DETERMINANTS OF INDIVIDUAL-LEVEL DEMAND FORECASTING PERFORMANCE

DISSERTATION

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AFIT-ENS-DS-17-S-045

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Abstract

The ability to accurately predict future demand for products and services is fundamental to effective supply chain management. As news articles and government reports have recently indicated, forecast inaccuracies by the military services and Defense Logistics Agency have adversely affected mission readiness and have even led to the misuse of tax payer dollars. Since Congress's 2010 mandate to remedy demand forecasting, Department of Defense supply chain leaders have made great progress in improving forecasting methods and policy. However, relatively little attention has been given to the human element of forecasting. According to Morelidge (2016) it is the quality of forecasts reviewed and adjusted by individual forecasters that are most impactful for supply chain planning. In addition to forecasting methods and procedures, research literature suggests management practices may also affect forecasters' performance. However, there has been limited empirical evidence supporting this claim.

This research effort sought to investigate if and how management practices are linked to forecaster performance. In particular, this research investigated if perceptions of the technology used for forecasting and the organizational context within which forecasting takes place could explain variation in individual-level forecasting performance. Using Air Force forecasters as the sampling frame, a combination of survey data and historical forecasting performance data were analyzed to explore the relationships between these variables. The results of this research effort suggest that management practices do indeed affect forecaster performance and make the case for broader forecasting improvement initiatives.

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To my family—thank you for your love, encouragement, and patience.

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DETERMINANTS OF INDIVIDUAL-LEVEL DEMAND FORECASTING PERFORMANCE

I. Introduction

Background

Demand forecasting is an essential business capability (Davis & Mentzer, 2007; Kalchschmidt, 2012; McCarthy & Golicic, 2002) with demand forecasts serving as key inputs for a variety of internal planning and decision making processes (Croxton et al., 2002; Moon & Mentzer, 2005). For example, demand forecasts are used in decisions related to new product development, product lifecycle management, risk management, and revenue management (Croxton et al., 2002; Danese & Kalchschmidt, 2011; Ogawa & Piller, 2006). More broadly, in supply chains, demand forecasting plays a central role in synchronizing market demand with procurement, production, and distribution capabilities (Croxton et al., 2002). Indeed, collaborative forecasting between supply chain partners has become a core tenet of supply chain management, with many touting the advantages of timely and accurate sharing of demand signals (Chen et al., 2000; Helms et al., 2000; Lee et al., 1997; McCarthy & Golicic, 2002).

The benefits that accrue from maintaining an effective demand forecasting capability are considerable. Operationally speaking, effective forecasting has been linked to reduced raw materials and finished goods inventories, enhanced asset utilization, and reduced logistics costs (Croxton et al., 2002). In some cases, it has been reported that just a one percent improvement in forecasting accuracy can equate to cost savings ranging

from just under $1 million for companies who under-forecast, to as high as $3.5 million for companies that over-forecast (Institute of Business Forecasting & Planning, 2005). From a more strategic perspective, accurate forecasting is said to enable firms and supply chains to better understand market dynamics and customer behaviors in addition to helping them identify market opportunities, enhance relationships, and anticipate future financial and capital requirements (Moon et al., 2003; Danese & Kalchschmidt, 2011a). As a byproduct, these benefits are said to translate into increased revenues, earnings, and even returns on shareholder value (McCarthy and Golicic, 2002; Mentzer, 1999).

Nonetheless, not all organizations possess robust or effective forecasting capability. In fact, throughout their studies of organizational forecasting process management, Moon and Mentzer (2005) noted substantial heterogeneity in forecasting capability across 45 case companies. In the face of growing market complexity, volatility, and uncertainty, the challenges associated with maintaining an effective forecasting capability seem to endure. For example, in a 20-year retrospective study of organizational forecasting practices, McCarthy et al. (2006) observed a decline in achieved forecast accuracy reported by practitioners. Most recently, the results of three consecutive annual Gartner surveys found that managers ranked forecast accuracy/demand planning related challenges as their number one barrier to achieving goals and objectives in their supply chains (Klappich & Eschinger, 2013). Thomas et al. (2011) reported similar findings from their study wherein they asked managers to identify one issue they would choose to solve if given one wish and a magic wand. Forecasting and demand planning related challenges were among the top 5 issues identified by managers in their study.

Forecasting in the Department of Defense

Though much of the research literature centers on demand forecasting in the context of business organizations, the challenge of achieving satisfactory forecasting performance is not unique to private sector organizations. This is perhaps no more apparent than in the case of the Department of Defense, which arguably maintains one of the most diverse and complex supply chains in the world. As of September 2015, the Department of Defense maintained a spare parts inventory consisting of approximately 4.9 million items with an estimated value of $91 billion in support of its vast collection of equipment, vehicles, and weapon systems (Government Accountability Office, 2017).

Over the past 30 years, the Department of Defense has struggled to maintain its massive spare parts inventory. Several reports have highlighted how deficiencies in inventory management practices have led to pervasive inventory imbalances throughout the defense supply chain. For example, a report from the Office of the Inspector General noted that, in 1999, the Department of Defense maintained an excess inventory valued at approximately $1 billion (Department of Defense Inspector General, 2015). Approximately 10 years later, excess inventory was valued at a reported $8.8 billion (Government Accountability Office, 2017). Notably, The Government Accountability Office identified weaknesses in forecasting future demand for spare parts as a leading root cause of the Department of Defense's ineffective inventory management practices.

In 2010, in response to these enduring issues, Congress mandated that the Secretary of Defense create a plan to improve inventory management. As part of that plan, Congress specifically directed a "comprehensive review of demand forecasting procedures to identify and correct any systematic weaknesses in such procedures,

including the development of metrics to identify bias toward over-forecasting" (Assistant Secretary of Defense for Logistics and Materiel Readiness, 2010; p. 2-1). In response, the Office of the Secretary of Defense drafted the Comprehensive Inventory Management Improvement Plan which expressed the goal of achieving a "forecasting process that captures best practices and minimizes systematic weaknesses" (p. 2-3).

Demand forecasting has improved considerably since 2010. Of note, standardized forecasting performance metrics were implemented and tracked across the Department of Defense. Additionally, multiple improvements were made to demand forecasting methods and procedures across the military services and the Defense Logistics Agency (Government Accountability Office, 2017). As a result, overall forecast accuracy (i.e. aggregate demand-dollar weighted accuracy) improved from 46.7 percent in fiscal year 2013 to 57.4 percent in fiscal year 2015. Furthermore, these efforts contributed to a reported $2 billion reduction of on-hand excess inventory between fiscal year 2010 and fiscal year 2015 (Government Accountability Office, 2017). In spite of these advances, efforts to further improve inventory management practices and, especially, demand forecasting are still in progress.

Of all the military services, the Air Force owns the largest proportion of the Department of Defense's spare parts inventory. Comprising 39 percent of the Department of Defense's spare parts inventory, the Air Force's inventory is valued at approximately $35.6 billion (Deputy Assistant Secretary of Defense Logistics & Material Readiness, 2016). Furthermore, while the Department of Defense inventory consists of both reparable and consumable items, reparable items constitute 75% ($68.9 billion) of the

inventory. Looking across the military services, the overwhelming majority of those reparable items—47.8 percent, or $32.9 billion—belong to the Air Force inventory.

Given the concentration of Department of Defense inventory (items and dollars) within the Air Force, it is reasonably expected that even subtle improvements in management practices would hold the potential to boost both the effectiveness and efficiency of inventory management practices. With regard to forecasting, Air Force supply chain leaders have primarily focused on improving forecast computations and business rules associated with managing items facing low or intermittent demand (Assistant Secretary of Defense for Logistics and Materiel Readiness, 2010; p. 2-8). However, few efforts have addressed how forecasting management practices affect forecasting performance. More specifically, though the Air Force approach to demand forecasting involves a heavy reliance upon individual forecasters, little is known about how management practices affect forecasting performance at the individual level. All of these considerations made Air Force forecasting management an ideal context for this research effort. Specific details of the chosen research setting are discussed in Chapter 3.

Theoretical Justification

Historically, forecasting literature tends to attribute the problems encountered by practitioners to not having the "right" level of sophistication in forecasting tools and techniques. Conversely, literature also consistently notes that, in practice, less sophisticated forecasting methods tend to be preferred by practitioners in real-world settings (McCarthy et al., 2006). Even more, complex forecasting techniques/models do not necessarily lead to more effective forecasting (Goodwin, 2011).

Yet another perspective attributes the challenges faced by practitioners to a lack of adherence to best practices in forecasting management. Nonetheless, there is evidence to suggest that implementation of best practices can be quite complex, often involving protracted effort, which may or may not pay off with improved accuracy (McCarthy & Golicic, 2002; Nagashima et al., 2015). Additionally, practitioners have few means of identifying whether and to what degree best practices can be implemented in their particular setting and if such practices will actually yield the benefits suggested by research (Fildes et al., 2003; Mentzer & Moon, 2005). As observed in Fildes et al. (2003), "…there is no well-articulated causal mechanism that relates proposed action to outcome" (p. 29). In other words, it is not enough to find that best practices are correlated with forecasting performance in certain organizations; what is needed is theoretically-grounded research that empirically validates proposed relationships between practice and performance. Furthermore, to inform managerial practice, research efforts must also account for how the organizational context influences the practice-performance relationship (Johns, 2006; Rousseau & Fried, 2001).

Fildes et al. (2003) aptly convey the need for theory development and testing in forecasting literature. Unfortunately, as noted by Smith & Mentzer (2010a) and, more recently, by Syntetos et al. (2016), few scholars have addressed this need. Fildes et al. (2003) attributed this to the fact that forecasting researchers do not typically come from disciplines that emphasize organizational theory and practice. Interestingly, in spite of the apparent significance of demand forecasting to logistics and supply chain management and the multi-disciplined make-up of the logistics and supply chain management field, there are surprisingly few theory development and testing efforts related to forecasting in

the logistics and supply chain management literature. Moreover, though coordinating forecasting activities was among the top five most impactful issues identified by managers in their study, Thomas et al. (2011) discovered that the topic was virtually absent from the most commonly researched topics in logistics and supply chain management research. They speculated that this phenomenon might be the result of a conceptualization of logistics and supply chain management that does not incorporate forecasting as a related discipline.

In addition to the need for further theory building, there is also a need for research more oriented toward issues which inform managerial practice. Commenting on the lack of forecasting research in logistics and supply chain literature, Thomas et al. (2011) concluded: “there is a clear disconnect between what managers view as relevant and what academics provide through research activities” (p. 664). Syntetos et al. (2016) echoed this disparity in their assessment of forecasting literature, candidly attributing the gap between forecasting theory and practice to the fact that “…the issues being tackled are simply of no practical importance at all” (p. 16). Given these assessments of both forecasting and logistics and supply chain management research, it is apparent that efforts to help close the gap require both theoretical grounding and consideration of issues of practical relevance to managers.

In line with the preceding assessments of forecasting and logistics and supply chain management research, this research endeavors to refine and test essential components of forecasting management theory. Forecasting management theory is concerned with how an organization's forecasting process and forecasting function are managed and holds that—in addition to the implementation and optimization of

forecasting techniques and tools—organizational forecasting performance is achieved through functional integration, forecast process quality, forecasting systems, and forecasting performance measurement (Mentzer & Moon, 2005; Doering & Suresh, 2016).

Moreover, where previous research has inductively identified and described mechanisms that contribute to forecasting performance (i.e. best practices), the current research employs a deductive research approach. That is, this dissertation operationalizes key constructs implied in forecasting management theory and tests the proposed relationships in order to clarify what evidence exists for prescriptions laid out in previous works. Taken together, this approach addresses three gaps in forecasting management theory.

Gap #1: Linking Forecasting Management Practices to Performance.

Bretschneider and Gorr (1989) referred to forecasting as a human activity and advocated that researchers "…ask questions about the way in which an organization's environment, culture, and process interact with the use of quantitative and qualitative techniques for generating a forecast" (p.306). Indeed, a significant portion of forecasting literature addresses the role of the individual forecaster in identifying and applying appropriate forecasting models and techniques. Nonetheless, where forecasting management theory is concerned, human involvement is typically viewed from a more macro perspective as one of several organization-level factors impacting an organization's forecasting performance. Specifically, such research is characterized by themes of functional integration and supply chain collaboration as means to mitigate the effects of functional biases upon the organization's forecasting process as well as to

improve forecasting from the broader perspective of supply chain management (e.g. Davis & Mentzer, 2007; McCarthy & Golicic, 2002; Nagashima et al., 2015). While this line of inquiry has undoubtedly made significant contributions to forecasting management theory and practice, it is also necessary to understand how organizational forecasting management practices impact forecasting performance at the individual forecaster level.

As has been captured in multiple surveys of organizational forecasting practices and has been repeatedly observed in case studies of business organizations, much of the forecasting process takes place at a disaggregate level where individual forecasters review and adjust statistical forecasts for hundreds, potentially even thousands of stock-keeping units (SKUs) (Davydenko & Fildes, 2013; Fildes & Goodwin, 2007; McCarthy-Byrne et al., 2011). Typically, statistical forecasts are generated by the organization's forecasting software/system and then, if necessary, adjusted by the forecaster based on information not captured in the statistical model. According to Morelidge (2016), when it comes to supply planning, it is the quality of forecasts at the lower levels of product hierarchies that is most impactful to forecasting performance. Kremer et al. (2016) found this to be true, especially when product demands are negatively correlated.

Forecasting literature concerned with the individual forecaster has focused on explaining forecaster performance as a function of various factors. However, limited research exists which directly investigates how *forecasting management practices* impact forecaster performance. This is surprising for two reasons. First, management practices are likely to affect the forecaster's scope of responsibility and the complexity of their assigned tasks. Second, management practices may potentially help guard against the

biases and inconsistencies of human judgment that have so often been found to degrade forecast quality. For these reasons, research addressing the effects of management practices on the forecaster's contribution to the forecasting process is essential in advancing forecasting management theory. This represents the first gap addressed by this research (Fildes and Goodwin, 2007; McCarthy-Byrne et al., 2011).

Gap #2: Assessing the Role of Tacit Knowledge

According to established principles of forecasting, it is advised to make maximum use of quantitative models and to reserve adjustments to statistical forecasts for situations where forecasters hold knowledge not able to be incorporated into the statistical model (Fildes & Goodwin, 2007; Sanders & Ritzman, 2001). Nonaka (1994) distinguished between two types of knowledge—tacit and explicit. *Explicit knowledge* refers to codified knowledge or knowledge that can be expressed formally and, thus, is amenable to being captured by historical records as may be found in libraries, archives, and databases. On the other hand, *tacit knowledge* is knowledge of a more personal nature and harder to formalize and communicate. It is described as consisting of cognitive and technical components with the cognitive component comprising mental models, paradigms, and beliefs that help individuals define and make sense of their environment. The technical component refers to "know-how" and is the domain of skills that apply to a specific context.

In general, forecasters depend upon both tacit and explicit knowledge when making adjustments to statistical forecasts. Furthermore, both types of knowledge have been studied in forecasting literature as they pertain to a forecaster's performance. Interestingly, evidence from past research suggests that tacit knowledge is the most

important of the two (Sanders & Ritzman, 1991, 2001). In particular, tacit knowledge is said to enable the forecaster to better gauge the value of incorporating various forms of contextual information (i.e. upcoming promotions, price changes, economic data, etc.) into forecasts. Such knowledge is particularly valuable when demand is volatile and uncertain (Sanders & Ritzman, 1990; Seifert et al., 2015). Given the volatile and uncertain nature of contemporary business environments, managers thus have a vested interest in managing the flow of contextual information (within organizations and across supply chains) and nurturing the domain knowledge of forecasters.

While contextual information may be easily captured within an organization's information systems (i.e. forecasting support systems), the same is not the case for tacit knowledge. Tacit knowledge is a function of personal experience and, thus, resides in individuals (Nonaka, 1994). For this reason, tacit knowledge is difficult to articulate and manage and is likely to go untapped without deliberate efforts to convert it into new knowledge (Nonaka et al., 2006). However, little research exists which assesses forecaster performance as a function of an organization's knowledge management processes. This represents yet another gap in forecasting literature as qualitative studies of organizational forecasting practices consistently report forecasters' frustrations with the lack of knowledge available for the forecasting task (Fildes & Hasings, 1994; Davis& Mentzer, 2007; McCarthy-Byrne et al., 2011). As such, the concept of knowledge management effectiveness is introduced as a means to capture the degree to which the organization's knowledge management efforts support the forecaster and contribute to forecasting performance.

Gap #3: Assessing the Impact of Organizational Context on Performance

Mentzer and Moon (2005) identify four main concerns with respect to forecasting management: functional integration, forecasting support systems, management approach to forecasting (e.g. top down vs. bottom up); and performance management. Doering and Suresh (2016) recently found evidence to support the appropriateness of these factors in their conceptualization of a forecasting management competence. However, in addition to these four facets, forecasting management literature also proposes that the organizational context within which forecasting takes place is yet another important element affecting forecasting performance. Indeed, early assessments of the theory-practice gap in forecasting research pinpointed the lack of research which considered the organizational context (Schultz, 1992; Mahmoud et al., 1992; Fildes & Hastings, 1994; Winklehofer et al., 1996; McCarthy et al., 2006; Davis & Mentzer, 2007; McCarthy-Byrne et al., 2011). In response, Davis and Mentzer (2007) proposed the concept of organizational sales forecasting climate as a determinant of organizational sales forecasting performance while McCarthy-Byrne et al. (2011) focused on several "environmental signals" that were hypothesized to motivate sales personnel to contribute to the forecasting process. Though McCarthy Byrne et al. (2011) quantitatively assessed the impact of the forecasting environment on forecaster satisfaction, seriousness, and effort, they did not assess the impact of the environment upon forecaster performance. As yet, there does not appear to be any empirical evidence that confirms the notion that organizational context can impact forecaster performance. This represents a third gap in the forecasting literature. This research addresses this gap by refining the concept of forecasting-focused climate and developing a forecasting-focused climate scale as a means to measure and assess the

impact of the forecaster's organizational context. Figure 1.1 previews the proposed theoretical model tested in this research and illustrates the portions of the model that address gaps in the literature.

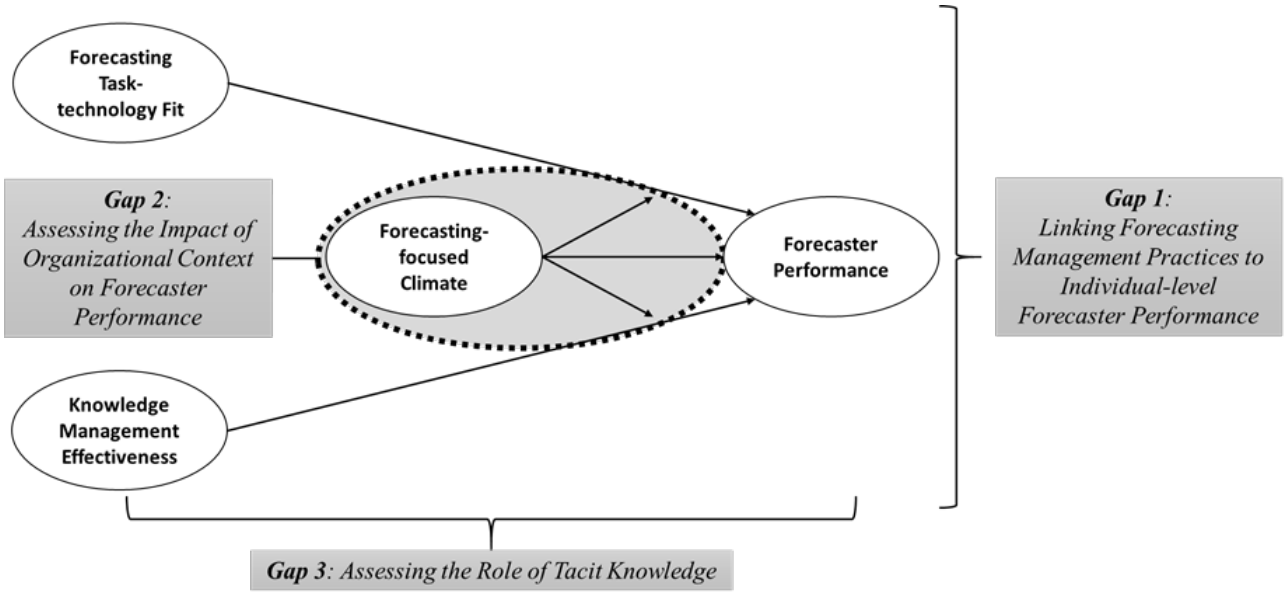


Figure 1.1. Gaps in Forecasting Management Theory and Research.

Statement of Purpose and Research Questions

The purpose of this research is to assess how "softer" factors germane to forecasting ultimately affect forecaster performance. Specifically, this research assesses the effect of forecasting task-technology fit, knowledge management effectiveness, and forecasting-focused climate on individual-level forecasting performance. To that end, this research seeks to answer the following research questions:

1. *What effect does forecasting task-technology fit have on individual-level forecaster performance?*

2. *What effect does knowledge management effectiveness have on individual-level forecaster performance?*

3. *What effect does forecasting-focused climate have on individual-level forecaster performance?*

4. *What is the relationship between forecasting task-technology fit, knowledge management effectiveness, and forecasting-focused climate?*

Potential Contributions

This research contributes to both forecasting management theory and practice. In terms of the contribution to theory, by addressing the gaps identified above, this dissertation builds on existing theory to clarify if and how management practices and attributes of the organizational setting contribute to a forecaster's performance. Moreover, this research refines the forecasting climate construct and contributes a valid and reliable instrument that may prove useful in future efforts wishing to account for contextual factors specific to organizational settings. Finally, this dissertation further contributes to theory by validating the impact of management practices on actual, objective measures of forecaster performance.

In terms of contributing to practice, this research addresses issues of practical relevance to logistics and supply chain managers. Task-technology fit, knowledge management practices, and forecasting-focused climate all represent levers that can readily be manipulated by management interventions thereby representing concepts that can provide actionable insight for improving the forecasting process. By simultaneously considering multiple factors, the findings from this theory-testing effort help provide insight on the relative impact of those factors thereby allowing managers to more effectively target and prioritize improvement initiatives and to efficiently allocate resources (Moon et al., 2003). Finally, through the development of a valid and reliable measurement scale, managers are provided with a tool that may be used to assess the degree to which forecasters perceive their work environment as supportive of the forecasting task and, therefore, are likely to elicit desirable forecasting behaviors/performance.

Dissertation Organization

This dissertation is divided into five chapters. Chapter 2 is a review of literature germane to the research questions posed in Chapter 1. The review assimilates and synthesizes the empirical literature relevant to understanding an individual's forecasting performance. The chapter concludes with the development and presentation of a conceptual model as well as the hypotheses to be tested. Chapter 3 begins with the presentation of the hypotheses generated from the literature review and then describes the research setting, design, development of the survey instrument, and methods of statistical analysis. Next, Chapter 4 presents descriptive data pertaining to the survey (i.e.

respondent characteristics, item-level data, etc.) as well as the results from an exploratory factor analysis and assessment of reliability and validity. Finally, Chapter 5 contains a discussion of the findings, implications for researchers and practitioners, limitations, and suggestions for future research.

II. Literature Review

Chapter Overview

Simply put, *forecasting* is the act of predicting future events and conditions (Bowerman et al., 2005). As Mentzer and Moon (2005) explain, *forecasting management* is concerned with how organizations efficiently and effectively carry out the business of developing and using forecasts. Although there are a variety of contexts within which forecasting activities might take place (e.g. political forecasting, technological forecasting, etc.), a great deal of research has focused on sales forecasting (also known as demand forecasting) and its role in marketing management (Mentzer & Moon, 2005; Winklehofer et al., 1996). According to Makridakis and Wheelwright (1977), "In the area of marketing however, forecasting is doubly important; not only does it have a central role in marketing itself, but marketing-developed forecasts play a key role in the planning of production, finance, and other areas of corporate activity" (p. 24).

Amid the predominately technique-oriented forecasting research, it is evident that issues of forecasting management have also been discussed early and often in the broader body of forecasting research. Markridakis and Wheelwright (1977) perceived that the importance of forecasting grew significantly as firms coped with the shortages and increased inflation of the early 1970's as well as a recession soon thereafter. Armstrong (1988) observed a significant growth in the demand for forecasting research in the early 1980s noting that in the first two years of its publication, the *Journal of Forecasting* was the seventh most frequently cited journal among the 84 other business management

journals of the time. Further, as Schultz (1992) noted, the first two papers published in a forecasting journal—which appeared in the first issue of the *Journal of Forecasting*—were on the topic of forecasting in organizations. In particular, he cited Jenkins's (1982) discussion of "practical aspects of forecasting in organizations" and Einhorn and Hogarth's (1982) discussion of forecasting within the context of decision making.

Since the early days of forecasting research, much has been revealed about aspects of forecasting management. Nonetheless, as discussed in Chapter 1, a review of the literature reveals that there is a need for greater theory development and testing in order to assess the validity of forecasting management practices prescribed by previous works. In particular, little is known about the effects of forecasting management practices on individual-level forecasting performance. This chapter represents the first step toward understanding and addressing existing gaps in the literature. Specifically, this chapter synthesizes literature pertaining to individual-level forecasting performance. In particular, the review identifies factors which are said to affect individual-level forecasting performance. Furthermore, an effort is made to also understand the theoretical underpinnings of previous works. Finally, the literature review concludes with a discussion of the conceptual model that guides this research effort. In order to frame the literature review, however, aspects of the forecasting task and forecasting performance measurement are first discussed.

The Forecaster's Role

In many settings, individual forecasters are an integral part of an organization's forecasting capability and are essential to coordinating day-to-day forecasting activities (Bretschneider & Gorr, 1989; Fildes & Hastings, 1994). This realization prompted Bretschneider and Gorr (1989) to describe forecasting as not only a science but also "a human activity". The forecaster's task has been described in different ways. For example, Fischoff (1988) described the forecaster's role as identifying the best possible predictors of demand; characterizing the relationships among predictors (i.e. the form of the prediction equation); estimating the inputs to the selected predictive model; and, finally, evaluating the model's predictive validity. Fildes and Hastings (1994) observed that a forecaster's time is spent engaged in several activities: data collection, model development, production of forecasts, monitoring forecasts, communicating forecasts, special analysis, and learning new techniques. Harvey (2001) described the forecasting task as a process involving formulation of the forecasting problem; choice of method; application of method; comparison and combination of forecasts; assessment of uncertainty in forecasts; adjustment of forecasts; and evaluation of forecasts. Regardless of the differences in how the forecaster's role has been defined, there is widespread agreement on at least one aspect of a forecaster's task—that human judgment often permeates throughout (Davydenko & Fildes, 2013; Fischoff, 1988; Harvey, 2001; Moritz et al., 2014; Lawrence et al., 2006; Sanders & Ritzman, 2001). For illustration, Figure 2.1 depicts a notional framework of the forecasting process that has been adapted from Silver et al. (1998).

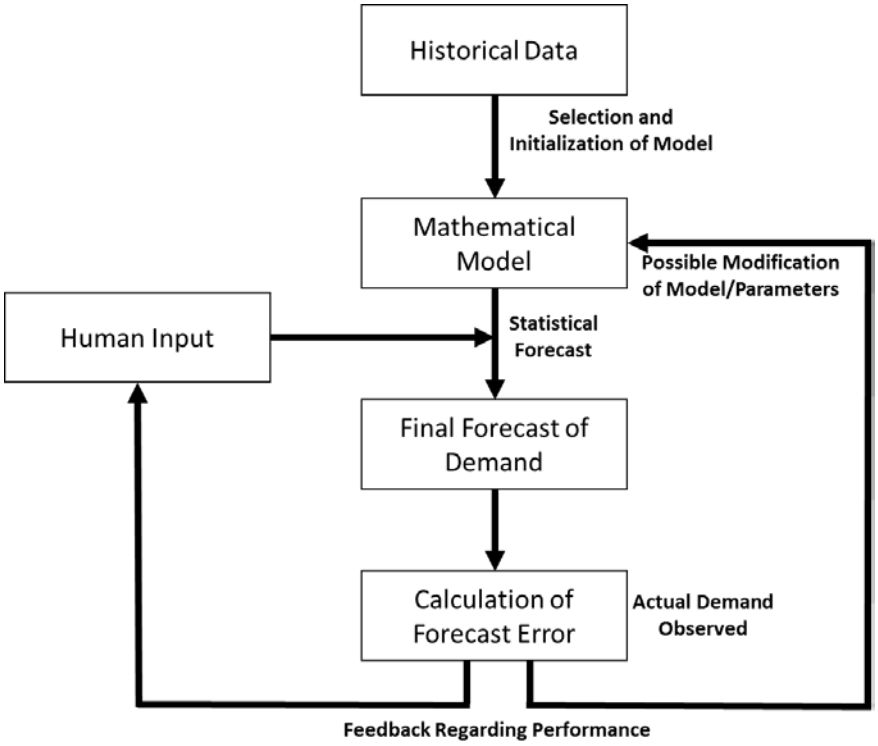


Figure 2.1. Notional Forecasting Framework. Adapted from Silver et al. (1998; p. 75).

The topic of human judgment as it pertains to forecasting has received considerable attention. Interest in the topic has, in part, been fueled by findings from multiple surveys and case studies of organizational sales forecasting practices which revealed that practitioners generally prefer qualitative forecasting methods to quantitative methods (Dalrymple, 1987; Fildes & Goodwin, 2007; McCarthy et al., 2006; Mentzer & Cox, 1984; Sanders & Manrodt, 1994). Furthermore, these studies also reveal that, even when quantitative methods are implemented, statistical forecasts are commonly subjected to adjustment by one or more parties within the organization. For example, in their survey of 149 forecasters, Fildes and Goodwin (2007) found respondents reported that only

about 17% of forecasts were based solely on statistical models while the other 83% of forecasts were influenced by forecaster judgment to some extent (i.e. exclusively qualitative methods, judgmental adjustments, etc.).

Researchers from a variety of disciplines have investigated this topic with the aim of understanding whether judgmental forecasts or judgmental adjustments to forecasts could actually offer benefits above and beyond quantitative forecasting techniques. Though early studies produced conflicting evidence, overall, researchers today tend to agree that forecaster judgment can indeed improve forecast quality (Fildes et al., 2009; Franses & Legerstee, 2010; Lawrence et al., 2006; Syntetos et al., 2009b). However, as will be discussed throughout the literature review, there is considerable nuance involved in how and when judgment improves forecasting. Before delving into the factors that affect forecaster performance, the following section briefly expounds upon the topic of forecast performance.

Forecasting Performance

Measuring and monitoring forecasting performance is an essential aspect of forecasting management (Doering & Suresh, 2016; Mentzer & Moon, 2005). Indeed, performance measurement is emphasized in research and practitioner-oriented literature as essential to selecting appropriate forecasting techniques as well as improving the organization's forecasting process (Davis & Mentzer, 2007; Davydenko & Fildes, 2013; Mentzer & Moon, 2005; Morelidge, 2016). Moreover, given the role of the individual forecaster, managers are encouraged to measure and monitor how each individual

forecaster's inputs contribute to or detract from forecast quality (Davydenko & Fildes, 2013; Fildes & Goodwin, 2007).

While forecasting performance can be measured in a variety of ways, at the heart of any objective measure of forecast performance is forecast error—the difference between what was predicted (e.g. forecasted sales) and what was observed (i.e. actual sales). In general, forecast performance has predominately been viewed in terms of forecast accuracy. Specifically, mean absolute percentage error (MAPE) and median absolute percentage error (MdAPE) are among the most common accuracy metrics (Fildes & Goodwin, 2007; McCarthy et al., 2006). Interestingly, researchers have repeatedly noted the shortcomings of these metrics, namely, that both MAPE and MdAPE equally weigh forecast errors resulting from over or under-forecasting demand. In spite of their shortcomings, recent research has revealed that both measures still persist as the most used in practice (Davydenko and Fildes, 2013; Morelidge, 2016).

It is beyond the scope of this research to provide an in-depth comparison of various forecasting performance measures. Instead, this research advocates the approach proposed by Mentzer and Moon (2005). Recognizing that no single performance measure provides a complete picture of forecasting performance, Mentzer and Moon (2005) recommended using multiple metrics to enable a more holistic assessment of forecasting performance. In particular, forecast bias complements measures of forecast accuracy as it provides a means to assess whether forecasts reflect a tendency to over- or under-predict demand. Each tendency affects planning and decision making processes differently. For example, a tendency to over-forecast demand may lead to excess inventory and, possibly,

inventory obsolescence. Alternatively, a tendency to under-forecast demand may lead to low inventory customer service levels and poor workforce scheduling.

Assessing forecast bias also holds implications for the solutions managers might pursue in order to improve forecasting. On one hand, forecast bias may lead managers to evaluate whether forecasters are appropriately specifying forecasting models. For example, in the case of simple exponential smoothing, a poorly specified smoothing constant could be the root cause of biased forecasts. Other potential sources of bias may be found in the formal and informal incentives and preferences conveyed to forecasters. As Lawrence and O'Connor (2005) noted, forecasters do not always face symmetry in terms of the organization's tolerance of errors. This corresponds with earlier work by Lawrence et al. (2000) who observed that, although some organizations express that accuracy is the main objective for their forecasting process, in reality there may be a real or perceived preference with regard to which direction forecast errors should be made. Interestingly, out of 13 organizations included in Lawrence et al.'s (2000) study, 5 expressed they preferred to over-forecast while 6 expressed they preferred to under-forecast. Only two organizations expressed a neutral stance. Hence, forecast bias provides useful insight to any evaluation of forecasting performance. With this understanding of forecasting performance measures, the following section now turns toward reviewing the factors found to affect various aspects of forecaster performance.

Factors Affecting Individual-level Forecasting Performance

In order to limit the scope of the review, articles were identified which 1) focused on individual-level forecasting performance, and 2) were empirical in nature. To be clear,

both conceptual and empirical works informed the overarching research effort. However, as the overarching motivation for this research effort was to assess evidence provided in support of existing theory and its associated prescriptions, the literature review primarily focuses on empirical articles. To further scope the literature review, research was restricted to the 40-year period between 1977 and 2016. In total, 40 articles were identified as relevant to the study of individual-level forecasting performance.

Two aspects of the literature were noteworthy. First, in terms of the methodologies used, the overwhelming majority of articles (32 of 40) employed either laboratory or field experiments. The remaining 8 articles employed case/field studies (4), surveys (3), and participation observation (1) methodologies. Second, the articles typically employed multiple forecasting performance measures. However, the majority of articles (35 of 40) investigated how factors related to forecast accuracy. The second most common aspect of forecasting performance considered was forecast bias, which appeared in 6 articles.

Furthermore, based on the review, multiple themes emerged with respect to the factors considered and the stated theoretical perspectives by which factors were linked to outcomes. With respect to factors considered, articles appeared to fall into four main categories, which are here used as a means to structure the literature review: 1) forecaster characteristics; 2) forecaster behaviors and abilities; 3) task and technology characteristics; and 4) contextual factors. The categories are not necessarily mutually exclusive. However, for ease of explication, all articles were assigned to a single category based on what appeared to be the primary focus of the article. Figure 2.2 provides a

summary illustration of the four categories and subcategories. Each category and subcategory is addressed in the remaining subsections.

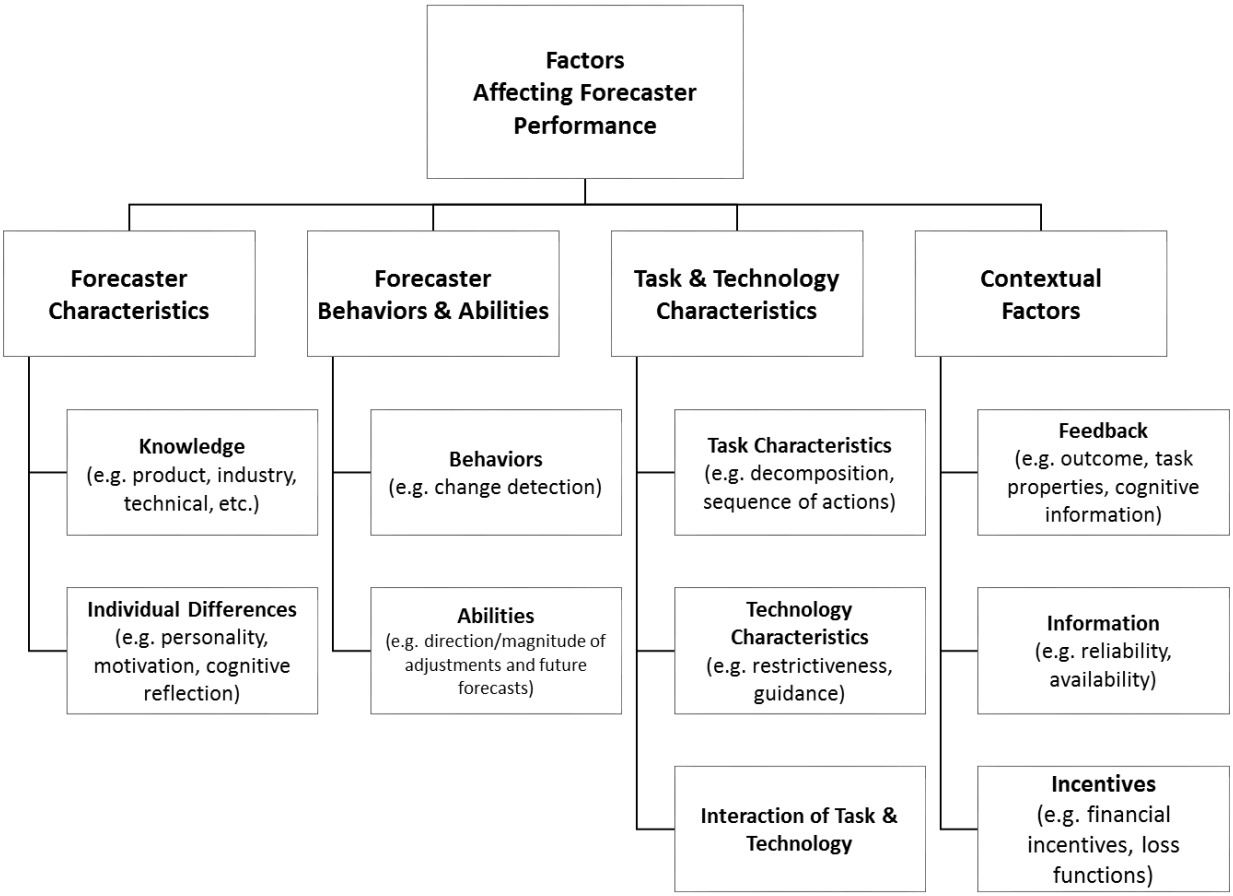


Figure 2.2. Factors Affecting Forecaster Performance.

Forecaster Characteristics.

Table 2.1 summarizes the 9 publications considering the effect of forecaster characteristics upon forecaster performance.

Table 2.1. Forecaster Characteristics.

Author(s)	Factors Considered	Outcome(s) of Interest	Theoretical Perspective(s)
Carbone et al. (1983)	Judgmental abilities, Technical expertise	Accuracy (MAPE)	None Stated
Edmundson et al. (1988)	Product knowledge, Industry knowledge	Accuracy (MAPE)	None Stated
Sanders & Ritzman (1992)	Contextual knowledge, Technical knowledge	Accuracy (MAPE/MdAPE)	None Stated
Sanders & Ritzman (1995)	Contextual knowledge, technical knowledge	Accuracy (MAPE)	None Stated
O'Connor et al. (1997)	Forecasting trends/changes in trends	Accuracy (smoothed APE)	None Stated
Welch et al. (1998)	Forecaster's knowledge of methods, Forecaster's information processing consistency	Accuracy (MAPE), Bias (MPE), Judgment Consistency, Task knowledge	Social Judgment Theory, Brunswick Lens Model
Eroglu & Knemeyer (2010)	Motivation, Gender	Accuracy Improvement (APE)	None Stated
Eroglu & Croxton (2010)	Personality, Motivation Orientation, Work Locus of Control	Bias	None Stated
Moritz et al. (2014)	Cognitive Reflection, Decision speed, Intelligence	Accuracy (Avg. Std. Absolute Forecast Error)	Dual Process Theory

Forecaster Knowledge.

Of the factors appearing in this category, forecaster knowledge stands out as the most common factor considered and is represented in 6 of the 9 articles falling under this category. It is no surprise that forecaster knowledge is among the top factors considered as it is a forecaster's knowledge that is said to serve as the basis for judgmental inputs.

Edmundson et al. (1988) and Winkler (1989) were among the first to advance this view suggesting that, in addition to a forecaster's technical knowledge, knowledge of events or other variables that might influence future demand represented valuable information for forecasting. Furthermore, to the degree that such information was not already captured in the underlying time series data, it represented a means to reduce uncertainty or increase forecast accuracy.

Remus et al. (1995) echoed this perspective calling it the "information integration hypothesis". Of note, Edmundson et al. (1988) considered how product knowledge and industry knowledge affected forecaster performance. They found that forecasts based on product knowledge outperformed forecasts based on industry forecasting experience. Forecasts grounded in product knowledge also outperformed forecasts produced from a statistical model. Overall, they concluded that product knowledge was the most impactful factor determining forecaster accuracy.

Similarly, Sanders and Ritzman (1992, 1995) found that forecasts produced by forecasters with contextual knowledge (i.e. knowledge gained through experience) performed better than forecasters possessing only technical knowledge (i.e. knowledge about data analysis and formal forecasting procedures) in terms of accuracy. Also, technical knowledge was not found to significantly affect forecaster performance (Sanders & Ritzman, 1992). Furthermore, Sanders and Ritzman (1995) found evidence suggesting that the more variable the data, the greater the benefit of contextual knowledge.

Though they researched different factors, Carbone et al. (1983) and O'Connor et al. (1997) investigated aspects of forecaster expertise. Where Carbone et al. (1983)

broadly studied the interaction between a forecaster's technical expertise and judgment when applying various types of forecasting models, O'Connor et al. (1997) evaluated forecasters' expertise in the specific instance of forecasting time series with trends and changes in trends. In the end, Carbone et al. (1983) found that technical expertise, judgmental adjustment, and "individualized analyses" failed to improve forecaster performance as compared to "black box", exclusively-statistical, forecast methods. O'Connor et al. (1997) found that forecasters performed well when forecasting flat or upward-sloping time series but struggle in the case of downward-sloping time series. They also reported forecasters' difficulties forecasting time series involving changes in slope from one segment to another.

Finally, Welch et al. (1998) studied the effects of forecaster task knowledge in terms of appropriately assessing potential predictor variables. Their results were congruent with the other studies in that they found higher levels of knowledge were associated with lower forecast errors.

Individual Differences.

The remaining 3 publications in the category address a variety of forecaster characteristics from an individual differences perspective. Eroglu and Croxton (2010) investigated the relationship between a forecaster's personality, motivation orientation, and locus of control on three different cognitive biases (anchoring, overreaction, and optimism bias). Their findings suggested that personality as well as various subscales of motivation orientation were significant determinants of the degree to which forecasters exhibited all three biases. A forecaster's work locus of control, on the other hand, only appeared to relate to a forecaster's overreaction bias. Eroglu and Croxton (2010) also

found motivation orientation to affect a forecaster's ability to improve upon statistical forecasts, though the effect differed based on gender. Finally, Mortiz et al. (2014) built upon dual process theory to investigate the link between a forecaster's cognitive reflection and forecaster accuracy. They found that individuals with higher cognitive reflection scores also had higher forecasting performance. They further found this to be true when controlling for intelligence.

Forecaster Behaviors and Abilities.

Table 2.2 summarizes the 4 publications that investigated the effect that forecaster behaviors and abilities have on forecaster performance. As compared to the publications that focused on forecaster characteristics, the publications focused on forecaster behaviors and abilities address an array of topics. Also interesting to note is the fact that this group of articles reflects recently published works with all articles having been published within the last 10 years. This may be attributed to the general trend toward behavioral research in multiple disciplines.

Table 2.2. Forecaster Behaviors and Abilities.

Author(s)	Factors Considered	Outcome(s) of Interest	Theoretical Perspective(s)
Fildes et al. (2009)	Selection, magnitude, and direction of adjustments	Accuracy (MAPE, MdAPE), Improvement, Efficient use of information, Bias	None Stated
Syntetos et al. (2009a)	Demand type, Magnitude/direction of adjustments	Accuracy (MAE, Relative Arithmetic MAE, Relative Geometric MAE), service level	None Stated
Kremer et al. (2011)	Change detection, system neglect	Accuracy (MAE, MAPE)	None Stated
Petropoulos et al. (2016)	Reactions to errors; Guidance, Restrictiveness	Accuracy (AvgRelMAE), Adjustment direction/magnitude	Prospect Theory

Forecaster Abilities.

Kremer et al. (2011) overlaps both the behavior and ability subcategories but primarily focuses on a forecaster's ability to interpret data and, in particular, time series data. Their research investigated the topics of change detection (i.e. forecasters' ability to decipher random noise from persistent change in a time series) as well as system neglect (i.e. a tendency to over- or under-react to information in a time series). They reported that both factors affected a forecaster's performance. Specifically, system neglect behavior led to poor forecaster performance in the case of stable environments while "high" levels of change detection ability were associated with better performance, particularly in highly volatile environments.

Forecaster Behaviors.

Multiple articles address how, upon interpreting forecasting-related data, forecasters react to the data and, ultimately, arrive to a final forecast. Borrowing from prospect theory, Petropoulos et al. (2016) considered how awareness of past forecast errors, especially large forecast errors, influenced a forecaster's adjustment behavior in future time periods. They found that "big losses" were associated with a tendency to poorly adjust forecasts in subsequent periods. Finally, they suggested three strategies to support forecasters and mitigate these negative behaviors.

Further, overlap exists between the works of Fildes et al. (2009) and Syntetos et al. (2009a). Both studies explored the tendencies of forecasters when making judgmental adjustments to real-world statistical forecasts and the associated effects upon forecasters' accuracy and bias. Specifically, they considered forecasters' adjustment behaviors in terms of both direction and magnitude, and how those behaviors affected multiple

measures of forecaster performance. Both studies reported similar findings, namely, that judgmental adjustments do improve accuracy. In particular, large negative adjustments were found to have a greater (positive) effect on forecaster performance as compared to small or upward adjustments. Perhaps the greatest difference between the two studies was that Syntetos et al. (2009a) investigated adjustment behaviors in the context of intermittent demand, in which case small positive adjustments were found to have some benefit (i.e. in periods of zero demand); whereas Fildes et al. (2009) studied adjustment behaviors in the context of fast moving items.

Task & Technology Characteristics.

Table 2.3 summarizes the 13 publications that considered how forecasting task and technology characteristics affect forecaster performance. While these factors could conceivably be explored separately, viewing them together reflects the reality of how forecasting is typically executed in practice. Surveys have revealed that the majority of organizations leverage technology to support forecasting activities. As Fildes et al. (2006) explain, the forecasting task commonly unfolds over two phases. In the first phase, the best fit forecasting model is selected. This can be accomplished automatically by the forecasting support system, manually by the forecaster, or by some combination of the two whereby the forecaster overrides the system's suggested best fit model. In the second phase, once the model has been determined, human judgment is applied to adjust the statistical forecast.

Table 2.3. Task and Technology Characteristics.

Author(s)	Factors Considered	Outcome(s) of Interest	Theoretical Perspective(s)
Willemain (1989)	Graphical adjustment of forecasts	Accuracy (MAE)	None Stated
Willemain (1991)	Graphical adjustment of forecasts	Accuracy, adjustment size, Overall Fit Ratio	None Stated
Harvey & Bolger (1996)	Data presentation format (graphs, tables)	Accuracy (MAE)	None Stated
Goodwin (2000)	Framing/decomposition of task, justification	Accuracy (MAPE)	None Stated
Lawrence et al. (2002)	User participation in system design	Accuracy (MAPE), Satisfaction, Confidence, Ease of Use	None Stated
Harvey & Harries (2004)	Task sequence, Weight given to own/others' forecasts	Accuracy (RMSE)	None Stated
Webby et al. (2005)	Decision support, Information load, Direction of time series	Accuracy (MAPE)	None Stated
Goodwin et al. (2007)	Forecaster's interaction with FSS	Accuracy, adjustment size, Overall Fit Ratio	None Stated
Lee et al. (2007)	Guidance provided, Promotion type, Noise level	Accuracy (MAPE)	None Stated
Onkal et al. (2008)	Framing of the task, Availability of forecast history	Accuracy (MAPE); Frequency/size of forecast modifications	None Stated
Soll & Mannes (2011)	Combination/weighting of forecasts, Forecast revision	Accuracy (% improvement)	None Stated
Goodwin et al. (2011)	Support type, signal type	Accuracy (MAPE, MAPA), Forecaster efficiency, learning, ease of use	None Stated
Kremer et al. (2016)	Forecast approach (direct or indirect)	Accuracy (MAE)	None Stated

Indeed, given the scope of the "typical" business forecaster's role, technology is an absolute necessity for the forecaster. Fildes et al. (2006) noted that, especially in supply

chain contexts, the scale and complexity of the forecasting task requires that forecasting must be automated, particularly if it is desirable to incorporate human judgment. For example, Fildes and Hastings (1994) found that approximately 52% of forecasters in their study had 20 or less products for which they provided forecasts each quarter while 38% reported responsibility for between 100 and 10,000 items. Approximately 7% of respondents reported responsibility for over 10,000 items. Fildes and Beard (1992) also observed that responsibility for 10,000 or more products was common in production and inventory contexts.

In their study, Fildes and Goodwin (2007) found that forecasters reported responsibility for as few as one stock keeping unit (SKU) all the way up to 34 million SKUs. However, the overall median number of SKUs managed by forecasters was found to be approximately 400. In their study, Mentzer and Moon (2005) reported that a forecaster produced and adjusted forecasts for between 200 and 300 SKUs per month.

Complicating matters even more is the observation that, in some organizations, forecasting may be just one of several tasks assigned to an individual (Herbig et al., 1993; McCarthy et al., 2011). Such an arrangement only emphasizes the need for technological support to help forecasters effectively and efficiently manage their workload as they confront the competing priorities of various tasks. Furthermore, if one factors in the frequency of forecasts, the associated time horizons, and the infinite number of variables that feed into the forecaster's decision making process, it becomes clear that the ability to automate and monitor forecasts becomes of great importance. Lastly, the overwhelming volume of data gathered and exchanged in business today is yet another reason the forecasting task and technology must be intertwined.

Technology Characteristics.

The publications assigned to this category address how a forecaster's interaction with the forecasting support system affects forecasting performance. For example, Lawrence et al. (2002) consider how the degree of control over features of the forecasting support system affects forecasters' satisfaction with the system as well as their forecasting performance. Their findings were illustrative of a paradox faced by managers: while providing forecasters with control of the support system is positively related with satisfaction, the higher level of control is actually associated with degraded forecasting performance.

Directly related to these findings is the work of Goodwin et al. (2011) who, borrowing from the decision support systems literature, operationalized and tested the concepts of restrictiveness and decisional guidance in the context of a forecasting support system. Surprisingly, they found that neither restrictiveness nor guidance seemed to affect forecaster performance. On one hand, restricting forecasters' autonomy with regard to the nature and timing of judgmental adjustments helped deter behaviors found to degrade forecasting performance (e.g. small, negative adjustments). However, they also found that restrictiveness seemed to deter the forecaster from making adjustments in situations where forecaster judgment has proven most beneficial. Likewise, decisional guidance was found to enhance forecaster's use of the system, however Goodwin et al. (2011) found that it was often ignored.

Also related to this work, Lee et al. (2007) evaluated forecasting support system design features that were expected to aid forecasters in identifying the appropriate magnitude of adjustments in the case where the adjustment is meant to reflect an

upcoming product promotion. They found that providing forecasters with varying levels of support produce differential effects on forecaster performance. Specifically, they found that memory support, similarity support, and adaptation support, when all made available to the forecaster, improved forecast accuracy.

Task Characteristics.

A total of 7 articles comprise the primarily task-focused sub-category with almost half of the articles investigating the forecasting task in terms of how data is presented to the forecaster. In a series of studies, Willemain (1989, 1991) investigated the performance of forecasters when required to judgmentally adjust statistical forecasts using visual cues (i.e. graphs). Both studies found that, for difficult to forecast time series (i.e. time series with significant excess error), graphical adjustment improved forecaster performance. Harvey and Bolger (1996) considered the effect of using both graphs and tables as part of the forecasting task. Similar to Willemain's studies, the results of their experimental study yielded evidence of the efficacy of graphs in aiding forecaster performance, though the efficacy of graphs was moderated by the nature of the underlying time series. In particular, forecasters were more effective when using graphs to forecast trended time series while, for un-trended time series, forecasters were more effective when using tables. Taken together, these studies provide evidence that factors related to data presentation format affect forecaster performance.

The remaining publications in the forecasting task and technology category consider diverse aspects of the forecasting task. Harvey and Harries (2004) considered how the sequence of steps taken in executing the forecasting task related to forecaster performance. In particular, they assessed differences in forecaster accuracy when

forecasters were tasked with one of two task sequences. The first task sequence required the forecaster to produce a forecast and then, eventually, to combine several forecasts to produce a second forecast. The second task sequence was the reverse of the first and required forecasters to combine several forecasts and then to produce their own individually-generated forecast. Overall, they found that forecast accuracy was impaired as a result of the forecaster's memory of previously computed forecasts. Additionally, they found that forecasters often placed too much weight on their own forecasts even when provided inputs from a more-knowledgeable advisor. In the end, forecast accuracy was generally lower in the forecast-then-combine task sequence. Interestingly, of the two task sequences they tested, the task sequence requiring forecasters to produce and then combine several forecasts closely-mirrored the typical task sequence for real world forecasters.

Soll and Mannes (2011) investigated how forecaster performance differed based on the forecaster's task. In particular, they researched how forecast accuracy changed based on whether forecasters were tasked with revising their own forecasts using inputs from an advisor or tasked with computing a new forecast based on the combination of others' forecasts. Similar to previous research, they found evidence to suggest that, forecasters approach these tasks differently although the "optimal" strategy tended to be the same regardless of the task. Specifically, their results suggested that, in the case of both tasks, a simple average of forecasts was generally associated with higher accuracy. Similar to Harvey and Harries (2004), they too observed that forecasters tended to ignore advice and over-weight their own forecasts.

Also somewhat similar to Harvey and Harries (2004), Kremer et al. (2016) considered the sequencing of events that make up the forecasting task, however they focused their efforts on the forecasting approach taken by the forecaster. Specifically, they considered the effects on forecaster performance from forecasting based on either disaggregated data (direct/bottom-up forecasting) or aggregated data (indirect/top-level forecasting). By considering different aspects of the forecasting environment, they were also able to identify nuances underlying this finding. In sum, they found that forecaster performance in indirect and direct approaches to forecasting depends upon the correlations between demands such that when sources of demand are positively correlated (e.g. complementary products) forecasters are more effective using a top-level (direct) forecasting approach. On the other hand, when demands from differing sources are negatively correlated (e.g. products are substitutes), they found that forecaster performance is enhanced through a bottom-up (indirect) approach.

Goodwin et al. (2007) took a novel approach to understanding how individual forecaster differences in interacting with an experimental forecast support system related to forecaster performance. In their study, they set out to understand the decision making strategies employed by forecasters as they selected statistical forecasting methods and made decisions on whether to adjust statistical forecasts. Their findings suggested that, regardless of the individual's familiarity with forecasting methods, forecasters employed a variety of strategies with some resulting in more accurate forecasts than others. Of note, they found that users typically only reviewed a small number of potential methods before making their selection of their preferred methods. Moreover, forecasters in their study did not always choose forecasting models on the basis of objective criteria (i.e. best fit). They

also observed that individuals who did not identify best fitting models were also likely to make adjustments with greater frequency and magnitude after the fact. As expected, this "strategy" was associated with lower levels of forecast accuracy. In the end, they categorized individuals based on their tendencies, finding that forecaster performance tended to be greater for individuals who took the time to familiarize themselves with the provided forecast support system. Forecaster performance also tended to be greater for forecasters who selected the best fitting forecasting models, made the fewest adjustments; and, given that they did make an adjustment, made the smallest adjustments.

As the last article in the task sub-category, Onkal et al. (2008) explored the effects of framing the judgmental aspects of the forecasting task for both point estimates and interval forecasts. They found that framing did not appear to have a significant effect for the frequency or accuracy of subsequent adjustments in the case of point forecasts. In the case of interval forecasts, however, when the forecaster was aware that a forecast had already been adjusted, they were less likely to further adjust the forecast. Furthermore, for both point estimates and intervals, explanations of why a forecast was adjusted was found to have the effect of limiting the size, magnitude, and frequency of further adjustments.

Interaction of Task and Technology.

With regard to the 2 publications which overlap sub-categories, the underlying theme for those articles was integrating findings from studies which focused exclusively on the task or forecasting support system. Generally, these works simultaneously leverage findings from research on ideal forecasting support system characteristics as well as findings pertaining to the ideal task structure for eliciting positive behaviors from

forecasters. For example, Goodwin (2000) simultaneously considers the effects of task decomposition as well as restrictiveness of forecasting support systems. Findings from his analysis suggested that task decomposition and measures to restrict forecaster judgment both had positive effects on forecaster performance. Notably, Goodwin's (2000) manipulations of restrictiveness did not seem to deter forecasters from injecting judgment when appropriate; a finding which contrasts with their later study (i.e. Goodwin et al., 2011) as was previously discussed.

Webby et al. (2005) evaluated how decomposing the forecasting task into key sub-tasks affected forecaster performance. At the same time, acknowledging the role of judgment, they considered how characteristics of the forecasting support system help the forecaster to cope with and make the most of increasing levels of information availability. In the end, they found that the FSS proved to be a significant contributor to forecasters' performance though they did not find evidence of an interaction effect based on the forecaster's information load.

Contextual Factors.

Table 2.4 captures 14 publications that provide evidence of the effect of various contextual factors upon forecaster performance. Considering that the majority of forecasting research has been concerned with sales forecasting, it is not surprising that researchers would be interested in such variables. Such inquiries have been influenced by the likes of Bagozzi (1978) who proposed that a salesperson's performance was a function of individual differences for various characteristics (e.g. self-esteem); the salesperson's relationships with others (e.g. role ambiguity); and situational conditions in a salesperson's environment which might affect performance (e.g. workload).

In the forecasting literature, researchers have also considered aspects of the context as important to forecaster performance. For example, Mentzer and Moon (2005), suggested the uncertainty faced by the forecaster, the nature of the data available to the forecaster, and the tolerance for forecast errors as important aspects of the forecasters' context. Another aspect they considered is the forecaster's workload, which can be viewed in terms of the number of SKUs requiring forecasts; the forecast intervals (i.e. monthly, quarterly, etc.), and the time horizon for which demand is to be forecast (i.e. one month ahead, three months ahead, etc.).

Table 2.4. Contextual Factors.

Author(s)	Factors Considered	Outcome(s) of Interest	Theoretical Perspective(s)
Benson & Onkal (1992)	Feedback (outcome, performance)	Skill, Bias, Calibration, Resolution, Slope, Scatter, Over-forecasting	None Stated
O'Connor et al. (1993)	Changes in time series (discontinuities)	Accuracy (MAPE)	None Stated
Lim & O'Connor (1995)	statistical method, Seasonality, Decision support	Accuracy, Accuracy Improvement (APE, MAPE)	None Stated
Remus et al. (1995)	Reliability of information	Accuracy (MAPE)	None Stated
Lim & O'Connor (1996)	Reliability/availability of contextual information	Accuracy improvement (APE)	None Stated
Remus et al. (1996)	Feedback (task, performance, cognitive)	Accuracy (MAPE)	None Stated
Sanders (1997)	Feedback (task properties)	Accuracy (MAPE)	None Stated
Remus et al. (1998)	Financial Incentives	Accuracy (MAPE)	None Stated
Fischer & Harvey (1999)	Feedback (outcome), Information (error history)	Accuracy (AE)	None Stated
Bolger & Onkal-Atay (2004)	Feedback (performance)	Bias, Calibration, Confidence	None Stated
Lawrence & O'Connor (2005)	Loss function shape/"kindness"	Accuracy (MAPE), Forecaster Earnings	Prospect Theory
O'Connor et al. (2005)	Feedback (task, cognitive), Judgmental Bootstrapping, Environmental stability	Accuracy (APE), Achievement, Knowledge, Consistency	Feedback intervention theory, social judgment theory, Brunswick Lens Model
McCarthy-Byrne et al. (2011)	Compensation, Performance evaluation, environmental conditions, Training, Feedback, Knowledge, FSS, Others' seriousness	Satisfaction, Seriousness, Effort	Need theory, expectancy theory, equity theory, job design
Trapero et al. (2013)	Promotions	Accuracy (MAPE, MdAPE, AvgRelMAE)	None Stated

Feedback.

Among the factors considered in this category, perhaps the most common factor was feedback given to the forecaster. This factor is represented in 7 of the 14 publications falling in this category. In general, studies proposed feedback as a means to mitigate forecasters' cognitive biases and to facilitate forecaster ability to integrate and process various cues. For example, Benson and Onkal (1992) considered outcome feedback as well as three different forms of performance feedback (calibration, resolution, and covariance) as they pertained to forecasters who predicted the probability of future events. Through laboratory experiments, they found that simple outcome feedback, along with resolution and covariance feedback, did not significantly affect forecaster performance. They did find, however, that calibration feedback improved forecaster performance by preventing forecasters from over-forecasting. Calibration feedback was also found to limit the variability of forecasters' probability forecasts. These results were later corroborated by Bolger and Onkel-Atay (2004) who found that calibration feedback also improved forecaster performance by reducing over-confidence bias. They also found that calibration feedback facilitated learning and, subsequently, enabled forecasters to more accurately specify confidence intervals.

Remus et al. (1996) also explored the efficacy of different types of feedback but in the specific context of unstable time series data. Like Benson and Onkal (1992), they investigated the role of outcome feedback in improving forecaster performance while also considering the effect of task information feedback and the combination of task information feedback with cognitive information feedback. In the end, they discovered that forecasters performed better in terms of accuracy when provided with task

information feedback as compared to simple outcome feedback while the combination of task and cognitive feedback was not found to have a significant effect upon forecaster performance. Sanders (1997) and, later, Fischer and Harvey (1999) also considered the effect of different types of feedback over different variants of forecasting tasks. Similar to Remus et al. (1996), Sanders found that task information feedback positively affected forecaster performance. Moreover, this finding was robust for group forecasts as well as adjustments to forecasts made by individual forecasters based on “high-noise” time series data. In contrast to Remus et al. (1996), however, Fischer and Harvey (1999) found that, in a forecasting task requiring individuals to combine multiple forecasts, simple outcome feedback improved forecaster performance such that the accuracy of their forecasts matched the accuracy of a simple averaging heuristic. Additionally, outcome feedback provided in such a manner as to ease the forecaster’s cognitive load improved forecaster performance beyond the simple averaging heuristic.

Finally, McCarthy-Byrne et al. (2011) provided both qualitative and quantitative evidence of the importance of feedback as it pertains to motivating salesforce personnel to engage in the sales forecasting process. That is, though research literature indeed provided evidence of the efficacy of feedback as a means to improve forecaster performance, from their interviews with forecasters from 24 industrial marketing firms, they observed that few organizations actually provided their forecasters with individual-level performance measures. Additionally, the individuals expressed frustration with the lack of such feedback. Subsequently, through analysis of survey data, McCarthy-Byrne et al. (2011) found that forecasters who perceived performance feedback to be adequate reported higher levels of satisfaction with their organization’s sales forecasting process.

They also reported that they invested greater effort into their forecasting-related responsibilities.

Information.

Another major theme common to the publications that considered contextual factors was the focus on the information available to the forecaster. Lim & O'Connor (1995) studied the effect of the reliability of statistical methods as a form of information discerned by the forecaster over time. They found that forecaster adjustments resulted in improvements for both low and high-reliability statistical methods. Furthermore, they found that, even though forecasters could discern that the reliability of the respective statistical methods improved over time, the forecasters still displayed a preference to adjust the forecasts. Moreover, even when provided decision support that allowed them to adjust the weight given to the statistical method and their own judgment, forecasters still favored the forecast derived primarily from their own judgment. For this reason, forecaster performance tended to decline over time.

Remus et al. (1995) and Lim & O'Connor (1996) both investigated the degree to which access to reliable causal/contextual information effected forecasters' performance. Both studies found evidence to support the notion that forecasters have the ability to incorporate non-time series related information into the forecasting task and that access to valid, reliable information improved forecast accuracy. Trapero et al. (2013) investigated forecasters' ability to leverage information about future product promotions in order to improve statistical forecasts. Results from their field study of weekly data from a manufacturing company suggested that judgmental adjustments can enhance statistical forecasts during product promotions, though not systematically.

Finally, McCarthy-Byrne et al. (2011) presented qualitative evidence of the importance of access to contextual information. In their interviews with forecasters, they noted forecasters strongly valued the ability to leverage contextual information to improve forecast accuracy. Furthermore, interviewees expressed frustration toward the lack of timely or accurate information about the forecasting environment. Interestingly, survey data did not support the researchers' proposition that use of judgment and access to information on environmental conditions would affect forecasters' motivation. The researchers attributed this to the common practice of game playing whereby forecasters intentionally under- or over-forecast based on information available to them, perceptions about their environment, and organizational incentives.

Incentives.

The remaining three publications cover even more aspects of the context. One common thread is the real or perceived incentives available to the forecaster. For example, in addition to McCarthy-Byrne et al. (2011), two of the three publications touched on the topic of incentives. Remus et al. (1998) explored the effect of financial incentives and McCarthy et al. (2011) explored the effect of compensation for forecasting as a form of incentive. Lawrence and O'Connor (2005) viewed incentives in terms of loss functions which induce forecasters to intentionally over- or under- forecast. Such loss functions, they said, were likely to be implicitly or explicitly communicated to forecasters by way of the top management team or organizational policies. With the exception of McCarthy-Byrne et al. (2011), these studies provide evidence that incentives, whether financial or otherwise, affect forecaster performance.

As the final publication within this category, O'Connor et al. (1993) represents an effort to understand how forecaster performance is affected by the nature of the time series data, in particular, the presence of significant fluctuations in the time series. Comparing the accuracy of forecasters' qualitative forecasts to the accuracy of forecasts computed using statistical methods, they found that, overall, judgmental forecasts were more error-prone than forecasts produced by statistical methods (i.e. simple exponential smoothing and adaptive response rate). As they did not specifically study the tendencies of forecasters, they attempted to explain this finding by hypothesizing that individuals over-reacted to values in the timer series. Support for this hypothesis was found in later works (e.g. Kremer et al. (2011)) which focused on forecaster tendencies as were previously discussed.

Theoretical Foundation

As the preceding literature review indicates, researchers have attempted to explain forecaster performance as a function of a variety of factors. Looking across the publications deemed relevant to this research, the factors considered in previous works are broadly categorized across four themes: 1) forecaster characteristics; 2) forecaster tendencies; 3) task and technology characteristics; and 4) contextual factors. Furthermore, the literature review also revealed a major gap in terms of the use of theory to investigate individual forecaster performance. In particular, only 6 publications were found as having explicitly stated the theoretical perspective used to identify potential factors affecting

forecasting performance and to derive hypothesized relationships. These publications are summarized in Table 2.5.

Table 2.5. Theoretical Perspectives Explaining Performance.

Author(s)	Factors Considered	Theoretical Perspective(s)
Welch et al. (1998)	Forecaster's knowledge of methods, Forecaster's information processing consistency	Social Judgment Theory, Brunswick Lens Model
Lawrence & O'Connor (2005)	Loss function shape Loss function kindness	Prospect Theory
O'Connor et al. (2005)	Feedback (task, cognitive), Judgmental Bootstrapping, Environmental stability	Feedback intervention theory, social judgment theory, Brunswick Lens Model
McCarthy-Byrne et al. (2011)	Compensation, Performance evaluation, Use of environmental conditions/judgment, Training, Feedback, Knowledge, FSS, Others' seriousness	Need theory, expectancy theory, equity theory, job design
Moritz et al. (2014)	Cognitive Reflection, Decision speed, Intelligence	Dual Process Theory
Petropoulos et al. (2016)	Reactions to errors; Guidance, Restrictiveness	Prospect Theory

As the table shows, very few studies explicitly state a theoretical perspective and often leave the reader to decipher the theoretical basis for the relationships proposed in a given study. Admittedly, this does not necessarily mean that researchers altogether neglected to incorporate theory into their research efforts. However, the finding is still problematic for several reasons, not least of which is that, without clear theoretical foundations, researchers cannot form a common or unified theoretical grounding from which to advance forecasting management theory and practice. This sentiment was expressed by Fildes et al. (2003) who noted that many of the prescriptions from forecasting management literature lack the necessary theoretical grounding to warrant

prescription. Smith and Mentzer (2010a) also pointed out the lack of theoretically-grounded frameworks linking forecasting practices to performance.

This research addresses this gap by leveraging multiple theories to explain individual-level forecasting performance. Moreover, special attention is given to identifying constructs that are readily influenced by management practices. Theories used by prior research do not appear to be ideal for facilitating this objective as they are more appropriate for explaining forecaster performance as a function of the forecaster's cognitive and psychological processes. Again, given the objective of this research effort, fresh theory is justified. In particular, this research draws from the management information systems and organizational behavior disciplines. Specifically, task-technology fit theory, organizational climate theory, as well as organizational knowledge creation theory are proposed as three potential means to explain how forecasting management practices and the organizational setting work together to enable forecaster performance. While there is some overlap between the theory applied in this research and the theory from past research, the three proposed theories are favored for their ability to provide a more accessible, comprehensive, and parsimonious approach to explaining individual-level forecaster performance *as a function of management practices*.

Task-technology Fit Theory

Task technology fit (TTF) theory originated from the management information systems (MIS) discipline as researchers endeavored to explain the value and effect of various technologies, particularly in organizational settings. At the time, researchers

theorized that the value of a given technology could be explained in terms of how various factors (e.g. the characteristics of a technology) influenced individual users' attitudes and how those attitudes, in turn, led to certain outcomes such as perceived value and utilization (Goodhue, 1988). However, as Goodhue (1988) noted, few researchers specified the theoretical structure of the user attitude construct or the theoretical basis for how antecedents or related outcomes were related to the construct. Moreover, he distinguished between user attitudes (i.e. an individual's positive or negative feelings toward an object) and user beliefs (i.e. an individual's information or opinions about an object), and posited that MIS researchers should focus their theory development and measurement efforts on the latter rather than the former. That is, if theory proposed that features and functionality of a given system determined the value of that system, beliefs were the more appropriate predictors.

In an effort to clarify and standardize the attitude construct as well as its proposed role in the "system-to-value chain", Goodhue borrowed from Dawis et al.'s (1968) theory of work adjustment which, in part, explained how an individual's job satisfaction leads to job performance. In particular, Goodhue (1988) drew upon that theory's conceptualization of "individual satisfactoriness", a construct capturing a supervisor's evaluation of the degree of "fit" between the abilities required by the job and an individual's actual abilities. This assessment, in turn, influenced the individual's satisfaction with the job and subsequent decision to remain or quit as well as the supervisor's satisfaction with the employee and subsequent decision to promote, retain, transfer, or fire the individual.

Adapting the theory to the MIS context, Goodhue proposed a parallel "satisfactoriness" construct for information systems. This construct was rooted in the idea that, outside the context of a certain task domain, technology has no inherent value. Thus, the success or value of a given information system had to be explained in terms of the system's ability to enable satisfaction of task requirements. Further, he proposed that the ability of an information system to enable success at a task hinged upon the degree of correspondence or "fit" between task requirements and the inherent characteristics of the information system. Moreover, this assessment of "fit" was able to be judged by the individual user much in the same way individual-job fit was said to be judged by supervisors in the theory of work adjustment.

Later, Goodhue (1995) and Goodhue and Thompson (1995) expounded upon the propositions from the 1988 article, formally introducing task-technology fit theory as a means to explain the value of technology as a function of its effect upon individual performance. As the focal point of the theory, the task-technology fit (TTF) construct was defined as, "the extent that technology functionality matches task requirements and individual abilities" (Goodhue, 1995; p. 1829). Furthermore, the theory was based on four propositions: 1) technology characteristics affect users' evaluations of TTF; 2) task characteristics affect users' evaluations of TTF; 3) individual skills and abilities affect users' evaluations of TTF; and 4) the interaction between task, technology, and individual skills and abilities affect users' evaluations of TTF (Goodhue, 1995). Figure 2.3 illustrates the task-technology fit model according to Goodhue (1998).

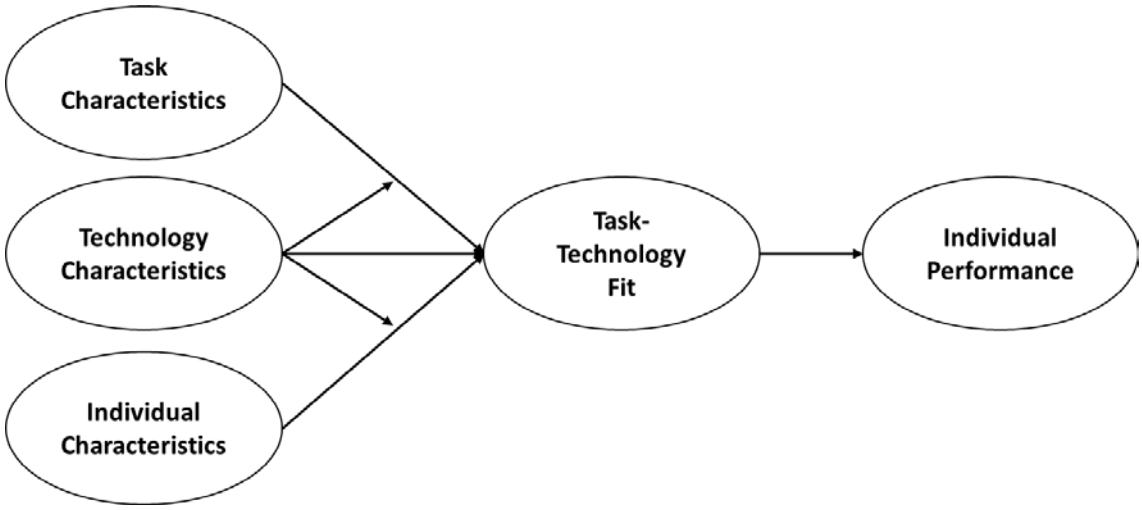


Figure 2.3. Task-Technology Fit Model. Adapted from Goodhue (1998; p. 108)).

Goodhue (1995) tested the first four propositions of the theory while Goodhue and Thompson (1995) tested the four propositions while also assessing the link between TTF and individual job performance. Both works yielded evidence supporting all four propositions while Goodhue and Thompson (1995) found evidence to support the hypothesized relationship between TTF and individual performance which was operationalized as the technology's perceived effects on individual performance, productivity, and job performance.

In terms of measurement, both works operationalized the TTF construct as user evaluations of TTF across a range of dimensions. Goodhue and Thompson (1995) identified eight distinct dimensions of TTF within the task domain of IT-supported decision making: quality, timeliness, compatibility, locatability, ease/training, reliability, authority, and relationship. In a separate study, Goodhue (1995) identified a total of 12 dimensions relevant to the task domain of using quantitative information in managerial

tasks, eight of which were unique as compared to Goodhue and Thompson's (1995) proposed dimensions: confusion, right level of detail, meaning, accessibility, assistance, accuracy, currency, and presentation. Later, Goodhue (1998) formally presented an instrument capable of measuring user evaluations of TTF within the broad task domain of using organizational information in managerial decision making. Ultimately, Goodhue defined TTF as a reflective construct consisting of the same 12 dimensions as outlined in Goodhue (1995) and provided extensive evidence of reliability and validity.

Organizational Knowledge Creation Theory

Organizational knowledge creation theory is attributed to Ikujiro Nonaka and was born out of an effort to explain how organizations create knowledge resources and how organizations could go about managing those resources. In this way, the theory expanded upon and complemented the then-emerging knowledge-based view of the firm (Nonaka & von Krogh, 2009). While it has typically been viewed as a means to explain organization-level outcomes such as product and process innovation, Nonaka and von Krogh (2009) suggest organizational knowledge creation theory can also be tied to more effective task performance at the individual level.

Nonaka's theory can be understood along two dimensions. The first dimension addresses the "epistemological" aspect of organizational knowledge; that is, the nature of organizational knowledge and how it is created. At the heart of this dimension is the individual who is considered the "prime mover" in knowledge creation (Nonaka et al., 2006). According to Nonaka (1994), *knowledge* is defined as "justified true belief". As

implied by this succinct definition, knowledge is not necessarily an object but, rather, a dynamic process whereby individuals, through personal experience, justify personal beliefs with the ultimate goal of arriving to the "truth". The process of justification depends on *information* which, distinguished from knowledge, is defined as a flow of meaningful messages capable of augmenting, reorganizing, or transforming knowledge. As individuals take in new information, they filter it relative to pre-formed beliefs and deeply-rooted value systems.

Furthermore, Nonaka (1994) distinguished between two types of knowledge—tacit and explicit. *Explicit knowledge* refers to codified knowledge or knowledge that can be expressed formally and, thus, is amenable to being captured by historical records as may be found in libraries, archives, and databases. On the other hand, *tacit knowledge* is knowledge of a more personal nature and harder to formalize and communicate. It is described as consisting of cognitive and technical components with the cognitive component comprising mental models, paradigms, and beliefs that help individuals define and make sense of their environment. The technical component refers to "know-how" and is the domain of skills that apply to a specific context.

The second or "ontological" dimension of the theory details four avenues through which tacit knowledge and explicit knowledge can each be converted into new knowledge. Specifically, Nonaka (1994) proposed four means by which new knowledge is created: 1) socialization, 2) externalization, 3) combination, and 4) internalization. Figure 2.4 depicts the four modes of knowledge conversion.

	Tacit Knowledge	*To*	Explicit Knowledge
Tacit Knowledge	Socialization		Externalization
From			
Explicit Knowledge	Internalization		Combination

Figure 2.4. Modes of Knowledge Conversion. Adapted from Nonaka (1994; p. 19).

As can be seen, *socialization* involves converting tacit knowledge into new forms of tacit knowledge and, as its name implies, involves social interaction or experiences shared by individuals (e.g. on the job training). Next, the process of *externalization* involves converting tacit knowledge into explicit knowledge and is facilitated by models (e.g. analogies and metaphors) which help make tacit knowledge comprehendible to others (Sabherwal & Becerra-Fernandez, 2003). Alternatively, *internalization* converts explicit knowledge into tacit knowledge. This takes place as individuals absorb the knowledge held by others (e.g. through books or presentations). Finally, the fourth conversion process entails translating explicit knowledge into new forms of explicit knowledge through a process of *combination* which might be achieved through information systems (Nonaka, 1994). As individual knowledge cycles between these forms of knowledge conversion, it is gradually amplified through social interactions

which help it transition through the hierarchical levels of the organization until it ultimately becomes organizational knowledge.

Nonaka et al. (2006) note that, in practice, the dependence on social interaction makes the knowledge conversion process “highly fragile”. This process is further exacerbated by time and cost constraints that prevent all available individual knowledge from being shared. As a result, individual knowledge often fails to benefit others in the organization. As a means to assess an organization’s efforts to facilitate the knowledge conversion processes, Sabherwal and Becerra-Fernandez (2003) introduced the concept of *knowledge management effectiveness* which reflects the degree to which an entity (i.e. an individual, group, or organization) receives and understands the knowledge needed to perform its tasks or objectives. Here, it is proposed that knowledge management effectiveness complements task-technology fit theory in explaining forecaster performance by accounting for the inherently tacit component of knowledge (i.e. product knowledge, industry experience, etc.) applied by forecasters when executing the forecasting task.

Organizational Climate Theory

Generally speaking, the consideration of contextual factors brings clarity to both theory and practice. Indeed, researchers in the management disciplines have been encouraged to account for the influence of contextual factor, both as a means to more accurately specify theoretical relationships, and to strengthen the interpretation of findings (Rousseau & Fried, 2001). Johns (2006) describes “context” as consisting of “situational opportunities and constraints” influencing the occurrence and meaning of

organizational behavior as well as theoretical relationships between variables. Particularly in organizational settings, contextual factors can influence behaviors as main effects or they may influence behaviors through interaction with other variables (Johns, 2006). Furthermore, contextual factors may serve to restrict the range of variation, change the direction or sign of relationships between variables, prompt curvilinear effects, or "tip" seemingly insignificant relationships toward significance (Johns, 2006; Rousseau & Fried, 2001).

As indicated by the preceding literature review, researchers in the forecasting discipline have assessed an array of factors pertaining to the context within which forecasting takes place. Nonetheless, on the whole, limited consideration has been given to how the forecaster's *organizational* context affects their performance. Indeed, multiple researchers diagnosing a theory-practice gap in the forecasting field have pinpointed the lack of research explicitly accounting for how organizational context affects the efficacy of forecasting practices (Davis & Mentzer, 2007; Fildes & Hastings, 1994; Mahmoud et al., 1992; McCarthy et al., 2006; McCarthy-Byrne et al., 2011; Schultz, 1992; Winklehofer et al., 1996). This deficiency has had the effect of weakening the prescriptive ability of forecasting management research as practitioners are unable to distinguish if and how forecasting "best practices" will translate to their particular setting (Fildes et al., 2003).

Rousseau and Fried (2001) note that there are a variety of ways to contextualize research in organizational settings and proposed three general approaches: "rich description" of the setting; direct observation and analysis of the effects of contextual factors; and conducting comparative studies across settings with substantial institutional

or cultural differences. Similarly, Johns (2006) adds that research can also be contextualized through elements of research design (e.g. cross-level/comparative research, collecting qualitative data, etc.) and measurement (e.g. considering multiple dependent variables, analyzing variances, within-unit agreement, etc.). Additionally, both allude to the role of organizational climate as a specific means of contextualizing research. Herein, organizational climate theory is proposed as a useful means to capture multiple facets of a forecaster's context that are likely to affect forecasting performance. Specifically, *psychological climate* is offered as a construct that can be used to represent a "bundle of practices" likely to be pertinent across a wide variety of organizational settings in which forecasting might be studied (Rousseau & Fried, 2001).

As somewhat of a misnomer, the term *organizational climate* refers to an area of research as opposed to a specific unit of analysis or construct (Schneider, 1975). This area of research is concerned with understanding behaviors in organizations as a function of how attributes of the organization (i.e. practices and procedures) are perceived by individuals (Schneider, 1975). Furthermore, while organizational climate has come to be studied across multiple levels, researchers generally agree that the fundamental unit of theory is individual-level climate or, more specifically, *psychological climate* (Schneider 1975; James et al., 2008; Schneider et al., 2017).

Simply put, "climates" refer to perceptions people have of their work settings (Schneider, 1975). More specifically, psychological climate refers to the significance individuals assign to their jobs, co-workers, leaders, pay, performance expectations, opportunities for promotion, equity of treatment, etc. (James et al., 2008). At its foundation, psychological climate is rooted in both the Gestalt and Functionalist schools

of psychology (Schneider, 1975). Based on the Gestalt perspective, individuals have an innate drive to understand the natural order of their environments and do so through thought processes whereby cues or attributes of the environment (and the perceived relationships between them) are assessed based on the degree to which they correspond with the individual's personal values (Schneider, 1975; James et al., 2008). As explained by James et al. (2008), work-related personal values generally fall along four dimensions: 1) desires for clarity, harmony, and justice; 2) desires for challenge, independence, and responsibility; 3) desires for work facilitation, support, and recognition; and 4) desires for warm and friendly social relations. Therefore, as an example, individual's assessing the nature of training opportunities (i.e. as an environmental cue/attribute) might perceive the work environment is not very supportive if said training programs are assessed as being inaccessible or infrequent. Moreover, based on the Functionalist paradigm, the process of discerning order through assessing cues and attributes of the work environment serves the purpose of allowing an individual to adapt their behavior and, thereby, achieve "homeostatic balance" in their surroundings (Schneider, 1975). In turn, this serves as the basis for studying psychological climate as a factor affecting behavior (i.e. job performance) in organizations.

Given the multitude of possible events and conditions that could be considered as relevant cues or attributes of the work environment, a mainstay of early psychological climate research was the effort to identify the appropriate dimensions of the psychological climate construct. Indeed, much of the early work on psychological climate was critiqued as being tautological, and as not offering much theoretical value due to both its overlap with a variety of pre-existing constructs and due to the lack of clarity

with regard to dimensions of the climate construct (James & Jones, 1974; Schneider et al., 2017).

Though there is still not perfect agreement with respect to the dimensions of psychological climate, in practice, researchers appear to have converged on four dimensions of psychological climate. These four dimensions were first identified by Jones and James (1979) and, in line with the proposition that climate perceptions are filtered through personal values, they parallel the dimensions of work-related values mentioned previously. Specifically, Jones and James (1979) identified the following dimensions: 1) role stress and lack of harmony; 2) job challenge and autonomy; 3) leadership facilitation and support; and 4) workgroup cooperation, friendliness, and warmth. These four dimensions were conceptualized as first-order factors and were later conceptualized as reflecting a higher-order factor called psychological climate-general or *PCg*. This factor was said to underlie all first-order factors and represented an individuals' general ability to assess the significance of the work environment as it pertained to the individual's well-being (James & James, 1989; James et al., 2008). Figure 2.5. illustrates the hierarchical model of psychological climate.

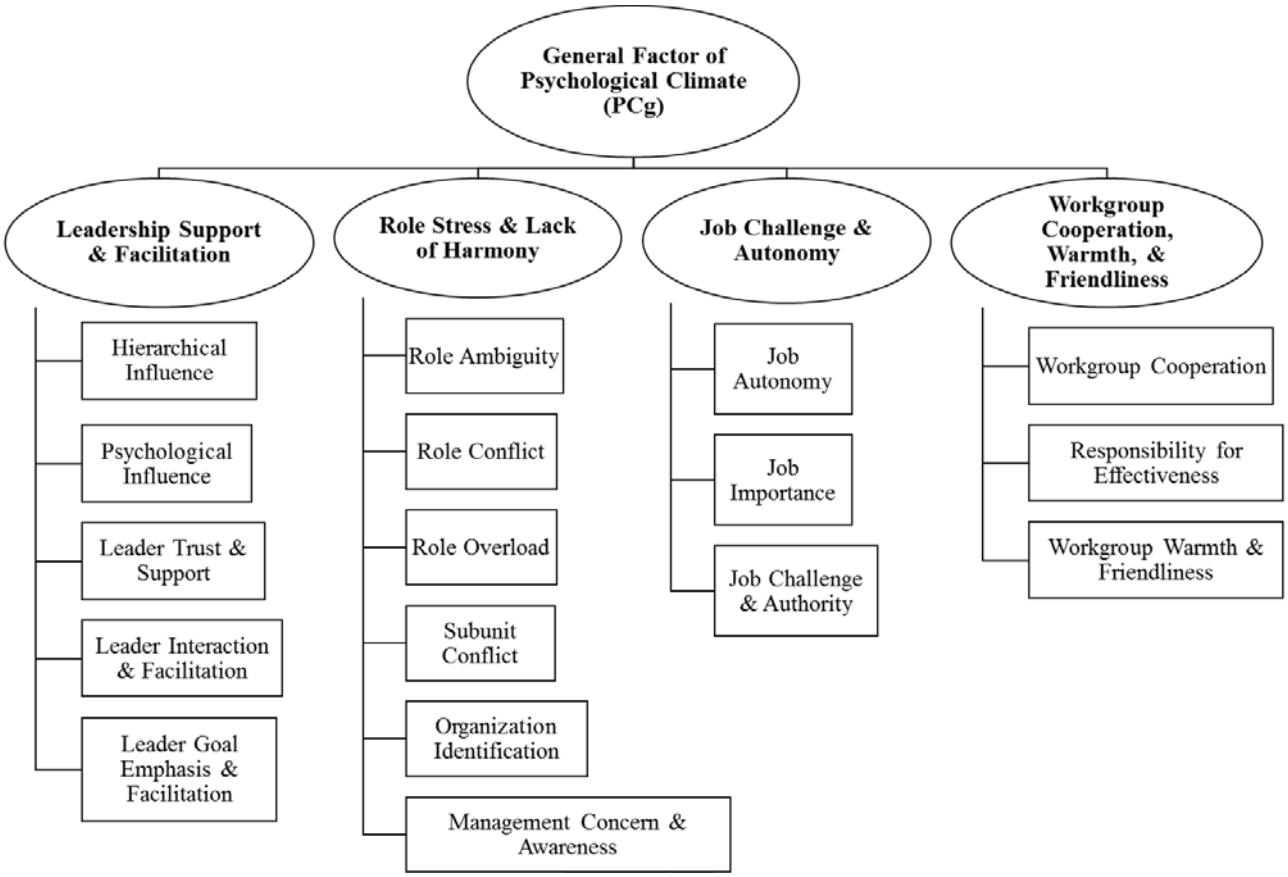


Figure 2.5. Dimensions of Psychological Climate. Adapted from James et al. (2008; p. 12).

One other aspect of organizational climate theory is also important to consider. As Schneider (1975) suggested, in any given organization it is likely that the over-arching organizational climate is made up of a number of sub-climates. As such, climate constructs can and should be defined in terms of the outcome behavior(s) they are expected to foster. For this reason, Schnieder (1975) suggested that researchers should tailor the dimensions of the psychological climate construct to the criterion of interest thereby creating "focused" climates.

Out of this suggestion, a number of focused climates have been conceptualized throughout management literature (e.g. service climate, safety climate, etc.). Based on the literature as well as organizational climate theory, it is possible to conceptualize a forecasting-focused climate which represents the perceptions of individuals with respect to how their work environment encourages and supports positive forecasting-related behaviors. As such, a forecasting-focused climate construct promises to serve as a means of capturing how aspects of the organizational context affect forecaster performance and interact with other variables.

The foundation for a forecasting-focused climate construct has already been established by forecasting researchers. Davis and Mentzer (2007) proposed the concept of organizational sales forecasting climate as a determinant of organizational sales forecasting performance while McCarthy-Byrne et al. (2011) focused on several "environmental signals" that were hypothesized to motivate sales personnel to contribute to the forecasting process. Davis and Mentzer (2007) did not operationalize or test their forecasting climate construct and, given that they only addressed their climate construct as part of a process model, they did not specify the exact role of forecasting climate (i.e.

as a main effect or intervening variable). Similarly, though McCarthy Byrne et al. (2011) quantitatively assessed the individual effect of each of their proposed “signals” on forecaster satisfaction, seriousness, and effort, they did not explicitly address the concept of forecasting-focused climate.

Conceptual Model and Hypothesis Development

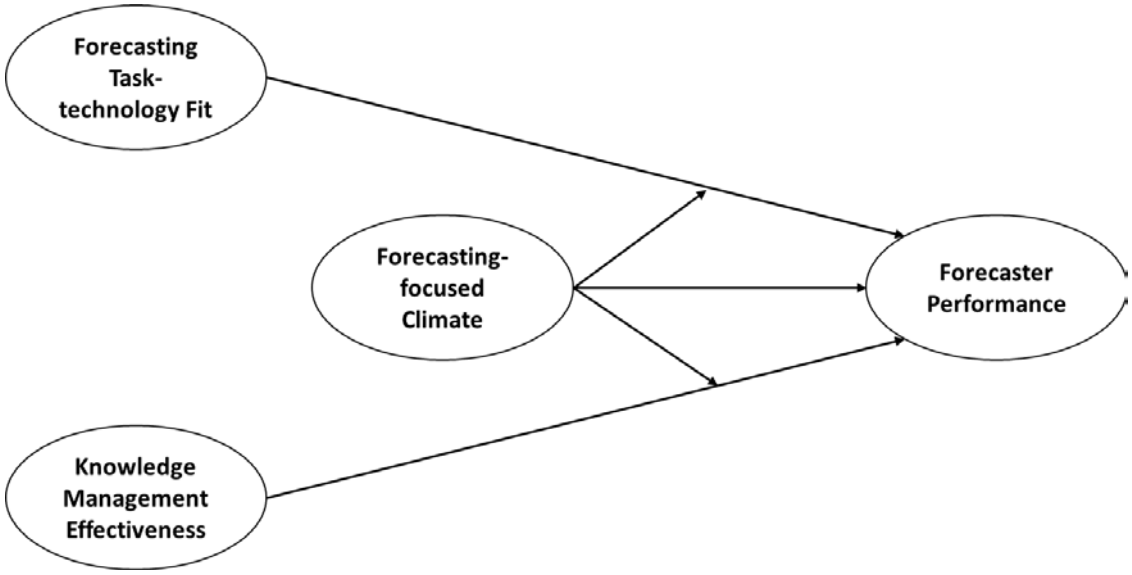


Figure 2.6. Conceptual Model.

Conceptual Model.

Based upon the review of the relevant literature, and the proposed theoretical perspectives, this dissertation proposes the following conceptual model as illustrated in Figure 2.6. Forecaster performance is the dependent variable while forecasting task-technology fit and knowledge management effectiveness are both independent variables. Forecasting-focused climate is assumed to be both an independent variable and intervening variable.

Hypothesis Development.

The purpose of this research is to discover the effect of forecasting task-technology fit, knowledge management effectiveness, and forecasting-focused climate on individual-level forecasting performance. This section develops and presents hypotheses based upon the review of relevant literature and the stated theoretical perspectives.

Forecasting Task-technology Fit and Forecaster Performance.

Research by Goodhue as well as by other MIS researchers has served to provide support for the fundamental propositions of task-technology fit theory as well as the link between task-technology fit and both subjective measures of individual performance (Goodhue et al., 1997b; Kositanurit et al., 2006; Staples & Seddon, 2004; Wu et al., 2007) and objective measures of individual performance (Goodhue et al., 2000; Junglas et al., 2008). As technologies have advanced and more attention has turned to explaining technology adoption and utilization, researchers have positioned task-technology fit alongside other models such as the technology acceptance models (i.e. TAM and TAM2) as well as Venkatesh et al.'s (2003) unified theory of acceptance and usage of technology (UTAUT). In particular, task-technology fit has been hypothesized as a key predictor of subjective measures of performance captured under the constructs of *perceived usefulness* and *performance expectancy*, both of which capture users' beliefs regarding how using a particular technology will help improve job performance (Venkatesh et al., 2003). Dishaw and Strong (1999); Zhou et al. (2010) and Oliveira et al. (2014) are just a few examples of research in this particular stream that present evidence of the relationship between task-technology fit and performance-related constructs within the context of other models.

Furthermore, task-technology fit theory is easily adapted to the forecasting context as is evidenced by its coverage of three of the four themes (categories) emerging from the literature. That is, in general, forecasting research aligns with the propositions of task-technology fit theory by studying the main effects of (and interactions between) individual (forecaster) characteristics and abilities as well as task- and technology-related

factors. Additionally, a precedent exists for using the theory to explain forecasting performance, albeit, at the organization level of analysis.

As one of very few theoretically-grounded frameworks of forecasting practice, Smith and Mentzer (2010a) leveraged task-technology fit theory to explain forecasting performance as a function of both task and forecast support system-related characteristics. Specifically, they operationalized technology characteristics along the lines of an "idealized" forecast support system while task characteristics were operationalized as the quality and accessibility of forecasting procedures guiding the forecast development task. Scales to assess both forecasting support system characteristics and forecasting procedures were developed based on findings from literature as well as in-depth interviews with practitioners from seven companies. Further, task-technology fit was operationalized as users' evaluations of forecasting task-technology fit measured along two dimensions they termed *system access* and *system quality*. Though they did not adopt the same dimensions of task-technology fit as previous works (e.g. Goodhue, 1995; Goodhue and Thompson, 1995; Goodhue, 1998), the items measuring forecasting task-technology fit were grounded in the scales proposed by Goodhue (1998) and drew from several dimensions, namely, right data, right detail, data accuracy, accessibility, ease of use, and system reliability. A pre-test of their survey instrument with 129 forecasting managers and subsequent analysis allowed for purification of scales and yielded evidence of acceptable convergent and discriminant validity for first-order and second-order factors.

The relationships hypothesized by Smith and Mentzer (2010a) mirrored the fundamental propositions of task-technology fit. Both forecasting support system

characteristics and forecasting procedures were expected to positively affect forecasting task-technology fit while forecasting task-technology fit was expected to positively affect forecasting performance. Smith and Mentzer (2010a) operationalized forecasting performance as organization-level forecast accuracy of monthly forecasts across three levels of aggregation (i.e. product line, SKU, and SKU by location). Through covariance-based structural equation modeling, Smith and Mentzer (2010a) found evidence to support all three hypotheses: characteristics of the forecasting support system as well as procedural quality and accessibility were both positively related to user evaluations of task technology fit and users' evaluations of forecasting task-technology fit were positively related to perceived forecasting performance. Here, forecasting task-technology fit is adapted to the originally-intended individual level of analysis. In line with task-technology fit theory, it is expected that, as individuals assess higher levels of TTF, levels of forecaster performance will also be high and vice versa. As such, the following hypothesis is tested.

> *Hypothesis 1: Forecasting task-technology fit is positively related to forecaster performance.*

Knowledge Management Effectiveness and Forecaster Performance.

As the literature review established, forecasting research highlights the role of knowledge as a resource forecasters draw upon when completing forecasting tasks. Interestingly, such studies demonstrate the effect of the more tacit forms of knowledge (i.e. product knowledge, industry knowledge, etc.) upon forecaster performance. However, as implied by organizational knowledge creation theory, tacit knowledge is difficult to manage, especially compared to explicit knowledge which can be managed

through IT systems or easily conveyed from person to person. Furthermore, while information systems such as a forecasting support system may also contribute to converting and sharing tacit knowledge, in general, tacit knowledge is highly dependent upon social interactions and experiences (i.e. socialization and externalization). As such, Nonaka (1994) noted the efficacy of "self-organizing teams" as a means to facilitate sharing of tacit knowledge both within and between business organizations. This same concept is paralleled in forecasting management theory which has emphasized functional integration and collaboration as a means to enhance forecasting performance (Davis & Mentzer, 2007; McCarthy & Golicic, 2002; Mentzer & Moon, 2005; Nagashima et al., 2015). As such, here it is proposed that knowledge management effectiveness will capture the degree to which management practices help make knowledge available to individual forecasters. In particular, knowledge management effectiveness captures the availability of tacit knowledge not capable of being captured by the organization's forecasting support system(s). Therefore, this research tested the following hypothesis.

> *Hypothesis 2: Knowledge management effectiveness is positively related to forecaster performance.*

Forecasting-focused Climate and Forecaster Performance.

As previously discussed, contextual factors have been considered throughout forecasting research, however, much remains to be discovered about the effects of contextual factors specifically linked to the organizational setting. This research leverages organizational climate theory and proposes psychological climate as the basis for developing a forecasting-focused climate which captures contextual factors specific to the organizational setting and which are expected to affect forecaster performance.

Although no known studies exist which have previously conceptualized a forecasting-focused climate or investigated its relationship to forecaster performance or other factors, multiple studies within the larger body of organizational climate research have provided evidence for both direct and indirect links between individual-level climates and individual-level performance (e.g. Brown & Leigh, 1996; Jaramillo et al., 2013; McKay et al., 2008; Schwepker, 2013). In the case of forecasting-focused climate, it is expected that forecasters will evaluate how certain forecasting-related policies, procedures, and practices either help or hinder their efforts to forecast effectively. Where individuals perceive a climate that is overall conducive to fulfilling their forecasting-related responsibilities, it is expected that levels of forecaster performance will be high. Alternatively, to the degree that individuals perceive their work environment is not conducive to fulfilling their forecasting-related responsibilities, it is expected that levels of forecaster performance will be low. Thus, the following hypothesis is tested.

> *Hypothesis 3: Forecasting-focused climate is positively related to forecaster performance.*

Furthermore, it is also expected that perceptions related to forecasting-focused climate can interact with perceptions of both task-technology fit and knowledge management effectiveness. Here again, although no known studies exist which have previously conceptualized a forecasting-focused climate or investigated its relationship to forecaster performance or other factors, multiple studies within the larger body of organizational climate research have provided evidence that individual-level climates can moderate the effects of various factors as they pertain to individual-level performance

(McKay et al., 2008; Zohar et al., 2015). Thus, this dissertation tested the following hypotheses.

> *Hypothesis 3A: Forecasting-focused climate moderates the relationship between forecasting task-technology fit and forecaster performance.*
>
> *Hypothesis 3B: Forecasting-focused climate moderates the relationship between knowledge management effectiveness and forecaster performance.*
>
> Figure 2.6 portrays the conceptual model and the associated hypotheses.

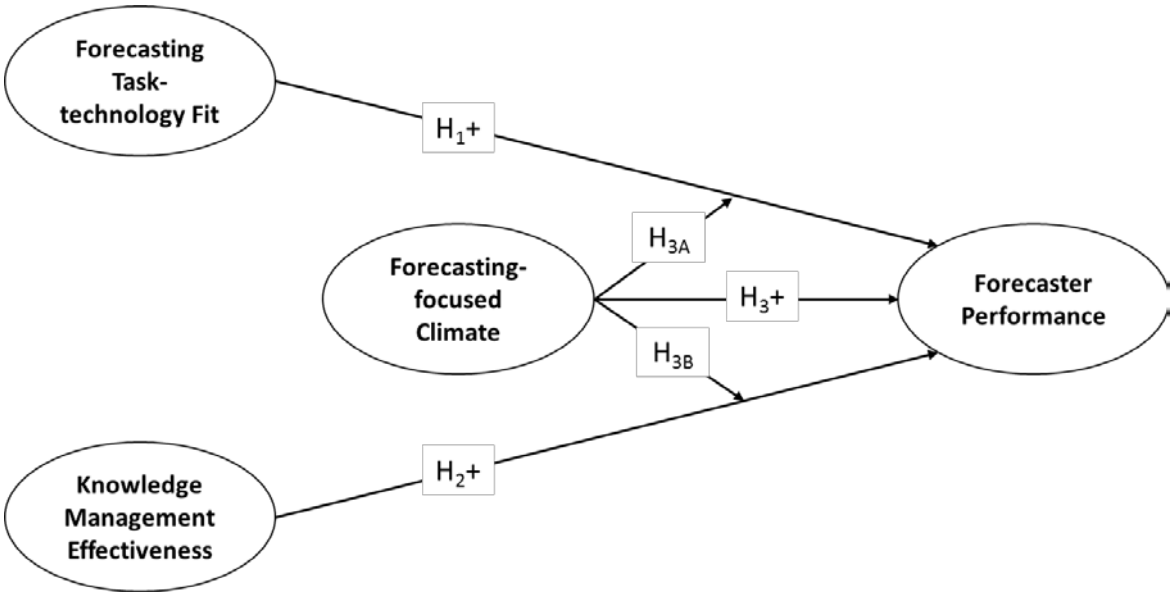


Figure 2.7. Conceptual Model.

III. Methodology

Chapter Overview

This chapter describes the research setting, design, and methods employed to answer the research questions and to test the associated hypotheses presented in Chapters 1 and 2, respectively. Efforts taken to ensure reliability and validity throughout each phase of the research effort are discussed. Furthermore, it should be noted that this research adhered to all institutional policies and procedures pertinent to research involving human subjects. Copies of all IRB exemption approval documents can be found in Appendix A.

Research Setting

As the Air Force focal point for supply chain planning, the 448th Supply Chain Management Wing (SCMW) served as the specific setting for this research. The 448th SCMW is one of two "virtual" wings in the Air Force and is made up of four supply chain management groups (SCMGs) which are collocated with air logistics complexes (ALCs) at Hill AFB, Utah; Tinker AFB, Oklahoma; and Warner Robins AFB, Georgia. The ALCs are the hubs for maintenance, repair, and overhaul of Air Force weapon systems and equipment. The 448th SCMW and its SCMGs support depot maintenance operations at the ALCs by forecasting demand (i.e. failure rates) for repairable items. Of the four SCMGs, one group provides enterprise-wide oversight for forecasting policy and procedures, while day-to-day execution of the forecasting process takes place within the 14 supply chain management squadrons (SCMSs) dispersed across the remaining three SCMGs. In general, each squadron is aligned with the weapon systems and components

repaired by the ALC to which it is assigned. Distributed across the 14 SCMSs are over 300 equipment specialists (ESs). For ease of oversight, ESs are grouped into teams of 5 to 10 with one individual per team serving as the lead ES. Furthermore, similar to forecasters in business settings, individual ESs are assigned a number of items for which they provide forecasts on a quarterly basis in accordance with Air Force and local policy and procedures. Each item is identified by way of a national stock number (NSN). The NSN is akin to a stock keeping unit (SKU) in business settings and consists of a 13-digit code that uniquely identifies a repair part or component.

As illustrated in Figure 3.1, equipment specialists drive the organization's forecasting and demand planning process. In particular, ESs are responsible for ensuring projected usage data are accurate through quarterly file maintenance routines. Equipment specialists also compute quarterly forecasts in the form of demand rates (e.g. projected repairs per flight hour) for each of their assigned NSNs. These forecasts are computed within the organization's forecasting support system—the Forecasting Assessment and Comparison Tool (FACT)—which provides ESs with a choice of three primary statistical techniques: eight-quarter moving average, four-quarter moving average, and simple exponential smoothing. By policy, the eight-quarter moving average has been designated the organization's preferred forecasting method, though ESs are permitted to override the system-provided eight-quarter moving average by choosing from one of the other forecast methods or by inputting an estimated demand rate derived from contextual information.

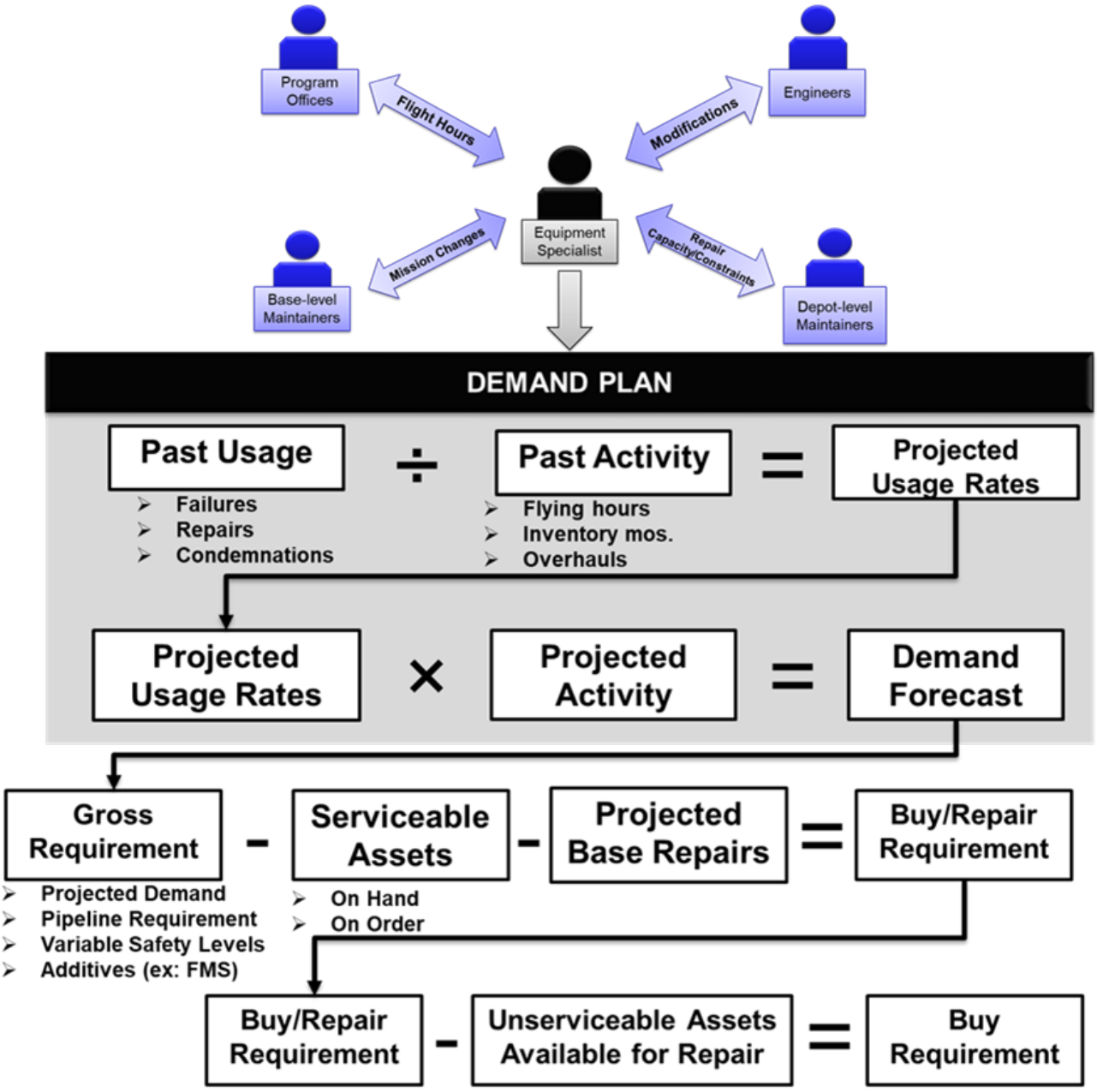


Figure 3.1. The Role of Equipment Specialist.

As in other forecasting settings, ESs commonly rely on information other than what is provided by the organization's forecasting system. Such information helps inform forecast decisions, especially with regard to selecting the appropriate forecasting method. Capturing and synthesizing contextual information is arguably the most challenging aspect of an ES's role. This is attributed to the fact that demand for a given repair part may be dependent upon fluctuations in flight hours across multiple aircraft. Additionally, technical modifications to parent systems or components as well as changes in base- and depot-level maintenance capabilities may also drive varying levels of demand. As a result, ESs must incorporate contextual information from a number of internal functional elements and external supply chain partners regarding such changes. The availability of contextual information may often be facilitated by recurring formal meetings, however, it is also the case that ESs may have to initiate contact in order to gain needed information.

Finally, as Figure 3.1 also illustrates, demand forecasts determined by ESs feed directly into the organization's purchasing and supply planning processes. In recognition of the influence ES forecast decisions have on these processes, the organization seeks to encourage accountability of ES forecast performance through several means. One of the primary means the organization employs to ensure accountability is by subjecting certain forecast decisions to management-level review and approval on the basis of dollar value. This is no surprise given the notoriously high costs of individual repair parts. Periodic management-level reviews of NSNs with poor forecast accuracy are also common. Furthermore, ES forecast performance is monitored regularly. Notably, ESs receive feedback on their forecast performance through forecast accuracy metrics displayed in the FACT as well as frequent management-level reviews of low-performing NSNs. The

organization also conducts periodic forecasting workshops whereby recurring issues or concerns can be voiced and addressed. Given their central role in the organization's demand forecasting process, the ESs were considered the best source of insight regarding the constructs of interest and were thus the target population for this dissertation.

Research Design

According to Creswell (2014), the decision of which research approach to take can be a function of several factors including the researcher's world view, design and methodology preferences, the research questions, and the researcher's personal experience. Given the stated purpose of this dissertation and the corresponding research questions, a mixed methods approach was deemed most appropriate. Specifically, an exploratory sequential mixed methods design was employed. The design consisted of an initial qualitative approach to refine and contextualize the concept of forecasting-focused climate as well as to develop a measurement scale. A second phase followed wherein a survey instrument was developed by combining the forecasting-focused climate scale with pre-existing scales for the forecasting task-technology fit (FTTF) construct and individual-level knowledge management effectiveness (KME) constructs. Finally, the third and final phase entailed deploying the survey instrument and collecting quantitative data. The following subsections detail the procedures taken in each of the respective phases.

Phase I: Qualitative Exploration.

As discussed in Chapter 2, organizational climate theory suggests that multiple climates exist in an organization and that scholars should, therefore, tailor the construct to

the outcome(s) of interest in their research. Though work by Davis and Mentzer (2007) previously identified relevant dimensions for a forecasting climate construct, the dimensions were specific to an organization level forecasting-focused climate. Moreover, their construct was tailored to the traditional sales forecasting context. While Davis and Mentzer's (2007) findings were certainly informative, a fresh attempt at identifying relevant dimensions of the forecasting climate construct was warranted due to the focus on the individual level of analysis and due to the unique context of a public sector (i.e. defense) organization. Therefore, the focus of the first phase of this research effort was to identify the relevant dimensions of individual-level forecasting-focused climate through theory-based interviews. The following subsections discuss the collection and analysis of qualitative data.

Qualitative Data Collection.

Qualitative data were primarily collected by way of semi-structured interviews. As Kvale (2007) notes, there are no set procedures for collecting qualitative data through interviews. However, Kvale (2007) does offer several general stages through which interview inquires progress in terms of data collection: 1) thematizing, 2) designing, 3) interviewing, and 4) transcribing.

In the *thematizing* stage of an interview inquiry, the researcher specifies the "why" and "what" of the interview inquiry. In other words, the researcher delineates the purpose of the inquiry and clarifies the theme(s) to be explored. As previously mentioned, the purpose of the interviews was to identify salient dimensions of forecasting-focused climate and to understand how they were experienced by forecasters in the research setting.

In line with Schneider's (1975) characterization of psychological climate as a function of cues or signals emanating from the work environment, the underlying theme of the interviews centered on the set of cues and signals perceived by ESs as indicative of desired or appropriate forecasting-related behaviors. Accordingly, the following research questions guided the qualitative phase of research:

1) *What cues of desired forecasting-related behaviors do forecasters perceive in their organizational environments?*
2) *How do forecasters respond to these perceived cues?*

Also considered during the thematizing stage were two other issues: who should be interviewed and how many interviews to conduct. In determining who should be interviewed, a purposeful sampling approach was taken. According to this approach, the researcher deliberately selects participants, sites, documents, or other material most likely to aid the research endeavor (Creswell, 2014; Creswell & Clark, 2011; Leedy & Ormrod, 2013). As day-to-day administration of forecasting activities was the main role of the ESs, it was reasonable to expect that ESs would be well-attuned to the forecasting-related cues and signals in their work environment. Thus, the sample consisted primarily of ESs from across the 14 SCMSs. Also, as suggested by Creswell and Clark (2011) and by Leedy and Ormrod (2013), an effort was made to ensure variability in the perspectives of the participants. In particular, an effort was made to ensure the sample reflected a range of forecasting experience levels. The desire to garner a variety of perspectives also prompted the inclusion of individuals from multiple hierarchical levels of the 448 SCMW, including multiple ES team leads and squadron commanders. One group

commander was also interviewed. This approach to sampling helped facilitate validity of the interview inquiry.

With regard to the required number of interviews, Kvale (2007) noted that most interview studies consist of between 5 and 25 interviews, though he advised researchers to simply interview as many subjects as necessary to find out what is needed. Other scholars, however, borrow from the grounded theory approach and suggest the need to achieve “theoretical saturation” before data collection ceases (e.g. Creswell, 2014; Creswell & Clark, 2011). While the concept of theoretical saturation is not well defined and is open to the subjective judgment of the researcher, there is evidence to suggest that theoretical saturation for theory-based interviews can be achieved anywhere between 6 and 12 interviews (Guest et al., 2006). For this research, an effort was made to conduct enough interviews so as to achieve theoretical saturation, however, the number of interviews which could realistically be accomplished were limited by Air Force policy constraints as well as issues of organizational access. In particular, due to challenges in coordinating approval by a local labor relations office, interviews were not able to be conducted with ESs from one of the three locations. In all, 10 interviews were conducted for this research.

Next, in the *designing* stage, the researcher takes actions to plan out interviews so as to ensure desired knowledge is obtained in an ethical manner. To maximize the likelihood that interviews achieved the stated purpose and aligned with the research questions, an interview protocol was created. Specifically, interviews were designed to be semi-structured and to cover multiple aspects of the underlying theme based on findings from relevant research. Moreover, a separate protocol was developed for individuals who

provided oversight or leadership for the forecasting process. The use of the interview protocols contributed to both the validity and reliability of the interviews by facilitating focused and consistent interviews. Finally, as part of the ethical considerations of the interview inquiry, two documents were developed to ensure informed consent from the interviewees. The background paper, informed consent form, and interview protocols are provided in Appendix B.

In the *interviewing* stage, the researcher considers the most appropriate style(s) of interview to apply based on the purpose of the interview inquiry as well as the associated setting. Kvale (2007) identified and discussed several styles that researchers might employ. According to Kvale (2007), conceptual interviews aid in exploring the meaning and dimensions of a particular phenomenon and its associated nomological network. Given the theoretical underpinnings of the interview study, a conceptual style was deemed most appropriate for uncovering the relevant dimensions of forecasting-focused climate.

Finally, with regard to the *transcribing* stage, the main concern for the researcher is preparing the interview material for analysis. With the exception of three interviews, all interviews were recorded using the Voice Record Pro iPhone application. The audio files were exported from the application directly to a restricted access DropBox folder from which a third party service could retrieve the files for transcription. To facilitate reliability of the transcription process, a list of common acronyms, technical terms, and phrases were provided. Additionally, to maintain participant confidentiality, transcribers were advised to omit the names of participants and to only identify speakers as either the

interviewer or interviewee. Finally, to facilitate validity of the interview transcripts, the interview recordings were transcribed verbatim.

All challenges notwithstanding, a total of 10 formal interviews were conducted between 11 and 14 July, 2016. Though more interviews may have been desirable, the sample size was deemed sufficient on the basis of the researcher's ability to fulfill the stated purpose of the interview inquiry as well as to answer the stated research questions. Moreover, documents and visual aids (e.g. emails, PowerPoint presentations, etc.) were also included in the data collection effort, which facilitated theoretical saturation. The inclusion of these items also facilitated triangulation and, thereby, contributed to the validity of the themes and patterns identified during the qualitative data analysis.

Of the 10 interviews, 7 were with ESs while the remainder were conducted with ES team leads. An additional 3 informal, unstructured interviews were conducted with squadron commanders (2) and one senior leader (a group commander and acting deputy wing commander at the time). Interviews conducted with ESs ranged from 30 minutes to an hour while informal interviews conducted with participants other than ESs were typically between 20 and 30 minutes.

The ESs interviewed as part of this study held diverse levels and types of experience. Overall, ESs reported a median of 9.5 years of forecasting experience. The least experienced ES reported 18 months of forecasting experience while the most experienced ES reported 15 years of forecasting experience. The ESs that were interviewed were also diverse in terms of the number and types of items they managed. Notably, interviewees reported responsibility for as few as 100 NSNs and as many as 500 NSNs.

Similar diversity of experience was found among the managers though the squadron commanders and group commander reported less direct forecasting experience. The ES team leads, on the other hand, typically possessed substantial forecasting experience. The least experienced team lead reported 8 total years of forecasting experience and the most experienced team lead reported 19 years of forecasting experience. Notably, 3 of the 4 team leads reported having gained forecasting experience as an ES prior to taking their management role. Furthermore, across all interviewees, 9 of the 14 SCMSs and two of the three SCMGs were represented. The 5 SCMSs not represented were assigned to the 748 SCMG at Hill AFB and were not available due to the coordination issues previously noted. Lastly, transcription of the interviews took place between 18 July and 1 August, 2016. With the exception of one audio file that was unable to be transferred due to a formatting error, all recordings were successfully transcribed resulting in 122 pages of single-spaced text data.

Qualitative Data Analysis.

Once all interviews were transcribed, the qualitative exploration phase continued with an analysis of the qualitative data. The primary means of extracting meaning from the 122 pages of text data was through *coding* and *theming* the data. As there are no strict guidelines for analyzing qualitative data, this research relied upon guidance provided by Saldaña (2016) and Braun and Clarke (2006).

Coding the Data. As one means of analyzing qualitative data, *coding* consists of using codes to "translate" data and, thus, attribute interpreted meaning to the data for the purposes of pattern detection and categorization (Saldaña, 2016). A *code* is defined as a researcher-generated word or short phrase that "symbolically assigns a summative,

salient, essence-capturing, and/or evocative attribute for a portion of language-based or visual data" (Saldaña, 2016; p. 4). The process of coding is often iterative in nature and may involve multiple coding approaches and cycles.

For the purposes of this research, the qualitative data was coded over two cycles which employed three coding techniques. Moreover, the coding process was facilitated by the free qualitative text analysis software, QDA Miner Lite. For the first cycle of coding, a combination of *provisional coding* and *in-vivo coding* was used to perform an initial analysis of the qualitative data. The provisional coding technique is appropriate when researchers seek to build on or corroborate previous research (Saldaña, 2016). With provisional coding, the researcher begins with a predetermined list of codes prior to beginning data analysis. The codes are typically generated on the basis of a review of relevant literature and previous research findings (Saldaña, 2016). Table 3.1 summarizes the 20 provisional codes used during first-cycle coding. Each code represents either a distinct dimension of psychological climate taken from widely-cited organizational climate publications or a potential dimension of forecasting-focused climate implied by relevant forecasting-specific literature.

Table 3.1. Provisional Codes.

Dimension	Source
Leader Facilitation and Support	James and James (1989)
Role Stress/Lack of Harmony	
Job Challenge and Autonomy	
Workgroup Cooperation, Warmth, and Friendliness	
Participation	Ostroff (1993)
Growth	
Innovation	
Achievement	
Hierarchy	
Structure	
Company Vision	
Open and Clear Communication	Schulte et al. (2006)
Training Focus	
Team Focus	
Clarity	
Rewards for Service	
Use of Judgment	McCarthy-Byrne et al. (2011)
Feedback	
Knowledge	
Others' Level of Seriousness	

In addition to the provisional coding technique, in-vivo coding was also used during first-cycle coding. In contrast to provisional coding, in-vivo coding draws codes directly from the actual language spoken by interviewees. As Saldaña (2016) suggests, this technique is appropriate as a check on whether or not the researcher has truly captured what is significant about the phenomena under study from the perspective of the interviewee. Through the course of first-cycle coding, a total of 127 unique in-vivo codes were generated. Taken together, both coding techniques enabled both a top-down,

deductive (provisional coding) and bottom-up, inductive (in-vivo coding) approach to refining the forecasting-focused climate construct.

Once provisional and in-vivo codes were applied to the interview transcripts, the qualitative data were refined through a second cycle of coding. According to Saldaﾠha (2016), the primary goal during second cycle coding is to organize the array of first-cycle codes (i.e. in-vivo codes). *Pattern coding* was deemed the ideal technique for accomplishing this objective. Pattern coding is considered an appropriate method when researchers seek to condense large amounts of data into smaller analytic units or develop major themes from the data (Saldaﾠha, 2016). In practice, the researcher examines first-cycle codes, assesses their commonality, and assigns a pattern code to capture "an emergent theme, configuration, or explanation" (Saldaﾠha, 2016; p. 236). That said, a total of 10 pattern codes were produced as a result of second cycle coding. The pattern codes captured 97 of the original 127 in-vivo codes while the other 34 in-vivo codes were subsumed under provisional codes. Table 3.2 summarizes the pattern codes and provides examples of associated in-vivo codes.

Table 3.2. Pattern Codes.

Pattern Code	Count	Examples of Associated In-Vivo Codes
Complexity	28	"Forecasting is intertwined with everything else that we do" "So many things involved" "It takes four years to understand the nuances"
"Checks and Balances"	15	"As long as you're justified" "Do not change numbers unless you have documentation" "Everything I do, I have a signature stamp"
The Goal/Expectation	14	"As accurate as possible" "Do it the best I can" "Never going to get one perfect" "Over-forecasting would be better"
Personal Pride/Motivation	11	"A personal thing" "A lot of people don't have that drive" "Some ESs don't put a lot into forecasting" "I have a drive and passion for this"
Role of Tacit Knowledge	9	"Got to understand your system" "Over time you figure out what to do" "Research, research, research" "Asking the old heads"
Differences	5	"Different mindset for each supervisor" "Some squadrons different" "Depending on structure"
Senior Leader Perspective	5	"War on excess" "Forecasting never seems to be on their radar" "Emphasis on supportability"
Uncertainty of Demand	2	"Sometimes it's a guess" "Basically a guessing game"
Forecasting Support System	2	"It red flags a lot of mistakes" "The systems are just so old"
Procedures/guidance	2	"23-1 helped me a lot" "I like for it to be in black and white"

As the last step of second cycle coding, the 10 pattern codes were further evaluated to identify any overlap with organizational climate theory (i.e. provisional codes). As a result, 3 pattern codes were aligned with provisional codes. Specifically, the "complexity" pattern code was considered as one aspect of the "role stress" dimension of

psychological climate; “the goal/expectation” and “differences” pattern codes were both found to overlap with the leadership facilitation and support dimension of psychological climate; and the “role of tacit knowledge” pattern code was merged with the “use of judgment” provisional code which was taken from McCarthy-Byrne et al. (2011) as a potential facet of forecasting-focused climate. The other pattern codes were omitted either due to alignment with other constructs in the conceptual model (e.g. differences, uncertainty of demand, forecasting support system, and procedures/guidance) or an association with constructs or ideas outside the scope of the dissertation (e.g. personal pride/motivation and senior leader perspective). In the end, only one of the pattern codes (“checks and balances”) was considered to represent a distinct dimension not already captured by the provisional codes. Notably, the “checks and balances” pattern code started as an in-vivo code, having emerged directly from interviews with multiple ESs. Looking across related excerpts of interview transcripts, “checks and balances” was found to capture signals and cues perceived by forecasters as indicative of the degree to which they would be held accountable for their forecasting related judgments and decision-making through inspections, audits, and other mechanisms. Though this was not included among the initial provisional codes, it is a concept which has received considerable attention in the forecasting management literature (e.g. Fildes & Goodwin, 2007; McCarthy-Byrne et al., 2011; Mentzer & Moon, 2005; Sanders & Ritzman, 2001).

Theming the Data. Following second cycle coding, an effort was made to “theme the data”. Specifically, efforts were made to further refine the remaining provisional codes and pattern codes and, thereby, identify the most pertinent dimensions of the forecasting-focused climate construct. Scholars acknowledge that identifying themes is

largely a subjective decision made by the researcher (Braun & Clarke, 2006; Harding, 2013; Saldaña, 2016). Nonetheless, this research relied upon the guidance found in Harding (2013) and Braun and Clarke (2006) with regard to identifying major themes from qualitative data. Of note, Harding (2013) suggested that a code shared by at least a quarter of interview transcripts qualified for consideration in the qualitative analysis while a code common to approximately three quarters of transcripts indicated a major theme. Additionally, Braun and Clarke (2006) suggested that, regardless of the approach to identifying themes, researchers should ultimately allow the overarching research question to guide the process of identifying themes. Applying both of these perspectives, a total of 9 themes were identified as representing potential dimensions of forecasting-focused climate. Table 3.3 ranks the themes based on their frequencies both in terms of their prevalence across individual interviews (% of cases) and how often the themes appeared overall (% of codes).

Additionally, selected publications that support inclusion of the respective dimensions are also provided. In two cases, themes were not directly supported by either the organizational climate literature (i.e. use of judgment and tacit knowledge) or the forecasting literature (i.e. workgroup cooperation). In the case of the former, while organizational climate theory does not specifically touch on the topic of judgment and tacit knowledge, this concept is somewhat captured by the concept of job autonomy (e.g. Jones & James, 1979; Patterson et al., 2003). Furthermore, in the case of the latter theme, though forecasting management literature does not specifically address the role of a forecaster's workgroup in supporting forecaster performance, research on the topic of

team based approaches to forecasting (e.g. Kahn & Mentzer, 1994; Moon et al., 2003) may be viewed as indirectly supporting this theme.

Lastly, it should be noted that two of the themes/dimensions (feedback and rewards, recognition, & incentives) were included despite having failed to achieve Harding's (2013) recommendations with regard to frequency. Though they appeared in less than three quarters of cases, their inclusion was considered justified based on the prominence of both themes in forecasting management literature as was discussed in Chapter 2. Moreover, their inclusion is in line with Braun and Clark's (2006) recommendation that inclusion be determined based on the degree to which a theme captures something important to the guiding research question.

Table 3.3. Proposed Dimensions of Forecasting-focused Climate.

	Frequencies				Supporting References	
Proposed Dimension	% codes	Rank	% cases	Rank	Climate Theory Literature	Forecasting Research
Knowledge ***Perceptions regarding the importance/impact of forecasting***	4.3	5	100	1	James & James (1989); Brown & Leigh (1996)	Fildes & Hastings (1994); McCarthy-Byrne et al. (2011); Moon et al. (1998)
Supervisor Support & Facilitation ***Perceptions of the supervisor's role in supporting the forecaster***	9.2	1	92.3	2	James & James (1989); Schulte et al. (2006); Lawthorn et al. (2005); Brown & Leigh (1996)	Fildes & Hastings (1994); Winklhofer et al. (1996); Mentzer et al. (1997); Mentzer et al. (1999)
Structure ***Perceptions of rules/accountability mechanisms***	6.7	2	84.6	3	Ostroff (1993); Lawthron et al. (2005)	Fildes & Hastings (1994); Sanders & Ritzman (2001); Winklhofer et al. (1996)
Use of Judgment/Domain Knowledge ***Degree to which forecaster's may leverage judgment/knowledge***	5.8	3	76.9	4	None Found	McCarthy-Byrne et al. (2011); Mentzer et al. (1999); Sanders & Ritzman (2001); Moon et al. (2003); Fildes et al (2009)
Training ***Adequacy of forecasting-related training***	4.4	4	76.9	5	Schulte et al. (2006); Lawthorn et al. (2005)	Fildes & Hastings (1994); McCarthy-Byrne et al. (2011); Winklhofer et al. (1996); Mentzer et al. (1999); Moon et al. (2003); Fildes et al (2009)
Role Stress & Perceived Complexity ***Degree to which competing priorities/entities interfere with forecasting***	3.7	7	76.9	6	James & James (1989); Schulte et al. (2006)	Winklhofer et al. (1996)
Workgroup Cooperation ***Degree to which the individual perceives their workgroup as supportive***	2.3	9	76.9	7	James & James (1989); Ostroff (1993)	None Found
Feedback* ***Perceptions of the adequacy/usefulness of forecasting-related feedback***	2.8	8	69.2	8	Lawthorn et al. (2005)	Fildes & Hastings (1994); McCarthy-Byrne et al. (2011); Winklhofer et al. (1996); Sanders & Ritzman (2001); Mentzer et al. (1999); Moon et al. (2003); Lawrence et al. (2006)
Rewards, Recognition, & Incentives* ***Perceptions of the rewards, recognition, and incentives related to forecasting performance***	1.8	10	46.2	9	James & James (1989); Parker et al. (2003); Schulte et al. (2006); Ostroff (1993); Brown & Leigh (1996)	McCarthy-Byrne et al. (2011); Mentzer et al. (1999); Davis & Mentzer (2007)

Scale Development.

The qualitative exploration phase of the research concluded with an effort to develop a scale for measuring forecasting-focused climate perceptions. The scale development stage was based on the guidance of DeVellis (2003). As a first step, DeVellis (2003) recommends that researchers clearly specify what is to be measured. This step was achieved through the review of relevant literature. As discussed in Chapter 2, forecasting-focused climate is conceptualized as an individual's perceptions of how their work environment encourages and supports positive forecasting-related behaviors. Moreover, given the findings of the qualitative data analysis individuals' perceptions of forecasting-focused climate were expected to vary along 9 dimensions: 1) knowledge; 2) supervisor support and facilitation; 3) structure; 4) use of judgment and tacit knowledge; 5) training; 6) role stress and perceived complexity; 7) workgroup cooperation; 8) feedback; and 9) rewards, recognition, and incentives.

Next, an initial pool of items was generated for each of the 9 proposed dimensions of forecasting-focused climate. Items were generated through a combination of adapting existing psychological climate scale items as well as generating statements grounded in key ideas originating from forecasting literature and the interviews. Furthermore, items were designed as declarative statements that would be evaluated by respondents in terms of agreement along a Likert scale. In all, 56 items were produced for the initial pool.

Once the initial pool of items was generated, 4 professors were consulted to review the items for relevance, clarity, and conciseness (DeVellis, 2003). Based on the feedback received, several items were revised and one was dropped altogether. In particular, all negatively-worded items were revised to be written as positively-worded

statements. Additionally, the “knowledge” dimension was renamed “job importance” in order to better align the dimension with its corresponding definition and items.

Following an expert review, DeVellis recommends administering the items to a development sample so as to conduct an initial assessment of the scale’s reliability and validity. However, given the relatively small size of the target population and the constraints on organizational access, a traditional pilot test of the new scale was not feasible. To overcome this limitation, an alternative approach was taken to assess the scale’s preliminary validity. Recognizing the common restrictions associated with research conducted in field settings, Anderson and Gerbing (1991) developed a methodology capable of predicting how likely an item was to be retained or deleted in an assessment of the validity of a measurement model. Specifically, their item-sort method provided a means to evaluate a measure’s *substantive validity.* Substantive validity of a measure is defined as “the extent to which that measure is judged to be reflective of, or theoretically linked to, some construct of interest” (Anderson & Gerbing, 1991; p. 732).

Accordingly, an item-sort task was developed to test the forecasting-focused climate scale. A total of 29 forecasting subject matter experts were invited to complete the task by electronic mail. As part of the task, participants were provided an Excel spreadsheet consisting of the 9 proposed forecasting-focused climate dimensions and their definitions across the columns and the items randomly listed in each row. Participants were instructed to carefully read the names of the dimensions and their associated definitions. Next, they were asked to classify each of the 55 items to one and only one of the dimensions by marking an “X” in the appropriate cell. A completed version of the task is provided in Appendix C. In all, 17 usable spreadsheets were

returned. Each spreadsheet was graded and, for each dimension, two measures of substantive validity were calculated: the proportion of substantive agreement (p_{sa}) and the substantive validity coefficient (c_{sv}).

The proportion of substantive agreement represents the proportion of respondents who assign an item to its intended dimension and ranges from 0 to 1 with larger values indicating greater substantive validity. While p_{sa} can be interpreted as indicating the degree to which an item reflects its intended dimension, it does not capture the degree to which an item may reflect an unintended dimension. For that reason, Anderson and Gerbing (1991) propose c_{sv} as a useful indicator of the degree to which participants accurately classify an item to its intended dimension. It may take on values from -1.0, indicating an item has high substantive validity for a dimension other than its intended dimension, to 1.0, which indicates strong substantive validity for an item assigned to its intended dimension. Both indices were calculated for each individual item and then aggregated for each of the respective dimensions. Table 3.4 reflects the initial findings from the pre-test.

Table 3.4. Initial Pre-Test Findings.

Dimension	# of Items	Substantive Validity (csv)	Proportion of Substantive Agreement (p_{sa})
Job Importance	5	0.86	0.93
Supervisor Support	9	0.75	0.88
Training	8	0.74	0.87
Feedback	6	0.69	0.84
Workgroup Cooperation	5	0.67	0.84
Use of Judgment	3	0.45	0.73
Rewards/Recognition	6	0.43	0.72
Role Stress	7	0.33	0.66
Structure	6	0.14	0.57

Of the 9 proposed dimensions, 4 (use of judgment, rewards/recognition, role stress, and structure) were found to require further attention. Specifically, 12 items across the 4 dimensions did not meet Anderson and Gerbing's (1991) recommended cutoff (c_{sv} ≥0.50). When c_{sv} is not satisfactory, researchers are advised to revise or reassign individual items and/or to refine definitions for the applicable dimensions. In the first iteration of refining the scales, a total of 5 items were deleted. Furthermore, 3 items from the "use of judgment" dimensions were realigned under the "structure" dimension which, borrowing from forecasting literature, was subsequently renamed "restrictiveness". The restrictiveness dimension was defined so as to specify a focus on forecasting-related restrictions and accountability measures enacted by policy, procedure, or local practice. Together these changes resulted in a reduction to 51 items and 8 dimensions. Finally, though it was not among the problematic dimensions, comments from subject matter experts suggested the definition for the workgroup cooperation dimension needed to be revised so as to clearly specify which of a forecaster's coworkers were considered part of their workgroup.

Following the initial efforts to refine the scale, the p_{sa} and c_{sv} indices were recalculated both for individual items as well as for each dimension. In spite of the changes made to the "role stress" dimension (i.e. deletion of 3 items), the dimension as a whole still failed to meet satisfactory substantive validity and was, therefore, omitted from the scale. All other changes to the scale resulted in improvements to substantive validity indices beyond the recommended cutoff. In the end, the scale was reduced to 7 dimensions and 44 items. Table 3.5 reflects the final results of the pre-test.

Table 3.5. Substantive Validity Results.

Dimension	# of Items	Substantive Validity (c_{sv})	Proportion of Substantive Agreement (p_{sa})
Job Importance	5	0.86	0.93
Supervisor Support	9	0.75	0.88
Training	8	0.74	0.87
Feedback	6	0.69	0.84
Rewards/Recognition	4	0.68	0.84
Workgroup Cooperation	5	0.67	0.84
Restrictiveness	7	0.53	0.77

Phase II: Instrument Development.

The objective of the second phase of the study was to leverage the insights from the qualitative exploration phase to develop a valid and reliable survey instrument. In combination with the forecasting-focused climate scale developed in the prior phase, existing measures were adapted and incorporated into a single survey instrument to capture beliefs about forecasting task-technology fit (FTTF) and individual-level knowledge management effectiveness (KME). Additional questions were included in the survey to collect demographic information from the participants.

Forecasting task-technology fit was measured with items borrowed from Smith and Mentzer (2010a). Forecasting task-technology fit is conceptualized as a higher order construct consisting of two first-order factors: forecasting system quality and forecasting system accessibility. Taken together, the construct represents the extent to which the forecasting procedures and features/technologies represented in the forecasting support system "fit" or facilitate efforts to complete the forecasting task. The construct was operationalized as respondents' evaluations of the quality and accessibility of the

forecasting systems(s) they depended upon for accomplishing their forecasting-related tasks. Survey respondents were asked to indicate a level of agreement or disagreement with a total of 8 items based on a 7-point Likert scale ranging from strongly disagree to strongly agree. As examples, one item from each subscale is provided below.

Forecasting System Quality: *The system I use for forecasting contains historical data at the right level of detail to support my forecasting efforts.*

Forecasting System Access: *The system I use for forecasting is easily accessible when I need to create forecasts.*

Knowledge management effectiveness was measured using items from Sabherwal and Becerra-Fernandez (2003). The items were minimally-adapted for the context including the addition of forecasting-specific terms as well as one unique item to capture perceptions pertaining to the flow of knowledge originating from outside the respondent's organization. Taken together, the items assessed individuals' satisfaction with the availability of forecasting-related knowledge available to them for use in the forecasting task. Specifically, knowledge management effectiveness was operationalized as respondents' beliefs regarding how knowledge was captured, stored, and made available for use in their forecasting-related tasks. Furthermore, "knowledge" was defined for the respondents as referring to the insight regarding future actions or events (i.e. by maintenance units, program offices, etc.) that could impact future demand for their assigned items (NSNs) and that was not reflected in the forecasting system(s). Respondents were asked to choose a level of agreement or disagreement with a total of 4 items along a 7-point Likert scale ranging from strongly disagree to strongly agree. As one example, respondents indicated their agreement with the following statement: "*The*

knowledge available to me from external individuals/organizations (i.e. program office, maintenance units, etc.) improves my ability to forecast effectively".

For the pre-existing scales, the original Cronbach's alphas were all reported to be 0.70 or above providing evidence of satisfactory reliability. The adaptations to the original scales were kept to a minimum and were only implemented in order to make the items appropriate to the forecasting context. Also, a total of 8 survey questions collected information pertaining to the respondent's gender, age, education, forecasting experience, job experience, and workload. A complete set of survey items including items for the forecasting-focused climate scale can be found in Appendix D.

Survey Pre-Test.

Once the survey instrument was assembled, a pre-test was conducted in order to ensure item specificity, representativeness, readability, and face validity. The survey was sent to four supply chain management professors for review. Based on the professors' feedback, the order of the questions and minor grammatical edits were made to improve the flow and readability of the survey.

Survey Pilot Test.

Following the initial pre-test of the survey instrument, the survey was built in the Air Force Institute of Technology's Web Survey Information Retrieval System (WebSIRS), a locally-developed platform for administering surveys. Shortly thereafter, seven forecasting subject matter experts from the 448th Supply Chain Management Wing were invited to pilot test the survey. Additionally, four professors and three doctoral students were also invited to take the online survey. Though the objective of the pilot test was similar to that of the pre-test, the main difference was that the pilot test sought to

simulate the actual conditions under which the survey would be taken (Fink, 2009). In particular, attention was given to evaluating the ease with which respondents could access and use the survey as well as estimating the time to complete the survey. Testing the effectiveness and reliability of the WebSIRS data collection protocol was also a priority.

In general, no major issues were reported with regard to survey accessibility or ease of use. However, some concerns were raised with regard to the length of the survey as some participants reported having taken 30 minutes to complete the survey. Also related to this issue was the inability to incorporate a progress bar due to a lack of that feature within the WebSIRS platform.

To address these issues, several survey items were deleted. In particular, one item from the training dimension of the forecasting-focused climate scale was deleted due to significant overlap with another item and all 5 items on the forecasting support system scale were deleted as they were not necessary from a theoretical standpoint. Furthermore, the survey cover page was revised to explicitly state the number of questions and estimated time of completion.

In addition to the above issues, feedback from the forecasting subject matter experts prompted efforts to further clarify terms used in a few of the survey items. Feedback also pinpointed the need to change survey settings so as to prevent survey respondents from skipping important questions. Finally, changes were made to the demographics-related questions in order to ensure they were appropriately-worded for the context. For example, a question asking respondents to indicate the extent of their forecasting experience was changed to simply ask how long respondents had been an ES.

Additionally, to facilitate collection of individuals' forecasting performance data, questions were added to mitigate the possibility that an individual's survey responses were inadvertently matched to the performance data for another forecaster (e.g. due to a reassignment of workload).

In conclusion, although researchers are advised to pilot test the survey on a large sample taken from the target population (i.e. Anderson & Gerbing, 1991; Churchill, 1979; DeVellis, 2003), as previously mentioned, the limited size of the target population as well as constraints on organizational access restricted the scope and scale of the pilot test such that calculating scale reliability and validity was not feasible prior to full survey deployment. Nonetheless, evidence of substantive validity from the pre-test of the forecasting-focused climate scale in addition to the use of pre-existing scales, and, finally, the results of the pilot test all contributed to the reliability and validity of the survey instrument.

Phase III: Quantitative Data Collection.

In the final phase of the research, the objective was to fully deploy the online survey and collect quantitative data. On February 1st, 2017, all 327 ESs in the 448th Supply Chain Management Wing were emailed an invitation to participate in the survey. The invitation contained information about the intent of the study, the survey sponsor, as well as the WebSIRS link to the online survey. The invitation also advised of the voluntary nature of the survey as well as an assurance of confidentiality. A copy of the invitation is provided in Appendix D.

Bi-weekly reminders were sent to the ESs with the final reminder sent on March 15th. Finally, in order to garner increased participation in the survey, face-to-face

informational meetings were conducted with ESs at Hill AFB, Tinker AFB, and Warner Robins AFB between April 10th and 17th. The meetings lasted between 10 and 15 minutes and consisted of a brief discussion regarding the research objectives and methodologies. Furthermore, as an incentive for individuals to complete the survey, individuals completing the survey following the informational meetings were given an opportunity to be entered into a random drawing for three $50 Amazon gift cards (one for each base).

Lastly, all survey responses were housed within the secure WebSIRS database, with access to the data limited to the primary researcher. No additional protection measures were deemed necessary to safeguard the confidentiality of participants at this stage of the research as the data file did not contain individual identifying information. Upon conclusion of the survey on April 19th, a total of 237 responses had been received. Given 327 individuals in the entire population of equipment specialists, this represented a response rate of 72.5%. However, of the 237 responses, only 154 were fully useable thus equating to an effective response rate of 47.1% of the population. Furthermore, of the 154 usable responses, only 78 provided national stock numbers (i.e. the link to historical data). Of the 78 responses providing NSNs, 20 were not usable due to workload changes over the preceding year. Specifically, the ESs were re-assigned to a different group of supply items which created the possibility of mismatching individuals' survey responses and historical performance data. Further, an additional three cases dropped from the analysis due to discrepancies in the organization's support system. The remaining 55 NSNs were consolidated in an Excel spreadsheet using randomly-generated respondent identification codes and sent to a data broker within the 448th Supply Chain Management Wing. In return, the data broker provided forecasting performance data and other relevant

information (i.e. item cost, forecast type, etc.) for each NSN. Once received, the forecast performance data was matched to individual survey respondents. This subsample represented 16.8% of the sampling frame. Figure 3.2 summarizes the results of the quantitative data collection process.

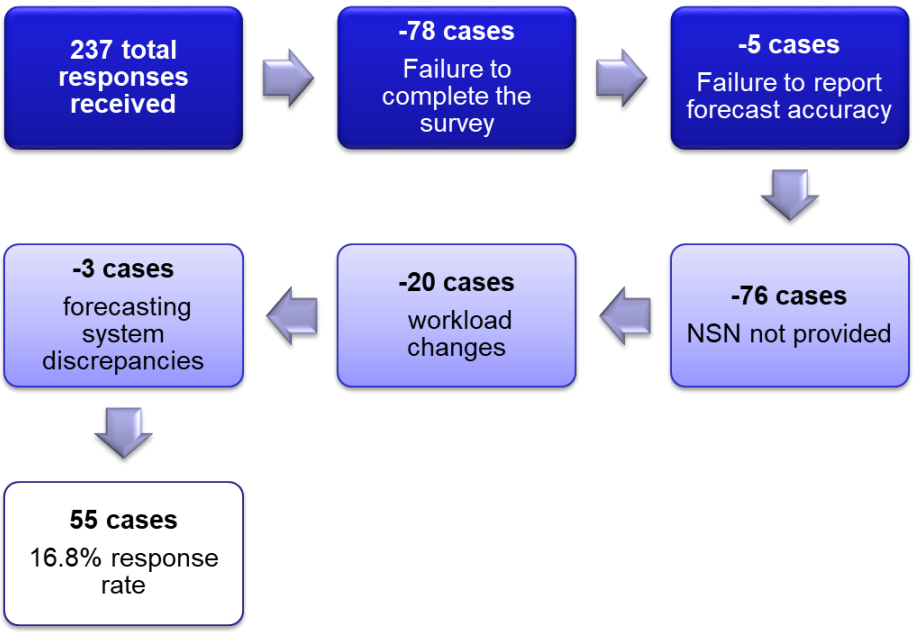


Figure 3.2. Quantitative Data Collection Results.

IV. Analysis and Results

Chapter Overview

This chapter presents the analysis of data collected through the methods discussed in Chapter 3. First, the chapter begins with an assessment of the survey responses including missing data, non-response bias, and participant demographics. Item-level descriptive statistics are also reported. Next, the results of confirmatory factor analysis are reported including measures of scale reliability and validity. Finally, the chapter concludes by reporting the results of tests of hypotheses using structural equation modeling and multiple linear regression techniques.

Data Screening

The sampling frame for this research effort consisted of Air Force forecasters, particularly the population of equipment specialists (ESs) assigned to the 448th Supply Chain Management Wing. As reported in Chapter 3, the survey was administered from February 1st to April 19th, 2017. As of the beginning of the survey period (February 1st, 2017), the ES population consisted of 327 individuals. Upon conclusion of the survey on April 19th, a total of 237 responses had been received. Given 327 individuals in the entire population of equipment specialists, this represented a response rate of 72.5%.

Item-Level Statistics.

As Hair et al. (2010) advise, the initial step in the data analysis process is to screen the data. In particular, researchers are advised to assess the nature and impact of missing data. As part of this assessment, researchers must weigh both substantive concerns (i.e. biased data) and practical concerns (i.e. reduction in sample size) in

deciding if the extent of missing data warrants action. An examination of the 237 survey responses suggested that the overwhelming majority of missing data were due to incomplete surveys. Specifically, of the 237 surveys, only 160 surveys included responses to all of the survey items related to the key constructs of interest. As a result, the 77 incomplete surveys were dropped from consideration in the analysis. Further examination of the 160 remaining responses revealed six surveys were missing responses for the dependent variable (self-reported forecast accuracy). In line with the recommendations of Hair et al. (2010), cases with missing values on the dependent variable were deleted so as to avoid the artificial increase of relationships with the independent variables. The remaining data set consisted of 154 usable responses. The only exception was one survey that was missing responses for the Rewards dimension of the Forecasting-focused Climate scale but was otherwise complete.

Given the low overall incidence of missing data for this survey, mean substitution was deemed an appropriate method for replacing missing data. Additionally, it should be noted that multiple surveys reflected missing data for items pertaining to demographic variables. Where possible, mean substitution was also used to replace demographic data. Appendix E contains all item-level descriptive statistics to include the mean, standard deviation, and frequency of missing values for the 154 usable responses. The final effective response rate for the survey was thus 47.1%.

Participant Demographics.

Based on the available demographic data, participants appeared to be predominantly male and, on average, 50 years of age. Additionally, participants most commonly indicated that they held between 5 and 8 years of forecasting experience and

an education level of “some college”. Interestingly, respondents most frequently indicated they held between 1 and 4 years of experience with their assigned supply items (i.e. national stock numbers) as well as with their assigned section (i.e. ES team) and assigned flight. This finding seemed to suggest considerable turnover among ESs as was reported by multiple interviewees during the qualitative phase of the research. In terms of assigned workload, participants most commonly reported a workload of between 175 and 224 national stock numbers (NSNs). Finally, all three locations were represented in the data set with most respondents (43.8%) indicating their assigned location as Hill Air Force Base, Utah. Appendix F provides further detail of all demographic data.

Assessment of Univariate and Multivariate Normality.

Next, the survey response data were examined for both univariate and multivariate normality. First, the distribution of responses to individual items were assessed graphically through visual inspection of histograms and empirically through examining skew and kurtosis statistics. Responses to several items appeared to be heavily skewed and were thus marked for deletion from subsequent analyses (Kline, 2011). This included one item each from the job importance, supervisor support, and restrictiveness dimensions of the forecasting-focused climate scale. In general, these items appeared to be artifacts of the organization’s standardized approach to forecasting across all locatios and sub-units. For example, one item on the restrictiveness scale (RE4) addressed the issue of providing justification for forecast adjustments. It is likely that responses for this item were negatively skewed due to the fact that organizational policy (i.e. across all locations/unites) mandated that ESs provide justification for their adjustments.

Additionally, distributions for all 5 items from the workgroup cooperation dimension of forecasting-focused climate reflected extreme skew. To further assess normality, the distributions of scores for each scale were also evaluated visually and empirically. As expected, the Workgroup Cooperation sub-scale reflected severe negative skew.

While it may have been possible to preserve the data pertaining to workgroup cooperation dimension (e.g. through transformation), it was deemed appropriate to completely omit the scale. This decision was justified on the basis of a combination of factors. First, although the scale met minimum recommended thresholds for substantive validity, it was nonetheless one of the lower-performing scales. Second, though social desirability bias was not directly assessed in this research, the highly (negatively) skewed item- and scale-level statistics could be indicative of an underlying social desirability bias. Further, the skew could possibly be attributed to the nature of the context. In particular, during the qualitative phase of the research, several ESs reported the importance of on the job training and the role of experience in enabling an ES to forecast accurately. It is possible that items related to workgroup cooperation touched on these themes.

Finally, univariate normality was also assessed for responses to all items pertaining to demographic data. Here again, several distributions displayed considerable skew. As a result, all demographic data (with the exceptions of gender and location) were re-coded to categorical variables representing “high” or “low” levels of a given attribute. For example, with regard to an ES’s reported experience with their assigned NSNs, the median response indicated ESs held between 1 and 4 years of experience, corresponding

to a Likert-scale response of “2”. For the categorical variable, responses were re-coded such that all Likert-scale responses less than or equal to 2 were designated as “low” while all other Likert-scale responses were designated as “high”. The decision to re-code variables into only two categories was primarily to maintain relatively uniform numbers of observations from one category to the next. Deleted items/scales are annotated in Appendix F.

Confirmatory Factor Analysis

After screening the data, the analysis moved toward assessing the appropriateness of the theorized measurement model. Confirmatory factor analysis (CFA) was the method of choice and was executed using Amos 18 structural equation modeling software. Although CFA entails testing the degree to which an *a priori* specified measurement model is supported by data, Kline (2011) notes that such analysis is not strictly confirmatory. That is, researchers may use CFA from a model generation perspective whereby specified models are assessed for fit and iteratively re-specified until the researcher arrives at a model that is aligned with theory, reasonably parsimonious, and reflects acceptable fit with the data (Kline, 2011). With this approach in mind, the CFA was executed based on the comparison of three models. For all three models, the knowledge management effectiveness and forecasting task-technology fit constructs were represented according to theory and findings from previous research. Specifically, Smith and Mentzer (2010a) provided evidence that forecasting task-technology fit is best represented as a higher-order factor reflecting both a system quality and system

accessibility dimension. With regard to knowledge management effectiveness, Sabherwal and Becerra-Fernandez (2003) specified a single first order factor.

Where the three competing models differed was in how the forecasting-focused climate construct was specified. First, a baseline model (Model #1) was specified such that the forecasting-focused climate construct was represented as a single latent variable with all 35 items from the hypothesized dimensions allowed to load directly on the factor. Next, Model #2 specified a forecasting-focused climate construct wherein the 35 items were assigned to their respective dimensions and each dimension was represented as a first-order factor. Finally, as suggested by theory, Model #3 directly represented the hypothesized structure of forecasting-focused climate as a higher-order factor reflecting 6 first-order factors as the various dimensions of the construct.

Each model was assessed for model fit using the model chi-square test statistic as well as four commonly-reported approximate fit indices: the Comparative Fit Index (CFI), the Tucker-Lewis Index (TLI), the Root Mean Squared Error of Approximation (RMSEA), and the Standardized Root Mean Squared Residual (SRMR) (Bagozzi and Yi, 2011). The model chi-squared statistic is associated with a test of the "exact-fit hypothesis"; a test of whether any discrepancies exist between the population covariances and those predicted by the measurement model (Kline, 2011). When conducting the test at the 0.05 level of significance, a p-value greater than 0.05 suggests the measurement model is consistent with the covariance data.

Several limitations of the chi-squared statistic have been noted in the literature. Notably, the statistic is notoriously sensitive to sample size such that, even in moderately large samples, it can result in a significant p-value (Iacobucci, 2010; Kline, 2011).

Additionally, the chi-squared statistic may also be sensitive to model complexity and reward models lacking parsimony (Iacobucci, 2010; Kline, 2011). For these reasons, researchers have come to rely on a variety of approximate fit indices to aid in assessing model fit.

Both CFI and TLI are considered “goodness of fit” indicators and range from 0 to 1.0. Both indices indicate the goodness-of-fit relative to a baseline model where only error variances are estimated (Bagozzi and Yi, 2011). However, TLI differs from CFI in that it is a non-normed index and, as such, tends to reward for model parsimony and penalize model complexity (Bagozzi and Yi, 2011).

Whereas CFI and TLI are goodness-of-fit measures, both RMSEA and SRMR are considered “badness-of-fit” indicators (Kline, 2011). Both indices are scaled such that higher values are indicative of poor model fit. Similar to the model chi-squared test statistic, the RMSEA tests the degree of fit between the measurement model and the data. However, where the chi-squared test statistic is associated with a test of exact fit, the RMSEA tests for close fit (Gefen et al., 2011). The SRMR is not associated with a hypothesis test and differs from the other three fit indices in that it assesses the overall difference between observed correlations in the data and the correlations predicted by the measurement model (Kline, 2011). Of all approximate fit indices, recent evidence suggests the SRMR to be the most reliable in identifying model misspecification as it is not overly-sensitive to sample size or violations of assumptions regarding multivariate normality (Iacobucci, 2010).

Various guidelines and rules of thumb exist with regard to recommended cut offs for approximate fit indices. For CFI and TLI, Hu and Bentler (1999) recommended

values “close to” 0.95 while Iacobucci (2010) and Gefen et al. (2011) recommended values of 0.93 and 0.90 respectively. Regarding RMSEA, evidence of close fit is indicated by values less than or equal to 0.05 while acceptable fit is indicated by values between 0.08 and 0.10 (Hu and Bentler, 1999; Kline, 2011). Finally, according to Iacobucci (2010), the recommended cut-off value for SRMR is 0.09, though Bagozzi and Yi (2011) recommend a more conservative cut-off value of 0.07 or less. Ultimately, recommended cut-off values represent rules of thumb and researchers are advised to not be too concerned if one or more fit indices do not meet recommended thresholds (Gefen et al., 2011; Iacobucci, 2010). Table 4.1 summarizes the performance of all three models in terms of model fit and illustrations of each model can be found in Appendix G.

Table 4.5. Assessment of Model Fit.

Model #	χ^2	*df*	p-value	CFI	TLI	SRMR	RMSEA (90%CI)
1: Forecasting-focused Climate as Single Latent Variable	5474.3	982	<0.001	0.52	0.49	0.12	0.17 (0.17, 0.18)
2: Forecasting-focused Climate as First-order Factors	1110.4	626	<0.001	0.94	0.93	0.05	0.07 (0.06, 0.08)
3: Forecasting-focused Climate as a Higher-order Factor	1173.3	650	<0.001	0.93	0.92	0.07	0.07 (0.07, 0.08)

It should be noted that all three models failed the test of exact fit at the 0.05 level of significance. This is indicated by the chi-squared statistics and associated significant p-values. Again, as noted by Iacobucci (2010), researchers should not be overly concerned by a significant chi-square value due to the test’s sensitivity to sample size. As such, the approximate fit indices were the primary means of determining the adequacy of each model’s fit to the underlying survey data. In the case of Model #1, each of the approximate fit indices suggested unacceptable fit. On the other hand, the fit indices for Model #2 reflect acceptable model fit for all of the approximate fit indices considered.

This is taken as evidence of the multidimensional nature of the forecasting-focused climate construct. Similar to Model #2, Model #3 also achieved acceptable model fit for all approximate fit indices considered. In particular, the fit indices for Model #3 suggested that it is appropriate to represent forecasting-focused climate as a higher-order construct. While Model #2 achieved the "best" overall model fit, Model #3 was ultimately selected as the desired measurement model because it best achieved the previously-stated attributes of alignment with theory and parsimony in addition to acceptable model fit.

Reliability and Validity

Following the assessment of the measurement model fit, the scales were assessed for reliability and validity. Reliability refers to the degree that scores computed from a given scale are free from random measurement error (Kline, 2011). In survey research, measures of reliability are typically reported in terms of the internal consistency of a given scale and represent the proportion of a scale's total variance that may be attributed to a common source (DeVellis, 2003; Leedy and Ormrod, 2013). Two commonly-reported measures of scale reliability are Cronbach's alpha and composite reliability (Bagozzi and Yi, 2011). The recommended cut-off values for both measures are 0.70 (Bagozzi and Yi, 2011; DeVellis, 2003).

Furthermore, scale validity was also assessed. Generally speaking, the validity of a scale refers to the extent to which the scale measures what it is intended to measure (Leedy and Ormrod, 2013). Two key aspects of validity are convergent validity and discriminant validity. Convergent validity refers to similarity between measures of

theoretically-related constructs while discriminant validity refers to the absence of similarity between measures of theoretically unrelated constructs (DeVellis, 2003). In the context of CFA, evidence of convergent validity is observed when all items specified as loading on a common factor have statistically significant and relatively high standardized factor loadings (i.e. ≥0.70). Additionally, evidence of convergent validity can also be said to exist when the estimated correlations between factors are not excessively high (i.e. are <0.90 in absolute value) (Hair et al., 2010; Kline, 2011). Moreover, Hair et al. (2010) suggest that an average variance extracted (AVE) of 0.5 or greater provides further evidence of convergent validity. Further, evidence of discriminant validity is said to exist when the AVE for a factor is greater than the square of the correlation between that factor and all other factors.

Table 4.2 summarizes construct-level statistics including measures of scale reliability and validity. All three scales reflected satisfactory reliability as indicated by the Cronbach's alpha and composite reliability values above 0.70. However, based on the high correlation between the forecasting-focused climate and knowledge management effectiveness scales, evidence of discriminant validity was not found initially. This finding prompted re-specification of the measurement model.

Table 4.2. Construct-level Statistics.

	Mean	S.D.	CA	CR	FFC	FTTF	KME
FFC	5.01	1.09	0.83	0.83	**0.45**	0.48	0.83
FTTF	5.02	1.26	0.91	0.97	0.69	**0.94**	0.46
KME	4.92	1.44	0.93	0.93	0.91	0.68	**0.77**

NOTE: Average variance extracted (AVE) is shown along the diagonal; correlations are shown below the diagonal; and squared correlations are shown above the diagonal. N = 154.

To facilitate accurate re-specification of the measurement model, both organizational climate theory and relevant forecasting research were re-appraised. The high correlation between forecasting-focused climate and knowledge management effectiveness suggested the knowledge management effectiveness construct was a possible dimension of forecasting-focused climate.

Although the knowledge management effectiveness scale was borrowed from previous research, the items were adapted to the forecasting context by incorporating relevant terminology. Additionally, one item was added to the scale in an attempt to capture respondents' perceptions regarding how well forecasting-related knowledge was managed for both internal and external sources. It is possible that the combined effects of changes made to the scale and the given research setting altered the original conceptualization of knowledge management effectiveness by Sabherwal and Becerra-Fernandez (2003).

From the perspective of organizational climate theory, literature generally supports a knowledge-related dimension of psychological climate. For example, James and Jones (1979) specified an "organizational communication" facet of psychological climate. Further, Patterson et al.'s (2005) "integration" facet of psychological climate

tapped perceptions regarding the degree to which internal departments shared information. Moreover, in their operationalization of psychological climate, Schulte et al. (2006) proposed an "open and clear communication" sub-dimension. Furthermore, though their research did not explicitly incorporate the psychological climate construct, McCarthy-Byrne et al. (2011) noted the importance of "access to information" as one of several "environmental signals" perceived by individual forecasters. Based on this reassessment of the literature, the measurement model was re-specified such that the knowledge management effectiveness construct became a "knowledge availability" dimension of the forecasting-focused climate construct.

A subsequent assessment of model fit for the re-specified model reflected no change in model fit indices, thus maintaining overall acceptable model fit: ($\chi^2(651) = 1183.6$; $p<0.001$; CFI = 0.93, TLI = 0.92; SRMR = 0.07, and RMSEA (90CI) = .07 (.07, .08)). Table 4.3 summarizes the resulting changes in construct-level statistics. All statistics indicated evidence of acceptable reliability, as well as satisfactory convergent and discriminant validity.

Table 4.3. Construct-level Statistics (Re-specified Measurement Model).

	Mean	S.D.	CA	CR	FFC	FTTF
FFC	4.93	1.20	0.87	0.88	**0.51**	0.48
FTTF	4.83	1.17	0.98	0.97	0.69	**0.94**

NOTE: Average variance extracted (AVE) is shown along the diagonal; correlations are shown below the diagonal; and squared correlations are shown above the diagonal. N = 154.

Assessment of Non-response and Common Method Biases.

Non-response Bias Assessment.

Following the assessment of reliability and validity, the measurement scales were specifically assessed for potential biases. In survey research at least two biases are important to assess: non-response bias and common method bias. Wagner and Kemmerling (2010) suggest two forms of nonresponse in survey research. First, they identify unit nonresponse as the inability to gather data from some unit of the sampling frame. The second type of nonresponse, item nonresponse, is said to be the result of participants not answering individual survey items. Given the small size of the target population and the relatively high response rate, unit nonresponse was not necessarily expected. However, given the high incidence of missing responses for most of the demographic related survey items, there was the potential for nonresponse bias in the form of item nonresponse. As a test for evidence of the presence of non-response bias, an extrapolation method was employed. The extrapolation method, otherwise known as wave analysis, compares early survey respondents to late survey respondents (Rogelberg and Stanton, 2007). The fundamental assumption of this approach is that late responders are similar to nonparticipants. While this assumption may not always be realistic, the approach has nonetheless been found to serve as a useful indication of whether nonresponse bias may be present (Wagner and Kemmerling, 2010).

For the purposes of this research, early responders (n = 55) were defined as individuals providing responses within the first two weeks of the survey window and prior to the first reminder message on February 15th. Alternatively, late responders (n = 39) were those individuals that provided responses within the last two weeks of the

survey window (April 6th-19th) following the final reminder. Conducting a series of t-tests on the mean scale responses and demographic attributes for each group suggested no significant differences existed between early and late responders. Therefore, nonresponse bias does not appear to be a major concern for this research.

Common Method Bias Assessment.

Next, the data were assessed for the presence of common method bias. Podsakoff et al. (2003) define common method bias as bias (i.e. in scores, relationships, etc.) due to systematic variance that can be attributed to the measurement method as opposed to the constructs under study. In particular, common method variance may inflate or deflate observed relationships thereby leading to spurious results and inaccurate inferences (Podsakoff, 2003).

There are several sources of common method variance though, in the context of survey research, perhaps the most discussed is the self-report bias, also known as the common rater bias or single source bias. The self-report bias is a potential source of method bias when "artifactual covariances" result from the fact that respondents provide scores for both the predictor variable(s) and criterion variable(s) (Podsakoff et al., 2003). However, as Conway and Lance (2010) argue, relationships between self-reported variables are not necessarily biased by default and the belief that common method bias automatically flows from self-reported data is a common misconception in behavioral research.

Other potential sources of common method bias in survey settings include social desirability bias (i.e. the need for social approval); consistency motif; and acquiescence bias (i.e. tendency toward agreement). Even more specific sources of bias in survey

research are biases due to scale length; biases due to grouping items from the same scale close together; and biases due to common scale formats and anchors. Given the multitude of potential sources of common method bias, Conway and Lance (2010) suggest that researchers cannot possibly prevent method effects in their research.

To formally test for the potential effects of common method bias, the Single Method Factor approach was employed (Podsakoff et al., 2003). In executing this test, a single latent variable or "method factor" was added to the measurement model. All items were specified to load on to the factor while also loading on their originally-specified substantive factor. Next, the unconstrained model ($\chi^2(619) = 1096.0$) was compared to the constrained model ($\chi^2(581) = 975.0$) wherein all loadings of items on the method factor are constrained to zero. A comparison of the models using the chi-squared difference test suggested a significant difference between the models ($\Delta\chi^2$ (df) = 121 (38); $p < 0.001$) and, thus, the presence of common method bias.

While evidence of common method bias can be said to exist, the results of the single method factor test are tempered by the findings of Richardson et al. (2009). Specifically, they found evidence to suggest that the single method factor approach does not reliably identify common method bias nor does it pinpoint if or how common method bias affects specific scales. Most importantly, they cautioned researchers against corrections based on the results of the test. Moreover, Conway and Lance (2010) suggest that evidence against the effects of common method bias can be found in satisfactory scale reliability as well as convergent and discriminant validity. Even more, proof of effort to proactively mitigate the effects of common method bias may also contribute toward addressing any concerns of the effects of common method bias.

As was previously discussed, evidence exists for satisfactory reliability, convergent validity, and discriminant validity in the present research (see Table 4.3). With regard to proactive efforts to mitigate the impact of common method bias, this research effort employed three actions recommended by Conway and Lance (2010). For example, in addition to asking respondents to self-report forecast accuracy as a measure of the criterion variable (i.e. individual-level forecasting performance) respondents were also asked to provide information that would allow for objective measures of the criterion by way of historical forecasting performance data from the organization's forecasting support system. As noted, however, only about half of the respondents provided the necessary information (national stock number) for gathering historical records of forecast performance.

Another proactive means of mitigating common method bias is by ensuring anonymity of survey responses (Conway and Lance, 2010). Efforts to safeguard survey responses and to protect the identities of individual respondents were explicitly stated in the invitation to take the survey as well as on the survey cover page. Nonetheless, safeguards notwithstanding, respondents still recognized the potential that providing the researcher with the information required to access historical records could be used to identify them individually. Regrettably, the effort to counteract the self-report bias seemed to compete with the effort to maintain anonymity of survey respondents.

Finally, common method bias may also be mitigated by incorporating certain design features into the survey instrument such as avoiding short scales and varying scale anchors. An effort was made to strike a balance between respondent convenience and ease in completing the survey on one hand, and the need to incorporate these features on

the other. Scale lengths ranged from four items to nine items and different anchors were used to capture responses for predictor variables as compared to the criterion variable. Taken altogether, the combination of the evidence of reliability and validity as well as the proactive steps taken to mitigate common method bias suggest that common method bias as a result of common method variance is not a significant limitation for this research effort. The next section discusses the results of tests of hypotheses using regression analysis. Based on the preceding discussion, the analysis and subsequent results are based on the data without any corrections for common method bias.

Analysis of Self-Reported Data

Given the changes to the measurement model, it was necessary to revise the conceptual model and associated hypotheses (Figure 4.1).

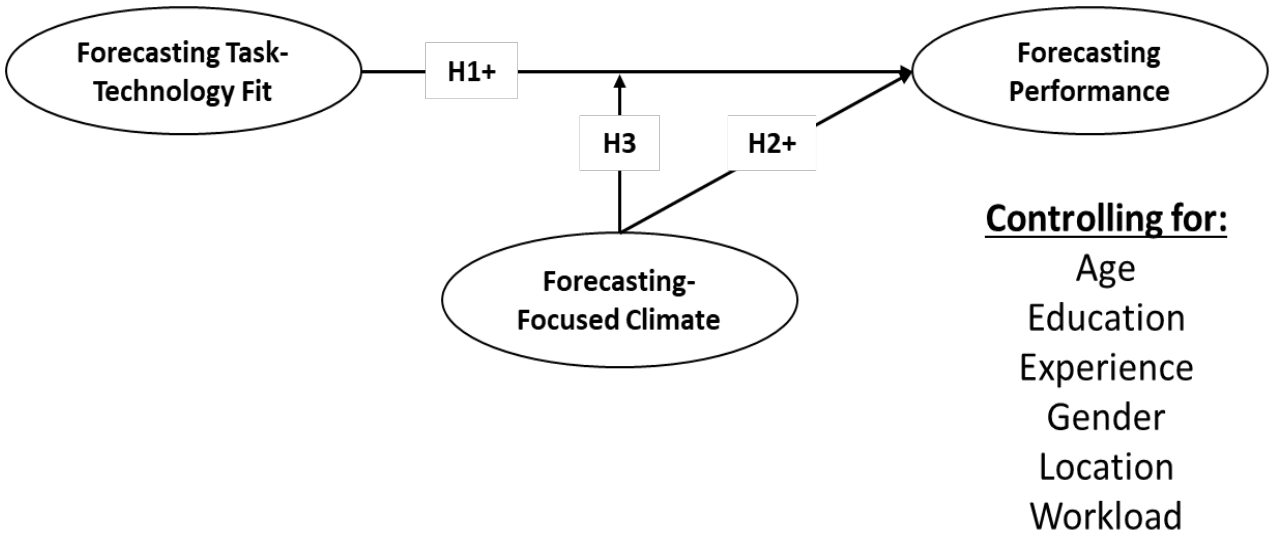


Figure 4.1. Revised Conceptual Model.

All hypotheses pertaining to knowledge management effectiveness were dropped while all others remain the same. Formally stated:

Hypothesis 1: Forecasting task-technology fit is positively related to forecaster performance.

Hypothesis 2: Forecasting-focused climate is positively related to forecaster performance.

Hypothesis 3: Forecasting-focused climate moderates the relationship between forecasting task-technology fit and forecaster performance.

Analysis of Historical Data

Having found acceptable fit for the measurement model as well as satisfactory evidence of scale reliability and validity, the analysis moved toward testing the specified hypotheses. Though a major goal of this research effort was to study how the various constructs related to objective measures of individual forecasting performance, the ability to do so was greatly limited by the lack of respondent willingness to provide identifying information. Ideally, self-reported forecasting performance data would serve as an appropriate alternative to historical data. Further, the use of self-reported data is necessarily grounded in the assumption that self-reported forecast performance is highly correlated with actual forecast performance. To test this assumption, the degree of agreement between self-reported forecast accuracy and actual forecast accuracy for the 55 respondents for which historical data was available was assessed using Cohen's kappa (κ). Actual forecasting performance was measured using the dollar-demand weighted forecast accuracy measure employed by the 448th Supply Chain Management Wing and computed for each respondent for which data was available. Since self-reported forecast performance was measured along a 7-point Likert scale, actual forecast performance was

coded so as to correspond to the same scale. In the end, the sample kappa was found to be 0.21 (95% CI: 0.07, 0.36) indicating poor agreement between the two measures (Agresti & Kateri, 2011). As a result of the poor agreement between self-reported and actual forecast performance, all subsequent analyses were based on the available historical data. Figure 4.2 provides the JMP output for the assessment of agreement.

Contingency Table

Weighted DFA (Ordinal)

Self Reported Accuracy: Count	1	2	3	4	5	6	7	Total
1	2	0	1	0	0	0	1	4
2	1	1	0	0	0	0	0	2
3	2	0	1	1	0	0	2	6
4	0	2	3	4	2	1	0	12
5	2	0	2	1	5	4	2	16
6	0	1	0	0	6	5	1	13
7	0	1	0	0	0	0	1	2
Total	7	5	7	6	13	10	7	55

Tests

Agreement Statistic

Kappa Coefficient

Degree of Agreement	Kappa	Std Err	Lower 95%	Upper 95%
	0.214597	0.075557	0.066509	0.362685

Figure 4.2. Results of Assessment of Agreement.

To understand the hypothesized relationships in relation to actual forecasting performance, further analysis was conducted using multiple linear regression. Although structural equation modeling was the preferred method to analyze the data, the limited sample size of respondents for which historical data were available rendered the data inappropriate for structural equation modeling (Bagozzi and Yi, 2011). Of note, of the 154 total useable survey responses, only 78 included information that allowed survey

responses to be linked to historical data (i.e. one of the ES's assigned national stock numbers). Of the 78 respondents that did provide NSNs, 20 also reported a change in their assigned workload at some point during the time period. A response of this nature indicated that forecasting performance data would likely reflect the results of forecasts made by another individual thus confounding the respondent's forecasting performance with that of another equipment specialist. As a result, those 20 responses were excluded from the analysis, leaving 58 responses. Of the 58 remaining responses, 3 were excluded due to discrepancies in the organization's forecasting support system that prevented historical data from being gathered for those responses. In all, 55 responses—representing 16.8% of the sample frame—were retained for use in the test of hypotheses by way of linear regression.

Given the substantial reduction in sample size, an effort was made to understand if and how respondents included in the analysis of historical data differed from those that were not included (i.e. those providing NSNs compared to those not providing NSNs). First, a multi-group analysis was conducted to assess if significant differences in the structure and fit of the measurement model existed between the two groups. The test of model invariance revealed no significant differences in the theoretical relationships represented by the measurement model ($\Delta\chi^2(33) = 39.5;\ p = 0.20$). As a result, evidence of scale reliability and validity found previously was safely extended to the analysis of the sub-sample (Byrne, 2004).

To understand differences in attributes between respondents providing NSNs and those that did not, the two groups were compared on the basis of demographic data. As

reflected in Table 4.4, results of the comparisons suggested the groups did differ along several attributes.

Table 4.4. Results of Group Comparisons.

Variable	Test Statistic	p-value
Forecasting Experience	$\chi^2(1) = 1.72$	$p=0.19$
Supply Item Experience	$\chi^2(1) = 5.60$	$p=0.02$
Section Experience	$\chi^2(1) = 3.90$	$p=0.048$
Flight Experience	$\chi^2(1) = 8.17$	$p=0.004$
Education	$\chi^2(1) = 1.23$	$p=0.27$
Age	$\chi^2(1) =4.27$	$p=0.04$
Workload	$\chi^2(1) =0.44$	$p=0.51$
Location	$\chi^2() =8.13$	$p=0.02$
Gender	$\chi^2 (1) =1.47$	$p=0.23$

Overall, respondents that provided NSNs tended to be older and have greater experience with their supply items. Respondents that provided NSNs also reported more time assigned to their section and flight. Further, results of a chi-squared test of independence indicated an association between location and whether respondents provided a NSN ($\chi^2(1) = 1.47; p = 0.02$). Further evaluation of the differences between groups revealed that, while the majority of respondents indicated Hill AFB as their location, only 53% of those individuals provided NSNs compared to 80% and 78% of respondents from Robins AFB and Tinker AFB respectively. The impact of the differences revealed by group comparisons will be further discussed in Chapter 5.

Multiple Linear Regression Models.

Before commencing the regression analysis of historical data, an appropriate measure of forecast performance was selected. As discussed in Chapter 2, there are a variety of measures capable of capturing forecasting performance. In reviewing the literature, mean absolute percentage error (MAPE) was observed as one of the most frequently-used forecasting performance metrics. However, traditional measures of forecast accuracy such as MAPE are not appropriate across all settings. In the present setting, calculating error relative to actual demand proves problematic due to the intermittent nature of demand for repair items managed by equipment specialists. The phenomenon of intermittent demand has been widely-discussed in inventory management literature as well as forecasting literature (e.g. Hoover, 2009; Syntetos et al., 2009a). As Syntetos and Boylan (2005) explain, compared to other types of demand, intermittent demand differs in that it is characterized by more frequent occurrences of zero values for actual demand. Thus, calculations of forecasting performance measures such as MAPE often result in uninterpretable results due to the "division by zero" problem (Syntetos and Boylan, 2005).

To overcome the limitations of MAPE and other similar measures of forecasting performance, researchers have advocated for the use of relative error metrics (e.g. Davydenko and Fildes, 2013; Morelidge, 2016). Relative error metrics typically compare the absolute value of forecast errors originating from different sources (i.e. competing methods). In particular, Davydenko and Fidles (2013) proposed the average relative mean of absolute errors (AvgRelMAE). When a single time period is all that is considered, AvgRelMAE is equivalent to the geometric mean of relative absolute errors (GMRAE).

As discussed by Davydenko and Fildes (2013), GMRAE overcomes the weaknesses of commonly-used forecast performance measures (i.e. MAPE). In particular, GMRAE is reliable when aggregated; comparable across different items/forecasts; takes “extreme” errors into account; and allows for comparable insights across choices of benchmark forecast. For the purposes of this research, the naïve forecast was chosen as the benchmark forecast as is common in forecasting research (Davydenko and Fildes, 2013). In addition to its wide-spread use, measuring forecasters’ errors relative to the naïve forecast has the added benefit of indirectly capturing the volatility associated with forecasting a particular item (Morelidge, 2016).

Here, the naïve forecast is computed as the actual demand for a given item in the previous time period (Fiscal Year 2015). As such, the calculation of GMRAE for a given respondent, *n*, is:

$$\text{GMRAE}_n = \prod_{ii=1}^{kk} (RRRRRR)^{\frac{1}{kk}} \text{ for all } k \text{ items}$$

$$\text{RAE}_k = \frac{|\text{Forecaster's Forecast for item k} - \text{FY 2016 Actual Demand for item k}|}{|\text{Benchmark Forecast for item k} - \text{FY 2016 Actual Demand for item k}|}$$

One limitation of GMRAE is data loss due to the inability to include zero-error forecasts (i.e. the geometric mean of zero is undefined). For the data considered here, this problem arises when either the equipment specialist’s or benchmark forecast’s absolute error was equal to zero. Across the 55 respondents considered in this analysis, a total of 3,786 forecasts were produced throughout fiscal year 2016. Of the 3,786 forecasts, 1,742 forecasts (46%) were omitted due to zero-value errors. While certainly an inconvenience, the level of data loss seems to be in line with previous forecasting research confronting

intermittent demand. For example, Syntetos et al. (2009a)—who also used GMRAE as the measure of forecast performance—reported a loss of 74% of available data for their study. Table 4.5 summarizes the reasons for data loss.

Table 4.5. Categories of Forecast Data Loss.

Category	Frequency
Absolute Error of the Forecaster = 0	210 (12.0%)
Absolute Error of the Naïve Forecast = 0	1,238 (71.1%)
Naïve Forecast Unavailable	294 (16.9%)

Given the selected measure of forecasting performance, weighted least squares regression was selected as the best approach to analyzing the data. The weighted least squares approach has proven advantageous in prior work as it allows for more precise analysis by giving more weight to observations that exhibit less variability (Eroglu and Knemeyer, 2010). This is due to the fact that the dependent variable represents an aggregate of each respondent's forecasts. Given that the number of forecasts generated over the time period varied by respondent, GMRAEs based on a higher number of forecasts arguably carry more information than those based on only a few forecasts. In line with the hypothesized relationships, the weighted least squares (WLS) regression model was specified as follows:

$$\sum w_i Y_i = \beta_{w0} + \beta_{w1} \sum w_i X_1 + \beta_{w2} \sum w_i X_2 + \beta_{w3} \sum w_i X_1 X_2 + \beta_{w4} \sum w_i X_3 + \beta_{w5} \sum w_i X_4 + \beta_{w6}$$

$$\sum w_i X_5 + \beta_{w7} \sum w_i X_6 + \beta_{w8} \sum w_i X_7 + \beta_{w9} \sum w_i X_8 + \beta_{w10} \sum w_i X_9 + \varepsilon_i$$

Table 4.6. describes each of the variables and how they were represented in the model:

Table 4.6. Summary of Regression Variables.

Variable	Format
Y_i = *GMRAE for respondent i (all non-zero error forecasts)*	Continuous/Historical Data
w_i = *total # of non-zero error forecasts made by respondent i*	Count/Historical Data
X_1 = *Forecasting-focused Climate*	Mean-Centered Score
X_2 = *Forecasting Task-technology Fit*	Mean-Centered Score
X_3 = *Forecasting Experience*	Categorical (low: -1, high: 1)
X_4 = *Supply Item Experience*	Categorical (low: -1, high: 1)
X_5 = *Team Experience*	Categorical (low: -1, high: 1)
X_6 = *Education*	Categorical (low: -1, high: 1)
X_7 = *Workload*	Categorical (low: -1, high: 1)
X_8 = *Age*	Categorical (low: -1, high: 1)
X_9 = *Location*	Categorical (Robins AFB: -1, Hill AFB: 0, Tinker AFB: 1)

Note that the hypothesized moderation effect was represented by a product term resulting from the multiplication of the centered scores for both the forecasting-focused climate scale and forecasting task-technology fit scale. Furthermore, in order to facilitate ease of interpretation, the control variables were coded using indicator coding as is recommend for regression models specifying an interaction effect (Frazier et al., 2004).

Results of Hypotheses Tests: Overall Forecast Performance.

Weighted least squares regression was performed using JMP 12 and produced an initial non-significant model ($F(14,42) = 1.19; p = 0.32$). A visual inspection of the raw residuals suggested the assumption of constant error variance was not maintained by the model. As a potential remedy, a transformation of the dependent variable was explored using JMP's Box-Cox Transformation function. Based on the table of estimates, the optimal power transformation of the dependent variable was found to be $\lambda = -1$. The WLS model was thus re-specified as follows:

$$\sum w_i Y^*_i = \beta_{w0} + \beta_{w1} \sum w_i X_1 + \beta_{w2} \sum w_i X_2 + \beta_{w3} \sum w_i X_1 X_2 + \beta_{w4} \sum w_i X_3 + \beta_{w5} \sum w_i X_4 + \beta_{w6}$$

$$\sum w_i X_5 + \beta_{w7} \sum w_i X_6 + \beta_{w8} \sum w_i X_7 + \beta_{w9} \sum w_i X_8 + \beta_{w10} \sum w_i X_9 + \varepsilon_i$$

where all predictors remain the same and Y^* represents a transformation of the dependent variable such that $Y^*_i = \frac{1}{\text{GGGGGGGGGG fffffff ffrrrrrrffrrrrrrrrrr ii}}$ for all non-zero error forecasts. Similar to the initial model, the second model was non-significant ($F(12,42) = 1.02$, $p = 0.45$). As it was noted that forecasting experience (X_3) appeared to be a significant predictor of forecasting performance (GMRAE) in both model attempts, an automatic search procedure was employed in order to identify the "best" model for predicting forecasting performance. In particular, backward stepwise regression was selected as the approach since it is more appropriate for small to moderate sized pools of potential predictor variables (Kutner et al. 2004). With backward stepwise regression, all predictors are entered into the model and iteratively removed based on the researcher's specified criteria. For the purposes of this research, the p-value threshold criteria were used such that a predictor variable was required to be significant at the 0.05 level to enter into the model and have a p-value less than 0.10 to remain in the model. Using these criteria, a significant model was found ($R^2_{adj} = 0.09$, $F(1, 53) = 6.04$, $p = 0.02$). The associated prediction formula was as follows:

$$\hat{y}^*_i = 0.13 + 0.09X_3$$

where X_3 corresponds to a respondent's forecasting experience ($t(54)= 2.46$, $p = 0.02$). Based on these results, a forecaster's experience appears to be the "best" predictor of

overall forecasting performance and, thus, no empirical evidence was found to support any of the hypothesized relationships.

As discussed in Chapter 2, a key aspect of a forecaster's role involves making adjustments to system-provided forecasts. Where the above model was derived from data encompassing all available forecasts, an additional analysis was conducted based solely on all available forecast *adjustments*. For this part of the analysis, the dependent variable consisted of all non-zero error forecast *adjustments* made by each respondent. As before, data were lost due to the nature of the forecasting performance metric. For the time period considered, a total of 658 forecast adjustments were made. It should also be noted that only 46 of the 55 respondents made forecast adjustments. Of the 658 forecast adjustments, 221 (33.6%) were omitted due to zero-error adjustments. Table 4.7 summarizes the reasons for data loss.

Table 4.7. Categories of Data Loss for Adjusted Forecasts.

Category	Frequency
Absolute Error of the Forecaster = 0	29 (13.1%)
Absolute Error of the Naïve Forecast = 0	133 (60.2%)
Naïve Forecast Unavailable	59 (26.7%)

By policy, the organization's preferred forecasting method is the eight-quarter moving average and, as a result, it is also the default in the organization's forecasting support system. Therefore, any forecast computed using a method other than the eight-quarter moving average (i.e. four-quarter moving average, estimated rate, etc.) was deemed a forecast adjustment. Each respondent's forecast performance was thus measured as the GMRAE of all non-zero error forecast adjustments and the following weighted least squares regression model was specified:

$$\sum w_i Z_i = \beta_{w0} + \beta_{w1} \sum w_i X_1 + \beta_{w2} \sum w_i X_2 + \beta_{w3} \sum w_i X_1 X_2 + \beta_{w4} \sum w_i X_3 + \beta_{w5} \sum w_i X_4 + \beta_{w6}$$

$$\sum w_i X_5 + \beta_{w7} \sum w_i X_6 + \beta_{w8} \sum w_i X_7 + \beta_{w9} \sum w_i X_8 + \beta_{w10} \sum w_i X_9 + \varepsilon_i$$

Table 4.8. describes each of the variables and how they were represented in the model:

Table 4.8. Summary of Regression Variables.

Variable	Format
Z_i = GMRAE for respondent i (all non-zero error forecast adjustments)	Continuous/Historical Data
w_i = total # of non-zero error forecast adjustments made by respondent i	Count/Historical Data
X_1 = Forecasting-focused Climate	Mean-Centered Score
X_2 = Forecasting Task-technology Fit	Mean-Centered Score
X_3 = Forecasting Experience	Categorical (low: -1, high: 1)
X_4 = Supply Item Experience	Categorical (low: -1, high: 1)
X_5 = Team Experience	Categorical (low: -1, high: 1)
X_6 = Education	Categorical (low: -1, high: 1)
X_7 = Workload	Categorical (low: -1, high: 1)
X_8 = Age	Categorical (low: -1, high: 1)
X_9 = Location	Categorical (Robins AFB: -1, Hill AFB: 0, Tinker AFB: 1)

Results of Hypotheses Tests: Forecast Adjustments.

As before, the WLS regression was performed using JMP 12 and produced an initially non-significant model ($F(12,33) = 0.95; p = 0.52$). Here too, a visual inspection of the raw residuals suggested the assumption of constant error variance was not maintained by the model. As a remedy, a transformation of the dependent variable was explored using JMP's Box-Cox Transformation function. Based on the table of estimates, the optimal power transformation of the dependent variable was found to be $\lambda = -0.4$ however, for the sake of interpretability, a value of $\lambda = -0.5$ was selected for the transformation (Kutner et al., 2004). The model was thus re-specified as follows:

$$\sum w_i Z^*_i = \beta_{w0} + \beta_{w1} \sum w_i X_1 + \beta_{w2} \sum w_i X_2 + \beta_{w3} \sum w_i X_1 X_2 + \beta_{w4} \sum w_i X_3 + \beta_{w5} \sum w_i X_4 + \beta_{w6}$$

$$\sum w_i X_5 + \beta_{w7} \sum w_i X_6 + \beta_{w8} \sum w_i X_7 + \beta_{w9} \sum w_i X_8 + \beta_{w10} \sum w_i X_9 + \varepsilon_i$$

where all predictors remain the same and Z^* represents a transformation of the dependent variable such that $Z^*_i = \frac{1}{\text{GMRAE for respondent } i}$ for all non-zero error forecast adjustments.

An automatic search procedure was employed in order to identify the "best" model for predicting forecasting performance. Similar to the earlier analysis, backward stepwise regression was selected as the approach since given the small pool of potential predictor variables (Kutner et al. 2004). Additionally, the same p-value threshold criteria were used. Using these criteria, a significant model was found ($R^2_{adj} = 0.21$, $F(4,41) = 3.93$, $p = 0.01$). The resulting prediction formula was as follows:

$$\hat{Z}^*_i = 0.33 + 0.15X_1 - 0.13X_2 - 0.16X_1X_2 + 0.23X_3$$

where X_1 corresponds to a respondent's score on the forecasting-focused climate scale ($t(45) = 2.10$, $p = 0.04$); X_2 corresponds to a respondent's score on the forecasting task-technology fit scale ($t(45) = -2.09$, $p = 0.04$); and X_3 corresponds to a respondent's forecasting experience ($t(45) = -3.30$, $p = 0.002$). Furthermore, the interaction effect represented by the product of centered scores for forecasting-focused climate and forecasting task-technology fit was also a significant predictor ($t(45) = -2.73$, $p = 0.01$).

Given the significant interaction effect, a partial F-test was performed to more accurately assess the significance of the main effects for both forecasting-focused climate

and task-technology fit. The results of partial F-tests indicated that the effect of task-technology fit was significant at the 0.05 level (F* = 3.24; p = 0.03) but that the effect of forecasting-focused climate was not significant at the 0.05 level (F* = 2.70; p = 0.06). Taken together these results provide empirical evidence in support of Hypothesis 1 and Hypothesis 3. Hypothesis 2 was not supported. Furthermore, forecasting experience emerged as the only significant control variable.

Whenever evidence of a significant interaction effect is found, researchers are advised to further investigate the interaction (Frazier et al., 2004). This is due to the fact that a moderated relationship implies that the influence of a given predictor changes over the range of the moderator (Hair et al., 2010). To better understand the nature of the interaction effect, the relationship between forecasting-focused climate and forecasting task-technology fit were plotted by level of experience as is captured in Figure 4.3. Note that "high" experience was defined as greater than eight years of forecaster experience while "low" experience was defined as less than or equal to eight years of forecaster

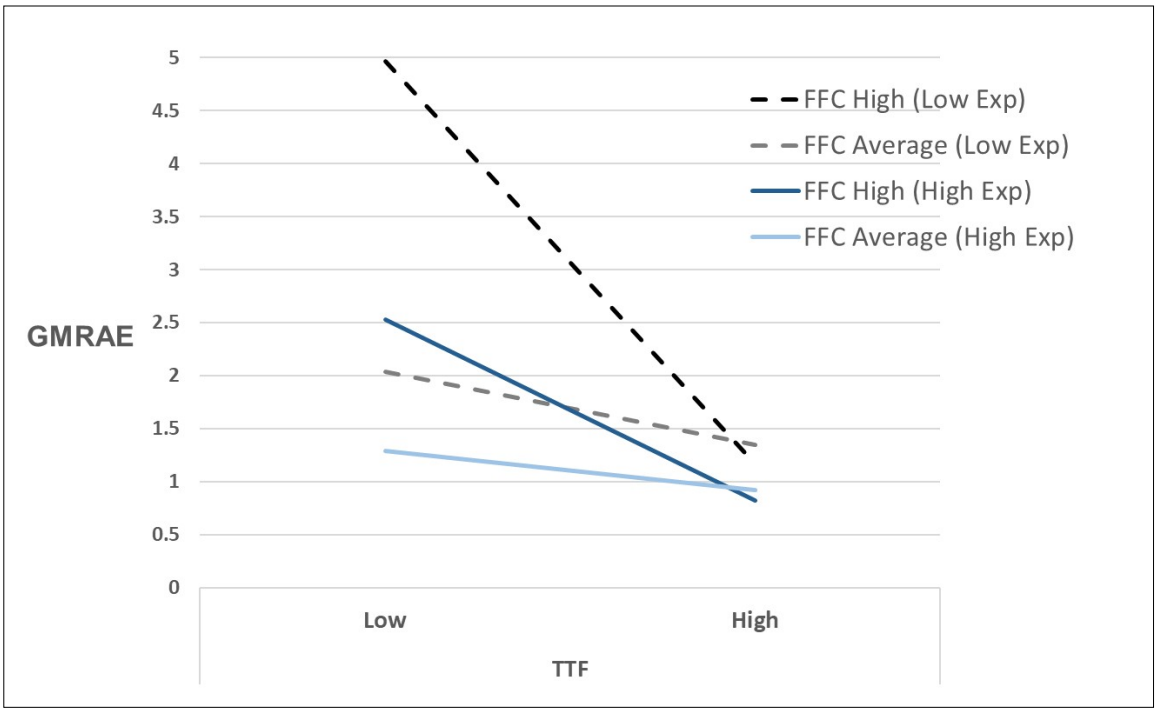


Figure 4.3. Plot of Interaction Effect by Experience Level.

experience.

Additionally, a “high” level of forecasting-focused climate was associated with the highest observed score of forecasting-focused climate (6.97) while the average level of forecasting focused climate corresponds to the sample average score of 5.37. In the case of the task-technology fit, the “high” level of perceived fit corresponded to the highest task technology fit score. Though, for the sake of symmetry, the “low” level of fit corresponded to the score of equal distance from the mean (3.28).

As a whole, the plot illustrates that the positive relationship between task-technology fit and forecast adjustment performance is intensified at higher levels of forecasting-focused climate. Of note, at low levels of perceived task-technology fit, higher levels of perceived forecasting focused climate appear to be associated with worse performance (i.e. higher levels of error). Furthermore, there appear to be differences in the intensity of the interaction effect across experience levels. In particular, for forecasters with low levels of experience, the positive relationship between higher levels of perceived fit and forecast adjustment performance appears to be greater in intensity given a high level of perceived forecasting-focused climate.

Table 4.9. 95% Confidence Intervals for Predicted GMRAE.

FFC	FTTF	Lower Bound	Predicted Value	Upper Bound
H	H	0.63	0.82	1.08
		0.89	1.17	1.57
Average	H	0.78	0.92	1.11
		1.07	1.35	1.79
H	L	1.34	2.53	6.62
		1.9	4.97	38.29
Average	L	1.04	1.29	1.62
		1.4	2.04	3.27

Lastly, even more insight is provided by the 95% confidence intervals for predicted performance at varying levels of both task-technology fit and forecasting-focused climate (Table 4.9). In general, the confidence intervals overlap when comparing similar levels of fit and climate across experience levels as well as within experience levels. The least overlap appears to be in the case of low perceived task-technology fit and high levels of climate. The results of the analysis performed in this chapter, and the associated implications, are discussed further in Chapter 5.

Summary

Chapter 4 described the analysis and the results of the data collected to test the hypotheses put forward in Chapter 3. The chapter discussed the sampling frame, participant demographics, as well as item and construct-level statistics. The analysis of the data included data screening; assessment of the measurement mode through confirmatory factor analysis; presentation of evidence of scale reliability and validity; and tests of hypotheses using weighted least squares regression models. The results presented in this chapter will be discussed in depth in Chapter 5.

V. Conclusions and Recommendations

Chapter Overview

The overarching goal of this research was to test and evaluate the relationships between forecasting task-technology fit, forecasting-focused climate, and individual-level forecasting performance. In Chapter 4, the survey data collected for this research effort was used to test three hypotheses:

> *Hypothesis 1: Forecasting task-technology fit is positively related to forecaster performance.*
>
> *Hypothesis 2: Forecasting-focused climate is positively related to forecaster performance.*
>
> *Hypothesis 3: Forecasting-focused climate moderates the relationship between forecasting task-technology fit and forecaster performance.*

As a reminder, the conceptual model and associated hypotheses are presented in Figure 5.1.

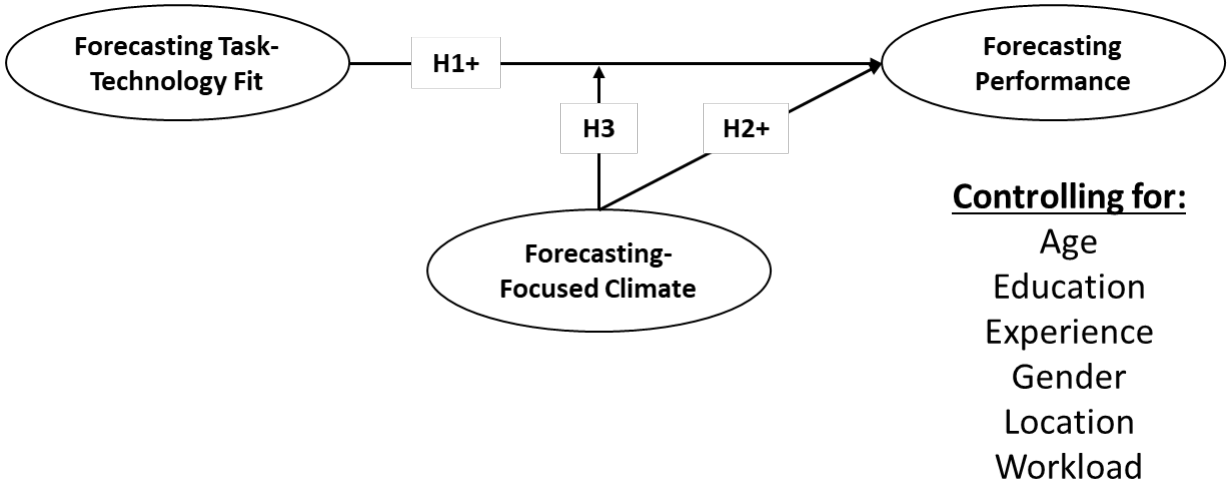


Figure 5.1. Conceptual Model.

This chapter presents a discussion of the results presented in Chapter 4. First, the findings and research implications are discussed. Next, the practical implications of the results are discussed. Finally, the chapter concludes with a discussion of the limitations of the research effort. Potential opportunities for future research are also reviewed.

Implications for Research

As discussed in Chapter 1, issues of demand forecasting have received relatively little attention from logistics and supply chain researchers. Moreover, existing literature tends to focus on forecasting at the organization and supply chain levels though there is evidence that, in practice, much of the forecasting process takes place at a disaggregate level where individual forecasters review and adjust statistical forecasts (Davydenko & Fildes, 2013; Fildes & Goodwin, 2007; McCarthy-Byrne et al., 2011). Further still, though research focused on individual-level forecasting performance has considered a variety of variables, few researchers have explored variables that help link management practices to individual level forecasting performance. This represents the first of three gaps this research effort was intended to address.

Taken as a whole, this research effort addressed this gap (Gap #1) in the literature by focusing on forecasting at the individual level, using objective measure of forecasting performance, and by employing constructs representing levers that can be and are often manipulated by managers to facilitate forecast accuracy. Specifically, findings from this research effort provide evidence that task-technology fit theory helps explain individual performance in the context of making forecast adjustments. As discussed in Chapter 2, the forecasting task and forecasting technology (i.e. forecasting support system) are

inextricably linked. This research effort demonstrates the efficacy of capturing aspects of the forecasting task and associated technology through a single construct. Of note, this research effort found that perceptions of forecasting task-technology fit were significantly related to actual individual-level forecasting performance ($\beta=-0.13$, $t=-2.09$, $p=0.04$) thereby lending support to *Hypothesis 1*. By linking perceptions of task-technology fit to individual-level performance this finding adds to previous findings from the management information systems literature from which task-technology fit theory was borrowed. It also adds to findings from forecasting-specific research that have demonstrated the link between forecasting support systems and the accuracy of forecast adjustments.

Counter to what was predicted in *Hypothesis 2*, forecasting-focused climate—a multi-dimensional indicator of a forecaster's organizational context—did not have a significant main effect on individual-level forecasting performance. However, the significant interaction effect ($\beta=-0.16$, $t=-2.73$, $p=0.01$), supported the hypothesis that forecasting-focused climate moderates the relationship between forecasting task-technology fit and forecasting performance (*Hypothesis* H_3). Moreover, even after controlling for forecasting experience which, by itself, explained approximately 11% of the variation in forecasting performance ($p=0.02$), the combination of forecasting task-technology fit and forecasting-focused climate significantly contributed to the ability to explain variation in forecasting performance in the context of forecast adjustments ($\Delta R^2=0.17$, $p=0.03$). Closer inspection of the interaction effect suggested that the positive relationship between forecasting task-technology fit is made more positive by high levels of forecasting-focused climate.

This finding helps address Gap #3. Namely, this research found that organizational context has an effect on individual-level forecasts by interacting with task-technology fit. Also implied is the efficacy of organizational climate theory and focused climates to help link management practices to individual-level forecasting performance. In particular, the construct helps link such concepts as training, feedback, supervisor support, knowledge availability, job importance, rewards, and restrictiveness to forecasting performance. It also represents a new discovery as no known prior research has empirically investigated the relationship between a forecaster's perceptions of the organizational context and actual individual-level forecasting performance.

Another goal of this research was to assess the role of tacit knowledge in enabling or detracting from individual forecasting performance (Gap #2). This gap was only partially addressed. Notably, this research effort discovered that tacit knowledge could be considered one of several facets of a forecaster's organizational context. However, the direct and singular impact of tacit knowledge on individual forecasting performance was not assessed and, therefore, cannot be discussed in great detail.

There were two findings resulting from this research that were not expected. First, as indicated, in the context of forecast adjustments, forecasting experience was found to be a significant predictor of forecasting performance along with task-technology fit and forecasting-focused climate. In the context of overall individual-forecasting performance, however, forecasting experience was the only significant predictor of forecasting performance. The finding that forecasting experience was a significant predictor of forecasting performance is not new. Previous research has linked forecasting experience to more accurate judgmental forecasts and judgmental adjustments of forecasts (Sanders

and Ritzman, 1991, Sanders and Ritzman, 2001). However, it was surprising that forecasting experience was the only significant predictor in the case of overall individual forecasting performance. This finding is likely context specific. In general respondents indicated perceptions of high fit in the context of both overall performance and in the context of forecast adjustments. However, a remark by one forecaster seems to suggest that while fit may have been assessed favorably, the impact of the forecasting system on individual performance was not to be expected. In particular, in spite of the requirement to make and adjust forecasts on a quarterly basis, it seems that, in practice, many ESs opt to forecast by exception due to the complex nature of their task. As one ES commented:

> *"Basically we call it "letting it ride". That's a very common thing in the ES world is "let it ride". They lock in a rate, and every quarter they're just stamping and going, and they let it ride…It really makes you–you really should get into it. There are a lot of contributing factors where you would continue to let that rate ride, but you really need to evaluate it every three months.*

If the dynamic of "letting it ride" is indeed wide-spread, perhaps the task-technology fit relationship would have been best observed in a longitudinal study measuring changes in perceptions of fit and performance over time.

Continuing on, evidence supporting the link between task-technology fit and performance in the context of forecast adjustments was found. A question that naturally flows from the preceding discussion is why the relationship is significant in the context of forecast adjustments and not in the context of all forecasts made? The explanation likely lies in the difference between day-to-day forecasting and the sub-task of making forecast adjustments. In particular, the issues regarding how the construct was operationalized would likely not be a limitation in this context because the system quality and system

accessibility dimensions would be particularly salient in context of making forecast adjustments. As previously discussed, in the case of day-to-day task requirements, ESs may or may not rely on the forecasting system(s) to aid in task accomplishment. In the case of adjustments to forecasts, however, it is possible that ESs rely more on the system due to organizational policy and due to features of the system that aid in making forecast adjustments.

For example, in an effort to promote accountability for forecast adjustments and to mitigate the impact of biased forecasts, organizational policy necessitates justification be provided by the individual making an adjustment. Depending upon the dollar value of the supply item involved, providing justification may involve inputting a short note directly into the forecasting system that explains the circumstances that prompted the adjustment as well as justification for the forecaster's method of adjustment (i.e. use of the four quarter moving average or use of an estimated rate). For adjustments involving high dollar value items or which might prompt a large buy requirement, individuals may be required to explain the purpose and method behind the adjustment in a more formal way. Adjustments involving such items are more likely to be reviewed by supervision and upper-level management.

In terms of system features that aid in making forecast adjustments, ESs have access to multiple tools that can aid in deciding upon an appropriate course of action. For example, ESs have the ability to accomplish a "what-if" analysis. This capability is provided in the Forecast Assessment and Comparison Tool (FACT) and allows ESs to assess the risk associated with their proposed adjustment. As another example, ESs also

have the capability to perform various queries and filters to historical data to assist in building the case for an adjustment and to help justify their approach to the adjustment.

Another unexpected finding was that survey respondents' self-reported forecast accuracy was found to be in weak agreement with actual forecast accuracy. This finding may be attributed to a few factors. First, this research employed a single item measure with a Likert-type scale to capture overall forecasting performance. A better approach would have been to use a multi-faceted measure of self-reported forecasting performance or to allow respondents to manually enter their forecasting performance. On a related note, discussions with a contact in the organization indicated that while forecasting performance was discussed very openly across the organization, the feedback individuals received with regard to their forecasting performance was not provided in aggregate form but, rather, by supply item. Thus, it is not likely that survey respondents could have provided a truly accurate indication of their overall forecast performance as asked on the survey. Regardless of these oversights, the implications for researchers are clear. As it is common for researchers to rely upon self-reported data, particularly in survey research, this finding serves to caution researchers against relying solely on self-reported data. This is especially true in the context of forecasting research where it has been noted that few organizations track forecasting performance or provide individual-level forecasting performance feedback (Davydenko and Fildes, 2013; Fildes and Goodwin, 2007; McCarthy-Byrne et al., 2011).

Implications for Management Practice

These findings hold implications for management practice. First and foremost, the findings reinforce Bretschneider and Gorr's (1989) view of forecasting as both science and "human activity". This is indicated by the fact that both task-technology fit and forecasting-focused climate are based on individuals' perceptions of the technology they use to accomplish their work and the perceptions of the organizational context within which that work takes place. This suggests that managers should take a broad approach to improving forecasting in their organizations and not simply focus on forecasting techniques and methods. Part of their approach should include making themselves familiar with the perceptions of the individuals performing the day-to-day forecasting process. This includes addressing perceptions of the organization's forecasting support system(s) as well as training, supervision, rewards, feedback, and knowledge availability.

A second implication for management practice is the importance of forecasting experience. As discussed, forecasting experience proved to be a key predictor of individual-level forecasting performance in both contexts considered. This finding further reinforces the importance of organizational context and the need to address issues such as training, feedback, and rewards. This finding also implies the need for effective human resources and talent management practices. As recent logistics and supply chain research has indicated, finding and retaining supply chain talent is a challenge that must be confronted by many organizations (Stank et al., 2011). The results of this research effort suggest that this observation may very well extend to forecasters and demand planners.

Limitations and Opportunities for Future Research

While this research addressed multiple gaps in forecasting as well as logistics and supply chain research, there were several limitations. First, the sampling frame for this research consisted of Air Force forecasters. Arguably, the dynamics and challenges associated with demand forecasting are pervasive in a variety of logistics and supply chain settings. Nonetheless, the ability to generalize from the findings of this research effort is limited. Although attributes of this research setting paralleled those observed in existing literature, the differences between public and private sector organizations must be acknowledged. For this reason, future research could investigate if the relationships between task-technology fit and forecasting focused-climate found in this research effort also hold in private sector organizational settings.

Additionally, the limited sample size also limits the generalizations that can be made from this research effort. The findings are based on samples of 55 and 46 respondents. A larger sample would be advantageous for broader generalizations and would also allow for more robust means of analysis. In particular, a larger sample allows for greater explanatory power and boosts the ability to further explore the nature of the interaction effect found here. Even more, a larger sample size could potentially allow for multi-level assessments incorporating shared climates at the group, and organizational levels. Such an effort would allow for the possibility to test the propositions of Davis and Mentzer (2004) who conceived of forecasting climate at the organization level.

Other limitations also existed in terms of measuring and operationalizing key constructs. In particular, while representing the forecasting-focused climate construct as a higher order factor was theoretically justified and offered model parsimony, it is not

known how the dimensions of forecasting focused climate individually relate to both forecasting performance and to perceptions of task-technology fit. Therefore, future research may be able to illuminate which dimensions of forecasting-focused climate are most impactful in these relationships.

Further, while the forecasting task-technology fit scales borrowed from Smith and Mentzer (2010a) were found to be valid and reliable in this research effort, the scales offer a relatively limited picture of how forecasters assess fit for a forecasting support system. Overall, respondents in this research effort seemed to assess fit as being relatively high. However, it is possible that this was due to the fact that fit was only assessed along two dimensions—accessibility and quality. Presumably, had respondents had the opportunity to assess systems along other facets of fit in addition to the two dimensions assessed here, a more accurate picture of perceptions of fit would have been achieved and more aptly related to variations in overall individual forecasting performance. A review of qualitative data provided by survey respondents would seem to support this notion. The following comments made by survey respondents are provided as examples:

> *"The system I use is archaic and is not real-time. The forecast is 12 months in the past for 24 months' prior data. I cannot see any change for 12 months. Very, very difficult to get accurate."*
>
> *"Data is not recent enough to fully accommodate forecasting and human interface with the supply systems dictate when an item is accounted for in the system. Delays on system input result in inaccurate alignment of supply turn in actions…"*
>
> "*IRIS is much more user friendly but D200 is old pulls in too much information from too many systems and timing issues make it almost impossible to find disconnects and possible flaws in data*".

The scale borrowed from Smith and Mentzer (2010a) was itself based on three of Goodhue's (1998) eight proposed dimensions of task-technology fit. Taken together, these comments suggest that more insight could have been garnered if at least two other dimensions (i.e. *currency* and *compatibility*) of task-technology fit proposed by Goodhue (1998) had been assessed. Future work should make an effort to employ more facets of forecasting task-technology fit as implied here.

A final limitation of this research effort is the inability to assert causation. This due to the cross sectional nature of the survey research employed. Thus, future research should exploit different research designs and methods in order to illuminate what causal relationships exist between forecasting task-technology fit, forecasting-focused climate, and forecasting performance. Research of this nature would be invaluable to informing forecasting improvement efforts.

Conclusion

The purpose of this research was to assess how "softer" factors germane to forecasting ultimately affect forecaster performance. Specifically, this research assessed the effects of forecasting task-technology fit, and forecasting-focused climate on individual-level forecasting performance. As part of this research effort, four research questions were posed:

1. *What effect does forecasting task-technology fit have on individual-level forecaster performance?*

2. *What effect does knowledge management effectiveness have on individual-level forecaster performance?*

3. What effect does forecasting-focused climate have on individual-level forecaster performance?

4. What is the relationship between forecasting task-technology fit, knowledge management effectiveness, and forecasting-focused climate?

Following a review of pertinent literature and theory, a mixed methods design was employed to answer the four research questions and associated hypotheses. The design consisted of a qualitative phase wherein interviews were conducted with Air Force forecasters, supply chain managers, and supply chain senior leaders. Based on the interviews, a new forecasting-focused climate scale was developed and assessed for substantive validity. Following the qualitative phase of the research, a quantitative phase ensued whereby a survey instrument was administered to capture forecasters' perceptions of forecasting task-technology fit, forecasting-focused climate, forecasting performance, and individual demographic attributes. A total of 154 useable responses were received. Of the 154 survey responses, 55 responses allowed for the use of historical performance data in subsequent tests of hypotheses. Due to weak agreement between self-reported data and historical performance data, only responses for which historical data were available were analyzed for hypothesis testing and, ultimately, used to answer the research questions.

Overall, three of the four research questions were answered. First, in the case of overall forecasting performance, forecasting experience was found to be the only significant predictor of individuals' forecasting performance. However, within the context of forecast adjustments, forecasting task-technology fit and forecasting focused climate were both found to explain an additional 17 percent of the variation in individuals' forecasting performance above and beyond forecasting experience.

Moreover, evidence for an interaction effect comprised of forecasting task-technology fit and forecasting-focused climate was discovered. In particular, the relationship between forecasting task-technology fit and individual level forecasting performance was found to become more positive at above average levels of forecasting-focused climate. Both theoretical and practical implications were drawn from these findings. Overall, this research effort contributed evidence that focusing on the "softer" aspects of forecasting holds the potential to improve forecast accuracy. In particular, this research effort helps explain how management practices that shape forecasters' tasks, technology, and organizational context may influence individual level forecasting performance. Moreover, the findings make the case for a broad approach to forecast improvement initiatives. These findings hold promise for supply chain leaders and managers in public and private sector organizations alike.

Appendix A: IRB Exemption Approval Documents

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

6 June 2016

MEMORANDUM FOR LT COL MATTHEW DOUGLAS, PHD

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

SUBJECT: Approval for exemption request from human experimentation requirements (32 CFR 219, DoDD 3216.2 and AFI 40-402) for your study, Forecasting Climate Scale Development.

1. Your request was based on the Code of Federal Regulations, title 32, part 219, section 101, paragraph (b) (2) Research activities that involve the use of educational tests (cognitive, diagnostic, aptitude, achievement), survey procedures, interview procedures, or observation of public behavior unless: (i) Information obtained is recorded in such a manner that human subjects can be identified, directly or through identifiers linked to the subjects; and (ii) Any disclosure of the human subjects' responses outside the research could reasonably place the subjects at risk of criminal or civil liability or be damaging to the subjects' financial standing, employability, or reputation.

2. Your study qualifies for this exemption because you are not collecting sensitive data, which could reasonably damage the subjects' financial standing, employability, or reputation. Further, the demographic data you are utilizing and the way that you plan to report it cannot realistically be expected to map a given response to a specific subject.

3. This determination pertains only to the Federal, Department of Defense, and Air Force regulations that govern the use of human subjects in research. Further, if a subject's future response reasonably places them at risk of criminal or civil liability or is damaging to their financial standing, employability, or reputation, you are required to file an adverse event report with this office immediately.

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

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

19 Oct 2016

MEMORANDUM FOR Dr. Jeffrey A. Ogden (AFIT/ENS)

FROM: Brett J. Borghetti, Ph.D.
AFIT IRB Exempt Determination Official
2950 Hobson Way
Wright-Patterson AFB, OH 45433-7765

SUBJECT: Approval for exemption request from human experimentation requirements (32 CFR 219, DoDD 3216.2 and AFI 40-402) for study "Forecasting Effectiveness Survey", dated 6 Oct 2016.

1. Your request was for exemption based on the Code of Federal Regulations, title 32, part 219, section 101, paragraph (b) (2) Research activities that involve the use of educational tests (cognitive, diagnostic, aptitude, achievement), survey procedures, interview procedures, or observation of public behavior unless: (i) Information obtained is recorded in such a manner that human subjects can be identified, directly or through identifiers linked to the subjects; and (ii) Any disclosure of the human subjects' responses outside the research could reasonably place the subjects at risk of criminal or civil liability or be damaging to the subjects' financial standing, employability, or reputation.

2. Your study **qualifies for this exemption** because you are using survey procedures and are not collecting personally identifiable data in the survey.

3. This determination pertains only to the Federal, Department of Defense, and Air Force regulations that govern the use of human subjects in research. Further, if a subject's future response reasonably places them at risk of criminal or civil liability or is damaging to their financial standing, employability, or reputation, you are required to file an adverse event report with this office immediately.

10/19/2016

X

Signed by: BORGHETTI.BRETT.J.1009082820

BRETT J. BORGHETTI, Ph.D.
AFIT Exempt Determination Official

Appendix B: Talking Paper, Informed Consent Form, & Interview Protocols

TALKING PAPER

ON

FORECASTING CLIMATE RESEARCH PROJECT

- The purpose of this talking paper is to introduce Air Force Sustainment Center (AFSC)-sponsored research study being conducted by the Air Force Institute of Technology (AFIT). The purpose of the study is to develop a measurement tool which captures an individual's perceptions of their organization's climate for forecasting. The tool will provide leaders with a view of how forecasting policies, procedures, practices, and priorities support or hinder positive forecasting behaviors.

- Issue / Research Problem Statement

  -- Weaknesses in accurately forecasting demand has been identified as a root cause of inventory imbalances throughout the DoD. Notably, Section 328 of the National Defense Authorization Act for Fiscal Year 2010 mandated that the DoD create a plan for the "comprehensive review of demand forecasting procedures to identify and correct any systematic weaknesses". In response, the Office of the Secretary of Defense drafted the Comprehensive Inventory Management Improvement Plan highlights some of the initiatives embarked upon by the Services and the Defense Logistics Agency to improve demand forecasting effectiveness.

  -- Overall, initiatives to improve demand forecasting appear to focus on the more technical aspects of demand forecasting. In order to truly improve forecasting effectiveness, managers must take a comprehensive view of forecasting capability and account for the impact that "non-technical" aspects of forecasting have upon forecasting performance. In particular, leaders must consider the degree to which an organization's policies, procedures, practices, and priorities encourage accurate and minimally biased forecasts.

- Research Objectives

  -- Identify indicators, in the demand forecasting context, that can be used to measure an individual's perceptions of their organization's climate for forecasting

  -- Identify how an individual's perceptions of their organization's climate for forecasting influences forecasting performance

- Research Methodology

  -- Measurement scale development and validation

- Points of Contact

  -- Researcher, Maj Anthonelli White, PhD Student, AFIT, Department of Operational Sciences

  -- Principal Investigator, Lt Col Matthew Douglas, Assistant Professor, AFIT, Department of Operational Sciences

  -- Sponsor, Col Stacey Scarisbrick, Deputy Director, Air Force Sustainment Center Logistics Operations, AFSC/LG

Maj White/AFIT/ENS/DSN785-3636x6173/aw/10May2016

CONSENT TO PARTICIPATE IN INTERVIEW

FORECASTING CLIMATE RESEARCH

You have been asked to participate in a research study conducted by researchers from the Air Force Institute of Technology (AFIT), Graduate School of Engineering and Management, Department of Operational Sciences. The main objective of the project is to develop a measurement tool designed to measure an individual's perceptions of their organization's climate for forecasting. The tool will provide leaders with a view of the shared perceptions among members of the unit with regard to forecasting policies, procedures, practices, and priorities. The results of this study will be included in a report and briefed to all research sponsors and may also be reported in research publications. You were selected as a possible participant in this study because of your knowledge of and experience in demand forecasting. You should read the information below and ask questions about anything you do not understand before deciding whether or not to participate.

- This interview is voluntary. You have the right not to answer any question, and to stop the interview at any time or for any reason. I expect that the interview will take 30-60 minutes.

- You will not be compensated for this interview.

- The information you tell us will be kept confidential.

- I would like to record this interview so that I can transcribe it and use it for analysis as part of this study. I will not record this interview without your permission. If you grant permission for this conversation to be recorded, you have the right to revoke permission and/or end the interview at any time.

- This project will be completed by July 2016. All interview documents will be stored in a secure work space until 1 year after that date. The documents will then be destroyed.

I understand the procedures described above. My questions have been answered to my satisfaction, and I agree to participate in this study. I have been given a copy of this form.

(Please initial)

[ ] I give permission for this interview to be recorded and transcribed.

Name of Subject:

Signature of Subject_____Date_____

Signature of Investigator_____Date _____

Please contact Major Anthonelli White at anthonelli.white@afit.edu or 937-255-3636 x 6173; or Lt Col Douglas with any questions or concerns at matthew.douglas@afit.edu.

Maj White/AFIT/ENS/DSN785-3636x6173/aw/10May2016

Purpose

The purpose of this interview study is to understand how the concept of forecasting climate manifests itself in the "life-world" of forecasters in DoD logistics and sustainment organizations.

Methodology

Semi-structured interviews will be used to clarify the concept of forecasting climate within the context of DoD logistics and sustainment organizations. The interview study will be guided by climate theory as it pertains to psychological climate as well as climate-related findings from forecasting management research (i.e. Moon et al., 2003; Davis and Mentzer, 2007). As such, the following themes are of interest to this study although the researcher will also be open to any new themes which emerge from interviewee responses:

- Leadership support and commitment to the forecasting function/process
- Credibility of/confidence in the forecasting function/process
- The degree to which positive/negative forecasting behaviors are incentivized/dis-incentivized

Research questions

1) *What cues (i.e. from leadership, rewards, etc.) of desired forecasting-related behaviors do DoD forecasters perceive in their organizational environments?*

2) *How do DoD forecasters respond to these perceived cues?*

2016 AFIT Forecasting Climate Study
Interview Script for Forecasters

1) Can you describe your role in the forecasting process here at [insert organization's name]?

2) Can you give me a sense of how important the forecasting process is here at [insert organization's name]? – ***RQ 1***
- Where does your impression of the importance of forecasting come from (e.g. leadership emphasis, organizational goals, improvement initiatives, etc.)? – ***RQ 1***

3) Given your role in the forecasting process here, how important is it that you forecast well? – ***RQ 1***
- Where does that impression come from (e.g. leadership emphasis, organizational goals, etc.)? – ***RQ 1***

4) Can you describe specific behaviors that are frowned upon when it comes to making forecasts (e.g. over-forecasting)? How do you know they are frowned upon? – ***RQ 1***
- What are the consequences of those behaviors? – ***RQ 1***
- How do they affect how you accomplish your forecasting-related tasks? -- ***RQ 2***

5) Can you describe specific behaviors that are appreciated when it comes to making forecasts? How do you know they are appreciated? – ***RQ 1***
- What are the consequences for those behaviors? – ***RQ 1***
- How do they affect how you accomplish your forecasting-related tasks? – ***RQ 2***

6) Can you explain how ***policies and procedures*** here at [insert organization's name] impact how you perform your forecasting-related tasks (e.g. how much effort or time spent on forecasting)? Can you provide examples of specific policies and procedures and their impact? – ***RQ 1 & RQ 2***

7) What about ***informal practices*** (i.e. unwritten rules), how do they impact how you perform your forecasting-related tasks? Can you provide examples of specific practices and their impact? --***RQ 1 & RQ 2***

8) Can you explain how ***leadership and management*** here at [insert organization's name] impact how you perform your forecasting-related tasks (e.g. how much effort or time spent on forecasting)? Can you provide examples? -- ***RQ 1 & RQ 2***

9) What level of confidence do you have in the forecasting process here (e.g. forecasts can be trusted, a lot of effort is put into the process, etc.)? – ***RQ 1***
- Where does that sense of confidence come from? – ***RQ 1***
- How does that impact how you accomplish your forecasting-related tasks? – ***RQ 2***

10) Is there anything else you would like to add or discuss?

2016 AFIT Forecasting Climate Study
Interview Script for Supervisors and Leaders

1) Can you describe your role in the forecasting process here at [insert organization's name]?

2) Can you give me a sense of how important the forecasting process is here at [insert organization's name]? – ***RQ 1***
   - Where does your impression of the importance of forecasting come from (e.g. leadership emphasis, organizational goals, improvement initiatives, etc.)? – ***RQ 1***

3) Given your role in the forecasting process here, how important is it that those who work for you forecast well? – ***RQ 1***
   - Where does that impression come from (e.g. leadership emphasis, organizational goals, etc.)? – ***RQ 1***

4) Can you describe specific behaviors that are frowned upon when it comes to making forecasts (e.g. over-forecasting)? How do those that work for you know they are frowned upon? – ***RQ 1***
   - What are the consequences of those behaviors? – ***RQ 1***
   - How do you believe they affect the individuals performing forecasting-related tasks? -- ***RQ 2***

5) Can you describe specific behaviors that are appreciated when it comes to making forecasts? How do those that work for you know they are appreciated? – ***RQ 1***
   - What are the consequences for those behaviors? – ***RQ 1***
   - How do you believe they affect the individuals performing forecasting-related tasks? – ***RQ 2***

6) Can you explain how ***policies and procedures*** here at [insert organization's name] impact the individuals performing forecasting-related tasks (e.g. how much effort or time spent on forecasting)? Can you provide examples of specific policies and procedures? – ***RQ 1 & RQ 2***

7) What about ***informal practices*** (i.e. unwritten rules), how do they impact individuals performing forecasting-related tasks? Can you provide examples of specific practices? -- ***RQ 1 & RQ 2***

8) Can you explain the role of ***leadership and management*** here at [insert organization's name] in impacting individuals performing forecasting-related tasks (e.g. how much effort or time spent on forecasting)? Can you provide examples? -- ***RQ 1 & RQ 2***

9) What level of confidence do you have in the forecasting process here (e.g. forecasts can be trusted, a lot of effort is put into the process, etc.)? – ***RQ 1***
   - Where does that sense of confidence come from? – ***RQ 1***
   - How do you believe that level of confidence impacts those that work for you in the performance of their forecasting-related tasks? – ***RQ 2***

10) Is there anything else you would like to add or discuss?

Appendix C: Completed Item Sort Task

Instructions: Please read the definition provided for each concept in the columns to the right. For every statement below, please indicate which concept you believe best corresponds to the statement by marking an X in the appropriate column. Each statement must be matched to one and only one concept. For example, the first statement best corresponds to the "Use of Judgment" concept and has already been marked appropriately.	**Job Importance:** the importance and impact of forecasting	**Restrictiveness: forecasting related** restrictions/accountability mechanisms	**Supervisor Support & Facilitation:** the supervisor's role in supporting the forecaster	**Role Stress:** Degree to which competing priorities or uncontrollable factors impact the individual's ability to forecast effectively	**Use of Judgment:** the individual's ability to leverage judgment/domain knowledge when forecasting	**Training:** the adequacy and accessibility of forecasting-related training	**Workgroup Cooperation:** support received from the workgroup to aid in forecasting decisions	**Feedback:** the adequacy and usefulness of feedback regarding individual forecasting performance	**Rewards/Recognition:** rewards, recognition, and incentives related to individual forecasting performance
I am encouraged to use technical knowledge about my assigned items to improve system provided-forecasts					X				
When it comes to forecasting, I am expected to follow all related policies, procedures, and guidance to the letter		X							
My forecasting-related decisions are subject to audit/review		X							
I have been adequately trained to execute all assigned forecasting-related tasks						X			
I regularly receive updates on the forecast accuracy for my assigned items/systems								X	
I can trust my supervisor to back me up on forecasting-related decisions			X						
I know exactly what my supervisor expects from me when it comes to forecasting			X						
I regularly receive updates on my forecasting bias (i.e. tendency to over- or under-forecast)								X	
My forecasts really make a difference	X								
My supervisor provides me the tools I need to forecast accurately			X						
The characteristics of my assigned items/systems make forecasting extremely difficult				X					
Factors outside of my control often prevent me from forecasting accurately				X					
The feedback I receive helps me improve my forecasting performance								X	
I understand the impact my forecasts have on how my customers perform	X								
I receive encouragement from my work group to forecast accurately							X		
I understand the impact my forecasts have on how resources are allocated	X								
The training I received helped me understand how to use inputs from outside sources (e.g. program manager, engineers, customers, etc.) to improve system-provided forecasts						X			
I can rely on my work group to help me resolve issues that interfere with my ability to forecast accurately							X		
My supervisor helps me resolve issues that interfere with my ability to forecast accurately			X						
I understand the impact my forecasts have on how my organization performs	X								
There are just too many variables to consider for me to forecast accurately				X					

The “checks and balances” related to adjustments (i.e. estimated rates, manual overrides, etc.) never get in the way of my ability to improve system-provided forecasts		x							
The training I received helped me understand how to use technical knowledge to improve system-provided forecasts						x			
I can rely on my work group to help me interpret forecasting-related guidance, procedures, and policies							x		
I regularly receive updates on my overall forecasting accuracy								x	
I receive adequate feedback on my overall forecasting performance								x	
The “checks and balances” related to forecasting never get in the way of my ability to forecast accurately		x							
My supervisor gives me the authority to make forecasts as I see fit			x						
I can rely on my work group to help me make sense of the inputs I receive from outside sources (e.g. program manager, engineers, customers, etc.)							x		
I am recognized for my forecasting performance									x
I am rewarded for the time and effort I put into forecasting									x
I am encouraged to use inputs from outside sources (e.g. program manager, engineers, customers, etc.) to improve system-provided forecasts					x				
My forecasting performance is considered in evaluations of my overall job performance									x
When necessary, I am permitted to make adjustments to system-provided forecasts (i.e. estimated rates, manual overrides, etc.)					x				
I regularly receive updates on how my adjustments to system-provided forecasts (i.e. estimated rates, manual overrides, etc.) impact forecast accuracy								x	
I receive periodic training to refresh my forecasting-related knowledge						x			
I understand what is done with my forecast after it has been submitted	x								
Incentives for forecasting accurately motivate me to put more effort into my forecasts									x
I have been adequately trained to use all forecasting-related systems						x			
My supervisor is flexible about how I accomplish my forecasting-related work			x						
Comparing notes with members of my work group helps me decide the best way to forecast in certain situations							x		
I am recognized for meeting forecasting goals									x
The training I received gave me a good grasp of my organization’s forecasting process						x			
Other duties/tasks often interfere with my ability to forecast accurately				x					

My assigned workload (i.e. NSNs, systems, etc.) is not manageable				x					
My supervisor has reasonable expectations regarding my forecasting performance			x						
External people/organizations prevent me from forecasting accurately				x					
I am always required to justify the adjustments I make to system-provided forecasts (i.e. estimated rates, manual overrides, etc.) with data/documentation		x							
I often receive pressure from others (e.g. program manager, engineers, customers, etc.) to adjust forecasts when it is not warranted/justified				x					
My supervisor helps me interpret forecasting-related guidance, procedures, and policies			x						
I have been adequately trained to understand all forecasting-related policies and procedures						x			
I have access to training resources to keep my forecasting-related knowledge fresh						x			
I am held accountable for my forecasting-related decisions		x							
My supervisor encourages me to forecast as accurately as possible			x						
My supervisor generally appreciates the time and effort I put into forecasting									x

Appendix D: Survey Invitation, Cover Page, & Items

DEPARTMENT OF THE AIR FORCE
AIR UNIVERSITY (AETC)

18 January 2017

MEMORANDUM FOR RECORD

FROM: AFIT/ENS

SUBJECT: Invitation to Complete AFIT Forecasting Effectiveness Survey

1. Greetings! You are invited to participate in a research study sponsored by AFSC/LG and conducted by researchers from the Air Force Institute of Technology (AFIT), Graduate School of Engineering and Management, Department of Operational Sciences. You are receiving this invitation to participate in this study because of your role in and knowledge of the demand forecasting process.

2. The main objective of this project is to understand how different aspects of the organization and work environment (e.g. systems, procedures, training, feedback, etc.) affect an individual's ability to produce accurate and unbiased forecasts. The findings from the study are expected to provide insight into how 448 SCMW leaders can further support and improve the demand forecasting process. The survey consists of 93 questions and is estimated to take approximately 15 to 25 minutes to complete based on your responses. Survey responses will be kept **strictly confidential** and at no time will survey responses be used to identify an individual. Findings will be disseminated in reports to AFSC/LG and 448th Supply Chain Management Wing leadership, as well as in research publications.

3. If you have any questions regarding this research study, I can be reached at anthonelli.white@afit.edu or DSN 785-3636, extension 6173. To participate in the survey, follow the link: https://surveys.afit.edu/index.cfm?id=41&STID=4101.

//SIGNED-aw//
ANTHONELLI WHITE, Maj, USAF
Logistics PhD Candidate
Air Force Institute of Technology

Cover Letter

The following information is provided as required by the Privacy Act of 1974:

Purpose: The purpose of this survey is to understand the role and impact of organizational and behavioral factors upon individual-level forecasting effectiveness. Specifically, our goal is to understand how forecasters perceive their work environment as well as the support systems, procedures, and information available to forecasters in the performance of their day-to-day forecasting tasks. Additionally, by linking survey responses to performance data, we hope to understand the relationship between these perceptions and an individual forecaster's ability to produce accurate and unbiased forecasts. The findings from the study are expected to provide insight into how managers can maintain and improve effective demand forecasting within their organizations.

This survey is sponsored by the Air Force Sustainment Center Logistics Directorate (AFSC/LG) and the 448th Supply Chain Management Wing Director (448 SCMW/CL). This survey has been approved by the Air Force Survey Office (Survey Control Number XXXXXX). Approval can be verified by following the link to the AF Portal Survey Office List of Approved Surveys: https://www.my.af.mil/gcss-af/USAF/ep/globalTab.do?channelPageId=sE3494DD04562FCC901456BE0545CO17A

Participation: We would greatly appreciate your participation in our data collection effort. However, your participation is **STRICTLY VOLUNTARY**. Your decision not to participate or to withdraw from participation will not jeopardize your relationship with the Air Force Institute of Technology, the U.S. Air Force, or the Department of Defense.

Confidentiality: We would greatly appreciate your participation. **ALL ANSWERS WILL BE KEPT STRICTLY CONFIDENTIAL**. In no way will the information you provide be used to determine who you are. The demographic information is valuable to this research and will only be used in analysis of the results. No one other than the research team will see your responses. Group trends and statistical findings may be published and briefed to leadership personnel as part of this research.

NOTE: We cannot provide confidentiality to a participant regarding comments involving criminal activity/behavior, or statements that pose a threat to yourself or others.

Instructions: This survey consists of various questions and statements which will measure your perceptions of various aspects of forecasting within your organization. For each section, please indicate the degree to which you agree or disagree with the associated statements. If you are uncertain how to answer a particular question, or if the statement does not apply to your unit, please choose the "not applicable" response. Additionally:

- ☐ Please answer all questions in the context of your unit which is defined as the squadron, directorate, or division in which you are currently employed.

- ☐ Please **DO NOT** complete the survey if:
    - You have previously participated in interviews with the research team.

- You are not directly involved in your organization's forecasting process.

☐ Please **DO NOT** discuss or comment on classified or operationally sensitive information.

☐ This survey should take approximately 15-20 minutes to complete. You may exit this survey and return to it at any time if you do not finish on your first attempt.

☐ Base your answers on your own thoughts and experiences.

☐ Please make your answers clear and concise when asked to answer in a response or when providing comments.

☐ Be sure to select the correct option button when asked.

For any questions regarding this survey, please contact Major Anthonelli White at anthonelli.white@afit.edu or at DSN 785-3636; extension 6173.

Job Importance Scale: The following statements refer to the general importance and impact of forecasting. Please indicate the degree to which you agree or disagree with the following statements:: (7-point Likert scale anchored by Strongly Disagree and Strongly Agree)	I understand what is done with my forecast after it has been submitted.
	My forecasts really make a difference.
	I understand the impact my forecasts have on how my organization performs.
	I understand the impact my forecasts have on how resources are allocated.
	I understand the impact my forecasts have on how my customers perform.1
	Please add clarifying comments for any response (as required):
Supervisor Support Scale: The following questions refer to how your equipment specialist supports you in the execution of your forecasting-related tasks. Please indicate the degree to which you agree or disagree with the following statements: (7-point Likert scale anchored by Strongly Disagree and Strongly Agree)	My lead ES helps me resolve issues that interfere with my ability to forecast accurately.
	My lead ES helps me interpret forecasting-related guidance, procedures, and policies.
	My lead ES ensures I have the resources I need to forecast accurately.
	I know exactly what my lead ES expects from me when it comes to forecasting.
	My lead ES has reasonable expectations regarding my forecasting performance.
	My lead ES is flexible about how I accomplish my forecasting-related work.
	My lead ES gives me the authority to make forecasts as I see fit.
	I can trust my lead ES to back me up on forecasting-related decisions.
	My lead ES encourages me to forecast as accurately as possible.
	Please add clarifying comments for any response (as required):
Restrictiveness Scale: The following statements refer to restrictions and accountability measures involved in forecasting; as reflected in policy, procedures, or local practice. Please indicate the degree to which you agree or disagree with the following statements: (7-point Likert scale anchored by Strongly Disagree and Strongly Agree)	When necessary, I am permitted to make adjustments (i.e. estimated rates, manual overrides, etc.) to system-provided forecasts.
	My forecasting-related decisions are subject to audit/review.
	The “checks and balances” related to forecasting never get in the way of my ability to forecast accurately.
	I am always required to justify the adjustments I make to system-provided forecasts (i.e. estimated rates, manual overrides, etc.) with data/documentation.
	The “checks and balances” related to adjustments (i.e. estimated rates, manual overrides, etc.) never get in the way of my ability to improve system-provided forecasts.
	I am permitted to adjust system-provided forecasts (i.e. estimated rates/manual overrides) based on my own personal knowledge (i.e. from experience) about an assigned item.
	I am permitteed to use inputs from outside sources (e.g. program office, engineers, customers, etc.) to improve system-provided forecasts.
	Please add clarifying comments for any response (as required):
Training Scale: The following statements refer to the adequacy and accessibility of forecasting-related training. Please indicate the degree to which you agree or disagree with the following statements: (7-point Likert scale anchored by Strongly Disagree and Strongly Agree)	I have been adequately trained to execute my assigned forecasting-related tasks.
	I have been adequately trained on forecasting-related policies and procedures.
	I have been adequately trained in the use of the system needed to perform my assigned forecasting tasks.
	The training I received helped me understand the forecasting process from beginning to end.
	The training I received helped me understand statistical techniques used for forecasting.
	The training I received helped me understand how to use inputs from outside sources (e.g. program office, engineers, customers, etc.) to improve system-provided forecasts.
	I receive periodic training to refresh my forecasting-related knowledge.
	Please add clarifying comments for any response (as required):

Work Group Cooperation Scale: The following statements refer to the degree to which your work group helps you accomplish your forecasting-related tasks. Work group refers to coworkers internal to your squadron and includes individuals in a similar or complementary role as well as individuals at a similar level and with whom you work closely on a day-to-day basis (e.g. other equipment specialists,item managers, etc.). Please indicate the degree to which you agree or disagree with the following statements: (7-point Likert scale anchored by Strongly Disagree and Strongly Agree)	I can rely on my work group to help me resolve issues that interfere with my ability to forecast accurately.
	I can rely on my work group to help me interpret forecasting-related guidance, procedures, and policies.
	I can rely on my work group to help me make sense of the inputs I receive from outside sources (e.g. program office, engineers, customers, etc.).
	I receive encouragement from my work group to forecast accurately.
	Comparing notes with members of my work group helps me decide the best way to forecast in certain situations.
	Please add clarifying comments for any response (as required):
Feedback Scale: The following statements refer to the adequacy and usefulness of feedback you receive regarding your forecasting performance. Please indicate the degree to which you agree or disagree with the following statements: (7-point Likert scale anchored by Strongly Disagree and Strongly Agree)	I receive adequate feedback on my overall forecasting performance.
	I regularly receive feedback on my overall forecast accuracy.
	I regularly receive feedback on the NSN-level forecast accuracy for each of my assigned items.
	I regularly receive feedback on my tendency to over- or under-forecast (forecast bias).
	I regularly receive updates on how my adjustments to system-provided forecasts (i.e. estimated rates, manual overrides, etc.) impact forecast accuracy.
	The feedback I receive helps me improve my forecasting performance.
	Please add clarifying comments for any response (as required):
Rewards Scale: The following statements refer to the rewards, recognition, and incentives offered for forecasting performance.Please indicate the degree to which you agree or disagree with the following statements: (7-point Likert scale anchored by Strongly Disagree and Strongly Agree)	I am recognized for my forecasting performance.
	I am recognized for meeting forecasting goals.
	I am rewarded for the time and effort I put into forecasting.
	Incentives for forecasting accurately motivate me to put more effort into my forecasts.
	Please add clarifying comments for any response (as required):
Knowledge Availability Scale: The following statements refer to how knowledge is captured, stored, and made available for use in your forecasting-related tasks. NOTE: Knowledge; refers to insight regarding future actions or events (i.e. by maintenance units,program offices, etc.) that could impact future demand for your assigned items and is not yet reflected in the forecasting system(s). Please indicate the degree to which you agree or disagree with the following statements: (7-point Likert scale anchored by Strongly Disagree and Strongly Agree)	In general, I am satisfied with the availability of knowledge for my forecasting-related tasks.
	The knowledge available to me from external individuals/organizations (i.e. program office, maintenance units, etc.) improves my ability to forecast effectively.
	I am satisfied with how the knowledge that I need for forecasting is managed.
	The knowledge available to me from internal individuals/organizations improves my ability to forecast effectively.
	Please add clarifying comments for any response (as required):
Forecasting Task Technology Fit System Quality Scale: The following statements refer to the quality and accessibility of the forecasting systems(s) you must use in order to accomplish your forecasting-related tasks. Please indicate the degree to which you agree or disagree with the following statements: (7-point Likert scale anchored by Strongly Disagree and Strongly Agree)	The system I use for forecasting contains historical data at the right level of detail to support my forecasting efforts.
	The system I use for forecasting contains the right methods (techniques) needed to create forecasts for my assigned NSNs.
	The system I use for forecasting contains historical data that is accurate enough for me to create effective forecasts.
	The system I use for forecasting contains all the historical data I need to create accurate forecasts.
Forecasting Task Technology Fit System Accessibility Scale: The following statements refer to the quality and accessibility of the forecasting systems(s) you must use in order to accomplish your forecasting-related tasks. Please indicate the degree to which you agree or disagree with the following statements: (7-point Likert scale anchored by Strongly Disagree and Strongly Agree)	The system I use for forecasting is easily accessible when I need to create forecasts.
	The system I use for forecasting makes it easy for me to get access to historical data.
	The system I use for forecasting makes it easy to access the forecasting methods (techniques) I need to develop forecasts.
	The system I use for forecasting is always “up” and available when needed.
	Please add clarifying comments for any response (as required):

Demographic Data	After the most recent cycle, my forecasts had an overall average accuracy of: (Less than 40%, 40 49%, 50-59%, 60-69%, 70-79%, 80-89%, more than 90%)
	How long have you been an equipment specialist? (Less than 1 year, 1-4 years, 5-8 years, 9-12 years, 13-16 years, 17-20 years, over 20 years)
	How long have you been assigned to your current set of NSNs? (Less than 1 year, 1-4 years, 5-8 years, 9-12 years, 13-16 years, 17-20 years, over 20 years)
	How long have you been in your current section? (Less than 1 year, 1-4 years, 5-8 years, 9-12 years, 13-16 years, 17-20 years, over 20 years)
	What is the highest level of education you have completed? (Less than high school, high school, associate's degree, some college, bachelor's degree, master's degree, Ph.D.)
	How many total NSNs are you assigned? (Less than 75, 75-124. 125-174, 175-224, 225-274, 275-324, over 325)
	How long have you been in your current flight? (Less than 1 year, 1-4 years, 5-8 years, 9-12 years, 13-16 years, 17-20 years, over 20 years)
	Thinking of all your assigned items, please provide between 1 to 3 "exemplar" NSNs you feel best represent the typical NSN you manage: (Typed Response)
	Gender: (Female/Male)
	Age: (Scale from 17 - 75+)
	Are you currently assigned to the same group of NSNs to which you were assigned in September of 2015? (Yes, No, Not Applicable) NOTE: If you became an equipment specialist after September of 2015, please select "Not Applicable".
	Please provide your office symbol (squadron/section, example: 420 SCMS/GUNAA): (Typed Response)

Appendix E: Item-level Statistics

Item	Statement	Mean	S.D.	Missing
JI1	I understand what is done with my forecast after it has been submitted.	5.48	1.45	0
JI2	My forecasts really make a difference.	5.34	1.55	0
JI3	I understand the impact my forecasts have on how my organization performs.	5.61	1.40	0
JI4	I understand the impact my forecasts have on how resources are allocated.	5.75	1.27	0
JI5	I understand the impact my forecasts have on how my customers perform.	5.65	1.32	0
SS1	My lead ES helps me resolve issues that interfere with my ability to forecast accurately.	5.61	1.67	0
SS2	My lead ES helps me interpret forecasting-related guidance, procedures, and policies.	5.61	1.64	0
SS3	My lead ES ensures I have the resources I need to forecast accurately.	5.59	1.61	0
SS4	I know exactly what my lead ES expects from me when it comes to forecasting.	5.45	1.72	0
SS5	My lead ES has reasonable expectations regarding my forecasting performance.	5.65	1.60	0
SS6	My lead ES is flexible about how I accomplish my forecasting-related work.	5.68	1.49	0
SS7	My lead ES gives me the authority to make forecasts as I see fit.	5.61	1.54	0
SS8	I can trust my lead ES to back me up on forecasting-related decisions.	5.65	1.59	0
SS9	My lead ES encourages me to forecast as accurately as possible.	5.89	1.48	0

Note: Survey items highlighted in gray were deleted due to lack of univariate normality.

Item	Statement	Mean	S.D.	Missing
RE1	When necessary, I am permitted to make adjustments (i.e. estimated rates, manual overrides, etc.) to system-provided forecasts.	5.79	1.20	0
RE2	My forecasting-related decisions are subject to audit/review.	6.32	0.90	0
RE3	The "checks and balances" related to forecasting never get in the way of my ability to forecast accurately.	4.95	1.57	0
RE4	I am always required to justify the adjustments I make to system-provided forecasts (i.e. estimated rates, manual overrides, etc.) with data/documentation.	6.37	0.83	0
RE5	The "checks and balances" related to adjustments (i.e. estimated rates, manual overrides, etc.) never get in the way of my ability to improve system-provided forecasts.	4.92	1.62	0
RE6	I am permitted to adjust system-provided forecasts (i.e. estimated rates/manual overrides) based on my own personal knowledge (i.e. from experience) about an assigned item.	5.04	1.74	0
RE7	I am permitted to use inputs from outside sources (e.g. program office, engineers, customers, etc.) to improve system-provided forecasts.	5.66	1.33	0
T1	I have been adequately trained to execute my assigned forecasting-related tasks.	5.14	1.76	0
T2	I have been adequately trained on forecasting-related policies and procedures.	5.19	1.73	0
T3	I have been adequately trained in the use of the system needed to perform my assigned forecasting tasks.	5.30	1.66	0
T4	The training I received helped me understand the forecasting process from beginning to end.	5.06	1.64	0
T5	The training I received helped me understand statistical techniques used for forecasting.	4.89	1.72	0
T6	The training I received helped me understand how to use inputs from outside sources (e.g. program office, engineers, customers, etc.) to improve system-provided forecasts.	5.10	1.63	0
T7	I receive periodic training to refresh my forecasting-related knowledge.	5.06	1.71	0

Note: Survey items highlighted in gray were deleted due to lack of univariate normality.

Item	Statement	Mean	S.D.	Missing
WC1	I can rely on my work group to help me resolve issues that interfere with my ability to forecast accurately.	5.83	1.20	0
WC2	I can rely on my work group to help me interpret forecasting-related guidance, procedures, and policies.	5.74	1.31	0
WC3	I can rely on my work group to help me make sense of the inputs I receive from outside sources (e.g. program office, engineers, customers, etc.).	5.75	1.30	0
WC4	I receive encouragement from my work group to forecast accurately.	5.76	1.35	0
WC5	Comparing notes with members of my work group helps me decide the best way to forecast in certain situations.	5.78	1.27	0
F1	I receive adequate feedback on my overall forecasting performance.	4.83	1.63	0
F2	I regularly receive feedback on my overall forecast accuracy.	4.84	1.74	0
F3	I regularly receive feedback on the NSN-level forecast accuracy for each of my assigned items.	4.74	1.73	0
F4	I regularly receive feedback on my tendency to over- or under-forecast (forecast bias).	4.84	1.70	0
F5	I regularly receive updates on how my adjustments to system-provided forecasts (i.e. estimated rates, manual overrides, etc.) impact forecast accuracy.	4.77	1.73	0
F6	The feedback I receive helps me improve my forecasting performance.	4.93	1.70	0
RR1	I am recognized for my forecasting performance.	3.85	1.63	1 (0.06%)
RR2	I am recognized for meeting forecasting goals.	3.89	1.67	1 (0.06%)
RR3	I am rewarded for the time and effort I put into forecasting.	3.70	1.73	1 (0.06%)
RR4	Incentives for forecasting accurately motivate me to put more effort into my forecasts.	3.68	1.72	1 (0.06%)

Note: Survey items highlighted in gray were deleted due to lack of univariate normality.

Item	Statement	Mean	S.D.	Missing
FKA1	In general, I am satisfied with the availability of knowledge for my forecasting-related tasks.	4.90	1.62	0
FKA2	The knowledge available to me from external individuals/organizations (i.e. program office, maintenance units, etc.) improves my ability to forecast effectively.	5.03	1.56	0
FKA3	I am satisfied with how the knowledge that I need for forecasting is managed.	4.70	1.58	0
FKA4	The knowledge available to me from internal individuals/organizations improves my ability to forecast effectively.	5.16	1.53	0
FTTF Q 1	The system I use for forecasting contains historical data at the right level of detail to support my forecasting efforts.	5.18	1.43	0
FTTF Q 2	The system I use for forecasting contains the right methods (techniques) needed to create forecasts for my assigned NSNs.	5.06	1.41	0
FTTF Q 3	The system I use for forecasting contains historical data that is accurate enough for me to create effective forecasts.	5.05	1.44	0
FTTF Q 4	The system I use for forecasting contains all the historical data I need to create accurate forecasts.	4.88	1.51	0
FTTF A 1	The system I use for forecasting is easily accessible when I need to create forecasts.	5.25	1.35	0
FTTF A 2	The system I use for forecasting makes it easy for me to get access to historical data.	5.12	1.45	0
FTTF A 3	The system I use for forecasting makes it easy to access the forecasting methods (techniques) I need to develop forecasts.	4.99	1.39	0
FTTF A 4	The system I use for forecasting is always “up” and available when needed.	4.74	1.54	0
Accuracy	After the most recent cycle, my forecasts had an overall average accuracy of:	4.48	1.68	0

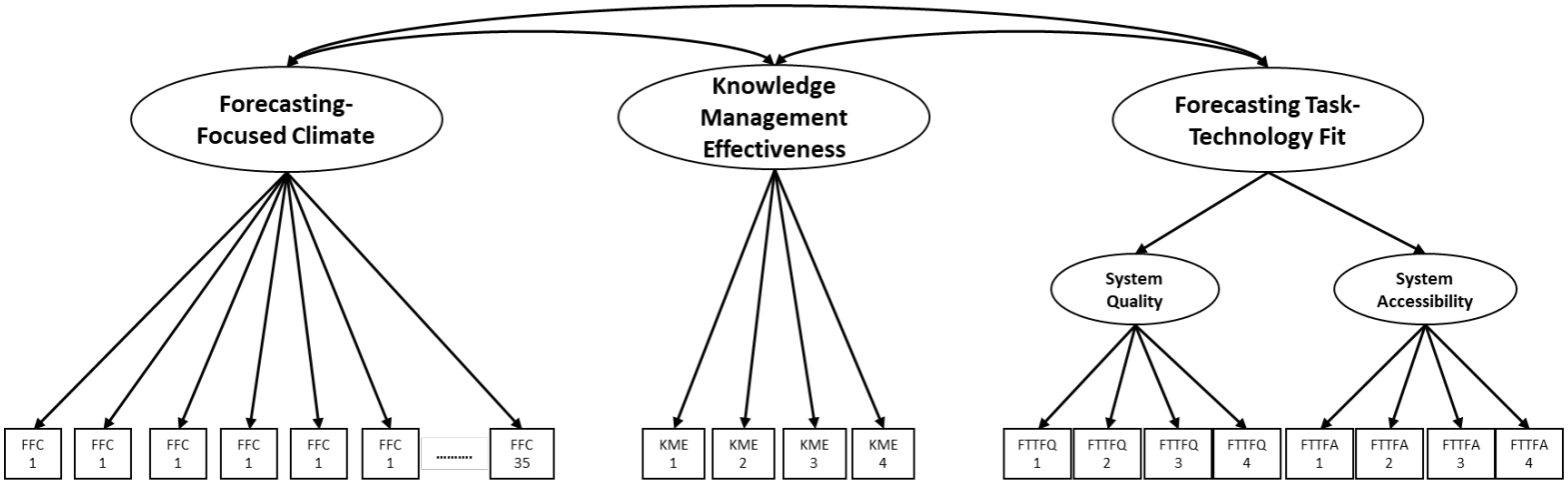
Note: Survey items highlighted in gray were deleted due to lack of univariate normality.

Appendix F: Participant Demographics

	Characteristic	Count	Percentage	Missing
Gender	Male	108	88.5%	32 (20.8%)
	Female	14	11.5%	
Age	<35	6	5.1%	37 (24.0%)
	35-49	43	36.8%	
	>49	68	58.1%	
Education	Less than High School	0	0%	29 (18.8%)
	High School	18	14.3%	
	Associate Degree	27	21.4%	
	Some College	42	33.3%	
	Undergraduate Degree	29	23.0%	
	Graduate Degree	9	7.1%	
	Doctorate	1	0.8%	
Workload	<75 items	15	11.8%	28 (18.2%)
	75-124 items	20	15.7%	
	125-174 items	31	24.4%	
	175-224 items	11	8.7%	
	225-274 items	9	7.1%	
	275-324 items	9	7.1%	
	>325 items	32	25.2%	
Forecasting Experience	<1 year	9	7.0%	28 (18.2%)
	1-4 years	46	35.9%	
	5-8 years	32	25.0%	
	9-12 years	27	21.1%	
	13-16 years	7	5.5%	
	17-20 years	4	3.1%	
	>20 years	3	2.3%	
NSN Experience	<1 year	20	15.7%	28 (18.2%)
	1-4 years	64	50.4%	
	5-8 years	26	20.5%	
	9-12 years	11	8.7%	
	13-16 years	3	2.4%	
	17-20 years	2	1.6%	
	>20 years	1	0.8%	

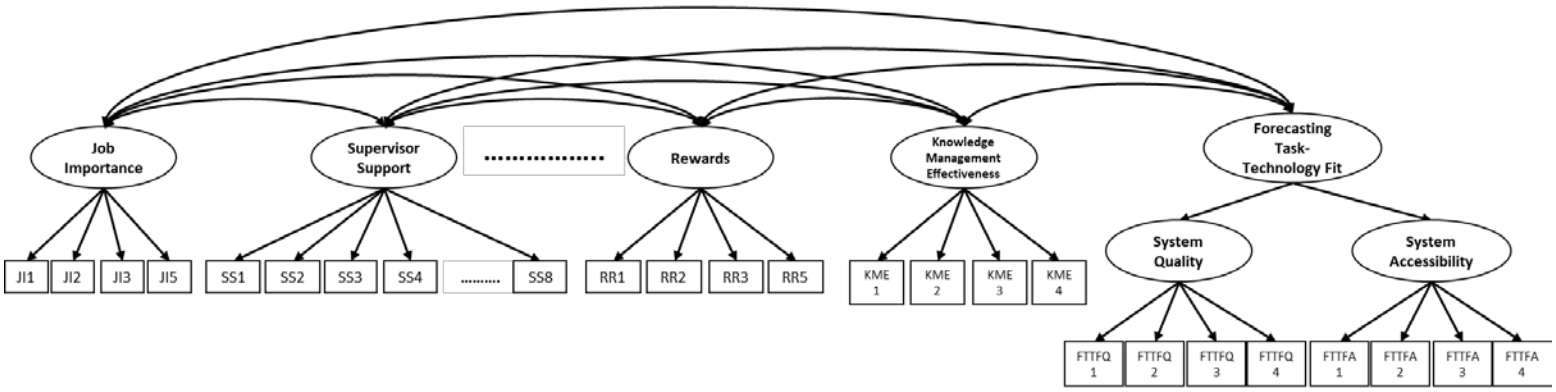
	Characteristic	Count	Percentage	Missing
Team Experience	<1 year	15	11.8%	28 (18.2%)
	1-4 years	60	47.2%	
	5-8 years	28	22.0%	
	9-12 years	17	13.4%	
	13-16 years	5	3.9%	
	17-20 years	1	0.8%	
	>20 years	1	0.8%	
Flight Experience	<1 year	14	11.0%	28 (18.2%)
	1-4 years	60	47.2%	
	5-8 years	32	25.2%	
	9-12 years	16	12.6%	
	13-16 years	3	2.4%	
	17-20 years	1	0.8%	
	>20 years	1	0.8%	
Location	Robins AFB, GA	21	18.8%	45 (29.2%)
	Hill AFB, UT	49	43.8%	
	Tinker AFB, OK	42	37.5%	

Appendix G: Confirmatory Factor Analysis Model Generation

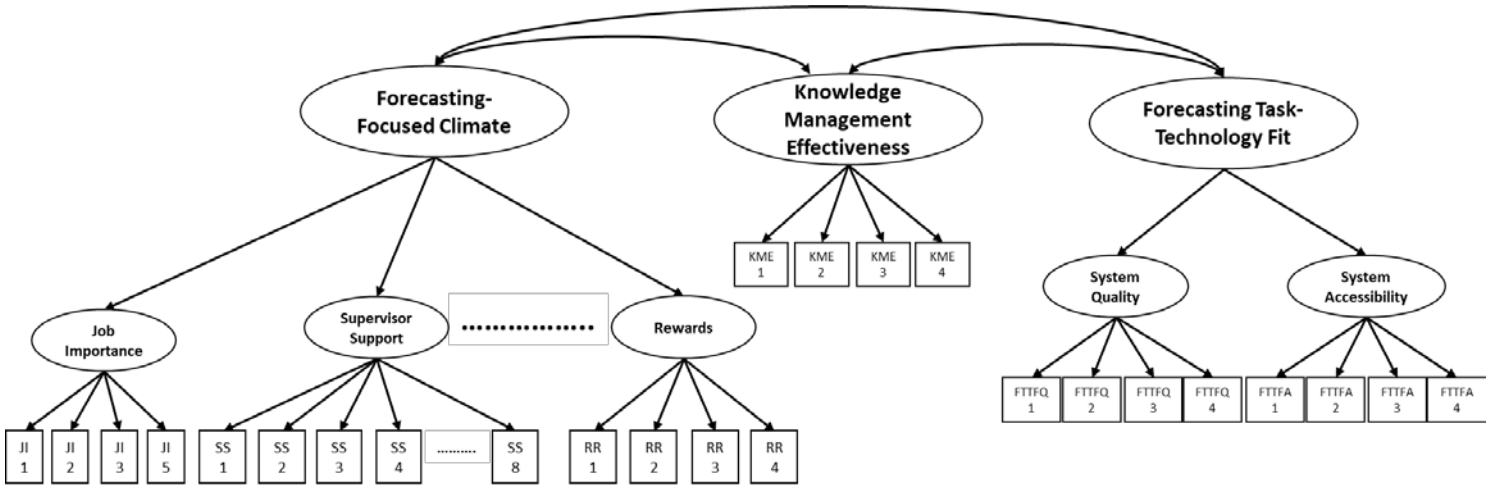


$\chi^2(982) = 5474.3$; $p<0.001$
CFI = 0.52; TLI = 0.49; RMSEA (90CI)= 0.17 (0.17, 0.18); SRMR =0.12

Model #1.

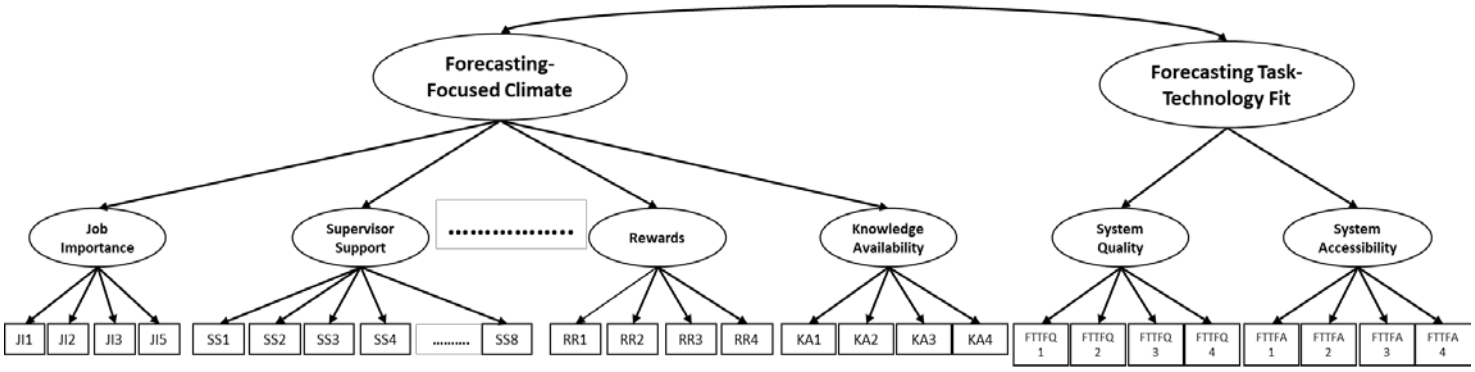


Model #2.



$\chi^2(650) = 1173.3$; $p<0.001$
CFI = 0.93; TLI = 0.92; RMSEA (90CI)= 0.07 (0.07, 0.08); SRMR =0.07

Model #3.



$\chi^2(651) = 1183.6$; $p<0.001$
CFI = 0.93; TLI = 0.92; RMSEA (90CI)= 0.07 (0.07, 0.08); SRMR = 0.07

Model #3 (Re-specified).

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14. ABSTRACT

Since Congress's 2010 mandate to remedy demand forecasting, Department of Defense supply chain leaders have made great progress in improving forecasting methods and policy. However, relatively little attention has been given to the human element of forecasting. According to Morelidge (2016) it is the quality of forecasts reviewed and adjusted by individual forecasters that are most impactful for supply chain planning. In addition to forecasting methods and procedures, research literature suggests management practices may also affect forecasters' performance. However, there has been limited empirical evidence supporting this claim. This research effort sought to investigate if and how management practices are linked to forecaster performance. In particular, this research investigated if perceptions of the technology used for forecasting and the organizational context within which forecasting takes place could explain variation in individual-level forecasting performance. Using Air Force forecasters as the sampling frame, a combination of survey data and historical forecasting performance data were analyzed to explore the relationships between these variables. The results of this research effort suggest that management practices do affect forecaster performance and make the case for a broader approach to forecasting improvement initiatives.

15. SUBJECT TERMS

demand forecasting, forecast accuracy, task-technology fit, organizational climate, knowledge

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