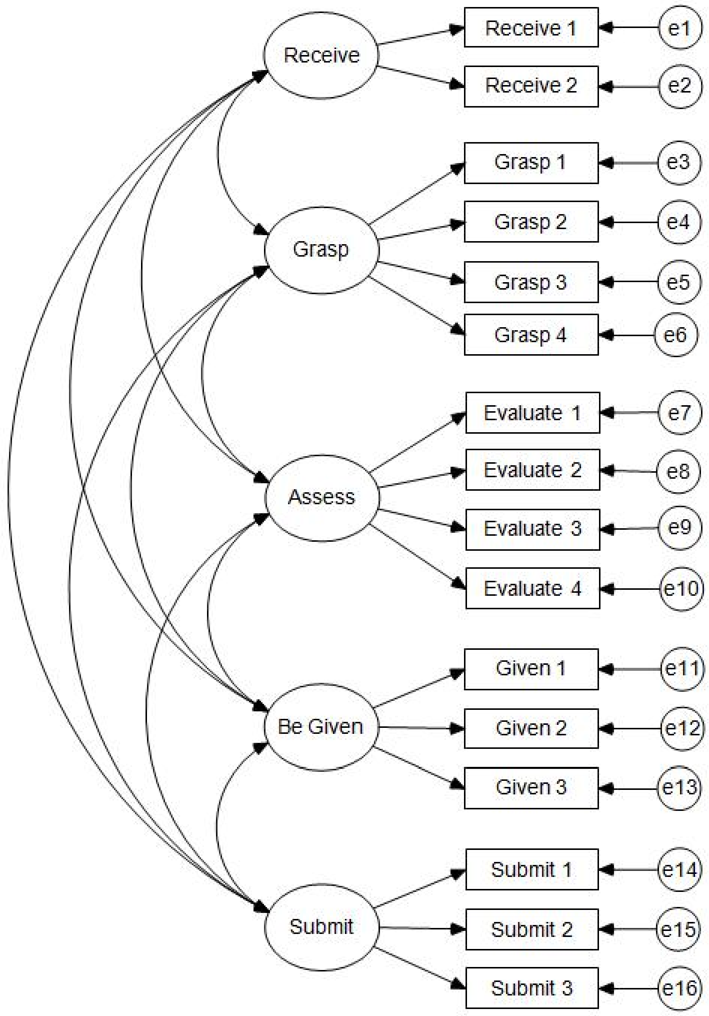

Figure 3.1 Research Model One

The model was used to assess the utility of the constructs, their distinctiveness and, in turn, the discriminant validity of the items.

To assess the utility of the constructs, we must determine if the constructs are tapping into unique notions. The analysis should show constructs with little covariance between them.

The distinctiveness of the constructs can be assessed with discriminant validity testing. This requires a series of tests where two constructs at a time are combined into one super construct. The resulting impact on model fit is assessed and this reveals support or lack-of-support for the distinctiveness of a construct. If a model with combined indicators has a significantly better fit, it would indicate that the combined constructs are tapping into a similar concept and this would suggest that the constructs are not distinct.

Once the distinctiveness of the constructs is assessed, we will examine the invariance of the model. Byrne (2001) calls for a procedure for invariance testing which begins with assessment of the model and its factor loadings with the multiple data sets. If the loadings are similar across all the data sets, we can proceed to group invariance testing.

The group invariance testing is a procedure outlined by Kline (2005) where a series of analyses are conducted with selected factor loadings constrained to be equal and thus, invariant. With this approach, one looks at the resultant fit of the model forced to be invariant. If the forced-invariant model shows a better fit than the baseline measurement model, it indicates a lack of invariance in the baseline model.

Path analysis will help assess the impact of the five constructs on a workplace outcome construct. To do this, path models were developed for each outcome in the form of the model shown in figure 3.2. The variance explained for each workplace outcome would contribute to a better picture of the relationship between the five constructs and workplace outcomes.

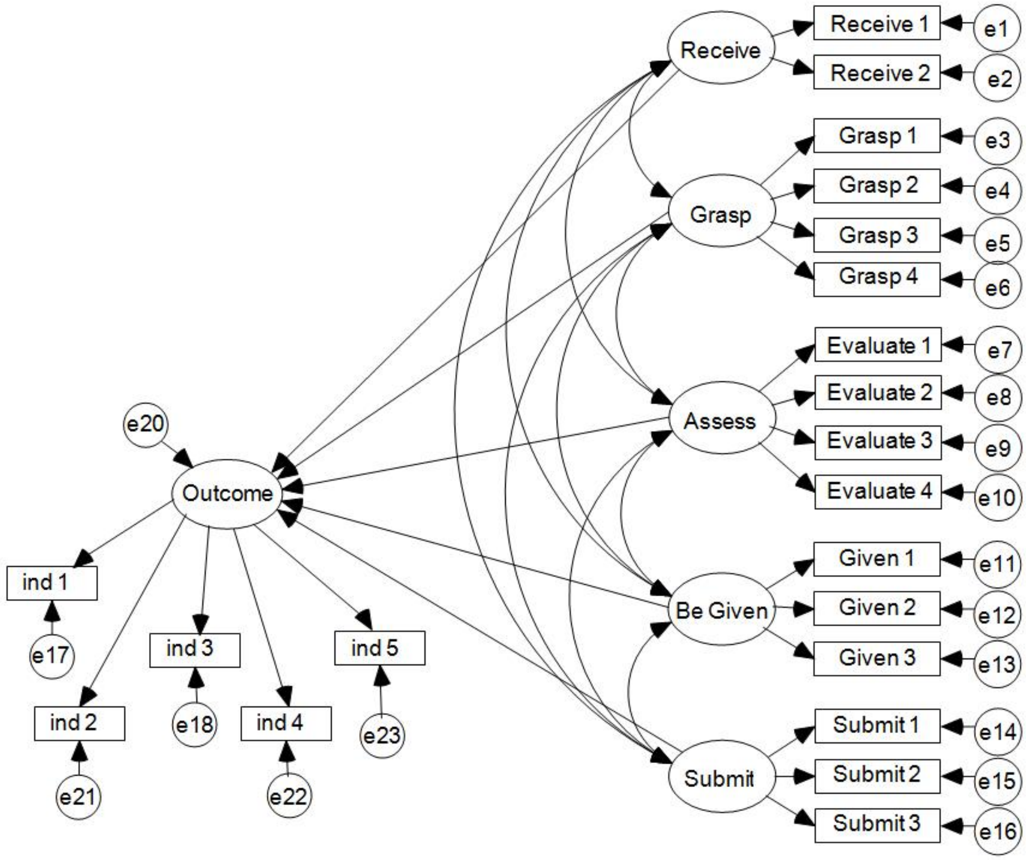

Figure 3.2 Workplace Outcome Research Model

Along with this analysis, we look at the path coefficients from the 5 constructs to each workplace outcome. From this result, we can assess the contribution of each construct to the outcome.

3.4 Limitations and Assumptions

Structural equation modeling (SEM) analysis is complex and requires certain assumptions and conditions for analysis. These and the limitations they impose are discussed in this section.

SEM analysis assumes a normally distributed data set. Small sample sizes and outlying data points contribute to non-normal distributions. Kline (2005) recommends screening data sets for non-normality and applying mathematical transformations to mitigate problems if necessary. Doing so, of course, brings the risk of altering the findings of the analysis. Another potential fix for normality problems involves the removal of outlying data points. One mitigation approach discussed by Kline (2005) trims data points that fall more than three standard deviations from the mean. Each of these approaches for dealing with non-normal data is available to us if our data turns out to be non-normal. We first checked for this by examining the skewness and kurtosis of the data. Indications of problems would have led us to consider mitigation procedures.

We did not expect survey participants to answer every question in the survey. Dillman (2007) points out that respondents may refuse to answer sensitive or intrusive questions as well as those that require effort and motivation to answer. This can yield missing data points which could impact data analysis so it is important to have a strategy to deal with them. First, we examined the data to better understand the degree of missing data. It is important to document any large subsets of missing data that indicate incomplete or unusable surveys. AMOS software deals with missing data by utilizing a full information maximum likelihood (FIML) procedure. A study by structural equation modeling researchers found FIML to be superior to other missing-point techniques including listwise and pairwise deletion (Enders and Bandalos 2001). However, for the case of items with systemic problems that lead to data points that are not randomly missing, the FIML algorithm should not be applied (Arbuckle 2007). Thus, the data was examined to identify the nature of the missing data. We found no patterns of missing data points – the missing data appeared to be randomly distributed within the sample.

Structural equation modeling relies on large samples to compute standard errors and make parameter estimates. The literature suggests some rules of thumb when estimating the sample size required for an analysis. A guideline by Hair et al. (2006) suggests that researchers supply at least 100-150 cases when the number of constructs is 5 or lower and each construct has at least 3 observed variables with high loadings. Another by Bentler and Chou (1987) calls for a minimum sample size based on the number of parameter estimates. In our model, there are 16 loadings, 16 error terms, and 10 covariances and thus 42 estimates. A sample size of 210 would meet the criteria. We aimed for sample sizes consistent with these rules of thumb.

In a deviation from the guidelines suggested by Hair et al. (2006), the measurement model contains a construct with only two observed variables. Although other research (Bhattacherjee and Sanford 2006) uses a construct with only two observed variables, we expect that this could lead to poor solutions in some scenarios. This is a limitation of the measurement model itself, but it is not expected to be a factor in the assessment of generalizability across three technology settings.

3.5 Research Plan

Implementation of the research that addresses the research questions required a comprehensive plan. The plan is presented in the following subsections.

3.5.1 Instrument

The instrument used was developed and tested by Schwarz (2003). Its measurement items are provided in appendix A.

3.5.2 Data Sets

An important part of this analysis is the use of multiple, distinct data sets. The use of multiple data sources is quite important to the invariance testing approach used in the chapter. Doing so allowed us to examine the performance of the model in different usage scenarios and adds richness to the findings.

3.5.3 Number of Data Sets Required

One consideration in invariance testing is the number of data sets required for testing. Certainly, testing at a very large number of unique worksites could demonstrate consistency in the findings and thus increase confidence in the invariance of the instrument, but it is also useful to understand what is sufficient to make a case for invariance. Given the resources required for each thorough sampling and analysis, it makes sense to limit the study to what is required to answer the questions in light of what data is available.

Along these lines, the study focused on the examination of a technology implementation at an organization. It was important to choose samples where we had access to the end users and that the end users were willing to answer a detailed survey with follow up. With that said, we only considered obtaining data sets of quality. It would have been senseless to add poor data sets to the study simply to make the claim that a lot of sites were studied.

Since our research involved invariance testing, we believe it makes more sense to have data that involves more than one technology implementation. Doing so will strengthen the validity of the conclusions regarding invariance of the instrument. Having data taken from more than one site helps demonstrate the consistency of the instrument.

However, there is research that splits a single data set in order to support claims of invariance (Doll, Hendrickson, and Deng 1998). We take the former approach of utilizing multiple unique technology implementations -- this is consistent with the objective of examining the invariance of an instrument for acceptance of information technologies to establish generalizability. That is, adding another site helps establish the contrast needed to claim invariance. If an instrument performs similarly at two different sites, it indicates some degree of invariance. However, even with 2 sites, there is a chance of haphazardly selecting two similar acceptance scenarios. For this reason, we believe there is value in adding a third unique site. With this, we have more comparisons on which to base our conclusions: the first set with the second, the first with the third and the second with the third. This is three times the comparisons of comparing one set with another.

Along these lines, there is the notion of data triangulation described by Denzin (1970). In it, the researcher gathers data from distinct sites, situations, or sets of people. Data triangulation differs from methodological triangulation where more than one method is used to investigate a problem. For this research, we are using the same method to collect the data – but doing so at different sites. This is consistent with the research problem of determining whether an instrument is invariant. The data collected from the use of the instrument itself is necessary for the analysis of the invariance of the instrument.

3.5.4 Site Selection

The data was collected at three organizations which are represented by the pseudonyms Feda, Stata, and PetroCo. Feda is a large United States federal government agency; Stata is a state government agency, and PetroCo is a multinational petroleum company.

3.5.5 Participants

Three sites were selected for the study. The criterion for selecting the sites was that they have rolled out information technology to a large group. Further, it was important that the organization provide access to the individuals who were the recipients of the technology. Thus, these were convenience samples.

The acceptance scenarios at the three sites appear to be unique. First, the data was collected at different types of organizations. The organizations types were a large federal government agency, a state government agency, and a multinational petroleum corporation. Second, there were different technologies being implemented at the organizations. The first was an accounting system at the federal agency. The other technologies were a document management system at the state government agency and a content management system at the multinational oil company. Together, the combination of different organization types and different technologies at the three sites helps provide unique acceptance settings for data collection and analysis.

The sampling frame consists of individuals who were made available by company personnel. There is no indication that any users were excluded from the data collection efforts. Thus, all of the users were eligible for sampling so the sampling frame is representative of all of the technology recipients for the three implementations being studied.

3.6 Data Collection and Analysis

The study utilized an existing data set for the purpose of assessing the generalizability. A description of the data collection and the plan for the analysis of the data used in this research is given in the following subsections.

3.6.1 Data Collection

A data set was available that met the requirements for this research. The data had never been analyzed or used in publication. As part of the data collection procedures for this research, extensive interviews were conducted with the data owner in order to fully understand the data, variables, and the context in which the data set was gathered. The data had been collected methodically with extreme care and with attention to detail.

A total of three sets of data were collected. Prior to collection, university institutional review board (IRB) approval was granted for the research efforts.

The first set of data was collected at Stata in an online survey completed by 111 users. The technology in place was an electronic document management system (EDMS) that stores all of the documents within the agency. The survey invitation was sent out by the head of the Records Management section. At the time the survey was conducted there were approximately 200 users of the technology which yields a response rate of about 56 percent.

The second set was collected at Feda from 268 users who completed the survey. The survey involved a core accounting and financial system. This was an implementation of SAP R/3, a bank card and business warehouse application. The survey invitation was posted on an internal Listserv by the change management team communications lead. At the time the survey was conducted, there were approximately 1,150 users of the system and 23 percent of these responded to the survey.

The third set of data was collected at PetroCo from 145 users who completed the online survey. The survey involved the Livelink content management system, which is an electronic document management system. The survey invitation was sent via e-mail to a list of users. At the time the server was conducted, there were 467 users and 31 percent of these participated in the survey.

3.6.2 Data Analysis

Once the survey data was made available, it was analyzed. The analysis plan was derived from the research questions. It begins with a general assessment of the data set itself. This revealed characteristics of the data relevant to the study. Importantly, we looked at descriptive statistics for hints of non-normality. Because of the possible implications to the structural equation modeling analysis, we would address any non-normality issues prior to conducting further analysis. Transformations and filtering are available to the SEM analyst for this purpose.

Another component of the data analysis is the characterizing of the data sets and the sites where the data was collected. This was done because it is critical to establish the differences in the technology implementations at the three sites.

The general theme of the analysis is tied to the research objective of assessing the generalizability of an instrument across different technology settings. We wanted to find out if the measures were consistent across different contexts. We did this statistically using invariance testing techniques. Accomplishing this required that we look at the reliability and accuracy of the construct measures. For this we examined the loadings in the result set to determine if the constructs are indeed tapping into something that is unique. Further the correlations between the constructs helped confirm this. The reseatch also looks at the distinctiveness of the constructs using discriminant validity testing techniques. Furthermore, we wanted to examine the relationship between the five constructs and workplace outcomes. Path analysis was used to do this work.

3.7 Summary

This section has described the plan to address the research question with a solid research methodology. It operationalized the five constructs, provided two research models for the analysis, discussed the methodological implications of the plan, and it presented the plan to implement the research. Together, it provides a solid foundation for the research.

4 RESULTS

The study was designed to evaluate the generalizability of an instrument in new settings. This was accomplished by first establishing that the 5 psychological technology acceptance constructs proposed by Schwarz and Chin (2007) are a useful way of looking at acceptance. We accomplish this with a series of multigroup invariance tests. With 3 independent data sets, we can combinatorially perform 3 pairwise comparisons of two data sets as well as a test comparing all 3 data sets simultaneously. Using both a confirmatory factor model and a structural modeling where the 5 technology acceptance constructs are used to predict an overall general acceptance construct, we examined whether the item measures are identically reliable and whether the relationships among the constructs remain the same across the multiple settings.

These analyses, therefore, address the research questions concerning the generalizability and utility of the acceptance constructs as well as the adequacy of the measures. Specifically, the results presented in this section address the questions:

(1) Do the five concepts of technology acceptance form reliable and accurate measures?

(2) Are they conceptually and empirically distinct from one another?

(3) Do they act similarly in different contexts?

(4) How do they differ on predictions of workplace outcomes?

The findings related to each of these questions are provided in subsections in this chapter.

Further analyses also examine the relationships between the constructs and the different workplace outcomes. To the extent that the impact of the constructs varies relative to the different workplace outcomes is suggestive of potential new areas for IS researchers to further investigate. These results are provided in subsection 4.3.

We begin with a thorough description of the data to determine whether there are any issues or problems within the data that could impact the study. Moreover, the data set characterization also helps us examine the contexts of the data collected. To the extent to that the three sets of data represent 'truly' different contexts provides a more rigorous test of invariance and, in turn, enhances generalizability (Sackett and Larson Jr. 1990).

4.1 Characterization of the Data Sets

The data was collected at three organizations: (1) Feda, a large United States federal government agency; (2) Stata, a state government agency; and (3) PetroCo, a multinational petroleum company. As discussed in the previous subsection, the use of 3 very different types of organizations provides for a richer and more generalizable analyses than those collected at a single site or at numerous organizations of the same type.

A summary of the three data sites is provided table 4.1. This table describes both the technology that was implemented and the people who used it.

Table 4.1 Summary of Sample Set

Item		**Description** Feda	Stata	PetroCo
Technology	Type	Accounting System	Document Management	Content Management
	Duration of use	4 months	3 years	3 years
People	Years at Org	Medium	Low	High
	Years of FT Work Exp.	High	Low	Medium
	Age	Balanced	Mostly Younger	Balanced
	Gender	Similar to Stata	Similar to Feda	Mostly Male
Organization		Federal Government	State Government	Publically Traded Co.
Sample Size		268	111	145

The technological contexts for the three organizations differ in several respects. Feda implemented an accounting system on a server while the other 2 technologies of study provided a different experience at client computers. The document management system at Stata provided a records management function while the document management implementation at PetroCo served knowledge management functions. Also, the technologies at Stata and PetroCo were in place a few years at the time of the data collection but that at Feda was only in place 4 months. The differences help show that the technology implementations are reasonably dissimilar.

Demographically, we can also see differences among the data sets. As shown in figure 4.1, the respondents in the PetroCo group were more than two thirds male while those in the Stata group were more gender-balanced. There were slightly more female respondents for the Feda group. Regarding age, more than two thirds of the respondents in the Stata group were under 45 years of age. In comparison, the Feda and PetroCo groups had relatively equal amounts of respondents above and below 45 years of age.

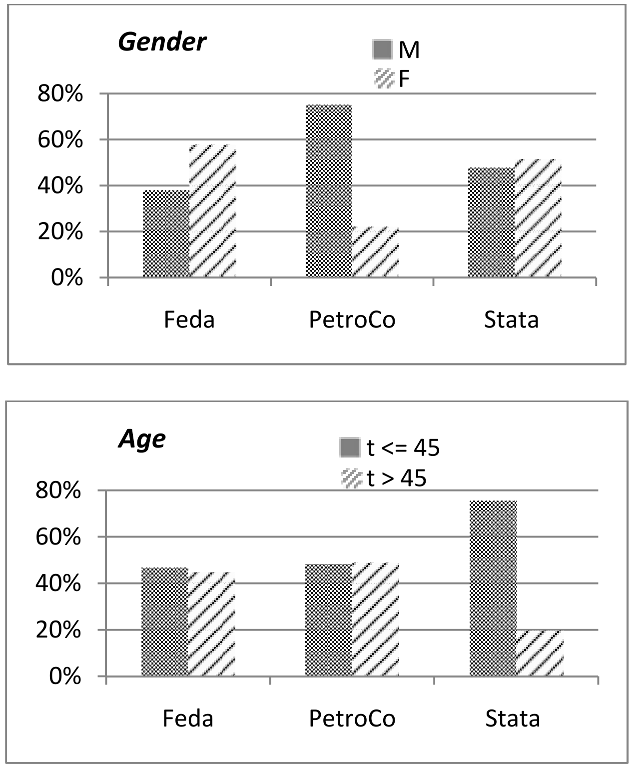

Figure 4.1 Demographics of Sample

The charts in figure 4.2 highlight the large percentage of Stata employees who have been at the organization less than 10 years. The fact that more than three-fourths of these respondents have been in the organization less than 10 years does not imply that the employees are inexperienced workers. More than half of the Stata employees had more than 20 years of full-time work experience. From this, it appears that this state agency hired more experienced workers rather than those who were fresh out of college. In contrast, the ages of the Feda employees appear more balanced, but most of the Feda employees who responded to the survey had more than 10 years experience at the organization.

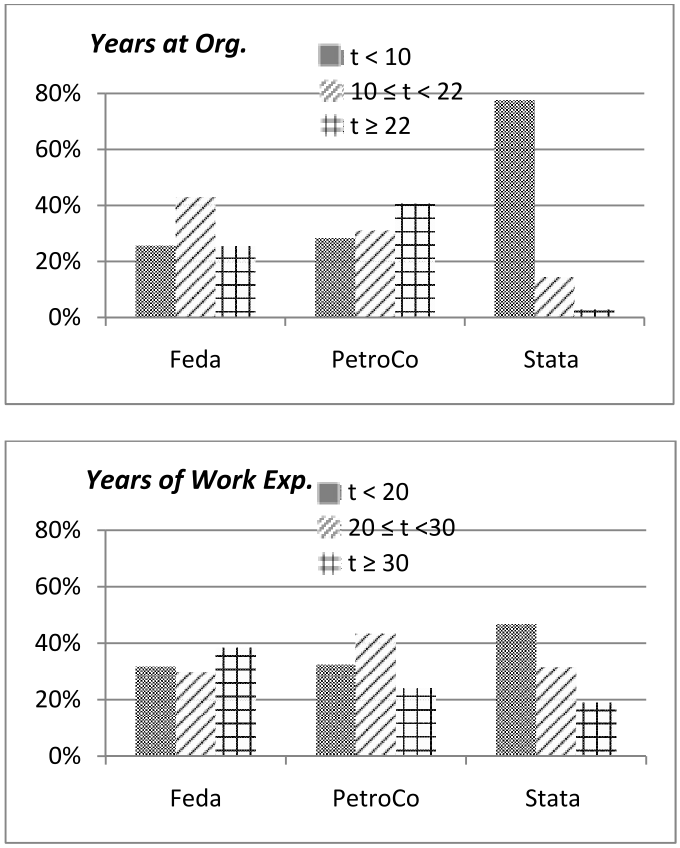

Figure 4.2 Work Experience of Sample

Based on the demographics and work experience data as well as the technology and organizational contexts, it appears the data sets have differences which contributed to a more rigorous study. For example, for the invariance testing described later in this chapter, a more non homogenous set of data provides a much stronger test then one performed on demographically similar data sets. Essentially, successful tests would suggest the measures developed respond similarly (in terms of reliability and construct validity) even if the organizational context (in terms of technology and employee experiences) and other demographics are significantly different.

In addition to the preceding descriptive comparisons, we invoked appropriate statistical tests of difference. In so doing, we can determine the degree to which the invariance testing involves different technology acceptance contexts.

First in this analysis is an examination of the independence of the demographic characteristics with respect to the organizations involved. A statistically significant result would suggest rejecting the assumption of homogeneity of the three organizations and that we cannot pool the data based on the demographic variable used as contrast. Rather, there is a relationship between each organization and the demographic variable in question.

Analysis was conducted to find out if any of the demographic characteristics were independent of the organization. For this, the chi-square test of independence was used. The first test determined if the age of an employee was statistically independent of the organization employing him or her. The observed and expected frequencies are given in table 4.3.

Table 4.2 Age of Respondents

Organization	**Age <= 45** [observed, (expected)]	**Age > 45** [observed, (expected)]	**Total**
Feda	125 (131.2)	120 (100.2)	245
PetroCo	70 (75.5)	71 (57.6)	141
Stata	84 (56.8)	22 (43.3)	106
Total	279	213	492

Expected frequencies were calculated using the methods described in (Black 2008). Namely, the expected frequency of a cell is the "product of (its) row and column totals divided by the grand total" (p. 484). This calculation determines each frequency by assigning weights to it based on the sample size.

The chi-square test involves a comparison of the observed chi-square statistic and a critical value that is based on the chi-square distribution. The distribution required for comparison has 2 degrees of freedom; this is calculated as

df = (number of employers – 1)(number of age categories -1)

For an alpha of 0.05, the critical value is 5.99 and for alpha of 0.01 the critical value is 9.21. Based on a test with a null hypothesis that age is independent of employer, we reject the null if the observed chi-square is greater than the critical value.

The observed chi-square can be calculated by summing for all cells, the square of the difference between the observed and expected frequencies. For example, the upper left cell contributes $(125-131.2)^2/131.2$ or 0.29 to the sum. The resulting observed chi-square is

$$\chi^2_{obs} = 0.29 + 3.93 + 0.40 + 3.09 + 13.07 + 10.50 = 31.29$$

This is to be compared to the critical value of

$$\chi^2{}_{(0.01,2)} = 9.21.$$

Since the observed chi-square is greater than the critical value, we reject the hypothesis that the age is independent of the employer. Thus, for the three data sets, employee age has a relationship with the employer.

For gender, the observed and expected frequencies are given in table 4.3

Table 4.3 Gender of Respondents

Organization	**Gender**		**Total**
	M [observed, (expected)]	F [observed, (expected)]	
Feda	102 (130.2)	155 (120.4)	257
PetroCo	109 (71.4)	32 (66.0)	141
Stata	53 (55.7)	57 (51.5)	110
Total	264	244	508

This yields an observed chi-square of

$$\chi^2_{obs} = 6.11 + 9.97 + 19.74 + 17.54 + 0.13 + 0.58 = 54.08$$

Clearly, this is greater than the critical value of 9.21 at an alpha level of 0.01 (and 5.99 for an alpha of 0.05). Thus, for the data set, we find support for the case that gender is dependent on employer.

The same test for independence was conducted for years of full-time work experience. For this, the observed and expected frequencies are given in table 4.4.

Table 4.4 Years of Full-time Work Experience for Respondents

Organization	**Years FT**			**Total**
	<20 [observed, (expected)]	20<=t<30 [observed, (expected)]	>=30 [observed, (expected)]	
Feda	85 (94.6)	80 (91.6)	103 (81.8)	268
PetroCo	47 (51.2)	63 (49.5)	35 (44.3)	145
Stata	52 (38.1)	35 (36.9)	21 (33.0)	108
Total	184	178	159	521

Since there are three categories for years of full-time work experience rather than the 2 categories used thus far, the critical chi-square value must be recomputed. The required distribution has 4 degrees of freedom computed as

df = (number of employers – 1)(number of categories for FT Work – 1) = 4

For an alpha of 0.01, the critical value is 13.28 and for alpha equal to 0.05, the value is 9.49. The observed chi-square is:

$$\chi^2_{obs} = 0.98 + 1.46 + 5.50 + 0.35 + 3.66 + 1.93 + 5.03 + 0.10 + 4.34 = 23.35$$

It exceeds the critical value and this supports the case that the two variables are not independent.

Similarly, for the variable describing years at the organization we find the observed and expected frequencies in table 4.5.

Table 4.5 Years at Organization of Respondents

Organization	**Years at Organization**			**Total**
	t <10 [observed, (expected)]	10<= t<22 [observed, (expected)]	t >=22 [observed, (expected)]	
Feda	69 (94.8)	115 (85.1)	68 (62.9)	252
PetroCo	41 (54.5)	45 (49.0)	59 (36.2)	145
Stata	86 (39.5)	16 (35.5)	3 (26.2)	105
Total	196	176	130	502

For this, the critical value is obtained from the chi-square distribution with degrees of freedom equal to 4. The critical value for an alpha of 0.01 is 13.27 and the value for an alpha of 0.05 is 9.49. The observed chi-square is:

$$\chi^2_{obs} = 7.0 + 10.5 + 0.4 + 3.4 + 0.3 + 14.4 + 54.7 + 10.7 + 20.5 = 121.97$$

This observed value of chi-square is greater than the cutoff value and thus we reject the hypothesis that the two variables are independent, that is, we find support for the thesis that work experience is dependent on organization.

In addition to dataset characterization, descriptive statistics were computed for the item measure values for all three data sets. These are given in table 4.6. The statistics were computed using SPSS 16.0 Graduate Student Version Release 16.0.0 (September 10, 2007).

Table 4.6 Descriptive Statistics for the Item Measures for 3 Data Sets

Item	**Mean**			**Standard Deviation**			**Skewness**			**Kurtosis**		
	Stata	Feda	PetroCo	Stata	Feda	PetroCo	Stata	Feda	PetroCo	Stata	Feda	PetroCo
Rec1	4.28	3.49	4.85	1.93	2.13	1.75	0.0	0.3	-0.5	-1.2	-1.3	-0.8
Rec2	4.26	3.40	4.67	2.04	2.10	1.68	-0.1	0.3	-0.4	-1.2	-1.2	-0.5
Grasp1	4.43	3.08	3.46	1.87	1.98	1.94	-0.3	0.5	0.3	-1.1	-1.1	-1.3
Grasp2	4.02	2.76	3.53	1.81	1.81	1.87	-0.2	0.7	0.3	-1.0	-0.9	-1.2
Grasp3	4.01	3.17	3.24	1.76	1.94	1.75	-0.1	0.5	0.4	-0.9	-1.1	-1.0
Grasp4	4.90	3.91	3.96	1.80	2.05	1.96	-0.6	0.0	0.1	-0.8	-1.3	-1.4
Eval1	4.24	3.49	4.28	1.92	2.02	1.75	-0.2	0.1	-0.4	-1.0	-1.3	-0.9
Eval2	4.17	3.45	4.19	1.65	1.91	1.66	-0.3	0.1	-0.3	-0.4	-1.2	-0.8
Eval3	4.27	3.50	4.38	1.75	1.93	1.66	-0.2	0.1	-0.5	-0.6	-1.2	-0.6
Eval4	4.15	3.42	4.30	1.74	1.87	1.59	-0.2	0.2	-0.6	-0.6	-1.1	-0.4
Give1	4.07	4.45	3.90	1.54	1.71	1.61	-0.3	-0.6	-0.3	-0.3	-0.5	-0.8
Give2	4.03	4.74	4.02	1.62	1.66	1.62	-0.1	-0.8	-0.4	-0.4	-0.1	-0.9
Give3	4.59	5.15	4.68	1.53	1.53	1.48	-0.5	-0.9	-0.8	0.0	0.4	0.1
Sub1	2.91	2.82	3.19	1.54	1.74	1.60	0.3	0.5	0.1	-0.6	-0.9	-1.0
Sub2	2.39	2.29	2.71	1.50	1.62	1.77	0.8	1.0	0.7	-0.3	0.0	-0.6
Sub3	2.30	2.23	2.70	1.54	1.58	1.73	1.0	1.0	0.8	0.2	-0.1	-0.4

Table 4.6—Continued

Item	Mean			Standard Deviation			Skewness			Kurtosis		
	Stata	Feda	PetroCo	Stata	Feda	PetroCo	Stata	Feda	PetroCo	Stata	Feda	PetroCo
Rout1	5.36	5.13	4.28	1.69	1.81	1.91	-1.1	-0.9	-0.3	0.6	-0.2	-1.0
Rout2	5.36	5.05	4.20	1.64	1.81	1.94	-1.1	-0.7	-0.1	0.8	-0.4	-1.2
Rout3	4.50	3.87	3.99	1.86	2.04	1.84	-0.4	0.0	-0.1	-0.7	-1.2	-1.0
Rout4	5.24	4.94	4.24	1.71	1.84	1.96	-1.0	-0.8	-0.3	0.3	-0.3	-1.1
Infus1	4.41	3.62	3.30	1.88	1.96	1.86	-0.3	0.2	0.4	-0.9	-1.1	-1.0
Infus2	4.50	3.56	3.35	1.84	1.99	1.77	-0.4	0.2	0.4	-0.8	-1.1	-0.9
Infus3	3.70	3.04	2.89	1.85	1.86	1.65	0.2	0.6	0.7	-0.9	-0.7	-0.3
Infus4	4.10	3.51	3.13	1.87	1.86	1.86	-0.1	0.2	0.5	-1.0	-1.0	-1.0
FAO1	2.86	4.92	4.43	1.54	1.64	1.64	-0.4	0.2	-0.3	-0.5	-1.2	-0.5
FAO2	2.68	5.37	4.63	1.63	1.64	1.53	-0.4	0.2	-0.2	-0.3	-1.1	-0.3
FAO3	2.50	5.48	4.99	1.58	1.48	1.46	-0.2	0.4	-0.2	-0.6	-1.0	-0.6
FAO4	2.45	5.48	4.71	1.54	1.58	1.59	-0.3	0.3	-0.4	-0.5	-1.1	-0.3
FAO5	2.55	5.35	4.57	1.64	1.63	1.60	-0.7	-0.1	-0.5	0.1	-1.1	-0.4
Deep1	3.39	2.35	2.33	2.04	1.83	1.82	-0.6	-0.2	-0.6	0.1	-1.0	-0.2
Deep2	4.07	2.96	3.10	1.92	2.02	1.99	-0.9	-0.4	-0.6	0.6	-0.7	1.1
Deep3	3.32	2.73	2.63	1.82	1.99	1.93	-0.8	-0.2	-0.8	0.3	-1.2	0.7
Deep4	3.83	3.27	3.22	1.85	2.00	1.81	-0.7	-0.3	-0.8	0.2	-1.0	1.0
Accept1	5.13	4.90	4.90	1.66	1.88	1.62	-0.8	-0.2	-0.7	-0.2	-1.1	0.8
Accept2	4.20	3.91	4.27	1.75	2.00	1.89	0.5	-0.3	-0.1	-0.2	-0.6	-0.7
Accept3	4.78	4.18	4.42	1.72	2.06	1.78	0.7	-0.8	0.0	-0.4	-0.2	-1.0

The statistics in table 4.6 indicate nothing unusual about the data. The low values of skewness and kurtosis suggest that the data is normally distributed. It is important to note that the means for the measures vary across the data sets. This is not alarming because we would expect the data to vary across organizations. Consider the simple analogy of a thermometer for example. We would expect a thermometer to yield the same value each time it was used to measure and object that is 80 degrees. Consistency of this instrument is important. But if the tool was used to measure a different object or an object under different conditions, such as some snow on the ground, we would not necessarily expect it to measure 80 degrees. This analogy illustrates what the measurement model should do. It should yield the same means under identical conditions, but if we attempt to apply the instrument to other organizations, the means could vary.

Thus far, we examined aspects of each data set and also looked at the data characteristics statistically. The results are consistent with the case that the contexts for the technology are different.

4.2 Construct Validation – Measurement Model

The following analysis determines if the measures are effectively capturing the constructs in question. The analysis results are organized by the research questions they answer.

4.2.1 Reliability and Accuracy

To address research question 1, we employed Research Model One across the three data sets. The resultant loadings and correlations are given in figures 4.3 through 4.5 and in table 4.7. We first look at the loadings in table 4.7 across all three data sets -- they appear to be similar for each item. For example, the loadings for “Evaluate 1” are all

0.91 for the Stata, Feda, and PetroCo data sets. Similarly, the loadings for the "Evaluate 2" item are 0.93 for Stata and PetroCo and 0.94 for Feda. The similarities in the loadings provide support for the argument that the items are acting consistently across the data sets.

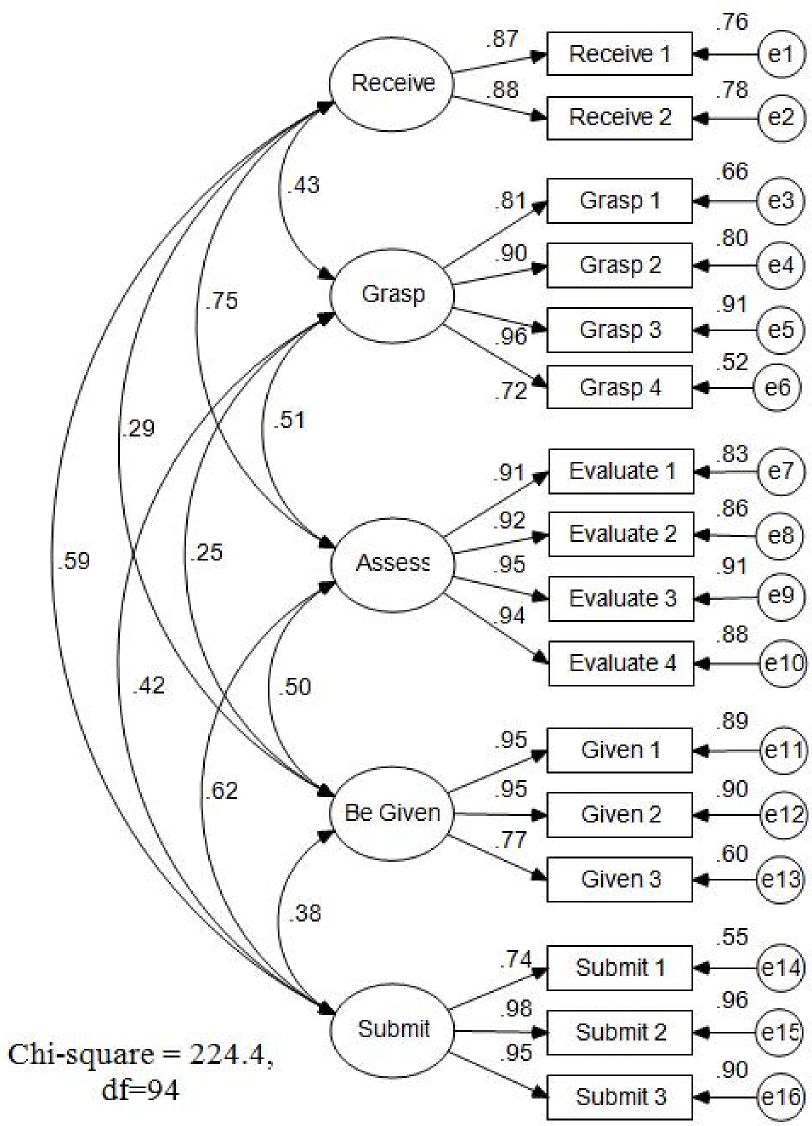

Figure 4.3 Estimates for Research Model One with Stata Data Set

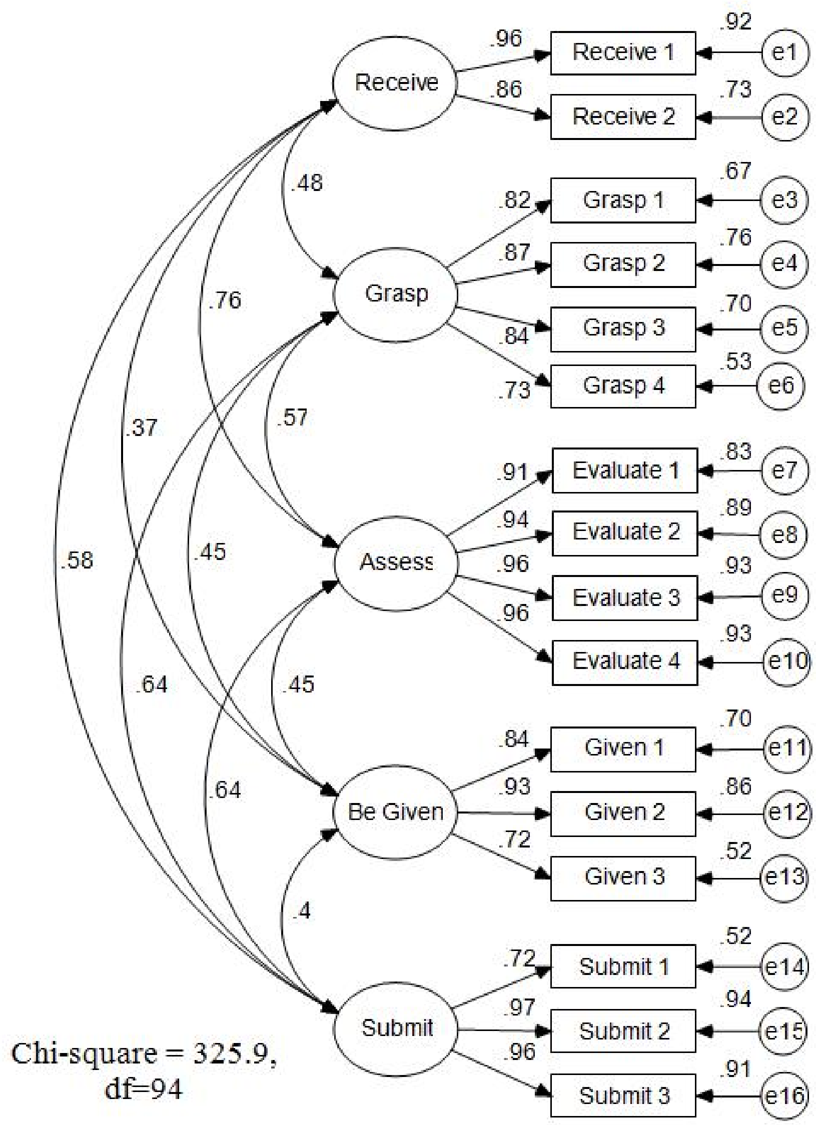

Figure 4.4 Estimates for Research Model One with Feda Data Set

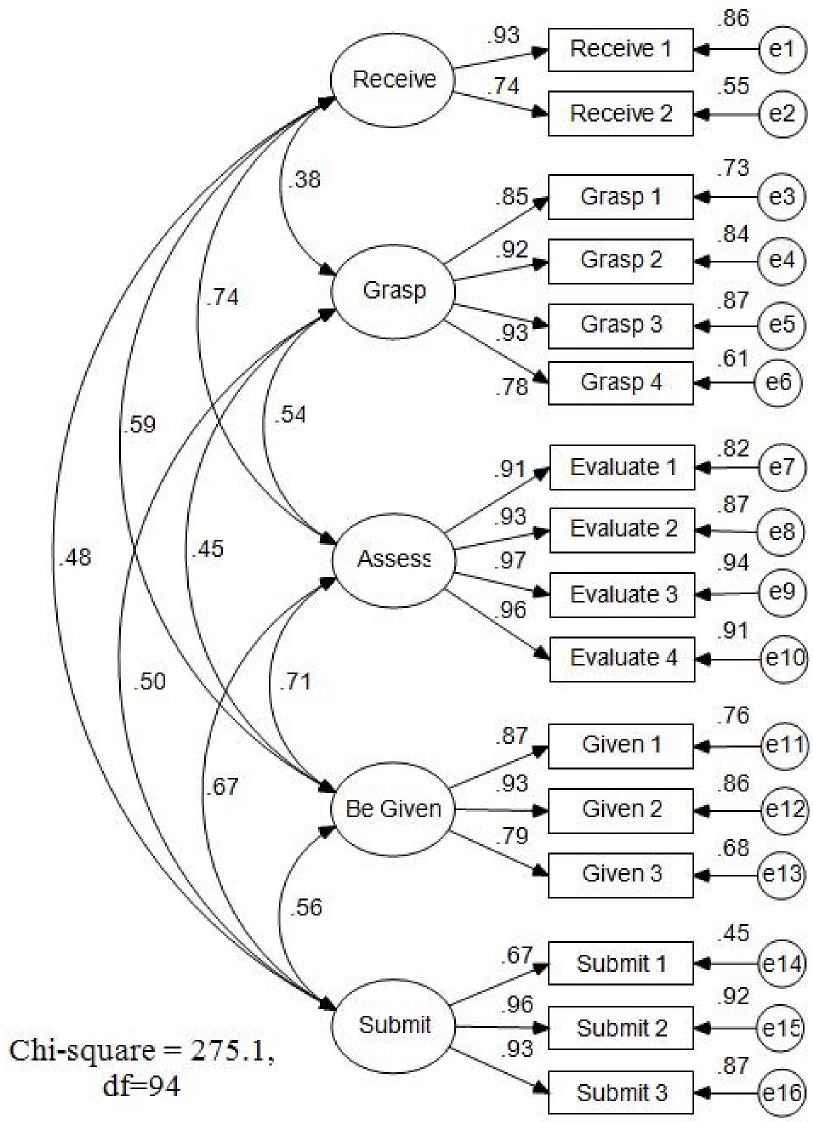

Figure 4.5 Estimates for Research Model One with PetroCo Data Set

Table 4.7 Standardized Loadings for Research Model One with 3 Data Sets

Construct	*Item*	*Loading* Stata *(n=111)*	Feda *(n = 268)*	PetroCo *(n = 145)*
Receive	Rec1	0.87	0.96	0.93
	Rec2	0.89	0.86	0.75
Grasp	Grasp1	0.81	0.82	0.85
	Grasp2	0.90	0.87	0.92
	Grasp3	0.96	0.84	0.93
	Grasp4	0.72	0.73	0.78
Assess	Eval1	0.91	0.91	0.91
	Eval2	0.93	0.94	0.93
	Eval3	0.95	0.96	0.97
	Eval4	0.94	0.96	0.96
Be Given	Give1	0.95	0.84	0.87
	Give2	0.95	0.93	0.93
	Give3	0.77	0.72	0.79
Submit	Sub1	0.75	0.72	0.67
	Sub2	0.98	0.97	0.96
	Sub3	0.95	0.96	0.93

Also, the construct correlations were examined to determine if the constructs are distinct and their respective items are tapping into something that's unique. The results in table 4.8 support this conjecture but there were some areas of concern -- particularly between the Receive and Assess constructs. These had correlation values of 0.75, 0.76, and 0.74 across the three data sets, respectively, indicating a 0.56 shared variance[1]. Although these constructs co-vary in the amount of 0.56, there remains 0.44 of the construct that is considered unique. The remaining correlations did not indicate such a high degree of overlap.

[1] The amount of shared variance is computed as the square of the standardized correlation. Thus a 0.75 correlation indicates a 56% overlap, computed as 0.75 * 0.75.

Table 4.8 Correlations Between Constructs for Research Model One with 3 Data Sets

Construct A	*Construct B*	*Correlation between Constructs A & B*		
		Stata *(n=111)*	Feda *(n = 268)*	PetroCo *(n = 145)*
Receive	Grasp	0.43	0.48	0.38
Receive	Assess	0.75	0.76	0.74
Receive	Submit	0.59	0.58	0.48
Be Given	Receive	0.29	0.37	0.59
Grasp	Assess	0.51	0.57	0.54
Grasp	Submit	0.42	0.64	0.50
Be Given	Grasp	0.25	0.45	0.45
Assess	Submit	0.62	0.64	0.67
Be Given	Assess	0.50	0.46	0.71
Be Given	Submit	0.39	0.34	0.56

More information related to research question one can be found by examining the fit of Research Model One. Selected fit indices for the model are provided in table 4.9. By looking at the fit statistics associated with all three data sets, we can see that the model fits are fairly consistent and are reasonable. Ideally, we desire a small value for CMIN/DF (Byrne 2001) and this is the case for the Stata and PetroCo data sets. Another important indicator of good model fit is CFI, which should be between 0.9 and 1.0 according to Bentler (1992). Other research suggests that CFI should be greater than .95 (Hu and Bentler 1999). The CFI values determined for the three data sets were 0.924, 0.927, and 0.944. This indicates respectable fits according to Bentler (1992).

Table 4.9 Goodness-of-Fit Statistics for Research Model One with 3 Data Sets

Statistic Name	*Value*		
	Stata *(n=111)*	Feda *(n = 268)*	PetroCo *(n = 145)*
CMIN (Default Model)	224	326	275
CMIN (Independence Model)	1930	4286	2506
DF	94	94	94
P	0	0	0
CMIN/DF	2.387	3.466	2.927
NFI/Delta1	0.884	0.924	0.890
RFI/rho1	0.832	0.890	0.841
IFI/Delta2	0.929	0.945	0.925
TLI/rho2	0.895	0.919	0.889
CFI	0.927	0.944	0.924
RMSEA	0.112	0.096	0.116
LO 90	0.093	0.085	0.100
HI 90	0.131	0.108	0.132
PCLOSE	0	0	0

4.2.2 Distinctiveness

The second research question asks if the constructs are distinct from one another. To address this question, discriminant validity testing was conducted. The results of one of the discriminant validity tests are given in figure 4.6. The model in this test has combined indicators for Receive and Grasp. We assess it by looking at the fit for model using the Stata data set. Had the model fit not changed much in the presence of the combined set of indicators, it would be a sign that the two constructs are tapping into a similar concept. But the fit had changed, supporting the case for discriminant validity. As is the case here, we expected the model fit to degrade for the combined indicator model. The original model with the distinct constructs is indeed tapping into individual items.

Specifically, a statistically negligible decrease in model fit would suggest that the constructs could be combined. That is, the combining of the constructs does not reduce model fit.

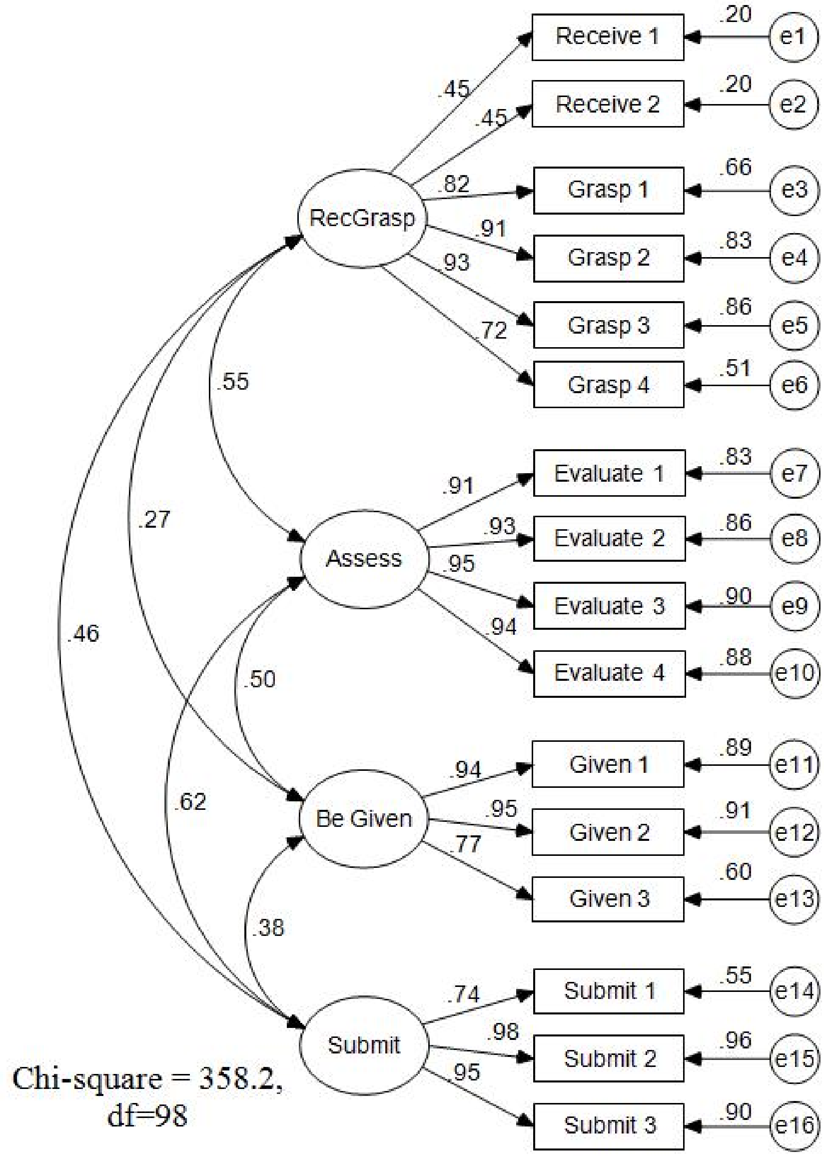

Figure 4.6 Discriminant Validity Test Estimates for the Receive and Grasp Construct Scale Pairs Using the Stata Data Set

Along with the discriminant validity tests for the Stata data set, similar analyses were conducted for the Feda and the PetroCo data sets. The results from these tests are illustrated in figures 4.7 and 4.8.

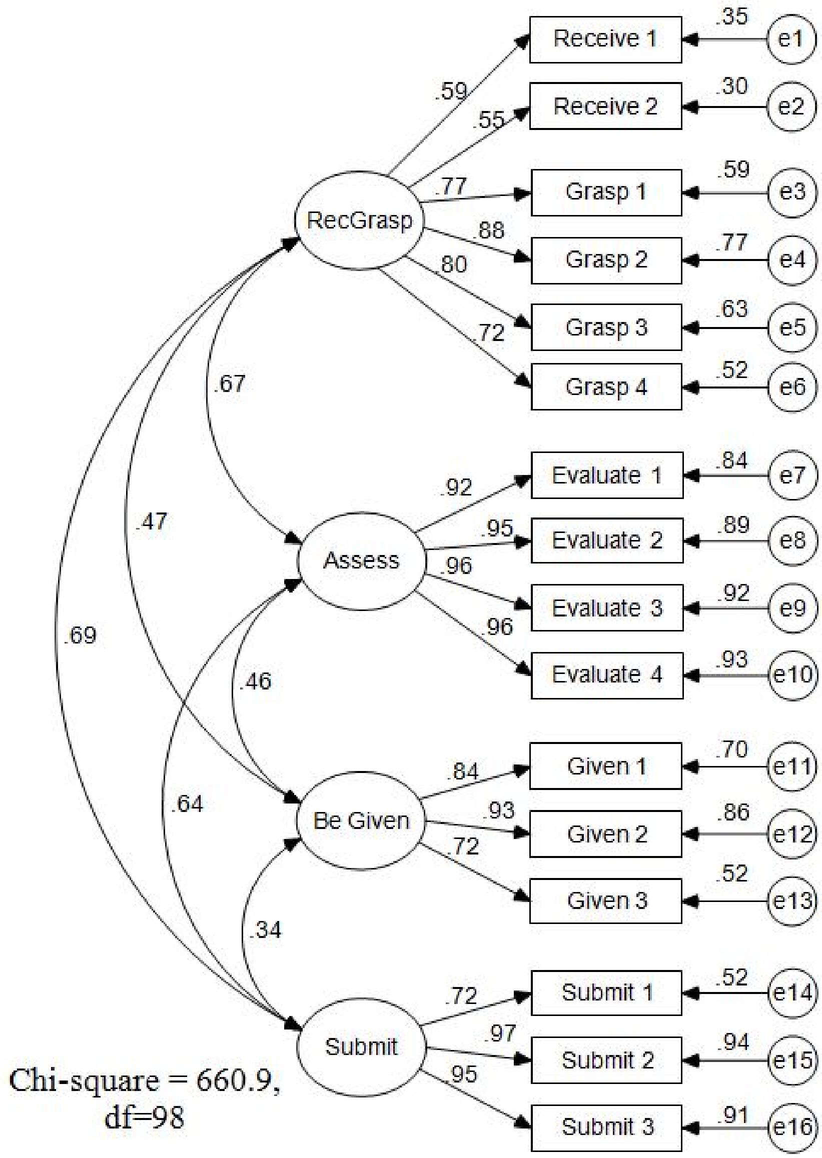

Figure 4.7 Discriminant Validity Test Estimates for the Receive and Grasp Construct Scale Pairs Using the Feda Data Set

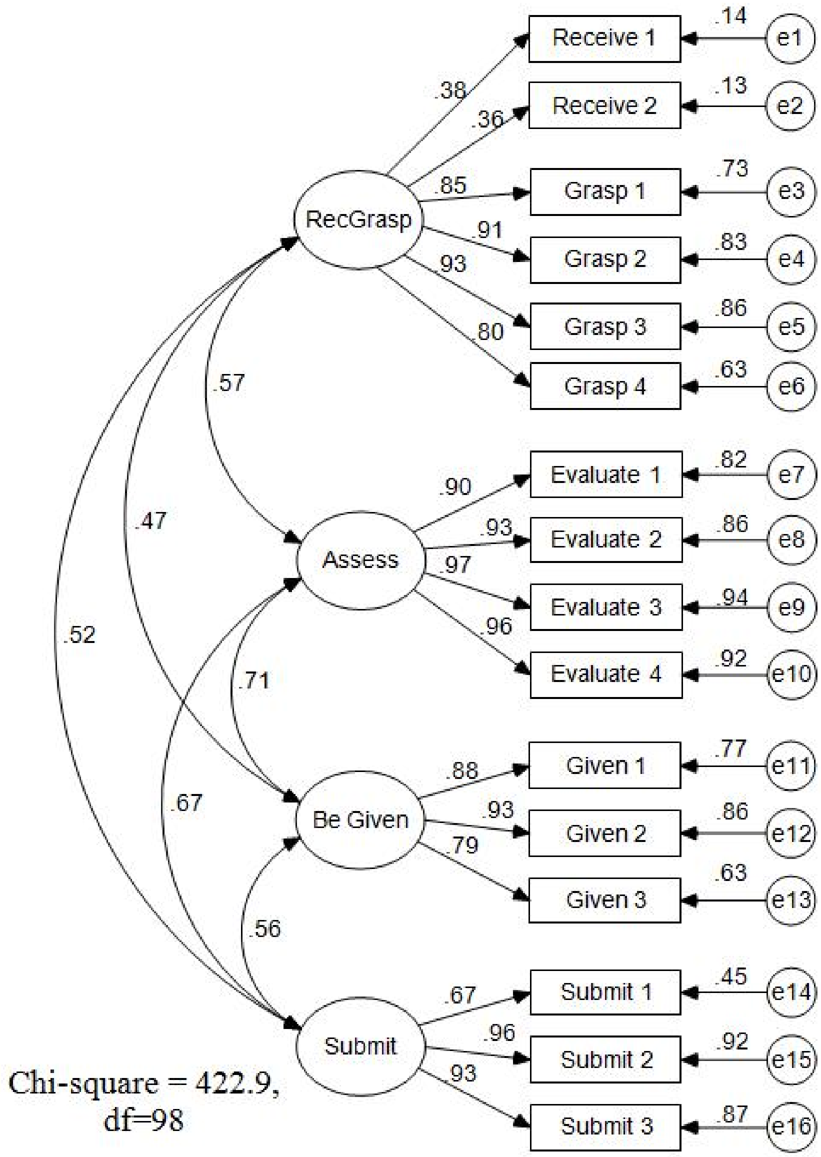

Figure 4.8 Discriminant Validity Test Estimates for the Receive and Grasp Construct Scale Pairs Using the PetroCo Data Set

For comparison purposes, the baseline model fit measures of Research Model One are given in table 4.10. This is the fit of the model depicted in figure 3.1. It does not combine indicators for any of the five constructs. Given this, we can call the discriminant validity testing successful if the model in figure 3.1 has the best fit with respect to the number of degrees of freedom in the model.

Table 4.10 Baseline Model Fit Measures for Discriminant Validity Tests

Model Name	*df*	χ^2		
		Stata *(n=111)*	Feda *(n = 268)*	PetroCo *(n = 145)*
Model 1 (Unconstrained)	94	224.4	325.9	275.1

The discriminant validity test results are given in table 4.11. For each of the construct pairs whose indicators were tied together (as illustrated in figure 4.6), the chi-square (χ^2) was computed and provided in the table. Note that by pooling together the indicators of the construct, we give up 4 degrees of freedom. For doing this, we expect a decrease in model fit as reflected in a higher chi-square. However we can tolerate an increase in chi-square of up to 13.28 which represents random fluctuations due to the chi-square difference. This critical value is computed using the chi-square distribution associated with 4 degrees of freedom at p = 0.01. Given this, any increase in chi-square due to combining the indicators for two construct pairs that is greater than the critical value would indicate a model which is worse in fit and therefore the original model should stand. Thus, a successful test of discriminant validity would show that all chi-square differences are greater than the critical value, meaning that the original model has a better fit with respect to the degrees of freedom sacrificed in the test models.

Table 4.11 Model Fit Indicators for Discriminant Validity Test Models[2]

Construct Scale Pairs Combined		*df*	Stata *(n=111)*		Feda *(n = 268)*		PetroCo *(n = 145)*	
			χ^2	χ^2 *Diff.*	χ^2	χ^2 *Diff.*	χ^2	χ^2 *Diff.*
Receive	Grasp	98	358.2	133.8	660.9	335.0	422.9	147.8
Receive	Assess	98	277.0	52.6	478.8	152.9	317.9	42.8
Receive	Be Given	98	377.1	152.7	670.7	344.8	363.4	88.3
Receive	Submit	98	327.0	102.6	622.1	296.2	385.8	110.7
Grasp	Assess	98	482.2	257.8	773.7	447.8	623.5	348.4
Grasp	Be Given	98	501.0	276.6	645.8	319.9	554.6	279.5
Grasp	Submit	98	511.5	287.1	695.8	369.9	526.7	251.6
Assess	Be Given	98	449.1	224.7	643.5	317.6	409.1	134.0
Assess	Submit	98	411.4	187.0	774.0	448.1	403.5	128.4
Be Given	Submit	98	485.9	261.5	705.5	379.6	417.5	142.4

As we see in table 4.11, all the chi-square indicators increased by more than critical value for p=0.01 so discriminant validity is established for the original model in all three data sets. This implies that the constructs are indeed distinct from one another at a p value of 0.01.

4.2.3 Invariance

The next question to address asks if the constructs act similarly in different contexts. One indicator of this can be ascertained from the performance of the parameter estimates across the 3 data sets. If the resulting item loadings and construct correlations are invariant (i.e., equivalent), it would be consistent with the argument that the constructs act similarly. Indeed, tables 4.7 and 4.8 show similar loadings and correlations across the data sets. For example, the standardized loadings for "Grasp 2" across the 3 data sets are 0.90, 0.87, and 0.92. Arguably, these are similar values because they fall

[2] The critical χ^2 value for 4 degrees of freedom at p=0.01 is 13.28.

within about 3 percent of 0.90. Similarly, the correlations between Grasp and Assess are 0.51, 0.57, and 0.54 respectively for the Stata, Feda, and PetroCo data sets. The values are within 6% of 0.54. Overall, the similarities of the loadings and correlations across the three data sets contribute to our confidence that the measures are acting similarly.

While much about similarity can be ascertained from visual examination of the estimates, it is important to analyze these estimates statistically. We can perform invariance testing to accomplish this. To do so, we perform a series of tests using constrained models based on Research Model One. Each test has a different constraint on either a loading or correlation. For example, in the first test model, we will constrain the Receive 1 indicator so that its parameter estimate (i.e., construct loading) is the same for the Stata data and the PetroCo data. While this constraint is in place, we can examine the overall model fit to determine the impact of the change. All things being equal, we would not want the added constraint to reduce the model fit. That is, after accounting for differences in degrees of freedom, the test model with selected loadings or correlations constrained to be invariant should not have a significantly worse fit than the original measurement model (Cheung and Rensvold 2002).

When multiple tests are run, it is possible to observe a significantly different model fit simply by chance. To account for this, we apply a Bonferroni correction by adjusting the critical alpha downward. For example, to assess significance at $p < 0.05$ when 48 test models are used, we adjust the alpha to account for the number of tests by dividing alpha by 48, resulting in a Bonferroni adjusted significance test for p less than 0.05/48 or approximately 0.001. This results in a more appropriate analysis.

In the following paragraphs, invariance test models are presented along with the results of their use. Each set of tests involves test models with constraints. The corresponding model fit in each test is compared to the fit of the original measurement model. For convenience, the original model fit is restated in table 4.12.

Table 4.12 Baseline Model Fit Measures for Invariance Tests

Model	*Fit Indicator*	
	χ^2	*Df*
Unconstrained Model	825.79	282

The first set of invariance tests yields three sets of results. The tests were conducted with constraints on factor loadings applied to the individual loadings 2 groups at a time. That is, loadings are constrained for 3 groups taken 2 at a time resulting in three sets of data: one for loadings with Stata and Feda constrained, one for loadings with Stata and PetroCo constrained, and then one for loadings with Feda and PetroCo constrained.

For the tests, we need a criterion for determining if each test model is significantly different from the baseline model. Given that there are a total of 16 loadings that we will constrain -- and that doing this for 3 groups taken 2 at a time results in 3 comparisons per loading, we multiply 16 by 3 to determine that the total number of tests is 48. Thus, our critical alpha for $p < 0.05$ is 0.05/48 or about 0.001. Also, we know that constraining a loading to be equal for 2 groups results in an additional degree of freedom in each test model. This allows us to find the critical value in a Chi-Squared distribution for $p < 0.05/48$ with 1 degree of freedom. The value, taken from the software StaTable (Version 1.0.1, 1996) using a continuous Chi-Squared distribution, is shown in figure 4.9.

With it, any test that results in a change in model fit that is less than 10.83 would be deemed to be indicative of an insignificant change in fit. Looking at it another way, if a change in model fit is less than 10.83, we cannot conclude that the change in fit is significantly different from the baseline (at $p < 0.05$), so we would be unable to reject the hypothesis of equivalency (i.e., invariance of the parameter between the data sets).

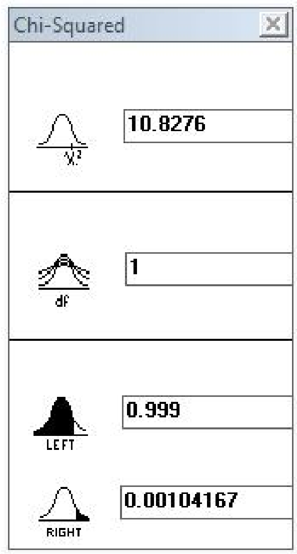

Figure 4.9 Determination of the Bonferonni-Adjusted Critical Chi-Square Change Criterion

The critical value calculations are summarized for the first part of the invariance testing in table 4.13. The critical value suggests that constrained models which result in a chi-square improvement of more than 10.83 are a significantly worse fit with respect to the difference in degrees of freedom. This would imply that the baseline model had a significantly different fit than the test model, indicating a lack of invariance. Ideally, we would not expect an invariant model to be significantly different than the test model that had a factor loading or correlation constrained to be invariant (Vandenberg and Lance

2000b). Thus, any invariance test models which yield a significantly worse fit with a chi-square difference larger than 10.83 would lead us to reject the conjecture that the baseline model is invariant.

Table 4.13 Critical Chi-Square for Invariance Tests with Constraints on Two Loadings per Test

Description	**Value**
Test Name	3 groups, taken 2 at a time - loadings
Number of comparisons	48 (16 loadings with 3 tests per loading)
Change in degrees of freedom	1 df change
Alpha	0.05/48
Critical Value	10.83

The first invariance test model is shown in figure 4.10. This represents one of 48 tests conducted. In the series of tests, each test has a factor or correlation constrained to be invariant across 2 data sets. The model represented in the figure is constrained so the value of the loading for the "Receive 1" measure in the Stata data is equal to the value of the loading for the same measure in the Feda data set. This is known as a constraint in AMOS software. The constrained test model in the figure results in a model fit (χ^2) of 829.51. This is compared to a fit of 825.79 for baseline model listed in table 4.12. We find that the constrained model has a fit improvement of 3.72. But to obtain that, we had to add a degree of freedom to the model. Since the 3.73 improvement is less than the critical value of 10.83, we find no support that the test model and the constrained model are significantly different in terms of fit. Therefore, for the first test model, invariance holds.

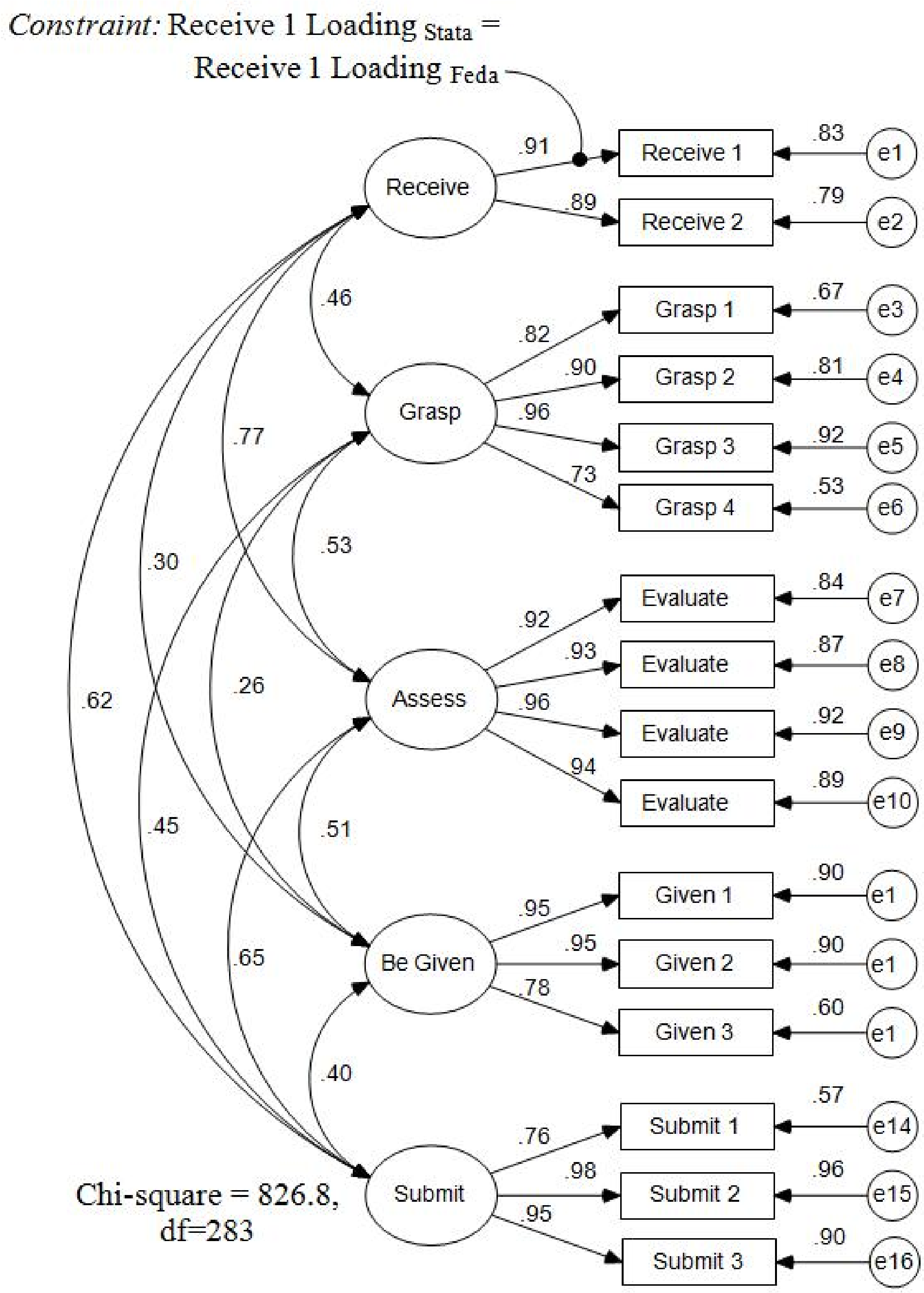

Figure 4.10 Invariance Test Estimates for Stata Data with Constrained Receive 1 Loadings for Stata & Feda Data Sets

There are more test models based on constraining the factors for the Stata and Feda data sets. For example, another test was run with the Receive 2 factor constrained much like the Receive 1 factor in the first test. The resulting model was compared to the baseline model using the same chi-square change criteria of 10.83. With it, we find the test model is not significantly different because the change in chi-square is less than the critical chi-square change criteria.

Along these lines, a series of invariance tests were run with constraints on the model using the Stata and Feda data sets and the results are summarized in table 4.14. They indicate that none of the constrained models resulted in a fit that exceed the change criteria of 10.83 and this provides some support that the baseline model is invariant.

Table 4.14 Results for Invariance Tests with Selected Stata and Feda Loadings Constrained

Indicator with Constraints	Stata & Feda Constrained			
	χ^2	$\Delta\ \chi^2$	*df*	*Δ df*
Receive 1	829.51	3.72	283	1
Receive 2	825.79	0.00	283	1
Grasp 1	826.09	0.30	283	1
Grasp 2	825.85	0.06	283	1
Grasp 3	825.89	0.09	283	1
Grasp 4	826.85	1.05	283	1
Assess 1	826.17	0.38	283	1
Assess 2	828.41	2.61	283	1
Assess 3	827.36	1.56	283	1
Assess 4	827.07	1.27	283	1
Be Given 1	825.82	0.02	283	1
Be Given 2	825.79	0.00	283	1
Be Given 3	826.07	0.27	283	1
Submit 1	826.33	0.53	283	1
Submit 2	826.35	0.55	283	1
Submit 3	825.97	0.17	283	1

The first set of invariance tests help support the case for invariance of the baseline model, but these first tests are only one of six sets of tests; there are 3 pairwise comparisons with constraints on loadings and 3 pairwise comparisons with constraints on correlations. In the following paragraphs, we detail the remaining tests. These include invariance tests with constraints on selected loadings with Stata and PetroCo constrained and then with Feda and PetroCo constrained. Following this are tests involving constraints on correlation values.

The next set of invariance tests involves constraints on loadings involving Stata and PetroCo data. The first such test is illustrated in figure 4.11 where the loading for the Receive 1 indicator is fixed so that the its loading for Stata is the same as the loading for PetroCo. This is one of several tests with loadings fixed between Stat and PetroCo.

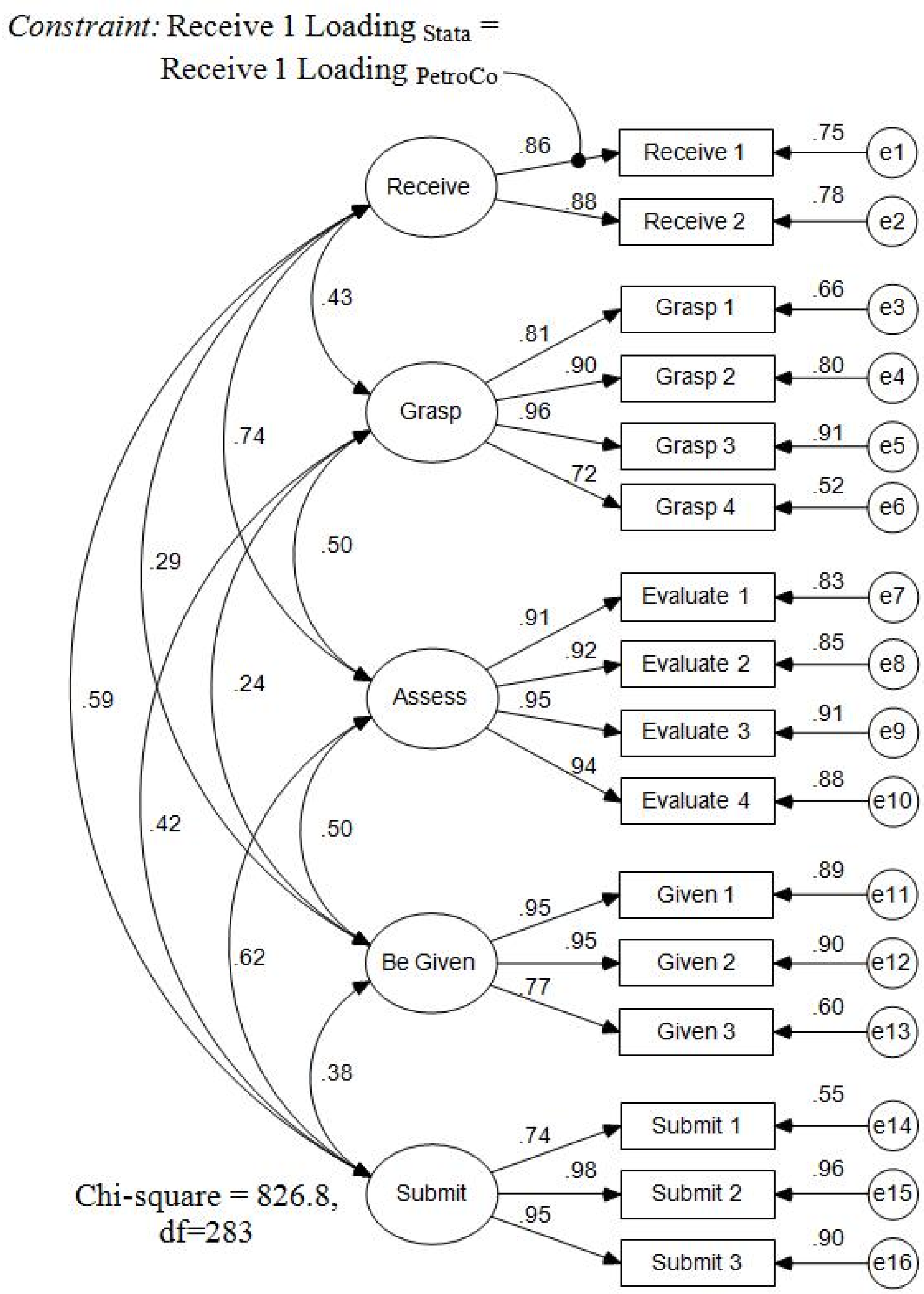

Figure 4.11 Invariance Test Estimates for Stata Data with Constrained Receive 1 Loadings for Stata & PetroCo Data Sets

The findings for the second set of invariance tests are given in table 4.15. They indicate that none of the resultant changes in chi-square exceed the criteria value of

10.83. Therefore, this supports the argument that the baseline model in figure 3.1 is not significantly different in fit than the second set of test models which had some factors constrained to be invariant.

Table 4.15 Results for Invariance Tests with Selected Stata and PetroCo Loadings Constrained

Indicator	Constrained Groups: Stata and PetroCo			
	χ^2	$\Delta\ \chi^2$	*df*	Δ *df*
Receive 1	825.9	0.08	283	1
Receive 2	832.7	6.93	283	1
Grasp 1	826.2	0.41	283	1
Grasp 2	826.1	0.28	283	1
Grasp 3	825.9	0.06	283	1
Grasp 4	827.0	1.19	283	1
Assess 1	826.5	0.74	283	1
Assess 2	825.8	0.00	283	1
Assess 3	826.0	0.18	283	1
Assess 4	826.3	0.50	283	1
Be Given 1	825.9	0.06	283	1
Be Given 2	825.8	0.03	283	1
Be Given 3	825.8	0.00	283	1
Submit 1	826.0	0.21	283	1
Submit 2	828.0	2.20	283	1
Submit 3	826.7	0.92	283	1

The next set of invariance tests involves constraints on selected loadings that are fixed between Feda and PetroCo. The first test model for this set is illustrated in figure 4.12.

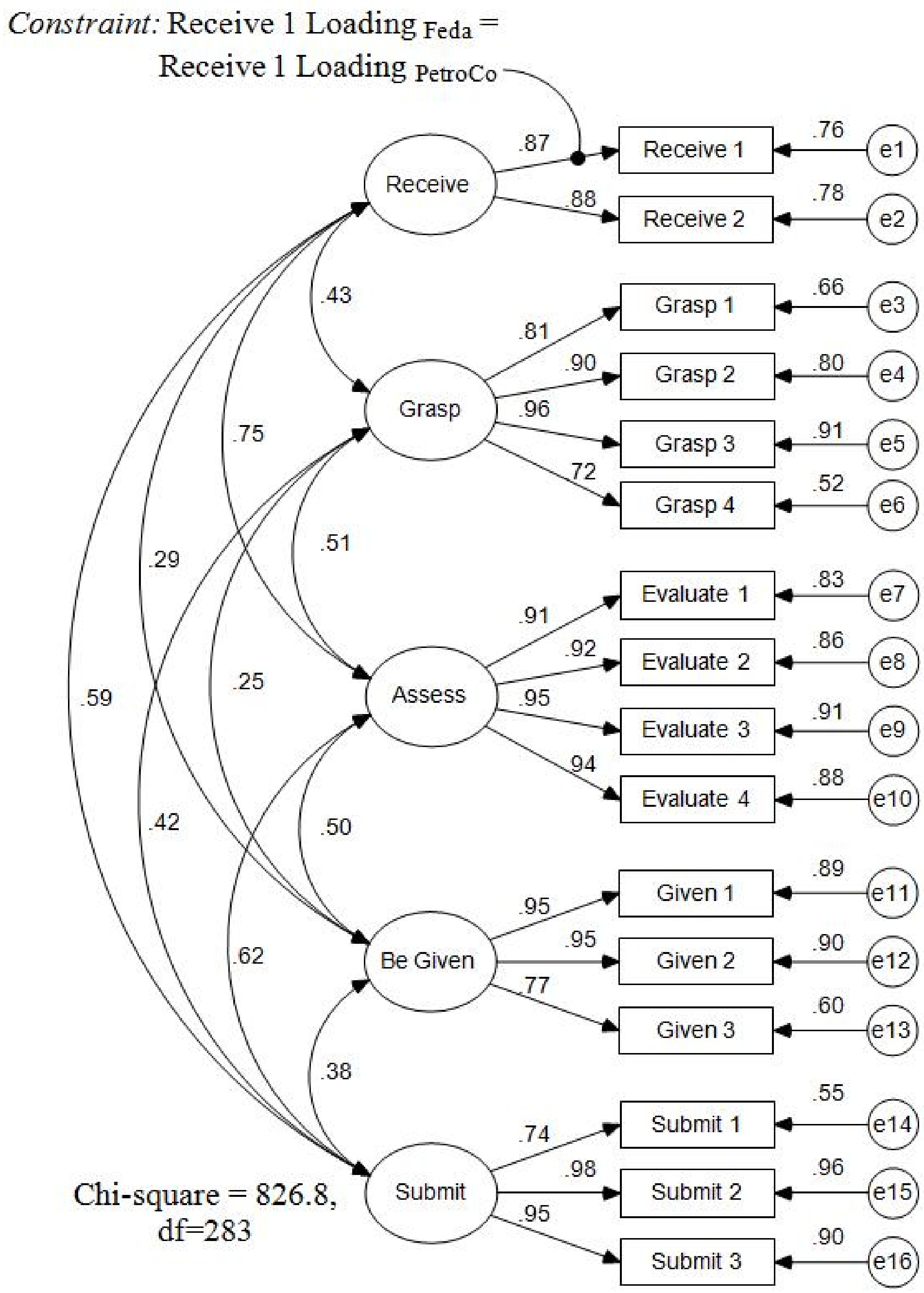

Figure 4.12 Invariance Test Estimates for Stata Data with Constrained Receive 1 Loadings for Feda & PetroCo Data Sets

The results of the third set of invariance tests are given in table 4.13. Again, the results indicate that the baseline model in figure 4.3 is not significantly different in fit than the third set of test models which had some factors constrained to be invariant. Note the high change in fit for the case of Receive 2 loadings constrained for the Stata and PetroCo data sets. Although the value stands out, it is still below our Bonferroni-adjusted criteria and is not a cause for concern.

Table 4.16 Results for Invariance Tests with Selected Feda and PetroCo Loadings Constrained

Indicator	Constrained Groups: Feda and PetroCo			
	χ^2	$\Delta\ \chi^2$	*df*	Δ *df*
Receive 1	832.3	6.46	283	1
Receive 2	835.8	10.02	283	1
Grasp 1	825.8	0.03	283	1
Grasp 2	826.6	0.82	283	1
Grasp 3	825.8	0.00	283	1
Grasp 4	825.8	0.02	283	1
Assess 1	828.8	2.96	283	1
Assess 2	829.0	3.24	283	1
Assess 3	829.5	3.68	283	1
Assess 4	830.4	4.60	283	1
Be Given 1	825.8	0.01	283	1
Be Given 2	825.8	0.04	283	1
Be Given 3	826.0	0.23	283	1
Submit 1	827.4	1.60	283	1
Submit 2	826.8	1.01	283	1
Submit 3	826.3	0.53	283	1

So far, the results of three sets of invariance tests have been presented. These tests focused on constrained loadings in the baseline model. The next three sets of tests focus on constrained correlations.

The set of tests for constrained correlations involve 3 groups taken 2 at a time. Fixing a correlation value between two data sets in the model results in the addition of 1 degree of freedom. And since there are a total of 10 correlations, we must perform multiple invariance tests. Therefore, there are a total of 10 correlations to be constrained and because there are 3 data sets, there will be 3 tests run per correlation to constrain 2 correlations at a time. This calls for a Bonferroni adjustment to offset any capitalization on chance that would occur with 30 tests. The critical alpha for $p < 0.05$ is 0.05/30 or about 0.0017. With this adjusted alpha and a 1 degree of freedom change, the Chi-squared distribution yields a critical change value of 9.55. This is summarized in table 4.17. With it, any change in model fit that is greater that the critical value of 9.55 would suggest that the baseline model is significantly different in fit than the test model. This would not bode well in an argument for the invariance of the baseline model.

Table 4.17 Critical Chi-Square for Invariance Tests with Constraints on Two Correlations per Test

Description	Value
Test Name	3 groups, taken 2 at a time - correlations
Number of comparisons	30 (10 correlations with 3 tests per loading)
Change in degrees of freedom	1 df change
Alpha	0.05/30
Critical Value	9.55

The first set of tests involves constraining selected correlations between the Feda and PetroCo data set. The first of these tests is illustrated in figure 4.13. This test constrains the correlation between the Receive and Grasp constructs to be equal for the Stats and Feda data sets.

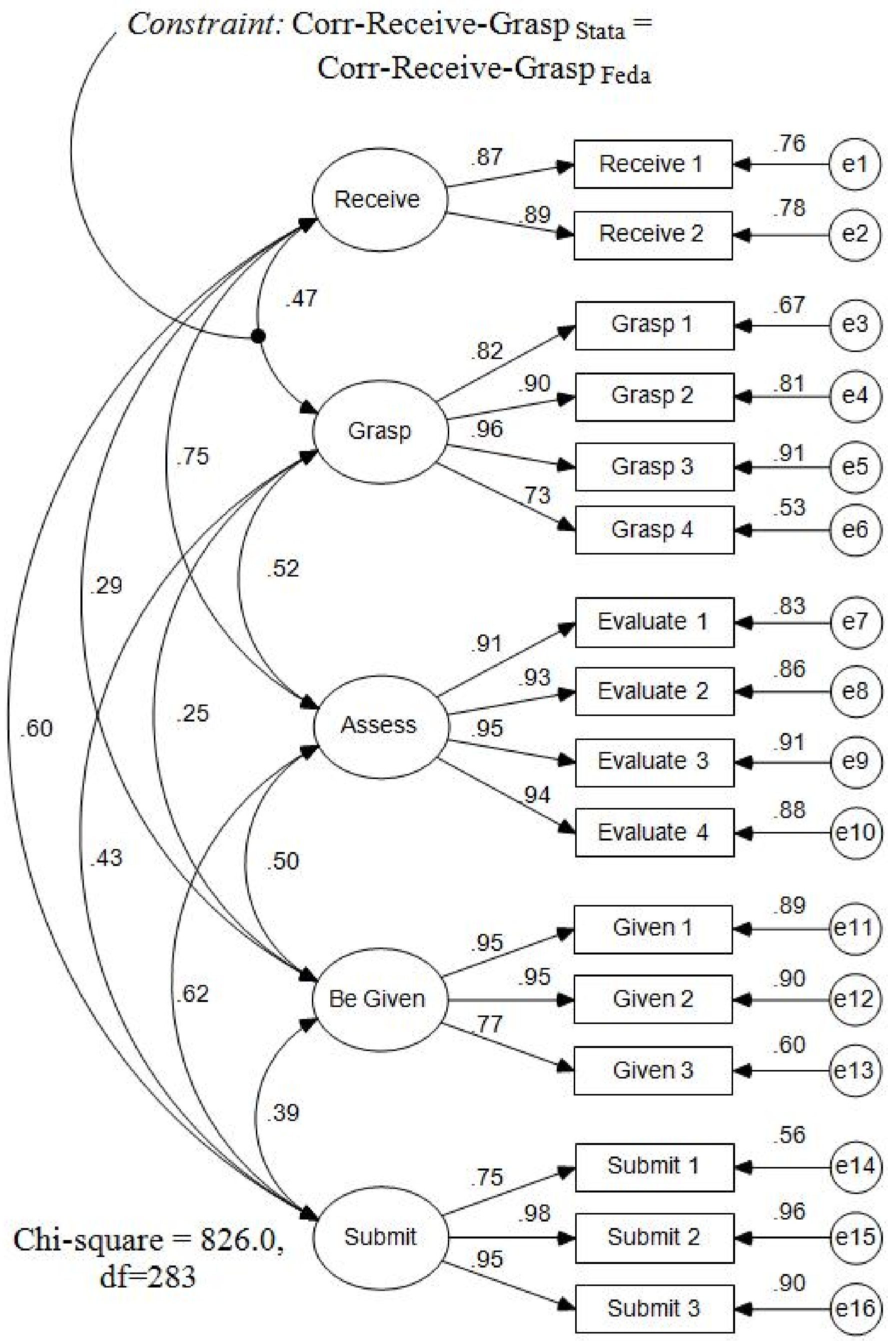

Figure 4.13 Invariance Test Estimates for Stata Data with Constrained Correlations Between Receive and Grasp for Stata & Feda Data Sets

Given the critical value, we can now examine the results for the test models presented in table 4.18. The results of this fourth set of tests do not contain a change in chi-square that is greater than the criteria of 9.55 so, again, we don't have evidence against the case for invariance of the baseline model.

Table 4.18 Results for Invariance Tests with Selected Stata and Feda Correlations Constrained

Factor Covariance Constrained	Stata and Feda Constrained			
	χ^2	$\Delta\ \chi^2$	*df*	*Δ df*
Φ Receive ● Grasp	826.0	0.00	283	1
Φ Receive ● Assess	825.8	-0.16	283	1
Φ Receive ● Be Given	826.3	0.31	283	1
Φ Receive ● Submit	825.8	-0.15	283	1
Φ Grasp ● Assess	826.4	0.41	283	1
Φ Grasp ● Be Given	829.3	3.35	283	1
Φ Grasp ● Submit	832.1	6.15	283	1
Φ Assess ● Be Given	826.1	0.08	283	1
Φ Assess ● Submit	825.8	-0.14	283	1
Φ Be Given ● Submit	826.0	-0.01	283	1

Similarly, we must test for invariance using the Stata and PetroCo data sets. In this series of tests, we constrain selected correlations to be invariant across the two data sets. The first of these tests is illustrated in figure 4.14 where the correlation values between the Receive and Grasp constructs are constrained to be equal for the Stata and PetroCo data sets.

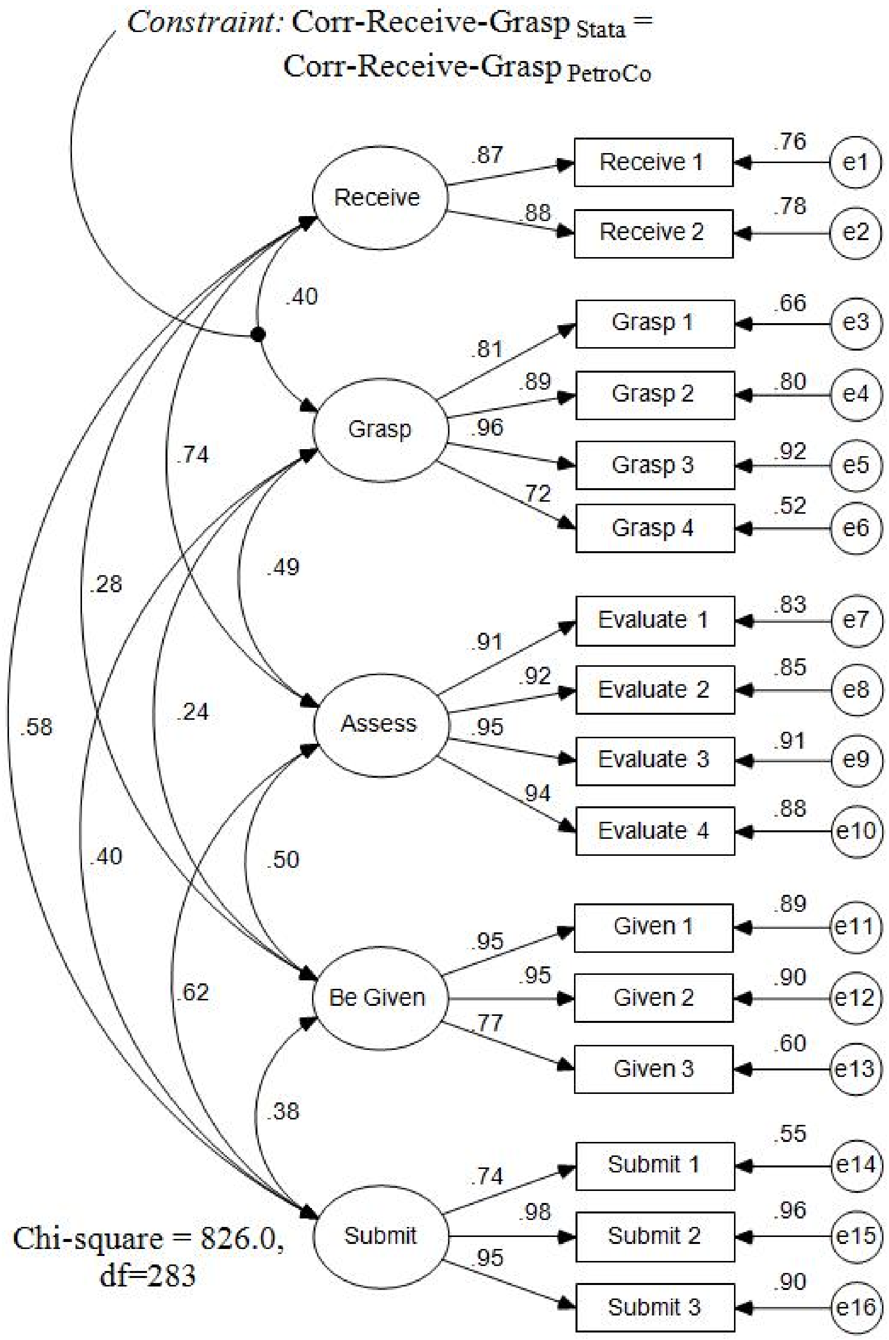

Figure 4.14 Invariance Test Estimates for Stata Data with Constrained Correlations Between Receive and Grasp for Stata & PetroCo Data Sets

This analysis was conducted for all 10 correlations and the results are summarized in table 4.19. The model fit of each is presented and the change in chi-square is compared to the critical value in table 4.17. Given that the largest change in chi-square is 6.13 and this value is less that the 9.55 critical value, we can say that the set of test models and the baseline model are not significantly different in terms of model fit. Thus, there is no new evidence of a lack of invariance in the baseline model.

Table 4.19 Results for Invariance Tests with Selected Stata and PetroCo Correlations Constrained

Factor Covariance Constrained	Stata and PetroCo Constrained			
	χ^2	$\Delta\ \chi^2$	*df*	*Δ df*
Φ Receive ● Grasp	826.0	0.04	283	1
Φ Receive ● Assess	825.8	-0.18	283	1
Φ Receive ● Be Given	832.1	6.13	283	1
Φ Receive ● Submit	826.8	0.83	283	1
Φ Grasp ● Assess	826.0	-0.03	283	1
Φ Grasp ● Be Given	828.6	2.63	283	1
Φ Grasp ● Submit	826.4	0.41	283	1
Φ Assess ● Be Given	831.7	5.68	283	1
Φ Assess ● Submit	826.2	0.20	283	1
Φ Be Given ● Submit	828.5	2.51	283	1

Finally, invariance tests involving the correlations are needed for the Feda and PetroCo groups. One of the test models is illustrated in figure 4.15 and the test results are given in table 4.20. Again, the resulting model fits must be compared with the critical value of 9.55 from table 4.17.

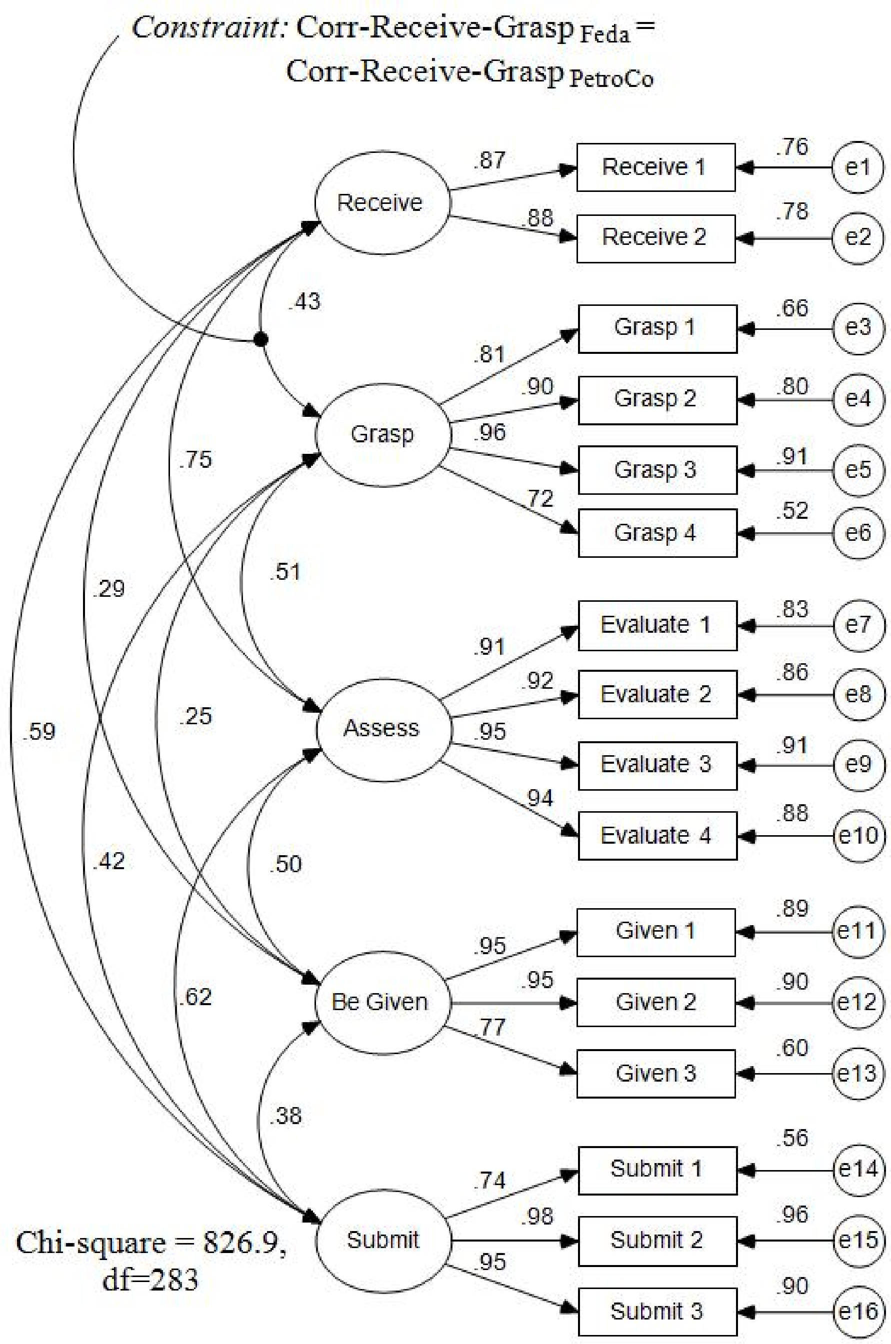

Figure 4.15 Invariance Test Estimates for Stata Data with Constrained Correlations Between Receive and Grasp for Feda & PetroCo Data Sets

As we can see, all but one of the test models had a chi-square change that is less than the critical value. This indicates that nine of the ten test models are not significantly different in fit than the baseline model; however, one model had a change in fit of 11.49, which exceeds the critical value. The test that failed involved the correlation between the Assess and Be Given constructs. The failure indicates that the test model is significantly different in terms of fit and it does not bode well for its invariance. This finding will be discussed at the end of this section.

Table 4.20 Results for Invariance Tests with Selected Feda and PetroCo Correlations Constrained

Factor Covariance Constrained	Feda and PetroCo Constrained			
	χ^2	$\Delta\ \chi^2$	*df*	Δ *df*
Φ Receive ● Grasp	826.9	0.92	283	1
Φ Receive ● Assess	825.9	-0.11	283	1
Φ Receive ● Be Given	831.1	5.15	283	1
Φ Receive ● Submit	826.9	0.87	283	1
Φ Grasp ● Assess	825.9	-0.05	283	1
Φ Grasp ● Be Given	825.8	-0.18	283	1
Φ Grasp ● Submit	829.0	3.07	283	1
Φ Assess ● Be Given	837.5	11.49	283	1
Φ Assess ● Submit	826.1	0.09	283	1
Φ Be Given ● Submit	831.5	5.52	283	1

For completeness, the invariance testing was conducted with constraints on selected loadings and correlations for three groups at a time. One test is illustrated in figure 4.16. In this test model, the loading for Receive 1 is set to be invariant across the Stata, Feda, and PetroCo datasets.

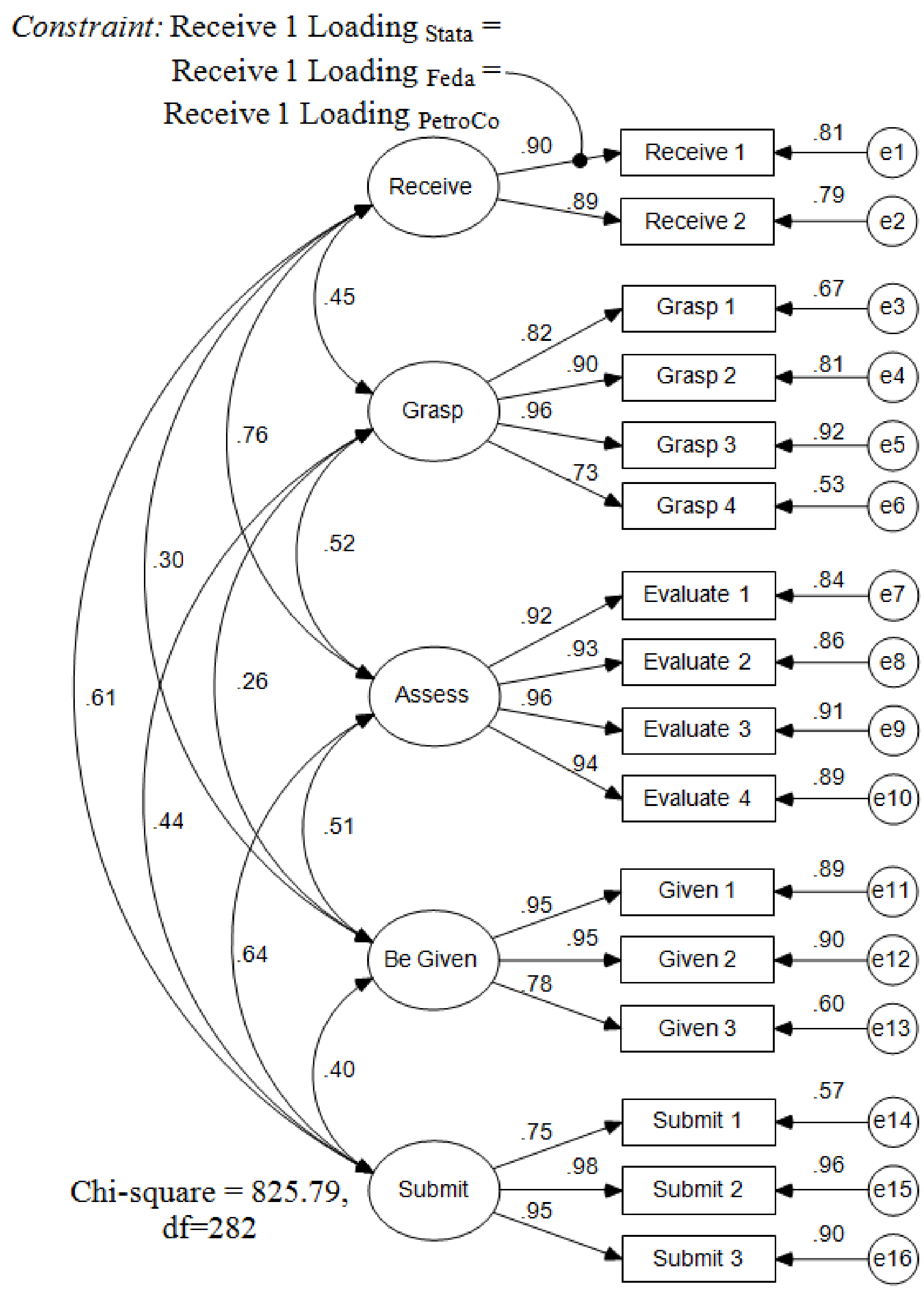

Figure 4.16 Invariance Test Estimates for Stata Data with Constrained Receive 1 Loadings for Stata, Feda & PetroCo Data Sets

For this series of tests, there are a total of 16 loadings. As with the previous set of tests, a Bonferroni correction is called for. The computation of the correction is outlined in table 4.21. Accounting for the number of comparisons and the change in degrees of freedom, the Chi-square distribution yields a critical value of 11.62.

Table 4.21 Critical Chi-Square for Invariance Tests with Constraints on Three Loadings per Test

Description	Value
Test Name	3 groups, taken 3 at a time - correlations
Number of comparisons	16 (16 loadings with 1 test per loading)
Change in degrees of freedom	2 df change
Alpha	0.05/16
Critical Value	11.618

The results of the first series of invariance tests for the case of 3 groups taken 3 at a time is presented in table 4.22. Accounting for the change in Chi-square for each test, we find that none of the test model fit values exceed the critical value. This means that none of the models are significantly different in fit that the baseline model and thus, model invariance is not challenged in this case.

Table 4.22 Results for Invariance Tests with Selected Stata, Feda and PetroCo Loadings Constrained

Indicator	Constrained Groups: Stata, Feda and PetroCo			
	χ^2	$\Delta\ \chi^2$	*df*	*Δ df*
Receive 1	833.8	8.04	284	2
Receive 2	836.8	11.03	284	2
Grasp 1	826.2	0.45	284	2
Grasp 2	826.6	0.83	284	2
Grasp 3	825.9	0.10	284	2
Grasp 4	827.2	1.38	284	2
Assess 1	828.8	2.97	284	2
Assess 2	830.4	4.56	284	2
Assess 3	830.0	4.20	284	2
Assess 4	830.7	4.89	284	2
Be Given 1	825.9	0.06	284	2
Be Given 2	825.8	0.05	284	2
Be Given 3	826.2	0.37	284	2
Submit 1	827.5	1.71	284	2
Submit 2	828.1	2.27	284	2
Submit 3	826.8	0.98	284	2

Interestingly, the table shows that the change in fit for the test involving the Receive 2 construct was relatively high at 11.03 compared to the other change values. But since this is still less than our computed critical value, it does not suggest problems with invariance because it is still less than the critical value.

Now that we have evaluated the invariance with respect to selected loadings taken three at a time, we can now focus on testing with correlations taken three at a time. The first of these tests is illustrated in figure 4.17.

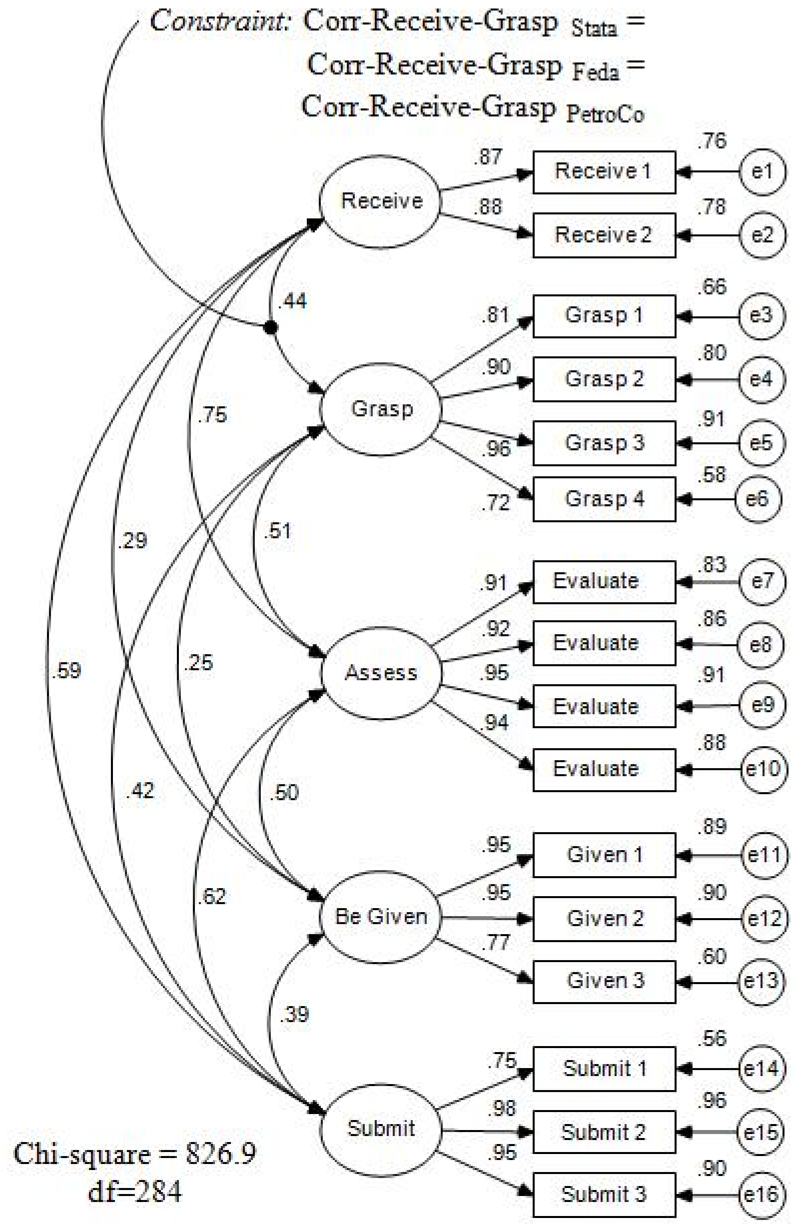

Figure 4.17 Invariance Test Estimates for Stata Data with Constrained Correlations Between Receive and Grasp for Stata, Feda & PetroCo Data Sets

As with the other invariance tests in this section, computation of the critical value must account for the possibility of capitalizing on chance given the number of comparisons made. In this case we have 10 correlations and 3 groups. Accounting for the number of comparisons made, we attain a critical chi-square value of 10.597. This is summarized in table 4.23.

Table 4.23 Critical Chi-Square for Invariance Tests with Constraints on Three Correlations per Test

Description	Value
Test Name	3 groups, taken 3 at a time - correlations
Number of comparisons	10 (10 correlations with 1 test per correlation)
Change in degrees of freedom	2 df change
Alpha	0.05/10
Critical Value	10.597

The test runs are to be compared to the critical value and the results of the tests are given in table 4.24. The data indicate that one test resulted in a change in fit which exceeds our criteria. When accounting for the change in degrees of freedom and the number of comparisons made, constraining the correlation between Assess and Be Given as invariant resulted in a better fit than the baseline model. This does indeed challenge the notion of invariance for the baseline model. However the other 9 test models were well within the critical value. The implications of this will be covered at the end of this section.

Table 4.24 Results for Invariance Test with Selected Stata, Feda and PetroCo Correlations Constrained

Factor Covariance Constrained	Stata, Feda and PetroCo Constrained			
	χ^2	$\Delta\ \chi^2$	*df*	Δ *df*
Φ Receive ● Grasp	826.9	0.00	284	2
Φ Receive ● Assess	825.9	-1.03	284	2
Φ Receive ● Be Given	833.3	6.42	284	2
Φ Receive ● Submit	827.1	0.21	284	2
Φ Grasp ● Assess	826.4	-0.51	284	2
Φ Grasp ● Be Given	829.8	2.87	284	2
Φ Grasp ● Submit	833.1	6.19	284	2
Φ Assess ● Be Given	837.9	10.97	284	2
Φ Assess ● Submit	826.2	-0.68	284	2
Φ Be Given ● Submit	831.7	4.74	284	2

In summary, a total of 104 invariance tests were conducted and 2 of the tests resulted in models that had a better fit than the baseline model. While the results for the $p<0.05$ tests indicate some issues, we must recognize that the problems are confined to less than 2% of the tests, which is small enough to alleviate concerns about major issues.

While technically, the 2 failures would lead us to say that the model lacks invariance under these conditions we cannot ignore the other, successful tests. The results suggest that under most conditions the model is potentially generalizable across multiple streams and is therefore a useful contribution to research. However, the exceptions should be explored in future research.

One of the useful outcomes of the invariance analysis, are the actual constrained values of the correlations between constraints computed during the testing process. These are presented in table 4.25. They provide insight into the true values of the correlations between constructs.

Table 4.25 Correlations Between Constructs from Invariance Testing with Constraints on Selected Correlations between the Receive and Grasp Constructs

Construct A	*Construct B*	*Correlation between Constructs A & B*			Φ constrained		
		Stata	Feda	PetroCo	Φ A • B Stata= Φ A • B Feda	Φ A • B Stata= Φ A • B PetroCo	Φ A • B Feda = Φ A • B PetroCo
Receive	Grasp	0.43	0.48	0.38	0.47	0.40	0.44
Receive	Assess	0.75	0.76	0.74	0.75	0.74	0.75
Receive	Submit	0.59	0.58	0.48	0.58	0.54	0.55
Be Given	Receive	0.29	0.37	0.59	0.35	0.46	0.45
Grasp	Assess	0.51	0.57	0.54	0.55	0.53	0.56
Grasp	Submit	0.42	0.64	0.50	0.58	0.47	0.59
Be Given	Grasp	0.25	0.45	0.45	0.39	0.36	0.45
Assess	Submit	0.62	0.64	0.67	0.63	0.65	0.65
Be Given	Assess	0.50	0.46	0.71	0.47	0.62	0.56
Be Given	Submit	0.39	0.34	0.56	0.35	0.48	0.42

4.3 Impact on Workplace Outcomes

The results presented so far establish the consistency and accuracy of the measures. What remains to be seen is how to the five dimensions of acceptance relate to different workplace outcomes.

Structural modeling with the Workplace Outcome Research Model was conducted with five different workplace outcomes whose item measures are given in Appendix A. The model illustrated as in figure 4.18. It shows the five acceptance constructs and proposes their influence on a given workplace outcome.

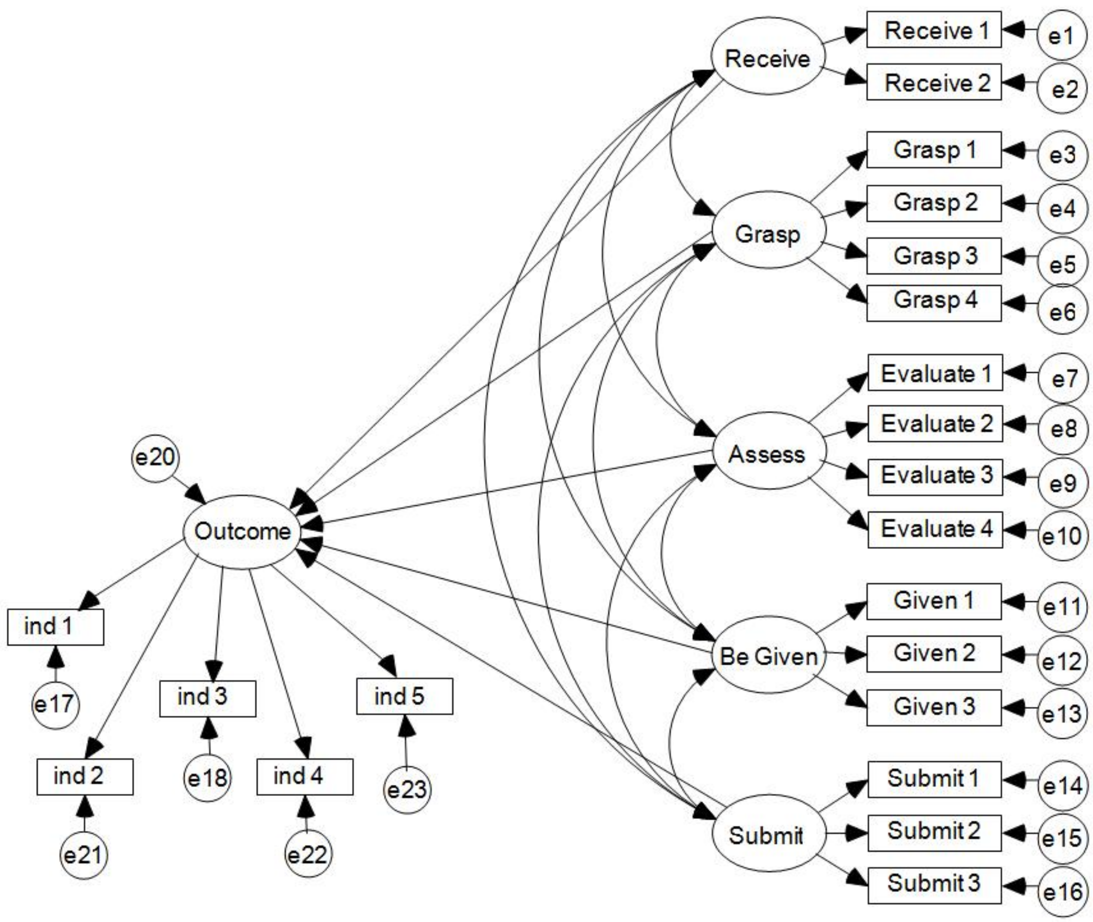

Figure 4.18 Modeling a Workplace Outcome

The analysis using the Workplace Outcome Research Model yielded item loadings, path coefficients, model fits, and the coefficients of determination for each workplace outcome of interest. Item loadings are presented in table 4.26. For the most part, the item measures for workplace outcomes are consistent across the three data sets. This was expected and it indicates that the items are acting consistently. One exception is for the item named “Rout 3.” With it, there were extreme differences between the 3 data sets. This exposes an area for interesting future research.

Table 4.26 Standardized Loadings for Workplace Outcome Items in Workplace Outcome Research Model for Three Data Sets

Workplace Outcome Construct	*Item*	*Loading*		
		Stata	Feda	PetroCo
Infusion	Infuse 1	0.92	0.92	0.91
	Infuse 2	0.93	0.91	0.95
	Infuse 3	0.77	0.58	0.70
	Infuse 4	0.81	0.68	0.79
Routinization	Rout 1	0.96	0.88	0.87
	Rout 2	0.98	0.94	0.96
	Rout 3	0.41	0.47	0.75
	Rout 4	0.81	0.74	0.94
Generic Acceptance	Accept 1	0.77	0.72	0.80
	Accept 2	0.63	0.64	0.76
	Accept 3	0.98	0.88	0.82
Deep Usage	Deep 1	0.67	0.63	0.65
	Deep 2	0.63	0.79	0.79
	Deep 3	0.81	0.64	0.74
	Deep 4	0.41	0.43	0.43
Faithfulness of Appropriation	FOA 1	0.61	0.50	0.53
	FOA 2	0.76	0.69	0.66
	FOA 3	0.69	0.70	0.62
	FOA 4	0.92	0.86	0.88
	FOA 5	0.86	0.83	0.77

Another part of the analysis includes looking at the structural path coefficients between the five constructs and each workplace outcome. For example, with the dependent variable of infusion, the path from the Grasp acceptance construct was influential and significant. However, with the generic acceptance construct, this is not the case. Influential constructs for "generic acceptance" include Receive, Assess, and Be Given. These findings make sense when one considers the definition of infusion as embedding the technology deep into an organization's systems (Zmud and Apple 1992a). This kind of impact requires the understanding or grasping of the technology to effectively embed it. On the other hand one can use and accept a technology without fully understanding its intent.

Table 4.27 Path Coefficients for Workplace Outcome Research Model

Workplace Outcome Construct	*Data Set*	*Path Coefficients (γ)*				
		Receive	*Grasp*	*Assess*	*Be Given*	*Submit*
Infusion	Stata	-0.05	0.53***	0.23	0.17	0.02
	Feda	-0.03	0.29***	0.12	0.11	0.26
	PetroCo	0.10	0.40***	0.07	0.17	0.18
Routinization	Stata	0.20	0.14	0.30	0.01	-0.13
	Feda	-0.11	0.21	0.30	0.24***	-0.05
	PetroCo	0.20	0.13	0.08	0.14	0.36***
Generic Acceptance	Stata	0.32	-0.02	0.45***	0.14	0.00
	Feda	0.29***	0.01	0.29***	0.26***	0.21***
	PetroCo	0.37***	0.04	0.21	0.11	0.33***
Deep Usage	Stata	-0.41	0.36***	0.45	0.02	0.18
	Feda	-0.21	0.34***	0.13	-0.05	0.25**
	PetroCo	-0.04	0.33***	0.05	0.00	0.46***
Faithfulness of Appropriation	Stata	-0.17	-0.53***	0.13	-0.19	0.15
	Feda	-0.22	0.18	0.17	0.28***	-0.04
	PetroCo	0.26*	0.36***	-0.11	0.15	0.06

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

In addition to structural path loadings, the construct correlations were collected for the Workplace Outcome Research Model. They are presented in table 4.28. The table shows that for a given outcome, the construct correlations are similar across companies. This is consistent with expectations because the relationships between the five constructs should remain the same even in the presence of different data values. What are expected to change in the presence of different dependent variables are the structural paths to the dependent variables, as shown in table 4.27.

Table 4.28 Correlations between Constructs in Workplace Outcome Research Model

Construct A	*Construct B*	*Correlation between Constructs A & B*																	
		Baseline Model			Infusion			Routinization			Generic Acceptance			Deep Usage			Faithfulness of Appropriation		
		Stata *(n=111)*	Feda *(n = 268)*	PetroCo *(n = 145)*	Stata	Feda	PetroCo	Stata	Feda	PetroCo	Stata	Feda	PetroCo	Stata	Feda	PetroCo	Stata	Feda	PetroCo
Receive	Grasp	0.43	0.48	0.38	0.43	0.48	0.37	0.43	0.48	0.37	0.43	0.48	0.37	0.43	0.48	0.38	0.44	0.48	0.37
Receive	Assess	0.75	0.76	0.74	0.75	0.76	0.74	0.75	0.76	0.74	0.75	0.76	0.73	0.75	0.76	0.74	0.75	0.76	0.74
Receive	Submit	0.59	0.58	0.48	0.59	0.58	0.48	0.59	0.58	0.48	0.59	0.58	0.47	0.59	0.58	0.49	0.59	0.58	0.48
Be Given	Receive	0.29	0.37	0.59	0.29	0.37	0.58	0.29	0.37	0.58	0.29	0.37	0.57	0.29	0.37	0.59	0.29	0.37	0.58
Grasp	Assess	0.51	0.57	0.54	0.50	0.57	0.55	0.51	0.57	0.55	0.51	0.57	0.55	0.51	0.57	0.55	0.51	0.57	0.55
Grasp	Submit	0.42	0.64	0.50	0.42	0.64	0.50	0.42	0.64	0.50	0.42	0.64	0.50	0.42	0.64	0.50	0.42	0.64	0.50
Be Given	Grasp	0.25	0.45	0.45	0.24	0.45	0.45	0.25	0.45	0.45	0.25	0.45	0.45	0.25	0.45	0.45	0.25	0.45	0.45
Assess	Submit	0.62	0.64	0.67	0.62	0.64	0.67	0.62	0.64	0.67	0.62	0.64	0.67	0.62	0.64	0.67	0.62	0.64	0.67
Be Given	Assess	0.50	0.46	0.71	0.50	0.45	0.71	0.50	0.45	0.71	0.50	0.46	0.71	0.50	0.46	0.71	0.50	0.45	0.71
Be Given	Submit	0.39	0.34	0.56	0.39	0.34	0.56	0.39	0.34	0.56	0.39	0.34	0.56	0.39	0.34	0.56	0.39	0.34	0.56

For completeness, model fit measures for the Workplace Outcome Research Model are included in the table below. All fits appear adequate for these structural models.

Table 4.29 Model Fit Measures for Five Workplace Outcomes in the Workplace Outcome Research Model

Workplace Outcome Construct	Model Fit (Chi-Square)			df
	Stata	Feda	PetroCo	
Infusion	360.2	419.2	396.9	155
Routinization	410.2	544.2	445.3	155
Generic Acceptance	271.7	411.7	331.0	137
Deep Usage	297.9	463.2	396.2	155
Faithfulness of Appropriation	375.3	471.3	386.7	174

Also, it is informative to examine the variances explained by each workplace outcome. The results indicate that the selected workplaces outcomes explain a fair amount of variance. This is presented in table 4.30.

Table 4.30 Coefficients of Determination for Five Workplace Outcomes in the Workplace Outcome Research Model

Workplace Outcome Construct	*Coefficient of Determination (R^2)*		
	Stata	Feda	PetroCo
Infusion	0.53	0.40	0.54
Routinization	0.23	0.27	0.55
Generic Acceptance	0.60	0.72	0.78
Deep Usage	0.38	0.25	0.49
Faithfulness of Appropriation	0.31	0.16	0.33

The explained variance helps identify the dependent variables most influenced by the five constructs. If we are to identify a subset of these dependent variables to be studied in more detail, the ones with the highest coefficient of determination (R^2) would produce the most salient results. For example if we are trying to establish the consistency of the five constructs in the presence of these dependent variables, models using dependent variables with the highest R^2 would be the best choice because they would have the greatest impact on the five constructs. Using the data in table 4.30, one would identify the workplace outcome models with generic acceptance and infusion as having large coefficients of determination across the data sets. Thus, we select these two dependent variables for further study in this section.

Now that the general characteristics of the Workplace Outcome Research Model have been assessed, we must now examine the performance of the model in the presence of two different workplace outcomes using the three data sets. It is expected that the models will show measurement consistency with respect to workplace outcomes. This is described in the following section.

4.4 Construct Validation – Predictive Model

To demonstrate measurement consistency in the presence of workplace outcomes, a series of tests were conducted. In these, the Workplace Outcome Research Model was utilized with the outcome of generic acceptance and also the outcome of infusion.

These tests determine if, in the presence of the two workplace outcomes, the Workplace Outcome Research Model: (1) forms reliable and accurate measures; (2) has constructs which are distinct from one another; and (3) acts similarly in different contexts. The analysis begins with a focus on question one, detailed in the following subsection.

4.4.1 Reliability and Accuracy

The analysis follows the procedures used to initially examine the research question about the reliability and accuracy a model. First, we will examine the model with the dependent variable of generic acceptance. Following this is a similar model with the workplace outcome of infusion.

4.4.1.1 Generic Acceptance

Figure 4.19 shows the Workplace Outcome Research Model with the outcome of generic acceptance. In it, the loading and path estimates were computed using the Stata data set.

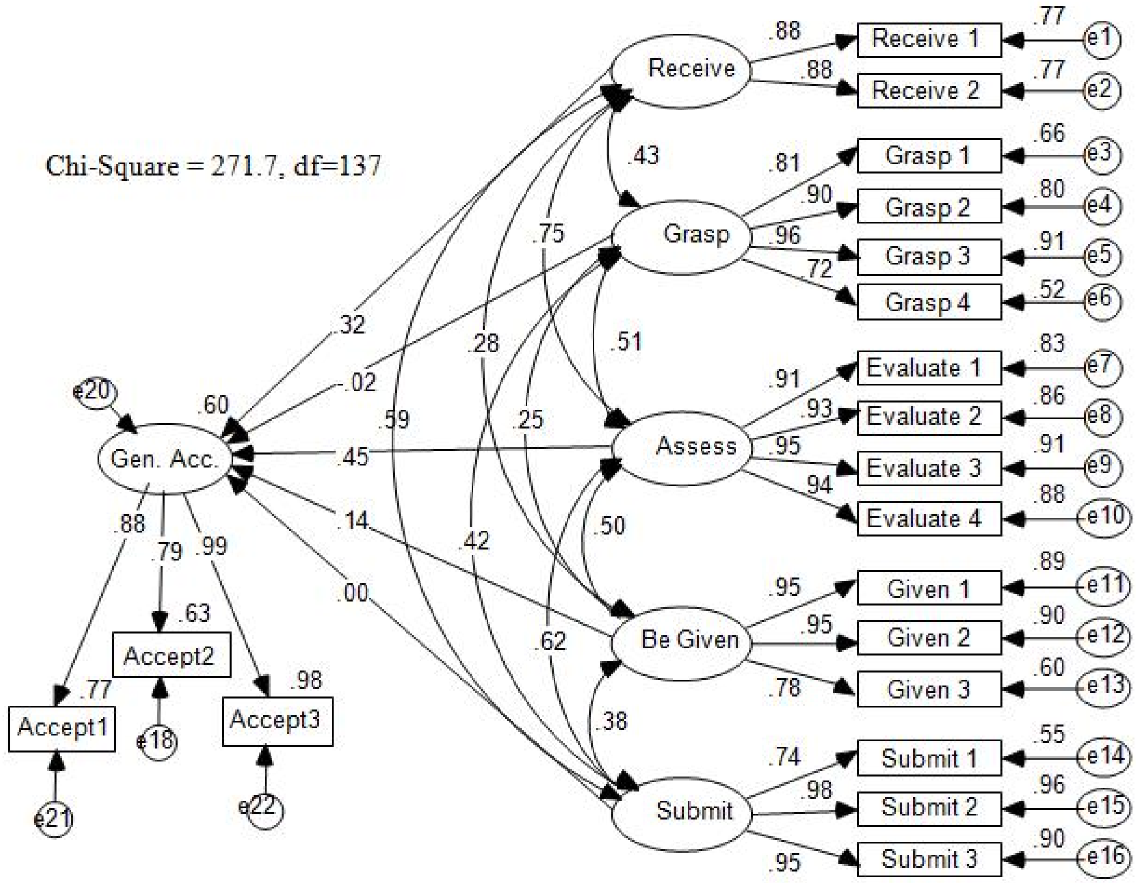

Figure 4.19 Modeling the Workplace Outcome of
Generic Acceptance Using the Stata Data Set

The first step in analysis is to examine the loadings for consistency across the three data sets. The values are given in table 4.31 and they are similar across the three data sets as we found for Research Model One. The similarities provide support for the case that the items are acting consistently.

Table 4.31 Standardized Loadings for the Workplace Outcome of Generic Acceptance for 3 Data Sets

Construct	*Item*	*Loading*		
		Stata *(n=111)*	Feda *(n = 268)*	PetroCo *(n = 145)*
Receive	Rec1	0.88	0.96	0.95
	Rec2	0.88	0.85	0.73
Grasp	Grasp1	0.81	0.82	0.85
	Grasp2	0.90	0.87	0.92
	Grasp3	0.96	0.84	0.93
	Grasp4	0.72	0.73	0.78
Assess	Eval1	0.91	0.91	0.91
	Eval2	0.93	0.95	0.93
	Eval3	0.95	0.96	0.97
	Eval4	0.94	0.96	0.96
Be Given	Give1	0.95	0.83	0.87
	Give2	0.95	0.93	0.93
	Give3	0.78	0.73	0.80
Submit	Sub1	0.75	0.72	0.67
	Sub2	0.98	0.97	0.96
	Sub3	0.95	0.95	0.93
Generic Acceptance	Accept1	0.99	0.96	0.91
	Accept2	0.88	0.85	0.87
	Accept3	0.79	0.82	0.90

What is new to this analysis is the introduction of the dependent variable. The loadings for the dependent variable also act consistently across the three data sets.

In addition to the loadings, we must examine the path estimates for the model. These path coefficients are given in table 4.32. As expected, the values vary across the data sets. All of this while the loading themselves are consistent. We expect the measures to behave similarly as reflected by the consistent loadings, but, as we found here, the paths should not. While the same concepts are being consistently measured, the values of the paths to them are expected to change depending on the situation. Thus, we find the five dimension model of acceptance acting consistently in the presence of the workplace outcome.

Table 4.32 Path Estimates for the Workplace Outcome of Generic Acceptance in the Workplace Outcome Research Model for 3 Data Sets

Construct	*Item*	*Path Estimate*		
		Stata *(n=111)*	Feda *(n = 268)*	PetroCo *(n = 145)*
Generic Acceptance	Receive	0.32	0.29	0.37
	Grasp	-0.02	0.01	0.04
	Assess	0.45	0.29	0.21
	Be Given	0.14	0.26	0.11
	Submit	0.00	0.21	0.33

One oversimplified example of this concept involves an analogy to a thermometer. While a thermometer is expected to read temperatures consistently and accurately, it will not indicate the same temperature values inside a 40 degree refrigerator as it would in a 75 degree room. That is, the values it indicates are different because the room temperatures are indeed different. However, it is still can be a reliable instrument for measuring several 75 degree rooms and also for measuring several 40 degree rooms.

Another measure of the Workplace Outcome Research Model looks at the distinctiveness of its constructs. For the workplace outcome of generic acceptance, the correlations between the five constructs were examined to assess the amount of distinctiveness of the constructs. These are presented in table 4.33. For the most part, the correlations were consistent across the three data sets in the presence of the generic acceptance construct. In a performance similar to that found in Research Model One, the correlation between the Receive and Assess constructs indicates significant overlap. However, for the most part the correlation values are consistent across the three data sets. One exception was the set of correlations between the Receive and Be Given constructs; they were 0.29, 0.37, and 0.57 for Stata, Feda and PetroCo respectively. While the first two datasets showed little overlap, the PetroCo data showed significant overlap between the constructs; and it also acted inconsistently between the data sets. While this is a concern, it is consistent with what was found for Research Model One.

Table 4.33 Correlations between Constructs in the Workplace Outcome Research Model with Generic Acceptance for 3 Data Sets

Construct A	*Construct B*	*Correlation between Constructs A & B*		
		Stata *(n=111)*	Feda *(n = 268)*	PetroCo *(n = 145)*
Receive	Grasp	0.43	0.48	0.37
Receive	Assess	0.75	0.76	0.73
Receive	Submit	0.59	0.58	0.47
Be Given	Receive	0.29	0.37	0.57
Grasp	Assess	0.51	0.57	0.55
Grasp	Submit	0.42	0.64	0.50
Be Given	Grasp	0.25	0.45	0.45
Assess	Submit	0.62	0.64	0.67
Be Given	Assess	0.50	0.46	0.71
Be Given	Submit	0.39	0.34	0.56

Model fit was examined for the Workplace Outcome Research Model with the generic acceptance outcome. The model fit data is presented in table 4.34. The data appear reasonably similar to what was found with Research Model One. The models provide reasonable fit for all three data sets.

Table 4.34 Model Fit Indicators for the Workplace Outcome Research Model with the Generic Acceptance Construct and 3 Data Sets

Statistic Name	*Value*		
	Stata *(n=111)*	Feda *(n = 268)*	PetroCo *(n = 145)*
CMIN (Default Model)	272	412	331
CMIN (Independence Model)	2327	5127	3055
DF	137	137	137
P	0	0	0
CMIN/DF	1.983	3.005	2.416
NFI/Delta1	0.883	0.920	0.892
RFI/rho1	0.838	0.889	0.850
IFI/Delta2	0.939	0.945	0.933
TLI/rho2	0.913	0.923	0.906
CFI	0.937	0.944	0.932
RMSEA	0.095	0.087	0.099
LO 90	0.078	0.077	0.086
HI 90	0.111	0.096	0.113
PCLOSE	0	0	0

In addition to examining the consistency of the measures for the workplace outcome of generic acceptance, we also looked for similar results for the workplace outcome of infusion. The results are presented in the following subsection.

4.4.1.2 Infusion

A workplace outcome research model that incorporates infusion is illustrated in figure 4.20. Infusion has four items whose measures are given in Appendix A.

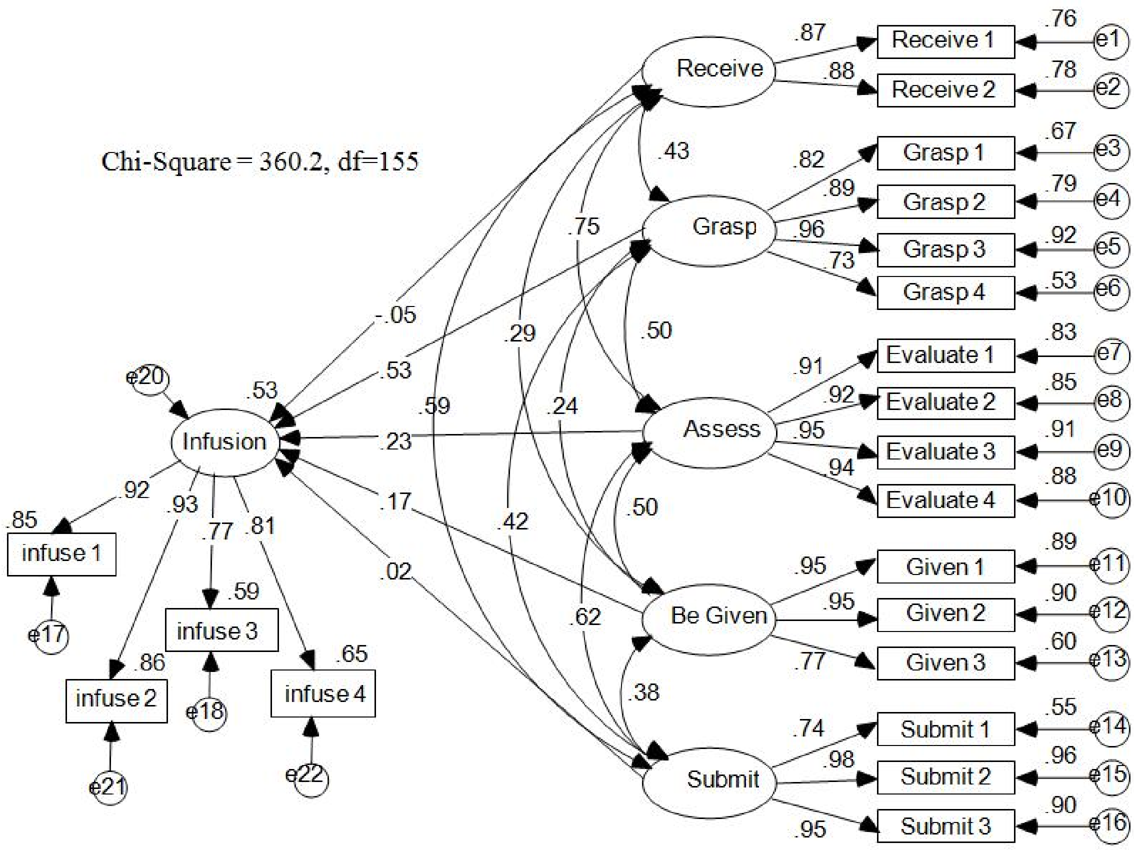

Figure 4.20 Modeling the Workplace Outcome of Infusion Using the Stata Data Set

The first step in this analysis is to look at the consistency of the loadings across three data sets. These are given in table 4.35. The loadings for the five constructs appear similar across a three data sets, providing confidence that the measures are acting consistently. This is similar to what was found for the workplace outcome of generic acceptance

Table 4.35 Standardized Loadings for the Workplace Outcome of Infusion for 3 Data Sets

Construct	*Item*	*Loading*		
		Stata *(n=111)*	Feda *(n = 268)*	PetroCo *(n = 145)*
Receive	Rec1	0.87	0.96	0.94
	Rec2	0.88	0.86	0.74
Grasp	Grasp1	0.82	0.82	0.85
	Grasp2	0.89	0.87	0.92
	Grasp3	0.96	0.83	0.94
	Grasp4	0.73	0.73	0.79
Assess	Eval1	0.91	0.91	0.91
	Eval2	0.92	0.94	0.93
	Eval3	0.95	0.96	0.97
	Eval4	0.94	0.96	0.96
Be Given	Give1	0.95	0.83	0.88
	Give2	0.95	0.93	0.93
	Give3	0.78	0.72	0.80
Submit	Sub1	0.75	0.72	0.67
	Sub2	0.98	0.97	0.96
	Sub3	0.95	0.96	0.93
Infusion	Infus1	0.92	0.92	0.91
	Infus2	0.93	0.91	0.95
	Infus3	0.77	0.58	0.70
	Infus4	0.81	0.68	0.79

Also, the path estimates for the workplace outcome model using infusion are consistent with what was found for the model with generic acceptance. These are given in table 4.36. As expected, the path estimates varied in the presence of different data sets. One exception to this was found in the relationship between Be Given and Infusion; its path estimates did not vary much. This was not expected for the path because it would be expected to vary among the data sets in the presence of different demographics in the workforce. In particular, variance was expected with respect to the amount of work experience of the employees. A plausible explanation might be that some overlap exists between the workplace outcomes of infusion and Be Given construct. Perhaps an individual fully using a technology would have partly been required to adapt his or her workplace routine to meet the needs of the new technology.

Table 4.36 Path Estimates for the Workplace Outcome of Infusion in the Workplace Outcome Research Model for 3 Data Sets

Construct	*Item*	*Path Estimate*		
		Stata *(n=111)*	Feda *(n = 268)*	PetroCo *(n = 145)*
Infusion	Receive	-0.05	-0.03	0.10
	Grasp	0.53	0.29	0.40
	Assess	0.23	0.12	0.07
	Be Given	0.17	0.11	0.17
	Submit	0.02	0.26	0.18

In addition to looking at item loadings and some path estimates, we must examine the construct correlations shown in table 4.37. The correlations are reasonably consistent as was found in the earlier in the workplace outcome model with a generic acceptance construct.

Table 4.37 Correlations between Constructs in the Workplace Outcome Research Model with Infusion for 3 Data Sets

Construct A	*Construct B*	*Correlation between Constructs A & B*		
		Stata *(n=111)*	Feda *(n = 268)*	PetroCo *(n = 145)*
Receive	Grasp	0.43	0.48	0.37
Receive	Assess	0.75	0.76	0.74
Receive	Submit	0.59	0.58	0.48
Be Given	Receive	0.29	0.37	0.58
Grasp	Assess	0.50	0.57	0.55
Grasp	Submit	0.42	0.64	0.50
Be Given	Grasp	0.24	0.45	0.45
Assess	Submit	0.62	0.64	0.67
Be Given	Assess	0.50	0.45	0.71
Be Given	Submit	0.39	0.34	0.56

Model fit statistics indicate that the overall model fit was acceptable in the presence of the three data sets. This information is presented in table 4.38.

Table 4.38 Model Fit Indicators for the Workplace Outcome Research Model with Infusion and 3 Data Sets

Statistic Name	*Value*		
	Stata *(n=111)*	Feda *(n = 268)*	PetroCo *(n = 145)*
CMIN (Default Model)	360	419	397
CMIN (Independence Model)	2473	5051	3139
DF	155	155	155
P	0	0	0
CMIN/DF	2.324	2.704	2.560
NFI/Delta1	0.854	0.917	0.874
RFI/rho1	0.803	0.888	0.829
IFI/Delta2	0.911	0.946	0.919
TLI/rho2	0.877	0.926	0.888
CFI	0.909	0.945	0.917
RMSEA	0.110	0.080	0.104
LO 90	0.095	0.071	0.092
HI 90	0.125	0.089	0.117
PCLOSE	0	0	0

Overall, the five construct measures held up well to tests for uniqueness and consistency. This occurred for Research Model One as well as for the Workplace Outcome Research Model with the dependent variables of infusion and generic acceptance.

4.4.2 <u>*Distinctiveness*</u>

The distinctiveness of the constructs in the presence of workplace outcomes was examined using discriminant validity analysis. This section provides the findings of this work.

4.4.2.1 Generic Acceptance

Discriminant validity analysis was performed on the Workplace Outcome Research Model with the generic acceptance workplace outcome. This is illustrated in figure 4.21.

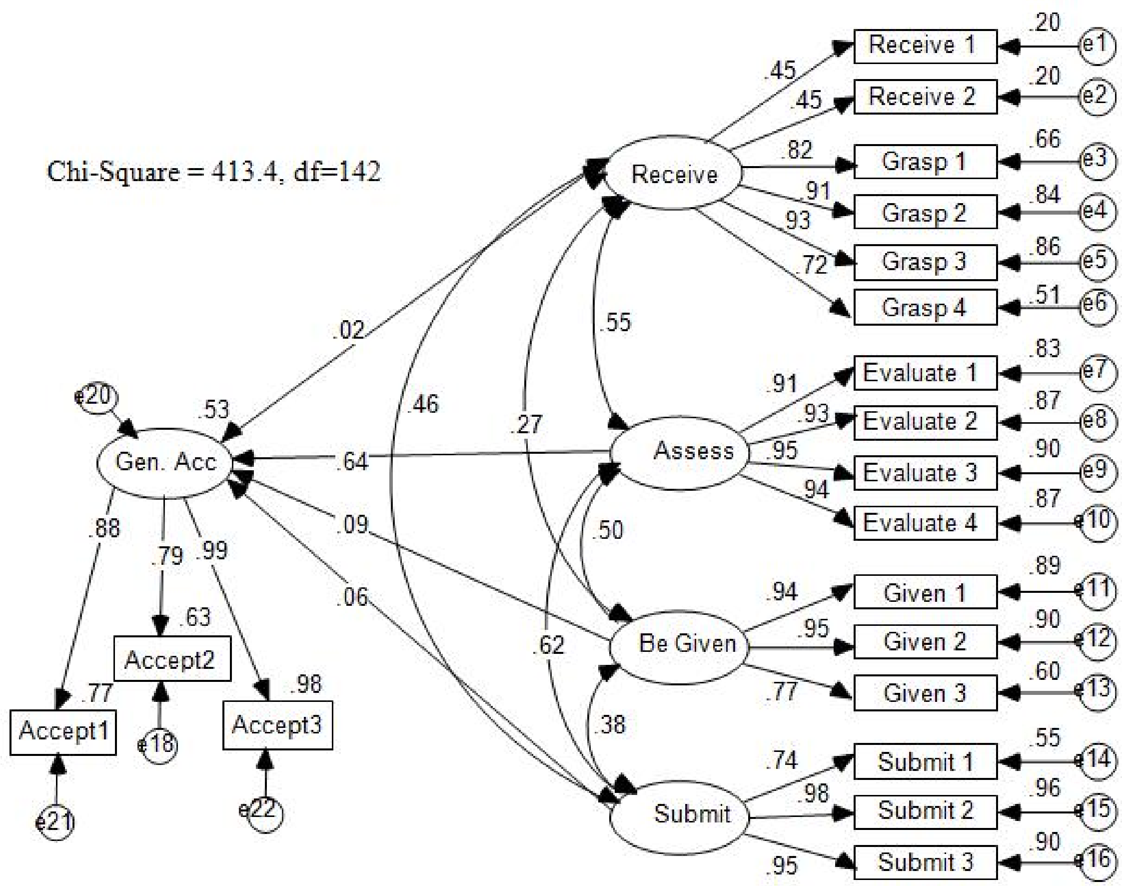

Figure 4.21 Discriminant Validity Test Estimates for the Receive and Grasp Construct Scale Pairs and the Workplace Outcome of Generic Acceptance Using the Stata Data Set

The first stage of this analysis involves establishing baseline measures for the research model. The measures are presented in table 4.39.

Table 4.39 Baseline Model Fit Measures for Discriminant Validity Tests for Workplace Outcome Research Model with Generic Acceptance

Model Name	*df*	χ^2		
		Stata *(n=111)*	Feda *(n = 268)*	PetroCo *(n = 145)*
Model 1 (Unconstrained)	137	271.7	411.7	331.0

The discriminant validity analysis involved a series of test models which combine the indicators for two constructs into a single construct. If the constructs are tapping into something unique, that test model with the combined indicators will fit worse than the baseline model with respect to the amount of degrees of freedom in the new model. The amount of allowable change in model fit was computed in StaTable software as shown in figure 4.22. The critical χ^2 is for increase of 5 degrees of freedom with a p value equal to 0.01. The computations indicate that a test model with chi-square change in fit less than 15.09 would suggest that the test model is a better fit than the baseline model, challenging the case for discriminant validity of the baseline model constructs.

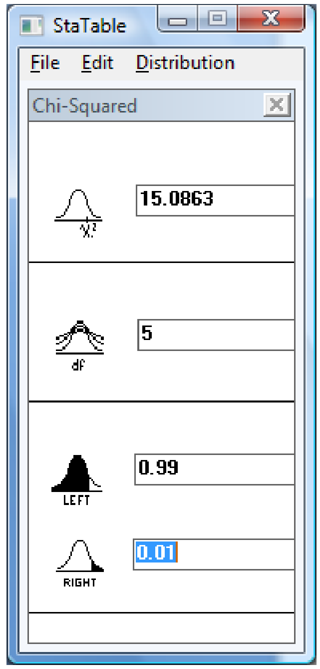

Figure 4.22 Determination of the Bonferonni-Adjusted Critical Chi-Square Change Criterion

As with the earlier research with Research Model One, a series of test models were created for discriminant validity testing. In each, a series of indicators were combined into one construct and the resulting model fit was assessed. For example, the indicators for the Receive and Grasp constructs were combined into one construct, resulting in an increase in the degrees of freedom for the model. The results of these tests are given in table 4.40.

Table 4.40 Model Fit Indicators for Discriminant Validity Test Models[3]

Construct Scale Pairs Combined		*df*	Stata *(n=111)*		Feda *(n = 268)*		PetroCo *(n = 145)*	
			χ^2	χ^2 *Diff.*	χ^2	χ^2 *Diff.*	χ^2	χ^2 *Diff.*
Receive	Grasp	142	413.4	141.7	766.3	354.6	501.4	170.4
Receive	Assess	142	329.5	57.8	581.1	169.4	392.6	61.6
Receive	Be Given	142	432.2	160.5	772.2	360.5	437.5	106.5
Receive	Submit	142	382.1	110.4	726.3	314.6	448.8	117.8
Grasp	Assess	142	529.0	257.3	859.4	447.7	678.6	347.6
Grasp	Be Given	142	551.2	279.5	755.1	343.4	613.0	282
Grasp	Submit	142	558.7	287	782.2	370.5	601.5	270.5
Assess	Be Given	142	497.9	226.2	754.5	342.8	466.4	135.4
Assess	Submit	142	458.5	186.8	870.5	458.8	475.3	144.3
Be Given	Submit	142	549.9	278.2	817.9	406.2	481.3	150.3

The table shows that each test model resulted in an increase in chi-square that is greater than the critical value of 15.09, suggesting that each test model has a significantly worse fit. Since the chi-square change in each test is greater than 15.09, we have support for the case of discriminant validity in the Workplace Outcome Research Model with the dependent variable of generic acceptance.

Since we have shown support for discriminant validity of the Workplace Outcome Research Model with the general acceptance construct, we must now examine the same for the case of infusion.

4.4.2.2 Infusion

The first test model for the discriminant validity tests of the workplace outcome model with infusion is given in figure 4.23.

[3] The critical χ^2 value for 5 degrees of freedom at p=0.01 is 15.09.

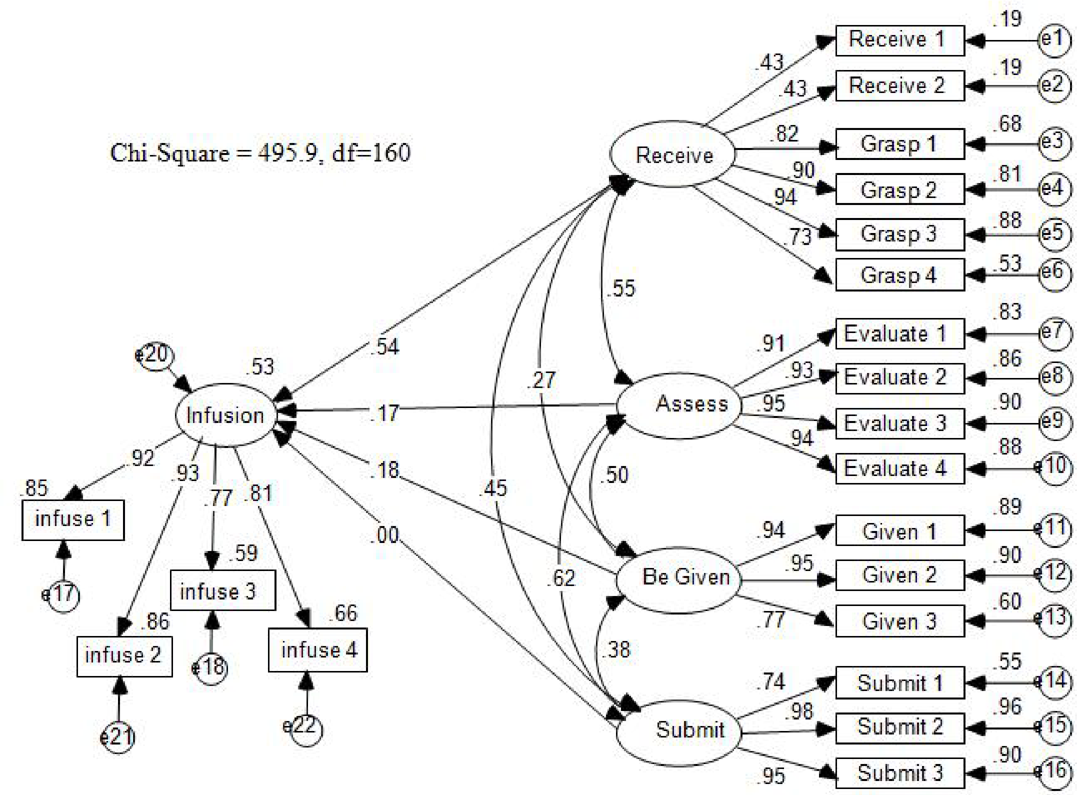

Figure 4.23 Discriminant Validity Test Estimates for the Receive and Grasp Construct Scale Pairs and the Workplace Outcome of Infusion using the Stata Data Set

The baseline model has 155 degrees of freedom and a model fit chi-square that ranges from 360.2 to 419.2. This is given in table 4.41.

Table 4.41 Baseline Model Fit Measures for Discriminant Validity Tests for Workplace Outcome Research Model with Infusion

Model Name	*df*	χ^2 Stata *(n=111)*	χ^2 Feda *(n = 268)*	χ^2 PetroCo *(n = 145)*
Model 1 (Unconstrained)	155	360.2	419.2	396.9

Combining the indicators necessary for discriminant validity testing leads to an increase of 5 degrees of freedom. For this increase, we must compute the critical value that would indicate the change in chi-square that would suggest a significantly different fit compared to the original model. This was computed with StaTable software, shown in figures 4.24.

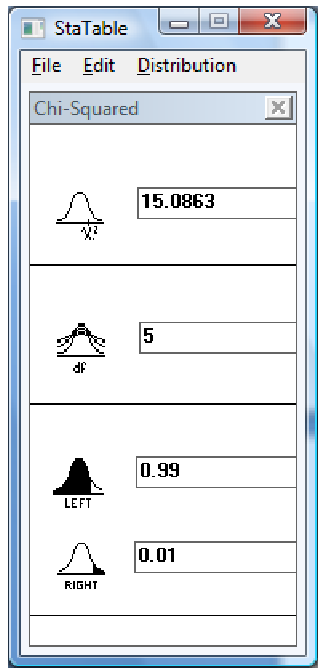

Figure 4.24 Determination of the Bonferonni-Adjusted Critical Chi-Square Change Criterion

Again, for this test we expect each test model to have a significantly worse fit if discriminant validity is to hold. Thus, if each test model has an increase in chi-square model fit of 15.09 or greater, support for discriminant validity is maintained. Any test model with a significantly lower fit would not support the case of discriminant validity.

The findings for discriminant validity testing of the research model are summarized in table 4.42. As with earlier discriminant validity tests, none of the test models exceed the test criteria providing support for the case of discriminant validity for this model.

Table 4.42 Model Fit Indicators for Discriminant Validity Test Models[4]

Construct Scale Pairs Combined		*df*	Stata *(n=111)* χ^2	Stata *(n=111)* χ^2 *Diff.*	Feda *(n = 268)* χ^2	Feda *(n = 268)* χ^2 *Diff.*	PetroCo *(n = 145)* χ^2	PetroCo *(n = 145)* χ^2 *Diff.*
Receive	Grasp	160	495.9	135.7	754.0	334.8	545.5	148.6
Receive	Assess	160	413.0	52.8	572.3	153.1	440.3	43.4
Receive	Be Given	160	512.9	152.7	767.4	348.2	485.7	88.8
Receive	Submit	160	462.9	102.7	715.5	296.3	509.7	112.8
Grasp	Assess	160	646.6	286.4	880.5	461.3	766.5	369.6
Grasp	Be Given	160	639.8	279.6	739.6	320.4	677.9	281.0
Grasp	Submit	160	649.1	288.9	797.7	378.5	650.2	253.3
Assess	Be Given	160	588.1	227.9	740.0	320.8	533.4	136.5
Assess	Submit	160	547.3	187.1	879.7	460.5	528.7	131.8
Be Given	Submit	160	638.7	278.5	801.8	382.6	541.0	144.1

The third series of analyses for the Workplace Outcome Research Model consist of invariance testing. The results of these tests are given in the following section.

4.4.3 Invariance

Invariance tests were conducted for the Workplace Outcome Research Model with the dependent variables of generic acceptance and infusion.

As with earlier analysis, three sets of tests were conducted. First, individual loadings were constrained to be invariant for two of the three data sets. Following this, correlations between constructs were constrained and the resulting model fits were examined. And finally, similar analyses were conducted while loadings and correlations

[4] The critical χ^2 value for 5 degrees of freedom at p=0.01 is 15.09.

were constrained to be invariant across three data sets. The results of these analyses are presented first for a model with generic acceptance and then for one with infusion.

4.4.3.1 Generic Acceptance

Invariance testing for the workplace outcome model with the dependent variable of generic acceptance begins with the analysis of a baseline model that is not constrained to be invariant. The model fit is stated in table 4.43.

Table 4.43 Baseline Model Fit Measure for Invariance Tests on Workplace Outcome Research Model with Generic Acceptance

Model	*Fit Indicator*	
	χ^2	*Df*
Unconstrained Model	1014.88	411

Since the analysis involves a series of tests, we must account for the possibility of capitalizing on chance by applying a Bonferroni adjustment. In the first set of tests, there are a total of 16 loadings to be constrained and this will be done for 3 cases per loading. Thus, there are 48 comparisons to be accounted for. For this, we downwardly adjust alpha, as shown in table 4.44.

Table 4.44 Critical Chi-Square for Invariance Tests with Constraints on Two Loadings per Test

Description	Value
Test Name	3 groups, taken 2 at a time - loadings
Number of comparisons	48 (16 loadings with 3 tests per loading)
Change in degrees of freedom	1 df change
Alpha	0.05/48
Critical Value	10.83

This results in a critical value of 10.83, which was taken from a chi-square distribution for 1 degree of freedom and an alpha of 0.05 divided by 48.

Next, the first in a series of invariance test models is shown in figure 4.25.

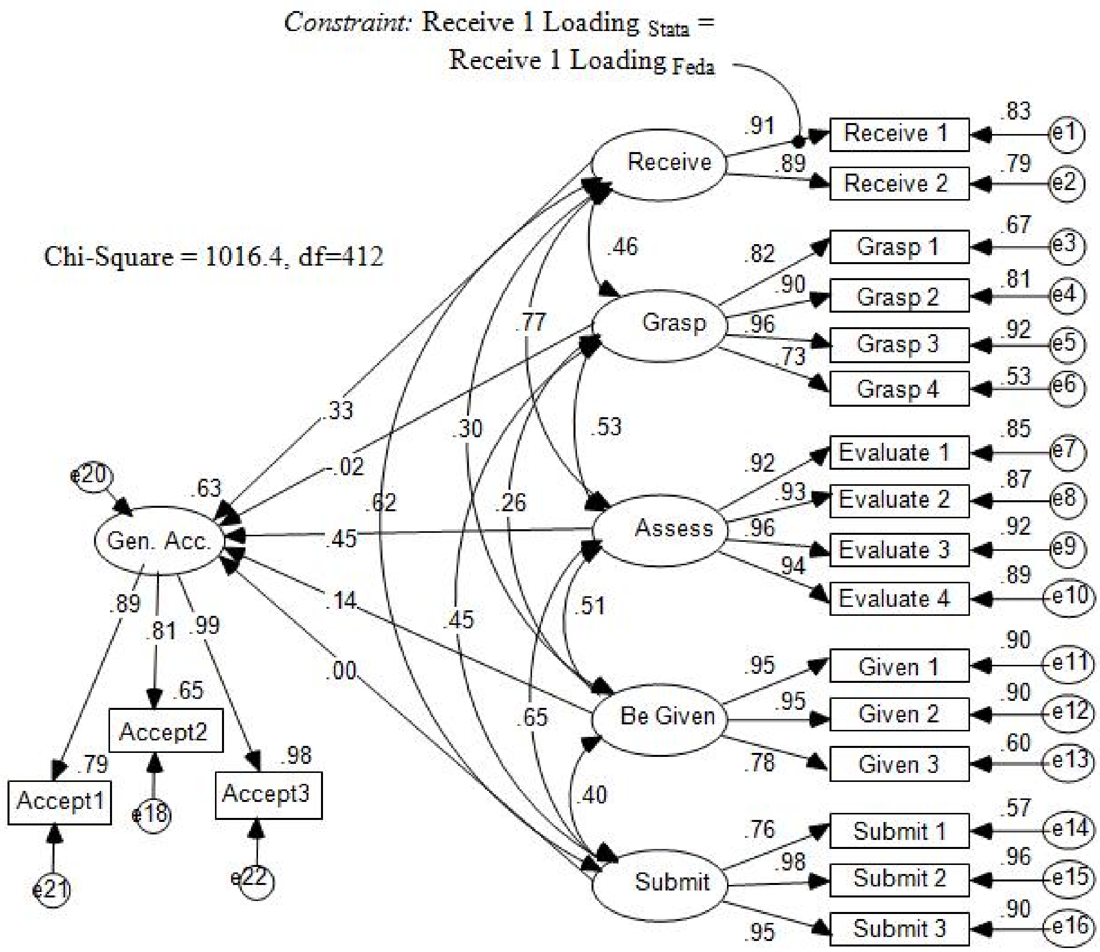

Figure 4.25 Invariance Test Estimates for the Workplace Outcome of Generic Acceptance for Stata Data with Constrained Receive 1 Loadings for Stata & Feda Data Sets

The test results for the first series of invariance tests are given in table 4.45. For the tests, selected loading were constrained to be invariant for the Stata and Feda data sets. For example, the rows for the Receive 1 item reports the results of an invariance test with the loading for the Receive 1 indicator constrained to equal for the Stata and Feda data sets. The resulting change in chi-square was an increase of 3.7. Given our critical value of 10.83, the results suggest that the fit of the constrained test model is not significantly different from the baseline model so model invariance is not challenged. As we can see, this is the case for the entire set of test results presented in table 4.45. Therefore, for the case of constraints on Stata and Feda loadings in the model, we find no challenge to invariance.

Table 4.45 Results for Invariance Tests with Selected Stata and Feda Loadings Constrained in a Generic Acceptance Context

Indicator with Constraints	Stata & Feda Constrained			
	χ^2	$\Delta\ \chi^2$	*df*	*Δ df*
Receive 1	1018.58	3.7	412	1
Receive 2	1014.89	0.0	412	1
Grasp 1	1015.18	0.3	412	1
Grasp 2	1014.94	0.1	412	1
Grasp 3	1014.97	0.1	412	1
Grasp 4	1015.95	1.1	412	1
Assess 1	1015.25	0.4	412	1
Assess 2	1017.51	2.6	412	1
Assess 3	1016.47	1.6	412	1
Assess 4	1016.19	1.3	412	1
Be Given 1	1014.93	0.0	412	1
Be Given 2	1014.88	0.0	412	1
Be Given 3	1015.09	0.2	412	1
Submit 1	1015.42	0.5	412	1
Submit 2	1015.49	0.6	412	1
Submit 3	1015.04	0.2	412	1

Similar tests were conducted for constrained loadings for Stata and PetroCo data. These results are given in table 4.46. As we can see, the results show no change in chi-square that is greater than the critical value of 10.83 and therefore this presents no challenge to the case of model invariance.

Table 4.46 Results for Invariance Tests with Selected Stata and PetroCo Loadings Constrained in a Generic Acceptance Context

Indicator with Constraints	Stata & PetroCo Constrained			
	χ^2	$\Delta\ \chi^2$	*df*	Δ *df*
Receive 1	1014.90	0.0	412	1
Receive 2	1022.42	7.5	412	1
Grasp 1	1015.31	0.4	412	1
Grasp 2	1015.16	0.3	412	1
Grasp 3	1014.94	0.1	412	1
Grasp 4	1016.10	1.2	412	1
Assess 1	1015.63	0.8	412	1
Assess 2	1014.88	0.0	412	1
Assess 3	1015.06	0.2	412	1
Assess 4	1015.37	0.5	412	1
Be Given 1	1014.95	0.1	412	1
Be Given 2	1014.91	0.0	412	1
Be Given 3	1014.89	0.0	412	1
Submit 1	1015.07	0.2	412	1
Submit 2	1017.02	2.1	412	1
Submit 3	1015.83	1.0	412	1

The third set of analysis in this series of tests involves constraining loadings for the Feda and PetroCo data sets. The results are given in table 4.47. The table reflects that the test model with the Receive2 item constrained to be invariant is significantly different from the baseline model, and thus, invariance is challenged by this item.

Table 4.47 Results for Invariance Tests with Selected Feda and PetroCo Loadings Constrained in a Generic Acceptance Context

Indicator with Constraints	Feda & PetroCo Constrained			
	χ^2	$\Delta\ \chi^2$	*df*	Δ *df*
Receive 1	1020.68	5.8	412	1
Receive 2	1025.97	11.1	412	1
Grasp 1	1014.91	0.0	412	1
Grasp 2	1015.70	0.8	412	1
Grasp 3	1014.88	0.0	412	1
Grasp 4	1014.91	0.0	412	1
Assess 1	1017.81	2.9	412	1
Assess 2	1018.16	3.3	412	1
Assess 3	1018.59	3.7	412	1
Assess 4	1019.50	4.6	412	1
Be Given 1	1014.89	0.0	412	1
Be Given 2	1014.93	0.0	412	1
Be Given 3	1015.05	0.2	412	1
Submit 1	1016.44	1.6	412	1
Submit 2	1015.77	0.9	412	1
Submit 3	1015.47	0.6	412	1

In summary, a series of tests with 48 models were conducted for the Workplace Outcome Research Model with the dependent variable of generic acceptance. Of the 48 tests, one test challenges the case for invariance of the constructs. It occurred for the case of constraints on the Receive 2 loading (table 4.47).

Invariance testing was also conducted with correlations. The first test model for these tests is given in figure 4.26.

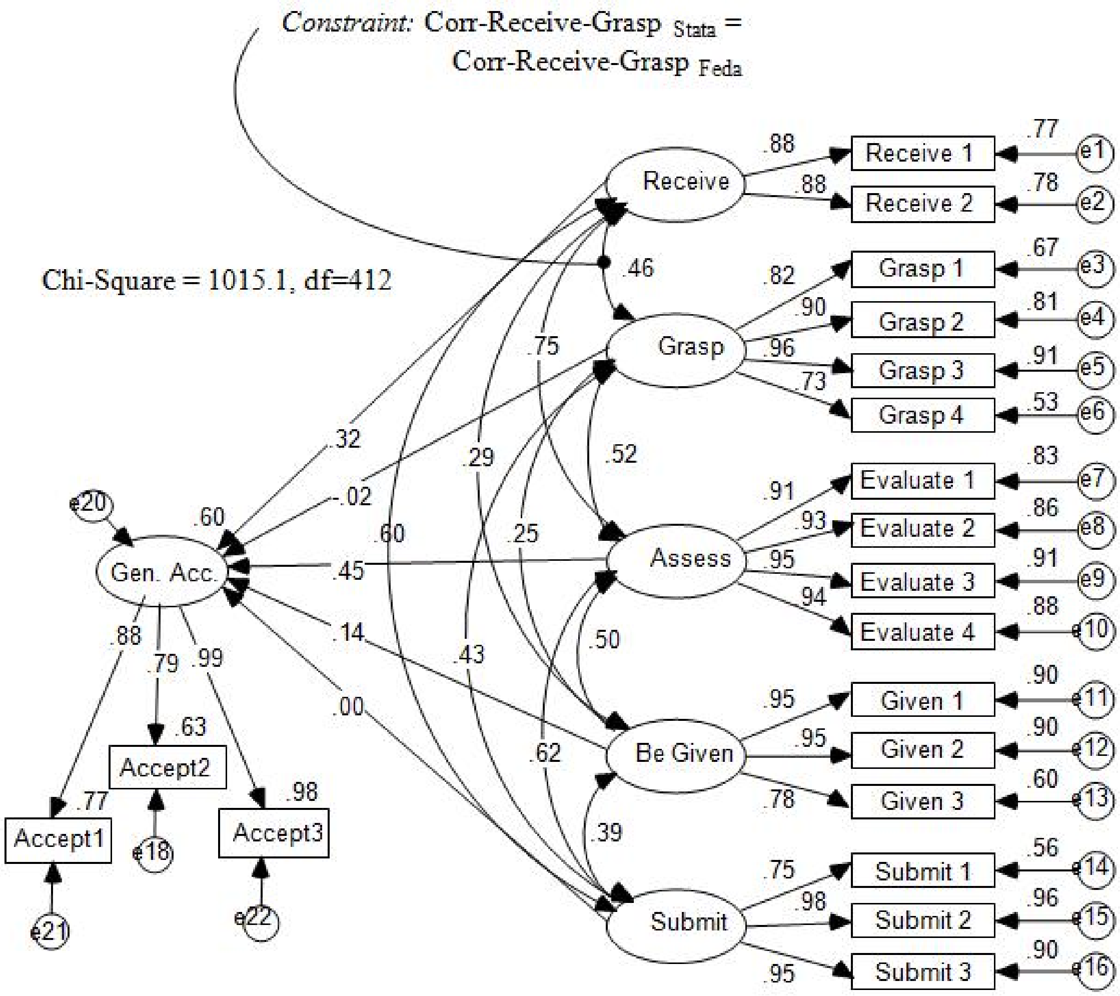

Figure 4.26 Invariance Test Estimates for the Workplace Outcome of Generic Acceptance for Stata Data with Constrained Correlations between Receive and Grasp for Stata & Feda Data Sets

This test of invariance involves a total of 30 tests, as described in table 4.48. The critical value is a chi-square of 9.55.

Table 4.48 Critical Chi-Square for Invariance Tests with Constraints on Two Correlations per Test

Description	Value
Test Name	3 groups, taken 2 at a time – correlations
Number of comparisons	30 (10 correlations with 3 tests per loading)
Change in degrees of freedom	1 df change
Alpha	0.05/30
Critical Value	9.55

The first sets of tests involving the correlations require constraining specific correlations to be invariant for the Stata and Feda data sets. The results are given in table 4.49. Of the 10 models with constrained correlations, none posed a challenge to invariance. All changes in chi-square were less than the critical value of 9.55.

Table 4.49 Results for Invariance Tests with Selected Stata and Feda Correlations Constrained in a Generic Acceptance Context

Factor Covariance Constrained	Stata and Feda Constrained			
	χ^2	$\Delta\ \chi^2$	*df*	*Δ df*
$\Phi_{\text{Receive} \bullet \text{Grasp}}$	1015.08	0.2	412	1
$\Phi_{\text{Receive} \bullet \text{Assess}}$	1014.91	0.0	412	1
$\Phi_{\text{Receive} \bullet \text{Be Given}}$	1015.43	0.5	412	1
$\Phi_{\text{Receive} \bullet \text{Submit}}$	1014.91	0.0	412	1
$\Phi_{\text{Grasp} \bullet \text{Assess}}$	1015.48	0.6	412	1
$\Phi_{\text{Grasp} \bullet \text{Be Given}}$	1018.48	3.6	412	1
$\Phi_{\text{Grasp} \bullet \text{Submit}}$	1021.23	6.4	412	1
$\Phi_{\text{Assess} \bullet \text{Be Given}}$	1015.12	0.2	412	1
$\Phi_{\text{Assess} \bullet \text{Submit}}$	1014.93	0.0	412	1
$\Phi_{\text{Be Given} \bullet \text{Submit}}$	1015.05	0.2	412	1

The correlation tests were also conducted with constrained models for the Stata and PetroCo data. These results are given in table 4.50. None of the models resulted in fits that exceeded the critical value and therefore invariance is not challenged for this case.

Table 4.50 Results for Invariance Tests with Selected Stata and PetroCo Correlations Constrained in a Generic Acceptance Context

Factor Covariance Constrained	Stata and PetroCo Constrained			
	χ^2	$\Delta\ \chi^2$	*df*	Δ *df*
$\Phi_{\text{Receive • Grasp}}$	1015.17	0.3	412	1
$\Phi_{\text{Receive • Assess}}$	1014.93	0.0	412	1
$\Phi_{\text{Receive • Be Given}}$	1020.82	5.9	412	1
$\Phi_{\text{Receive • Submit}}$	1016.18	1.3	412	1
$\Phi_{\text{Grasp • Assess}}$	1015.04	0.2	412	1
$\Phi_{\text{Grasp • Be Given}}$	1017.70	2.8	412	1
$\Phi_{\text{Grasp • Submit}}$	1015.49	0.6	412	1
$\Phi_{\text{Assess • Be Given}}$	1020.80	5.9	412	1
$\Phi_{\text{Assess • Submit}}$	1015.30	0.4	412	1
$\Phi_{\text{Be Given • Submit}}$	1017.60	2.7	412	1

The third and final portion of invariance testing involving correlations and the generic acceptance dependent variable involved constraining selected correlations for the Feda and PetroCo data sets. The results of this are given in table 4.51. Unlike earlier tests, invariance is challenged in one case because the change in chi-square for it is greater than the critical value. That is, the fit of the model with the correlation between Assess and Be Given forced to be invariant in the Feda and PetroCo data suggests that the forced invariant model has a worse fit than the baseline. Invariance is challenged in this case.

Table 4.51 Results for Invariance Tests with Selected Feda and PetroCo Correlations Constrained in a Generic Acceptance Context

Factor Covariance Constrained	Feda and PetroCo Constrained			
	χ^2	$\Delta\ \chi^2$	*Df*	Δ *df*
$\Phi_{\text{Receive} \bullet \text{Grasp}}$	1016.20	1.3	412	1
$\Phi_{\text{Receive} \bullet \text{Assess}}$	1015.08	0.2	412	1
$\Phi_{\text{Receive} \bullet \text{Be Given}}$	1019.64	4.8	412	1
$\Phi_{\text{Receive} \bullet \text{Submit}}$	1016.37	1.5	412	1
$\Phi_{\text{Grasp} \bullet \text{Assess}}$	1015.02	0.1	412	1
$\Phi_{\text{Grasp} \bullet \text{Be Given}}$	1014.88	0.0	412	1
$\Phi_{\text{Grasp} \bullet \text{Submit}}$	1018.11	3.2	412	1
$\Phi_{\text{Assess} \bullet \text{Be Given}}$	1026.42	11.5	412	1
$\Phi_{\text{Assess} \bullet \text{Submit}}$	1015.18	0.3	412	1
$\Phi_{\text{Be Given} \bullet \text{Submit}}$	1020.55	5.7	412	1

In summary, a series of 30 tests were conducted where selected correlations were constrained to be invariant between two data sets. Of these, one of the 30 exceeded the criterion that suggests invariance is challenged. This was the case for the correlation between Assess and Be Given being constrained as invariant between the Feda and PetroCo data sets.

An additional series of invariance tests were conducted where selected loadings and correlations were constrained to be invariant across three data sets at a time. The first of these involved the model loadings and it is illustrated in figure 4.27.

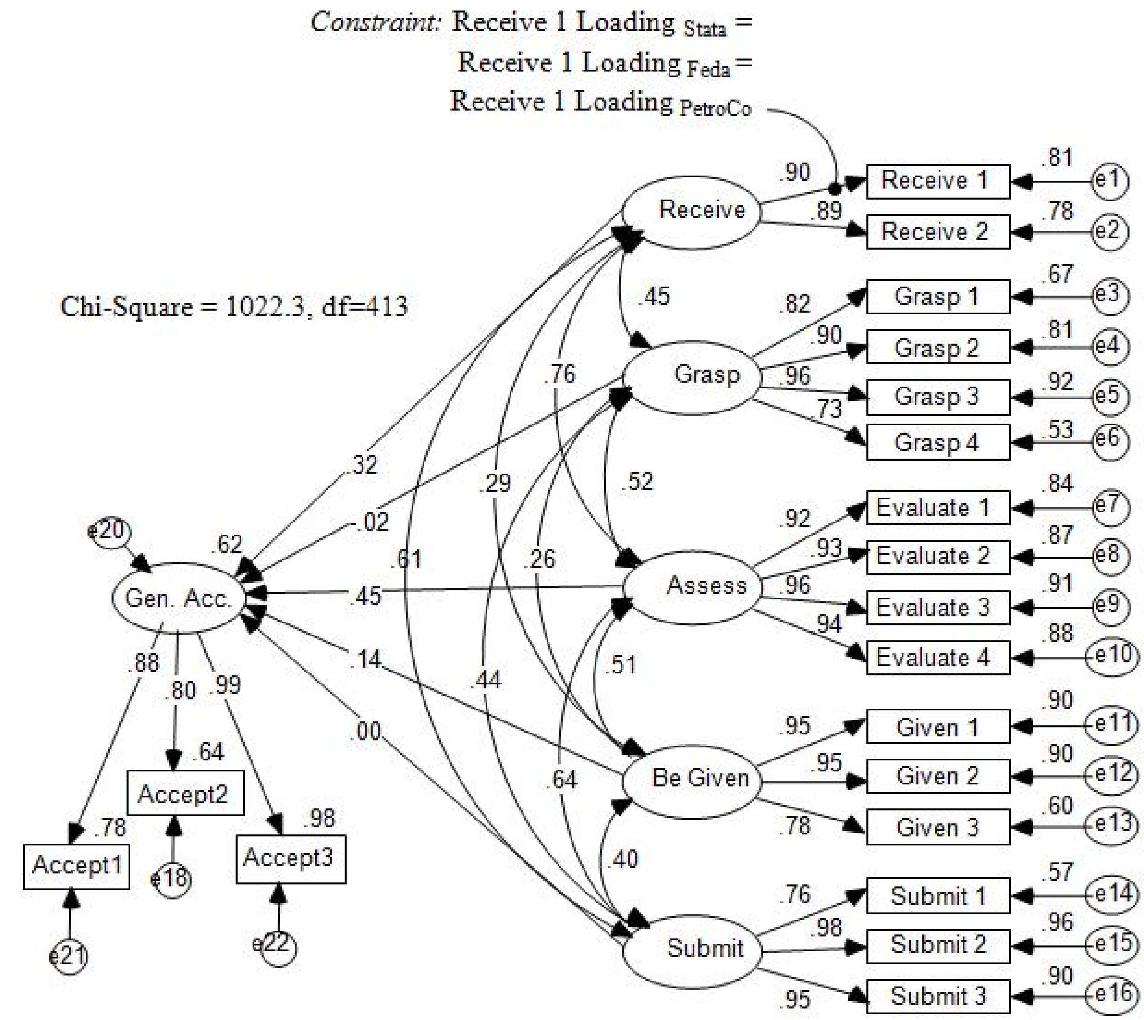

Figure 4.27 Invariance Test Estimates for the Workplace Outcome of Generic Acceptance for Stata Data with Constrained Receive 1 Loadings for Stata, Feda & PetroCo Data Sets

As shown in table 4.52, there are a total of 16 tests being conducted. After a Bonferroni correction is applied, the critical value for testing is 11.62.

Table 4.52 Critical Chi-Square for Invariance Tests with Constraints on Three Loadings per Test

Description	**Value**
Test Name	3 groups, taken 3 at a time – correlations
Number of comparisons	16 (16 loadings with 1 test per loading)
Change in degrees of freedom	2 df change
Alpha	0.05/16
Critical Value	11.62

The findings for the tests with constrained loadings are given in table 4.53. The results indicate one challenge to invariance. This is for the case where the “Receive 2” indicator was constrained equal between the three data sets. The resulting change found in the model which was forced to be invariant was a chi-square value of 12.1, exceeding the criteria of 11.62. Again, this does not bode well for the case of invariance of the measures.

Table 4.53 Results for Invariance Tests with Selected Stata, Feda and PetroCo Loadings Constrained in a Generic Acceptance Context

Indicator	Constrained Groups: Stata, Feda and PetroCo			
	χ^2	$\Delta\ \chi^2$	*df*	Δ *df*
Receive 1	1022.34	7.5	413	2
Receive 2	1026.96	12.1	413	2
Grasp 1	1015.33	0.5	413	2
Grasp 2	1015.70	0.8	413	2
Grasp 3	1014.98	0.1	413	2
Grasp 4	1016.28	1.4	413	2
Assess 1	1017.82	2.9	413	2
Assess 2	1019.48	4.6	413	2
Assess 3	1019.12	4.2	413	2
Assess 4	1019.81	4.9	413	2
Be Given 1	1014.96	0.1	413	2
Be Given 2	1014.93	0.0	413	2
Be Given 3	1015.16	0.3	413	2
Submit 1	1016.55	1.7	413	2
Submit 2	1017.06	2.2	413	2
Submit 3	1015.92	1.0	413	

Analysis was also conducted for the case of correlations being constrained as invariant over the three data sets. There were a total of 10 tests and the first one is illustrated in figure 4.28.

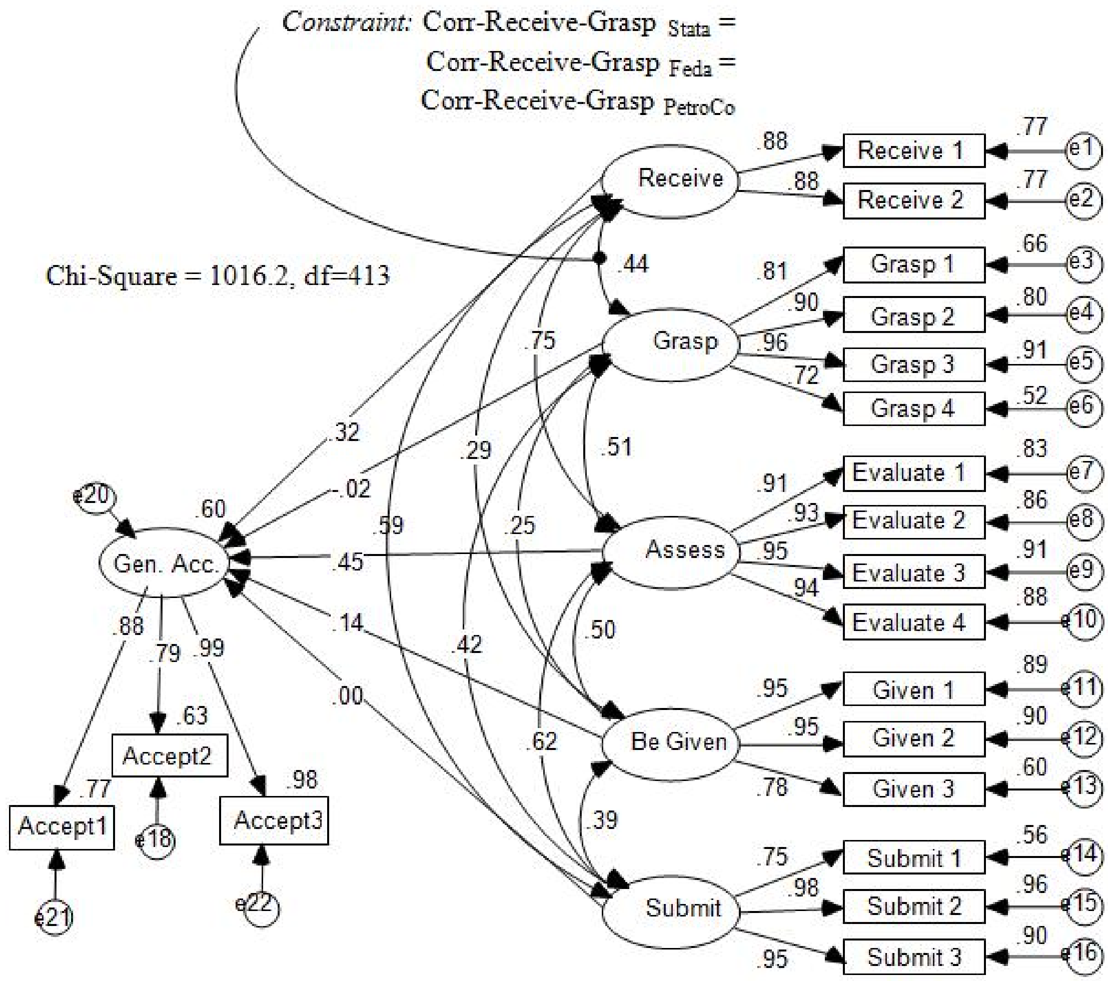

Figure 4.28 Invariance Test Estimates for the Workplace Outcome of Generic Acceptance for Stata Data with Constrained Correlations between Receive and Grasp for Stata, Feda & PetroCo Data Sets

As shown in table 4.54, the critical value for the tests is 10.60.

Table 4.54 Critical Chi-Square for Invariance Tests with Constraints on Three Correlations per Test

Description	Value
Test Name	3 groups, taken 3 at a time - correlations
Number of comparisons	10 (10 correlations with 1 test per correlation)
Change in degrees of freedom	2 df change
Alpha	0.05/10
Critical Value	10.597

The findings for the tests are given in table 4.55. Of the 10 tests, one resulted in a change in chi-square that exceeds the criteria. This is for the test with the correlations between the Assess and Be Given constructs constrained to be equal. The change in chi-square for research model was found to be 12.0, which exceeds the critical value of 10.6. This raises questions about the invariance of the model.

Table 4.55 Results for Invariance Tests with Selected Stata, Feda and PetroCo Correlations Constrained in a Generic Acceptance Context

Factor Covariance Constrained	Stata, Feda and PetroCo Constrained			
	χ^2	$\Delta\ \chi^2$	*df*	Δ *df*
$\Phi_{\text{Receive} \bullet \text{Grasp}}$	1016.21	1.3	413	2
$\Phi_{\text{Receive} \bullet \text{Assess}}$	1015.08	0.2	413	2
$\Phi_{\text{Receive} \bullet \text{Be Given}}$	1021.87	7.0	413	2
$\Phi_{\text{Receive} \bullet \text{Submit}}$	1016.66	1.8	413	2
$\Phi_{\text{Grasp} \bullet \text{Assess}}$	1015.49	0.6	413	2
$\Phi_{\text{Grasp} \bullet \text{Be Given}}$	1018.91	4.0	413	2
$\Phi_{\text{Grasp} \bullet \text{Submit}}$	1022.19	7.3	413	2
$\Phi_{\text{Assess} \bullet \text{Be Given}}$	1026.85	12.0	413	2
$\Phi_{\text{Assess} \bullet \text{Submit}}$	1015.36	0.5	413	2
$\Phi_{\text{Be Given} \bullet \text{Submit}}$	1020.71	5.8	413	2

In summary, a total of 26 tests were run for the Workplace Outcome Research Model for generic acceptance with three variables constrained a time. Of these, one test with a constrained loading and one test with a constrained correlation exceeded the allowable criteria. This raises questions about the invariance of the Workplace Outcome Research Model.

Now that the findings for the Workplace Outcome Research Model with the dependant variable of generic acceptance are presented, we now focus on a similar model with the dependent variable of infusion. Invariance test results for this model are given in the following subsection.

4.4.3.2 Infusion

We begin invariance analysis of the Workplace Outcome Research Model with infusion by analyzing a baseline model that is not constrained to be invariant. The model fit is given in table 4.56.

Table 4.56 Baseline Model Fit Measure for Invariance Tests on Workplace Outcome Research Model with Infusion

Model	*Fit Indicator*	
	χ^2	*Df*
Unconstrained Model	1177.06	465

The first series of tests involved constraining selected loadings as invariant. There are a total of 48 tests as outlined in table 4.57. The critical value for the tests is 10.83. Should the fit of any of the test models exceed the criterion, the test would raise questions about model invariance.

Table 4.57 Critical Chi-Square for Invariance Tests with Constraints on Two Loadings per Test

Description	Value
Test Name	3 groups, taken 2 at a time – loadings
Number of comparisons	48 (16 loadings with 3 tests per loading)
Change in degrees of freedom	1 df change
Alpha	0.05/48
Critical Value	10.83

The model for the first test is given in figure 4.29. It shows the loading for Receive 1 constrained to be equal for the Stata and Feda data sets.

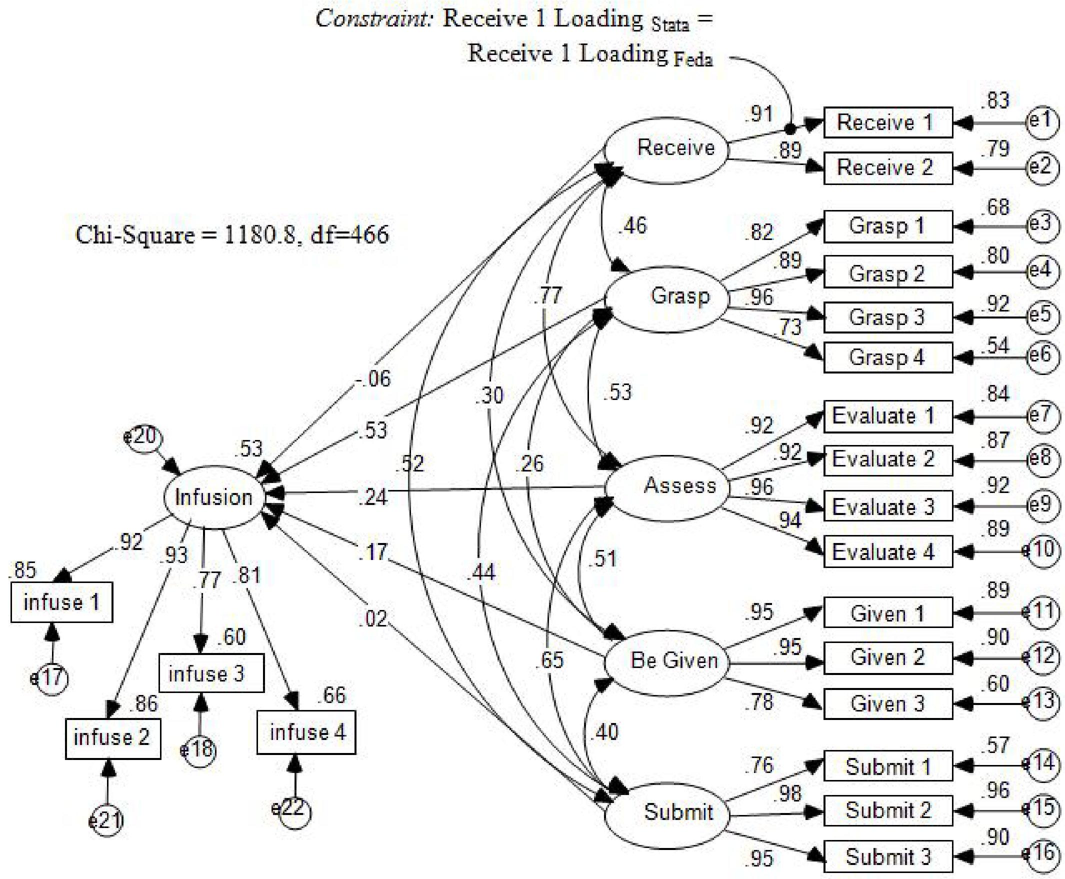

Figure 4.29 Invariance Test Estimates for the Workplace Outcome of Infusion for Stata Data with Constrained Receive 1 Loadings for Stata & Feda Data Sets

Invariance test results for constrained loading are presented in the next three tables. The first set of tests involved selected loadings being constrained for the Stata and Feda data sets. The results of these tests are found in table 4.58.

Table 4.58 Results for Invariance Tests with Selected Stata and Feda Loadings Constrained in an Infusion Context

Indicator with Constraints	Stata & Feda Constrained			
	χ^2	$\Delta\ \chi^2$	*df*	Δ *df*
Receive 1	1180.77	3.71	466.00	1
Receive 2	1177.06	0	466.00	1
Grasp 1	1177.31	0.25	466.00	1
Grasp 2	1177.08	0.02	466.00	1
Grasp 3	1177.20	0.14	466.00	1
Grasp 4	1178.09	1.03	466.00	1
Assess 1	1177.45	0.39	466.00	1
Assess 2	1179.70	2.64	466.00	1
Assess 3	1178.62	1.56	466.00	1
Assess 4	1178.32	1.26	466.00	1
Be Given 1	1177.09	0.03	466.00	1
Be Given 2	1177.06	0	466.00	1
Be Given 3	1177.34	0.28	466.00	1
Submit 1	1177.59	0.53	466.00	1
Submit 2	1177.61	0.55	466.00	1
Submit 3	1177.25	0.19	466.00	1

The results in the table indicate that no test with loadings constrained for Stata and Feda resulted in a fit that exceeded the criteria. A similar analysis was conducted with constraints on selected Stata and PetroCo loadings. The results of this are given in table 4.59.

Table 4.59 Results for Invariance Tests with Selected Stata and PetroCo Loadings Constrained in an Infusion Context

Indicator with Constraints	Stata & PetroCo Constrained			
	χ^2	$\Delta\ \chi^2$	*df*	Δ *df*
Receive 1	1177.10	0.04	466.00	1
Receive 2	1184.26	7.2	466.00	1
Grasp 1	1177.42	0.36	466.00	1
Grasp 2	1177.39	0.33	466.00	1
Grasp 3	1177.13	0.07	466.00	1
Grasp 4	1178.25	1.19	466.00	1
Assess 1	1177.78	0.72	466.00	1
Assess 2	1177.06	0	466.00	1
Assess 3	1177.25	0.19	466.00	1
Assess 4	1177.59	0.53	466.00	1
Be Given 1	1177.11	0.05	466.00	1
Be Given 2	1177.10	0.04	466.00	1
Be Given 3	1177.06	0	466.00	1
Submit 1	1177.26	0.2	466.00	1
Submit 2	1179.21	2.15	466.00	1
Submit 3	1178.01	0.95	466.00	1

Again, none of the tests with these constrained loadings resulted in exceeding the critical value of change in model fit. This helps support the case for invariance, but we must also examine the research model with selected loadings for Feda and PetroCo constrained. The results of this are given in table 4.60.

Table 4.60 Results for Invariance Tests with Selected Feda and PetroCo Loadings Constrained in an Infusion Context

Indicator with Constraints	Feda & PetroCo Constrained			
	χ^2	$\Delta\ \chi^2$	*df*	*Δ df*
Receive 1	1183.06	6	466.00	1
Receive 2	1187.44	10.38	466.00	1
Grasp 1	1177.09	0.03	466.00	1
Grasp 2	1177.77	0.71	466.00	1
Grasp 3	1177.07	0.01	466.00	1
Grasp 4	1177.09	0.03	466.00	1
Assess 1	1180.01	2.95	466.00	1
Assess 2	1180.29	3.23	466.00	1
Assess 3	1180.75	3.69	466.00	1
Assess 4	1181.70	4.64	466.00	1
Be Given 1	1177.07	0.01	466.00	1
Be Given 2	1177.12	0.06	466.00	1
Be Given 3	1177.31	0.25	466.00	1
Submit 1	1178.65	1.59	466.00	1
Submit 2	1178.03	0.97	466.00	1
Submit 3	1177.59	0.53	466.00	1

The results in table 4.60 show no change in the model fit that exceeds the test criteria. The change in the fit while the Receive 2 loading was constrained as invariant is high compared to the others, however. This is interesting because it may provide further insight into the behavior of the item. But since its change does not exceed the test criterion it does not pose a challenge to invariance.

To complete this series of invariance testing, we must examine the invariance of the construct correlations. The first in a series of tests to accomplish this is illustrated in figure 4.30.

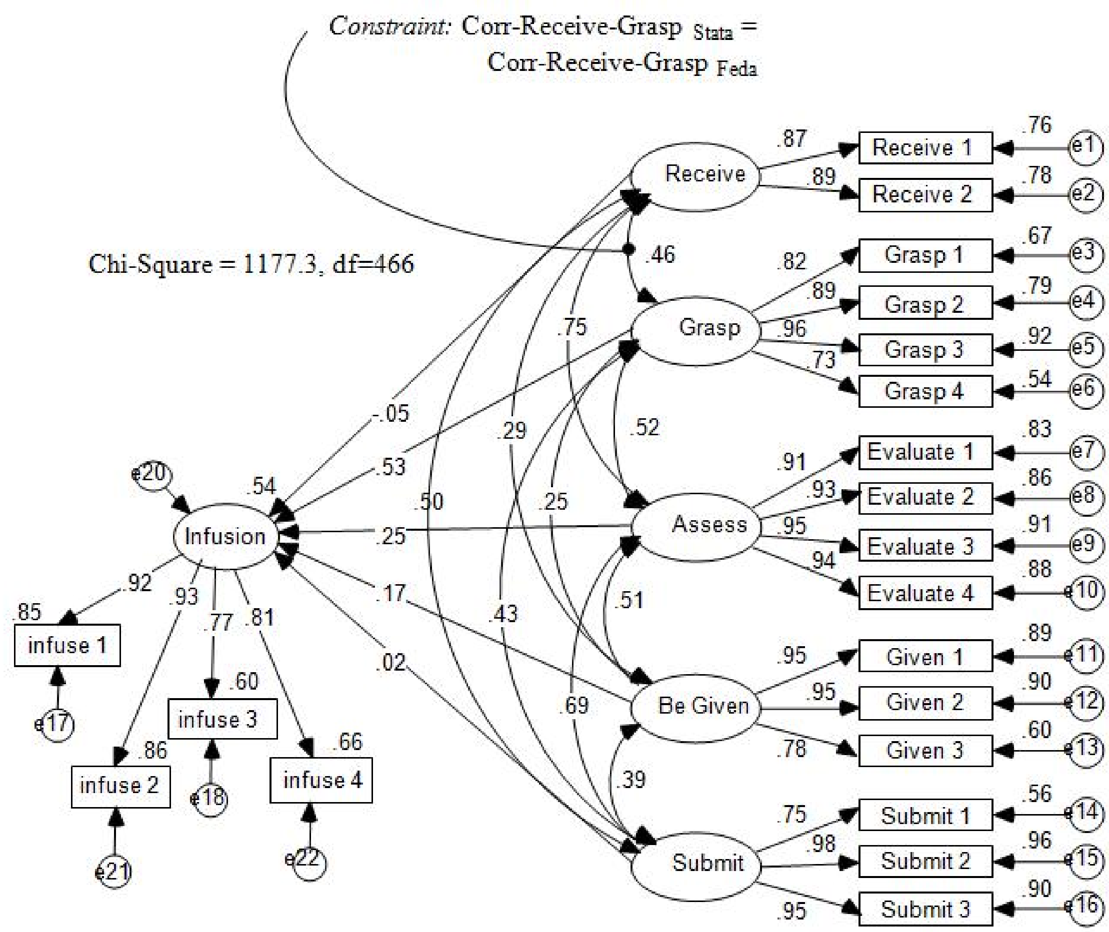

Figure 4.30 Invariance Test Estimates for the Workplace Outcome of Infusion for Stata Data with Constrained Correlations between Receive and Grasp for Stata & Feda Data Sets

The critical value for this test was found to be 9.55. This is detailed in table 4.61. The calculations for the Bonferroni correction were based on the need to perform 30 tests in total.

Table 4.61 Critical Chi-Square for Invariance Tests with Constraints on Two Correlations per Test

Description	Value
Test Name	3 groups, taken 2 at a time - correlations
Number of comparisons	30 (10 correlations with 3 tests per loading)
Change in degrees of freedom	1 df change
Alpha	0.05/30
Critical Value	9.55

The first series of tests involves constraining selected correlations to be invariant over the Stata and Feda data sets. The results of this are given in table 4.62. In these, none of the test cases had model fits that exceed our test criterion.

Table 4.62 Results for Invariance Tests with Selected Stata and Feda Correlations Constrained in an Infusion Context

Factor Covariance Constrained	Stata and Feda Constrained			
	χ^2	$\Delta\ \chi^2$	*df*	*Δ df*
$\Phi_{\text{Receive} \bullet \text{Grasp}}$	1177.29	0.23	466.00	1
$\Phi_{\text{Receive} \bullet \text{Assess}}$	1177.08	0.02	466.00	1
$\Phi_{\text{Receive} \bullet \text{Be Given}}$	1177.54	0.48	466.00	1
$\Phi_{\text{Receive} \bullet \text{Submit}}$	1177.10	0.04	466.00	1
$\Phi_{\text{Grasp} \bullet \text{Assess}}$	1177.73	0.67	466.00	1
$\Phi_{\text{Grasp} \bullet \text{Be Given}}$	1180.70	3.64	466.00	1
$\Phi_{\text{Grasp} \bullet \text{Submit}}$	1183.68	6.62	466.00	1
$\Phi_{\text{Assess} \bullet \text{Be Given}}$	1177.33	0.27	466.00	1
$\Phi_{\text{Assess} \bullet \text{Submit}}$	1177.11	0.05	466.00	1
$\Phi_{\text{Be Given} \bullet \text{Submit}}$	1177.24	0.18	466.00	1

The second set of tests involved constraining selected correlations to be invariant across the Stata and PetroCo data sets. The results are shown in table 4.63. Again, none of these tests exceeded our criterion for model fit change.

Table 4.63 Results for Invariance Tests with Selected Stata and PetroCo Correlations Constrained in an Infusion Context

Factor Covariance Constrained	Stata and PetroCo Constrained			
	χ^2	$\Delta\ \chi^2$	*df*	Δ *df*
$\Phi_{\text{Receive} \bullet \text{Grasp}}$	1177.27	0.21	466.00	1
$\Phi_{\text{Receive} \bullet \text{Assess}}$	1177.08	0.02	466.00	1
$\Phi_{\text{Receive} \bullet \text{Be Given}}$	1183.13	6.07	466.00	1
$\Phi_{\text{Receive} \bullet \text{Submit}}$	1178.20	1.14	466.00	1
$\Phi_{\text{Grasp} \bullet \text{Assess}}$	1177.24	0.18	466.00	1
$\Phi_{\text{Grasp} \bullet \text{Be Given}}$	1179.98	2.92	466.00	1
$\Phi_{\text{Grasp} \bullet \text{Submit}}$	1177.72	0.66	466.00	1
$\Phi_{\text{Assess} \bullet \text{Be Given}}$	1182.98	5.92	466.00	1
$\Phi_{\text{Assess} \bullet \text{Submit}}$	1177.46	0.4	466.00	1
$\Phi_{\text{Be Given} \bullet \text{Submit}}$	1179.80	2.74	466.00	1

The final test involving correlations with the Workplace Outcome Research Model and infusion required constraining selected correlations for Feda and PetroCo data. The results are presented in table 4.64. Of the 10 correlations constrained, one resulted in exceeding the critical value of 9.55. This correlation is between the Assess and Be Given constructs and its test model resulted in a change in chi-square of 11.82, exceeding the criteria.

Table 4.64 Results for Invariance Tests with Selected Feda and PetroCo Correlations Constrained in an Infusion Context

Factor Covariance Constrained	Feda and PetroCo Constrained			
	χ^2	$\Delta\ \chi^2$	*df*	Δ *df*
Φ Receive ● Grasp	1178.25	1.19	466.00	1
Φ Receive ● Assess	1177.17	0.11	466.00	1
Φ Receive ● Be Given	1182.16	5.1	466.00	1
Φ Receive ● Submit	1178.24	1.18	466.00	1
Φ Grasp ● Assess	1177.21	0.15	466.00	1
Φ Grasp ● Be Given	1177.06	0	466.00	1
Φ Grasp ● Submit	1180.35	3.29	466.00	1
Φ Assess ● Be Given	1188.88	11.82	466.00	1
Φ Assess ● Submit	1177.35	0.29	466.00	1
Φ Be Given ● Submit	1182.86	5.8	466.00	1

The next series of invariance tests involves constraining 3 groups at a time rather than 2. The first of these tests is illustrated in figure 4.31.

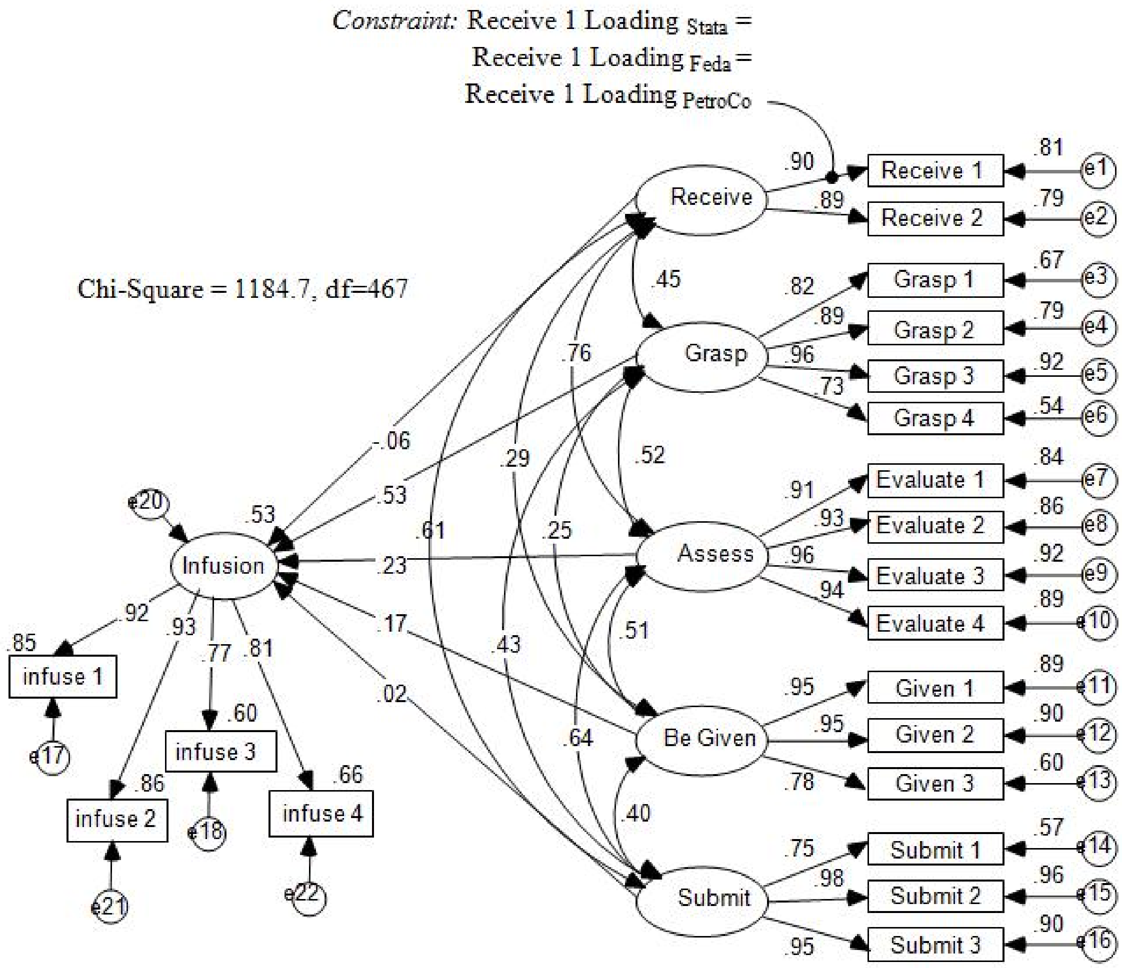

Figure 4.31 Invariance Test Estimates for the Workplace Outcome of Infusion for Stata Data with Constrained Receive 1 Loadings for Stata, Feda & PetroCo Data Sets

For the Workplace Outcome Research Model with infusion, there are 16 tests required for the constrained loadings tests. The critical value for these is 11.62. This is outlined in table 4.65.

Table 4.65 Critical Chi-Square for Invariance Tests with Constraints on Three Loadings per Test

Description	**Value**
Test Name	3 groups, taken 3 at a time - loadings
Number of comparisons	16 (16 loadings with 1 test per loading)
Change in degrees of freedom	2 df change
Alpha	0.05/16
Critical Value	11.62

The first set of test results are given in table 4.66. In the results, no change in chi-square exceeded the critical value so invariance is not challenged. It is noted that the test involving Receive 2 resulted in a large change in chi-square. While the change is less than the critical value, it is still relatively high. This issue presents an opportunity for future research.

Table 4.66 Results for Invariance Tests with Selected Stata, Feda and PetroCo Loadings Constrained in an Infusion Context

Indicator	Constrained Groups: Stata, Feda and PetroCo			
	χ^2	$\Delta\ \chi^2$	*df*	Δ *df*
Receive 1	1184.70	7.64	467.00	2
Receive 2	1188.47	11.41	467.00	2
Grasp 1	1177.44	0.38	467.00	2
Grasp 2	1177.80	0.74	467.00	2
Grasp 3	1177.20	0.14	467.00	2
Grasp 4	1178.42	1.36	467.00	2
Assess 1	1180.02	2.96	467.00	2
Assess 2	1181.63	4.57	467.00	2
Assess 3	1181.26	4.2	467.00	2
Assess 4	1181.99	4.93	467.00	2
Be Given 1	1177.12	0.06	467.00	2
Be Given 2	1177.12	0.06	467.00	2
Be Given 3	1177.45	0.39	467.00	2
Submit 1	1178.75	1.69	467.00	2
Submit 2	1179.27	2.21	467.00	2
Submit 3	1178.07	1.01	467.00	2

The next series of tests for the workplace outcome model using infusion involves constrained correlations. The first test is illustrated in figure 4.32.

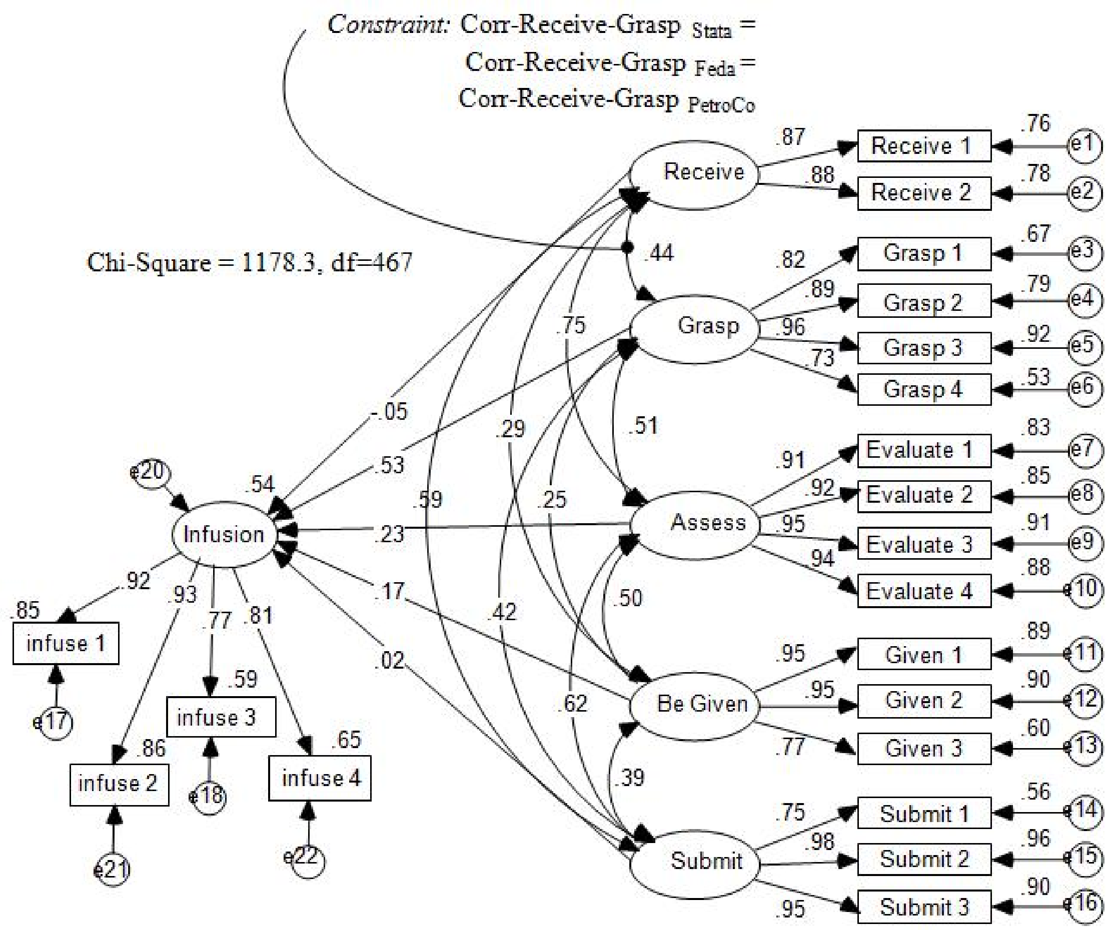

Figure 4.32 Invariance Test Estimates for the Workplace Outcome of Infusion for Stata Data with Constrained Correlations between Receive and Grasp for Stata, Feda & PetroCo Data Sets

For the correlations, a critical value of 10.60 was calculated for the 10 required tests. This is shown in table 4.67.

Table 4.67 Critical Chi-Square for Invariance Tests with Constraints on Three Correlations per Test

Description	Value
Test Name	3 groups, taken 3 at a time - correlations
Number of comparisons	10 (10 correlations with 1 test per correlation)
Change in degrees of freedom	2 df change
Alpha	0.05/10
Critical Value	10.60

The results of invariance testing of the constructs taken three at a time are given in table 4.68. They show that one test resulted in an excessive chi-square change. This test involved constraints on the correlation between the Assess and Be Given constructs.

Table 4.68 Results for Invariance Tests with Selected Stata, Feda and PetroCo Correlations Constrained in an Infusion Context

Factor Covariance Constrained	Stata, Feda and PetroCo Constrained			
	χ^2	$\Delta\ \chi^2$	*df*	*Δ df*
Φ Receive ● Grasp	1178.3	1.24	467	2
Φ Receive ● Assess	1177.2	0.14	467	2
Φ Receive ● Be Given	1184.3	7.24	467	2
Φ Receive ● Submit	1178.5	1.44	467	2
Φ Grasp ● Assess	1177.7	0.64	467	2
Φ Grasp ● Be Given	1181.2	4.14	467	2
Φ Grasp ● Submit	1184.6	7.54	467	2
Φ Assess ● Be Given	1189.3	12.24	467	2
Φ Assess ● Submit	1177.5	0.44	467	2
Φ Be Given ● Submit	1183.0	5.94	467	2

Overall, the workplace outcome models with generic acceptance and infusion held up well in terms of reliability and accuracy, distinctiveness and invariance. Next we used the model to explore the relationship between the five dimensions of acceptance and workplace outcomes.

Now that the results have been presented, we will discuss them in the following section.

5 DISCUSSION AND CONCLUSIONS

5.1 Summary

This research included invariance tests performed utilizing three unique data sets and to make a strong case for generalizability of the measures. Further, the research demonstrated the utility of the five acceptance constructs proposed by Schwarz and Chin. It was shows that the constructs can be captured by reliable and accurate measures and that they are distinct and invariant.

5.2 Contributions

5.2.1 To Researchers

The research demonstrates a broader view of what constitutes technology acceptance. The five constructs were shown to be useful in examining technology acceptance and is useful for other researchers who might want to explore other notions of acceptance. Rather than focus on acceptance processes tied to usage or intention to use a system, we examined other outcome processes such as infusion as an acceptance process. In doing so, we provided a more complete view of the process.

The research approach used truly independent sample sets, rather than different slices of the same data sets. To the best of our knowledge, no other papers in the field of information systems do this.

5.2.2 *Implications for Practitioners*

Examination of the results yields some implications for managers and employees involved in technology implementation. First, the path coefficients in table 4.27 indicate that the construct of Grasp had strong, significant impact on infusion for the employees in all three data sets. Thus, to help increase the level of technology infusion, practitioners should promote the “grasp” of the technology. To do so, they should include in their training, not just technical information, but also information about the ultimate or “big picture” purpose of the technology. Helping the users understand the goals of the technology will help promote grasping and thus improve the levels of its infusion.

Also, the findings suggest that employees do not often consider the beneficial and value-added aspects of the technology. In order to achieve the desirable workplace outcome of infusion, it is incumbent on the technology implementer to enhance the assessment processes among employees. This could be done by sending occasional reminders to employees that convey the value-added aspects of the technology. This must be done periodically, because promoting assessment requires periodic reminders and assessment is required to increase the levels of infusion.

5.3 *Discussion*

Overall, the research successfully addressed the research questions. It successfully demonstrated the relevance of an expanded notion of psychological acceptance and demonstrated a predictive value toward the workplace outcomes of generic acceptance and infusion. The work is not without issues and limitations, however. These are discussed in this section.

First, the item measures for the Receive construct occasionally yielded large delta chi-square values during invariance testing. This can be seen, for example, in table 4.22. While the large values do not exceed the test criteria, they are still unusual with respect to the items for the other constructs. A plausible explanation for the unusual results is that the item measures for this construct are somewhat inadequate. Taken along with the suggestion by Hair et al. (2006) that calls for a minimum of 3 observed variables per construct, it is recommended that the measures for the Receive construct be revisited.

Next, there are some limitations to this research. One such limitation is that TAM variables were not included in the study. Research by Jones et al. (2002b) suggests that TAM antecedents lack predictive value towards infusion, while we propose that the five dimensions of acceptance do. Comparison of the predictive value of TAM antecedents and the five dimensions of acceptance would add value to this research.

Another limitation is that the study is a cross-sectional one. As suggested by Hsieh and Wang (2007), we expect that the extent of infusion and other constructs studied should change over time as users become more familiar with the technology. A longitudinal study would capture the dynamics of this and, indeed, this is an avenue for future research.

Lastly, we are limited by the study of only 3 organizations. The claim of generalizability calls for an instrument that is effective in multiple business environments. While we studied three different implementations, it is likely that more implementations would have yielded additional nuances of acceptance that would broaden the findings. Again, this is an area for future research.

5.4 Future Work

An extension to the study of generalizability across technology settings involves examining the notion of generalizability across time. Studying the generalizability of an instrument in a longitudinal study would expose it to additional settings where time has passed and provide a richer perspective of generalizability.

The findings indicate that grasping a technology enhances the level of infusion. Given that this research involved fairly complex corporate applications, it would be interesting to explore the impact of other, less complex technologies on the infusion process. Specifically, intuitive applications such as a handheld music player do not require much effort to grasp, so some of the four remaining dimensions of technology acceptance could be more salient in the process of acceptance and infusion of the technology. That is, future work could explore which acceptance constructs are salient in the absence of a need for grasping a technology.

Another topic for future study involves the study of acceptance in a mandatory use scenario. Earlier, we suggested that infusion and other workplace outcomes are more appropriate proxies for usage than intention to user in mandatory use environments. Under the appropriate conditions, this could be studied to better understand how outcomes perform as measures of acceptance.

5.5 Conclusions

We have demonstrated the generalizability of the instrument associated with the five psychological acceptance constructs. The measures have utility across several technology settings and they are expected to be of value in other constructs as well.

The five dimensions of acceptance have utility for the examination of technology acceptance. It stands as an alternate conceptualization of acceptance that diverges from the many models that focus solely on usage or intent to use. While the five dimension model is expected to be useful for future research, it is only one of many alternate conceptualizations of acceptance that may exist. It is hoped that future research will develop and investigate other models of acceptance.

APPENDIX A.

RESEARCH INSTRUMENT

The instrument used in this analysis was developed by Schwarz (2003). Its items are given in table A-1.

Table A.1. Instrument for Dimensions of Acceptance. (Taken Verbatim from Schwarz (2003))

Construct	Construct Definition	Source	Variable	Quantitative Questions
Receive: state of being (End state)	The final psychological state of taking the technology without question	[Schwarz (2003)]	Recieve1	1. I have very little to no regret about our organization going with [the technology]
			Recieve2	2. I no longer second guess the original decision of our organization to use [the technology]
Grasp: state of being (End state)	The final psychological state of fully comprehending the intentionality (e.g. functionality and design) of the technology	[Schwarz (2003)]	Grasp1	1. I fully comprehend everything [the technology] is supposed to be used for
			Grasp2	2. I totally understand the rationality for all of the features of [the technology]
			Grasp3	3. I am completely aware of all of the goals of all of the features of [the technology]
			Grasp4	4. I totally grasp the role [the technology] was designed to play in my work
Assess worth to me: state of being (End state)	The final psychological state of evaluating the value of the technology to me	[Schwarz (2003)]	Assess1	1. I often find myself considering more of the positive aspects than the negative aspects that [the technology] offers to me
			Assess2	2. I frequently find myself evaluating more of the value-adding ways versus the negative impacts that [the technology] has on me
Assess worth to my organization: state of being (End state)	The final psychological state of evaluating the value of the technology to my organization	[Schwarz (2003)]	Assess3	1. I often find myself considering more of the positive aspects than the negative aspects that [the technology] offers to my organization
			Assess4	2. I frequently find myself evaluating more of the value-adding ways versus the negative impacts that [the technology] has on my organization

Table A.1—Continued

Construct	Construct Definition	Source	Variable	Quantitative Questions
Be given: state of being (End state)	The final psychological state of an individual willing to adapt their routines to what was required by the technology	[Schwarz (2003)]	BeGiven1	1. If necessary, I am willing to substantially compromise how I do work in relation to how [the technology] requires
			BeGiven2	2. If necessary, I am willing to make a dramatic change to how I do work to how [the technology] requires
			BeGiven3	3. If necessary, I am willing to adapt my work to what is required by [the technology]
Submit to: state of being (End state)	The final psychological state of the individual surrendering to the intentionality of the technology	[Schwarz (2003)]	Submit1	1. I buy into everything about [the technology]
			Submit2	2. I would describe myself as an apostle of [the technology]
			Submit3	3. I have become evangelical about [the technology] to others
Routinization (Outcome of Be Given)	The extent of which an individual's work patterns are consistent with the technology	Jones et al. (2002b)	Routinize1	1. My use of [the technology] has been incorporated into my regular work schedule
			Routinize2	2. My use of [the technology] is pretty much integrated as part of my normal work routine
			Routinize3	3. My use of [the technology] fits right into the way I work
			Routinize4	4. My use of [the technology] is now a normal part of my work

Table A.1—Continued

Construct	Construct Definition	Source	Variable	Quantitative Questions
Infusion	The extent to which an individual fully utilizes the technology to enhance his/her productivity	Jones et al. (2002b)	Infuse1	1. I am using [technology] to its fullest potential for supporting my own work
			Infuse2	2. I am using all capabilities of [technology] in the best fashion to help me on the job
			Infuse3	3. I doubt that there are any better ways for me to use [technology] to support my work
			Infuse4	4. My use of [technology] on the job has been integrated and incorporated at the highest level
Faithfulness of appropriation (Outcome of Grasp)	The extent to which an individual's use of the technology is consistent with the original design intent of the system developers	Chin, et al., (1997)	FAO1	1. The developers of [the technology] would disagree with how I use it
			FAO2	2. I probably use [the technology] improperly
			FAO3	3. The original developers of [the technology] would view my use of it as inappropriate
			FAO4	4. I fail to use [the technology] as it should have been used
			FAO5	5. I do not use [the technology] in the most appropriate fashion
Deep usage (Outcome of Submit To)	The extent, or variety of use of different functionalities of a technology (adapted from Marcolin, Compeau, and Huff)	[Schwarz (2003)]	N/A	In a typical one-month period, what is the likelihood of you…
			Deep1	1. Using all of the features of [the technology]
			Deep2	2. Using more features than the average user of [the technology]
			Deep3	3. Using more obscure aspects of [the technology]

Table A.1—Continued

Construct	Construct Definition	Source	Variable	Quantitative Questions
Generic acceptance construct	None	[Schwarz (2003)]	N/A	*Strongly agree/strongly disagree*
			Accept1	1. All things considered, I believe that I have accepted [the technology]
			Accept2	2. I would describe myself as a [technology] individual
			Accept3	3. My life is more complete now that I am using [the technology]
Demographics	None	[Schwarz (2003)]	Gender	Male/Female
			Age	What is your age?
			YearsFTWork	How many years have you worked full time (anywhere)
			YearsAtThis Org	How many years have you worked at this company or organization

APPENDIX B.

MISSING DATA POINT SUMMARY

The data was examined to determine the extent of missing data. A summary of the findings is given in table B-1.

Table B-1. Missing Data Point Analysis

Item	Number of Valid Responses			Number of Missing Responses			Missing Responses as Percent of Total Responses (%)		
	Stata	Feda	PetroCo	Stata	Feda	PetroCo	Stata	Feda	PetroCo
Rec1	109	257	144	3	11	1	2.7	4.1	0.7
Rec2	108	258	145	4	10	0	3.6	3.7	0
Grasp1	111	265	145	1	3	0	0.9	1.1	0
Grasp2	111	265	145	1	3	0	0.9	1.1	0
Grasp3	111	264	144	1	4	1	0.9	1.5	0.7
Grasp4	111	266	144	1	2	1	0.9	0.7	0.7
Eval1	110	266	145	2	2	0	1.8	0.7	0
Eval2	109	264	145	3	4	0	2.7	1.5	0
Eval3	111	264	144	1	4	1	0.9	1.5	0.7
Eval4	111	265	145	1	3	0	0.9	1.1	0
Give1	111	260	144	1	8	1	0.9	3	0.7
Give2	110	262	145	2	6	0	1.8	2.2	0
Give3	111	263	145	1	5	0	0.9	1.9	0
Sub1	111	265	143	1	3	2	0.9	1.1	1.4
Sub2	111	265	145	1	3	0	0.9	1.1	0
Sub3	109	265	144	3	3	1	2.7	1.1	0.7

Table B-1--Continued

Item	Number of Valid Responses			Number of Missing Responses			Missing Responses as Percent of Total Responses (%)		
	Stata	Feda	PetroCo	Stata	Feda	PetroCo	Stata	Feda	PetroCo
Rout1	111	266	144	1	2	1	0.9	0.7	0.7
Rout2	111	266	143	1	2	2	0.9	0.7	1.4
Rout3	111	266	144	1	2	1	0.9	0.7	0.7
Rout4	111	265	144	1	3	1	0.9	1.1	0.7
Infus1	111	266	144	1	2	1	0.9	0.7	0.7
Infus2	111	266	143	1	2	2	0.9	0.7	1.4
Infus3	110	266	144	2	2	1	1.8	0.7	0.7
Infus4	111	266	144	1	2	1	0.9	0.7	0.7
FAO1	110	267	145	2	1	0	1.8	0.4	0
FAO2	111	267	144	1	1	1	0.9	0.4	0.7
FAO3	111	267	145	1	1	0	0.9	0.4	0
FAO4	111	267	145	1	1	0	0.9	0.4	0
FAO5	111	267	145	1	1	0	0.9	0.4	0
Deep1	111	260	145	1	8	0	0.9	3	0
Deep2	110	259	145	2	9	0	1.8	3.4	0
Deep3	111	258	144	1	10	1	0.9	3.7	0.7
Deep4	111	258	145	1	10	0	0.9	3.7	0
Accept1	111	261	145	1	7	0	0.9	2.6	0
Accept2	111	260	144	1	8	1	0.9	3	0.7
Accept3	111	259	144	1	9	1	0.9	3.4	0.7

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