12-2017

How Decision Makers Learn to Choose Organizational Performance Measures

AnneMarie N. Hooge
University of the Incarnate Word, ahooge@uiwtx.edu

HOW DECISION MAKERS LEARN TO CHOOSE ORGANIZATIONAL PERFORMANCE MEASURES

by

ANNEMARIE N. HOOGE

A DISSERTATION

Presented to the Faculty of the University of the Incarnate Word
in partial fulfillment of the requirements
for the degree of

DOCTOR OF PHILOSOPHY

UNIVERSITY OF THE INCARNATE WORD

December 2016

ACKNOWLEDGEMENTS

My deepest thanks to Dr. Barrington Young who accepted no excuses—without whom I would not have found the courage to *start*; to Dr. Woody Spivey, who nurtured my love of learning; to Dr. M. Sharon Herbers who opened my eyes to new ways of understanding myself and others; to Dr. Osman Ozturgut, who introduced me to the splendor of caring about other cultures; to Dr. Noah Kasraie, who helped me distinguish a person who knows *about* leadership from a person who *is* a leader; to Dr. Mark Teachout, for his indispensable expertise and generosity; to Dr. Norman St Clair, my most challenging mind bender, who graciously stepped up; and to Dr. Audra Skukauskaite who helped me find the courage to *finish*.

To Gary, Kelli, Glenn, Craig, and Wade, my managers at work during this journey, who valued my development not just in word, but in action; to my upper management, Tilman, Shannon, Jeff, and Mike, who put the full weight of their support behind me.

To my interview participants and survey respondents for sharing of their experiences.

And to my beloved mother, Kathleen; my ever-faithful husband, James; my children, Laura and James—Believers, cheer leaders, and utterly essential to my success; to my father, Philip, who only wanted to see me 'do him one better;' and to my muses, the brothers of my heart, Alan and Mark, who enabled me to find the vision.

AnneMarie N. Hooge

HOW DECISION MAKERS LEARN TO CHOOSE ORGANIZATIONAL PERFORMANCE MEASURES

AnneMarie N. Hooge, PhD

University of the Incarnate Word, 2016

This study, framed by decision making, program theory, and performance measurement theory, explored the knowledge and experience that enable decision makers to identify organizational performance measures. It used a mixed method, exploratory sequential research design to discover the experience, knowledge, and skills (EKS) senior decision makers felt were important in learning to choose organizational performance measures. From the analyzed interviews, a survey was designed to measure the importance of the EKS characteristics.

Qualitative analysis identified 55 life, work, or educational experience; knowledge; or skill characteristics and 23 effective measure characteristics. Regression analysis and PCA were used to extract 6 components. One-way ANOVA found no significant differences in these factors between gender groups, age groups, and process complexity levels, but found differences for decision-making tenure. MANOVA found no significant differences by the same dimensions. The limited sample size and high number of variables confounded component extraction. Further research with a suitable sample size is required before findings can be generalized.

TABLE OF CONTENTS

Table of Contents–Continued

Table of Contents–Continued

Table of Contents–Continued

Table of Contents–Continued

Table of Contents–Continued

APPENDICES

LIST OF TABLES

List of Tables–Continued

List of Tables–Continued

List of Tables–Continued

LIST OF FIGURES

Development of Decision Makers

Leaders make situationally-sensitive decisions to run their businesses (Khatri & Ng, 2000; Papenhausen, 2006; Tingling & Brydon, 2010) using evidence gathered and tested against their prior knowledge and experience (Franklin, 2012; Merriam, Caffarella, & Baumgartner, 2007; Williams, 2012). How do organizational decision makers learn to identify, assess, select and implement the metrics that guide them in running their businesses effectively? I will explore theories of decision making, program theory, performance measurement, and strategy in this study to identify how decision makers acquire the skills and knowledge needed to choose metrics and to lay a foundation for the exploration of this question.

Background

An organizational leader's ability to make decisions is impacted by the available information. Organizations may be collecting data redundantly, needlessly, or in such a way that the decision makers who need information are left unaware (Mendonça, Basili, Bhandari, & Dawson, 1998). Often, there is an abundance of data, but a lack of contextually relevant information for the decision maker to use for effective decision making (Kalantari, 2010; Neely, Gregory, & Platts, 2005) and what these decision makers consider useful is influenced by their experience (Baba & HakemZadeh, 2012). The ability to make decisions is an essential skill for managers and the way they frame a problem has a strong influence on how they approach problem solving (Franklin, 2013). That framing will also influence the decision maker's ability to identify appropriate measures of organizational performance.

Assessing a decision maker's work experience is one way to explore how they learn to identify effective measures. Quinones, Ford, and Teachout (1995) developed a framework intended to guide work experience research based on two dimensions that describe work experience: the measurement mode and the level of specificity. A person gains work experience while working in a specific field or occupation, whether paid or not. Some measures of work experience use job tenure, the number of times individual tasks are performed, as well as lateral and upward movement of employees within the organizational structure to measure job performance. Quinones et al. name three modes of measuring work experience: number of distinct tasks, the activity (number of times each task is performed), and the task type (difficulty or criticality of the task). The framework expresses the modes and task types in a three-by-three matrix (1995).

Literature about decision making, program theory, and performance measurement calls out skills and knowledge found to be important, sometimes crucial in the achievement of an organization's objectives. A decision maker can find guidance pointing to an overall model for connecting measures to the achievement of desired program outcomes in the literature surrounding individual decision making (Baba & HakemZadeh, 2012; Franklin, 2013; Matzler, Bailom, & Mooradian, 2007; Papenhausen, 2006; Steptoe-Warren, Howat, & Hume, 2011); the application of program theory (Brousselle & Champagne, 2011; Monroe et al., 2005; Rey, Brousselle & Dedobbeleer, 2012; Savaya & Waysman, 2005); and performance measurement (Basili & Weiss, 1984; Briand, Morasca, & Basili, 2002; Courty & Marschke, 2003; Franceschini, Galetto, & Turina, 2013; Hanson, McInyk, & Calantone, 2011; Kaplan & Norton, 1996; Mendonça & Basili, 2000; Mendonça et al., 1998).

Decision makers need to understand the purposes for measuring performance, as well as the pitfalls and errors in choosing, implementing, and interpreting measures in order to use them effectively. Halamachi (2011) writes that performance measurement is conducted in order to understand business activities and to control and improve them. Measures provide insight to the combinations of activities and conditions that result in success and those that produce less-than-desirable results. Measures also allow decision makers to manage costs, financial and non-financial, and provide information to allow them to adjust their management choices accordingly (Halamachi, 2011).

Leading an organization effectively in a competitive environment requires effective decision making, ideally influenced by organization performance measures (Baba & HakemZadeh, 2012). According to the Hawthorne effect, measuring drives both desirable and undesirable behavior in the organization. Conflicting, arbitrary, or poorly designed measures can drive costly undesirable impact, like rewarding bad behaviors (Buytendijk, 2007). Determining which organization performance measures to use in decision making can mean the difference between an organization's success and failure (Baba & HakemZadeh, 2012). Even when measures are chosen carefully, it is important to review their relevance and effectiveness in the face of changing world, business, and organizational conditions and to remove measures that no longer speak to current objectives (Bazett, Bowde, Love, Street, & Wilson, 2005; Pun & White, 2005).

Hammer (2007) discusses the seven deadly sins of performance measurement: vanity, provincialism, narcissism, laziness, pettiness, inanity, and frivolity. These speak to issues, not of the measures themselves, rather to the decision maker's mindset in choosing measures that do not satisfy the essential reason for measuring. Illustrating Hammer's pettiness sin—measuring only a perspective or part of a larger condition or phenomenon, Behn (2003) writes of the folly of rewarding one behavior while hoping for another. This is echoed by Lengacher's (2009) concern about another of the seven sins, frivolity—measuring for the sake of measuring, rather than for the purpose of driving a particular action or decision. These examples speak to the need for decision makers to be aware of, understand, and guard against these measure mistakes.

Decision makers need to understand how to approach problem solving and how to determine whether the measures they are considering are meaningful indicators of the problem and its intensity, to avoid delivering a plethora of insignificant and irrelevant measures (Lengacher, 2009; Sureshchandar & Leisten, 2006). One observed response to measurement is the tendency to 'game the measures,' that is, to do things that make the numbers look better, but are contrary to the performance intent of the measurement (Courty & Marschke, 2003; Lengacher, 2009; Sureshchandar & Leisten, 2006). Decision makers need to use care in choosing meaningful measures in order to avoid a potential organizational response to game the measures.

Focusing on the alignment and linkage between the organization's strategy and its measures is one way to facilitate selection of the right measures (Hanson et al., 2011). Neely, Mills, Platts, Gregory, and Richards (1994) hypothesized that "firms will attribute greatest importance to those performance measures which most closely match their firm's manufacturing task" and found it to be true in those firms which did not compete on price (p. 142). Another point for the decision maker's attention is the impact of the measurement activity and the outcomes, considering both expected and potential unexpected impacts (Franceschini et al., 2013). In considering these aspects of measure selection, the decision maker increases the relevance of the measures for driving the organization's strategy objectives.

Problem Statement

How do organizational leaders learn the skills and knowledge needed to make decisions, define program theory, and assess performance? When organizations do not design the programs to implement their strategies in a way that enables measurement of progress toward the achievement of their objectives, it is difficult to evaluate their performance during and after implementation (Rossi, Lipsey, & Freeman, 2004). This omission makes it more difficult for the organization to know how well it is performing relative to its stated objectives or whether further investment in the implementation of the strategy is appropriate. Organizations expend significant effort in the implementation of new strategies and when they do not realize desired returns, reassessment of the strategies is appropriate (Bazett et al., 2005; Pun & White, 2005). Failing strategies should be abandoned or re-defined, necessitating reassessment of the chosen performance measures (Pun & White, 2005).

Decision makers may discount the value of measures that are not clearly connected to the organization’s business objectives, while proper alignment would illuminate their usefulness (Humphreys & Trotman, 2011). Even careful implementation poses potential risk, as measuring may have unforeseen and undesirable consequences. Measuring business activity in one part of the organization may drive undesirable behaviors in other parts with competing objectives (Azevedo, Carvalho, & Cruz-Machado, 2013; Courty & Marschke, 2003; Richard, Devinney, Yip & Johnson, 2009). The decision maker needs to use foresight to consider the likely response of the organization to the chosen measures (Courty & Marschke, 2003).

Purpose of the Study

While the literature is verbose about the importance and impact of well-identified, soundly designed, and effectively deployed organizational performance measurement, it is less so regarding the development of decision makers in the knowledge and skills necessary to identify, design, and deploy such measures. Given the focal areas identified in the decision making, program theory, and performance measurement literature, the purpose of this study is to explore and understand the types of knowledge and experience that enable decision makers to identify and select organizational performance measures, promoting the benefits and avoiding the risks described in the literature.

Research Questions

In the first phase of this study, I interviewed decision makers who are assigned as process owners in a Fortune 200 Financial Services company to understand the experiences, activities, and knowledge that contributed to their ability to select effective organizational performance measures. The interview protocol (Appendix B) includes questions for these decision makers about the types of life, work, and educational experiences they feel prepared them to select effective measures of organizational performance—as well as inviting them to share their perspective of what constitutes an *effective measure*. For the purpose of this work, the initial definition of an effective measure is one that enables the decision maker to understand, control, and improve business activities; that provide insight into the activities and combinations of activities that are beneficial or detrimental; and that allows the decision maker to adjust management choices and manage cost (Halamachi, 2011).

I asked decision makers to focus on the experiences that enable them, in their own estimation, to choose effective, even if not optimal, measures. It is difficult to choose organizational measures because determining their value is a context dependent, subjective assessment--unlike time or magnitude (Mandić & Basili, 2010). Additionally, there are some aspects of business that may be deemed non-quantifiable, such as innovation and creativity. Care must be taken to distinguish aspects that are unmeasurable from those that are difficult to measure (Warren, 2000). Assessment of the goodness of selected measures includes consideration of generating an outcome that is good for customers, shareholders, stakeholders, and employees, as well as for the decision maker. In the second phase, I explored the degree to which the experiences discovered in the interviews pervaded in the process engineering population in the company.

To explore the question of the decision makers' experiences, I used a basic qualitative interpretive approach, including interviews of successful decision makers in a Fortune 200 Financial Services company (referred to hereafter as 'the company'). I made a purposeful selection of interview participants based on recommendations from a company officer responsible for enterprise data and analytics functions, which is predominantly responsible for performance measurement in the company. For the second phase I designed a simple, cross-sectional survey to explore the presence of these experiences among the population of process owners in the company, leveraging the common themes in the life, work, and educational experiences discovered through qualitative analysis of the interview encounters.

The study's research questions are, (1) what are the life, work, and educational experiences that contributed to the ability of the organization's decision makers to choose effective organizational performance measures? (2) What constructs represent the important content of experience, knowledge and skill, and what constructs encapsulate the concept of the effective measures? (3) How are those constructs impacted by various dimensions within the respondent community.

Foundational Theory

To provide a framework within which to explore this question, I will look at theory involving individual decision making, program theory, and performance measurement. The purpose of generating and using organizational performance measures is to provide information with which to make decisions about the organization in order to achieve organizational objectives. The organizational objectives might be articulated using program theory and a way to measure achievement of those objectives might be defined in a performance measurement framework. Decisions about how to manage the organization might then be executed in accordance with decision making paradigms. Each of these will be discussed in order to understand the knowledge and skills required to engaged in the practices,

Decision making. Cabantous and Gond (2011) found that there are three common features that make rational decision making elusive. People assume rationality is possible; that they can know all information, identify all options, and identify all possible outcomes. Decision makers may not always have known objectives that can be articulated clearly enough to enable decision making to occur (Basili & Weiss, 1984; Choong, 2013; Frisk, Lindgren, & Mathiassen, 2014) and as a result, rely on suboptimal information with constraints imposed, real or artificial, that limit the available options.

Although decision makers deal with both tangible data and intangibles such as sentiment, the intangibles, known with less certainty, fall into bounded rationality (Frisk et al., 2014; Kalantari, 2010). Because all the options and consequences cannot be known, bounded rationality results in *satisficing* (Kalantari, 2010). In addition, the system of beliefs held by the decision maker may limit her field of vision and affect selective perception (Robbins & Judge, 2011). Sometimes rationality and bounded rationality (data-driven decision making) is not appropriate. Intuition has been demonstrated to be more effective when making decisions on poorly structured problems or problems with a high degree of uncertainty or lack of information (Tingling & Brydon, 2010).

Decision making processes are executed 1) to make a decision, 2) to inform a decision, or 3) to support a decision that has already been made (Baba & HakemZadeh, 2012; Tingling & Brydon, 2010). For non-routine, strategic-level decision processes, characterized by vagueness, intuition may be a more effective basis of decision making (Papenhausen, 2006; Williams, 2012). Intuition is formed through the decision maker’s experiences, reflection, and internalization of those experiences (Khatri & Ng, 2000; Matzler et al., 2007; Robbins & Judge, 2011; Weaver, 2014; Williams, 2012), whereas rational thinking tends to confirm established patterns (Weaver, 2014).

Competency is defined as the “skill that an individual and thus the organization possesses that enables it to perform activities” (Steptoe-Warren et al., 2011, p. 241), suggesting that decision makers require certain competencies to make good decisions. Framing is one of the competencies required of a decision maker. The way a decision maker frames a problem has a significant impact on the solution, so a decision maker must have the ability to frame a decision objective in a way that clearly articulates the need (Franklin, 2013; Robbins & Judge, 2011). Decision makers typically have richer experiences and larger amounts of relevant knowledge not commonly available to less experienced people or to those lower in the organization (Khatri & Ng, 2000; Papenhausen, 2006; Simon, Kumar, Schoeman, Moffat, & Power, 2011; Weaver, 2014) and they may also have more of this relevant knowledge in memory and related in more complex ways, allowing them to make connections not visible to others (Franklin, 2013; Steptoe-Warren et al., 2011). This rich, interconnected knowledge is a strong source of competency in the decision maker.

Decision makers collaborate to get the information they lack, to validate their own knowledge, to broaden their perspective of alternatives, to gain commitment, and to identify shortcomings (Schwarber, 2005; Steptoe-Warren et al., 2011). Communication of the measures, that is, quantified assessments of some important characteristic, and the relationships between the measures and the organizational objectives has been shown to be important (Humphreys &

Trotman, 2011; Kaplan & Norton, 1996; Kasperskaya & Tayles, 2013; Morard, Stancu, & Christophe, 2012; Olsson & Runeson, 2001; Theriou, Demitriades, & Chatzoglou, 2004; Wongrassamee, Gardiner, & Simmons, 2003; Wu, 2005). One way of effectively communicating the complex relationships between measures and objectives is using metaphors (Weaver, 2015; Zaltman, 1996).

Program theory. Program theory explicitly describes the assumptions about resources and activities and how these are expected to lead to intended outcomes (McLaughlin & Jordan, 2010; Rogers et al., 2000). By communicating program theory precisely in a logic model, program managers can identify and align the capabilities and expected outcomes of a program (Basili & Weiss, 1984; Monroe et al., 2005; Rogers, Petrosino, Huebner, & Hasci, 2000; Rossi, Lipsey, & Freeman, 2004). By articulating what they seek to accomplish, they can identify common components and simplify objectives—learning when to simplify and when to complicate (Rey et al., 2012; Rogers et al., 2000). Removing undesirable complexity enables them to measure more effectively and determine the degree to which they have achieved their objectives. Because program theory is organized as causal chains, the interdependencies among measures would also be visible (Rogers et al., 2000).

A logic model is an illustration of program theory, showing how a program works in a given environment and under stated assumptions (McLaughlin & Jordan, 2010; Taylor-Powell & Henert, 2008). The program logic is about the connections among the components in the program's logic model. Those components include resources, activities, and outcomes/goals or objectives (Brousselle & Champagne, 2011; McLaughlin & Jordan, 2010; Rey et al., 2012; Rogers et al., 2000). The ability to design or assess the logic model influences the decision maker's ability to align measures to the program objectives (Savaya & Waysman, 2005; Steptoe-Warren et al., 2011; Van der Stede, Chow, & Lin, 2006).

There are some challenges for developing program theory. Practitioners cannot always say why the components of the program theory work or not. Their ability to see and comprehend cause and effect in the program may be limited and they may not have the knowledge or skill to develop appropriate measures to assess their outcomes (Monroe et al., 2005). They may not have the time or the tools necessary to collect data; develop analytical models; and deliver clear, actionable information for decision making (Rogers et al., 2000).

Performance measurement. There are three general classes of criteria to assess candidate measures: acceptability, actionability, and usability (Hedge & Teachout, 2000). Bhatti, Abdullah, and Gencel (2009) identified seven measures selection criteria: feasibility, availability of personnel, availability of tools, disruptiveness of data collection, the personal preferences of the decision makers, and the ease of interpretation and presentation. These were grouped in five factors: 1) collection time, 2) cost, 3) value, 4) type, and 5) repetition (Bhatti, Abdullah, & Gencel, 2009). Gencel, Petersen, Mughal, and Iqbal (2013) call out two criteria for selecting metrics: the cost of producing the measure and the priority of achieving the goal. These metrics can then be selected and organized into a measurement framework.

A measurement framework is a set of related metrics, data collection mechanisms, and data used to support a business (Mendonça, Basili, Bhandari, & Dawson, 1998). The desired qualities of a measurement framework are soundness, completeness, leanness, and consistency (Mendonça & Basili, 2000). An example of a measurement framework, the balanced scorecard (BSC), was developed by Kaplan and Norton in 1992 to provide new perspectives (customer, the business processes, and learning and growth) to address organizational capabilities and intangible assets (Kaplan & Norton, 1996). The term *balanced* refers to the balance in consideration given to long- and short-term objectives, financial and nonfinancial measures, leading and lagging indicators, and external and internal perspectives (Deem, Barnes, Segal, & Preziosi, 2010).

In its original form the BSC did not provide review, update, and assurance of continued relevance of each measure. Decision makers assume causality, when it may not exist (Akkermans & van Oorschot, 2005), however, causality is assumed in the BSC (Kaplan & Norton, 1996). The dynamics of the real world have a direct impact on the metrics we choose to measure performance within our organization (Bazett et al., 2005), whether in the BSC or other measurement frameworks. One benefit of the effective use of a measurement framework is to facilitate organizational learning. Organizational learning, including learning that may enable decision makers to identify, assess, and select the right organizational performance measures, occurs during BSC development (Kaplan & Norton, 1996; Kasperskaya & Tayles, 2013). Kaplan and Norton (1996) stresses the importance of the feedback loop. This feedback enables organizational learning and strategic learning (Kaplan & Norton, 1996; Senge, 1990; Wongrassamee et al., 2003; Wu, 2005).

Organizations may fail to realize *metric return on investment* (ROI) by having too many measures or relying on too few, or continuing to rely on historical financial data rather the BSC (Deem et al., 2010). In addition, organizational culture plays a significant role in the effectiveness of adopting and using the BSC effectively, perhaps because understanding the insight delivered by a performance measurement framework is difficult (Deem et al., 2010). Schalken and van Vliet (2007) suggest the use of an iterative qualitative/quantitative cycle to assess and explain the usefulness of the measures. Bhatti et al. (2009) found that expert judgment is required to identify the right metrics, to avoid the temptation to use too many metrics, or to rely heavily on too few. Lack of this expert judgment in organizations is one of the problems that cause performance measurement to give poor return for the investment.

Münch, Fagerhold, Kettunen, Pagels, and Partanen (2013) discuss the need to identify and link organizational objectives and strategies across an entire organization. Kaplan and Norton (1996) describe a strategic management system assuming that we have the explicit linkages between measures and objectives. The finding of the common measures bias related to the effectiveness of the balanced scorecard demonstrates the importance of explicit linkages between measures and strategy. Incomplete strategy-measure linkage (or failure to deliver information about the strategy) may lead to common measures bias, resulting in diminished decision-making quality (Humphreys & Trotman, 2011). When the strategy is not communicated clearly and effectively to the organization the scorecard itself is not as effective as it might be otherwise (Kaplan & Norton, 1996).

For another performance measurement framework, the goal question metric (GQM) approach, one difficulty is that decision makers may not know the specific goals or objectives required by the approach (Boyd, 2005; Markovic & Kowalkiewicz, 2008). When the objectives are known, the GQM is a model that provides a clear line of sight between the goals and measures in a technical environment. Two types of measures that can be articulated using the GQM are process measures and outcome measures. These measures might address tangible things or intangible characteristics, which may be difficult to identify and quantify. It is in the intersection of the concepts of performance measurement systems that one begins to see the end-to-end connection between the business objectives in the key performance measures of the balanced scored card and in the data necessary to derive the measures in the GQM model. One of the strengths of GQM is that it seeks to identify what the decision maker needs to know—not what measure to use, but what a measure should enable the decision maker to understand (Boyd, 2005).

Significance of the Study

A possible application of this research is in the formation of a development program—activities, work assignments, and educational experiences—to establish and hone decision makers' skills in identification, selection, and long-term management of organizational performance measures (Matzler et al., 2007; Schwarber, 2005; Weaver, 2014; Williams, 2012). This curriculum could also be used in leadership and management mentoring programs, enabling emerging leaders to learn to assess performance in a focused, efficient approach.

This study has potential to produce learning that may be used to direct the development of mentoring and training materials to help emerging decision makers and other process engineering practitioners develop. They may be aided in understanding the life, work, and educational experiences that are likely to facilitate their development in the identification, assessment, selection, deployment, and interpretation of organizational performance measures. Beyond the objectives of the study, the opportunity for the interview participants to reflect on the types of experiences that formed their abilities may be of personal value. It may be that this cognition, thinking about how they think (Merriam et al., 2007), may provide immediate benefit to their day-to-day decision making.

Role of the Researcher

I have participated in the identification and definition of measures in various data implementation projects for over 30 years, most often in a data technologist's role and more recently in a business information owner's role. In various roles in data projects, I have provided information about the meaning and derivation of selected organizational performance measures. I conducted interviews and analyzed the results, seeking to understand the participants' experiences, that is, how they learned to identify and select effective process measures. Then, I designed, piloted, and administered a survey and provided descriptive statistics for the responses to discover the occurrence of the discovered experiences across the population. In addition, I conducted a confirmatory factor analysis of the survey results.

In formulating this research approach, I made the following assumptions: (1) that the participants have the knowledge and heuristics, possibly tacit, for identifying and choosing the measures for their processes, (2) that, through the interview process, they would be willing to articulate those, and (3) that the information to be obtained from the participants would be sufficient to answer the primary research question. The interview participants are decision makers and leaders. They will be referred to by all three terms throughout this study. The survey respondents will be referred to as respondents, but not as participants for clarity. The interview process will allow the participants to step back from their leadership and management activities to consciously consider their decision processes (Merriam et al., 2007), providing them with opportunity for reflection and reflexivity. With this motivation and interest in mind, the following literature review is presented to provide a framework of the knowledge and skill required in selecting performance measures for decision making and performance management.

Literature Review

This literature review will focus on research that shows the importance of decision making and measuring organizational performance in achieving leadership objectives, in leading and managing the organization's people, and in leading change in organizations based on the insight generated from the things the organization chooses to measure. Literature was selected based on searches of several databases, including ABI Complete, EBSCO, ERIC, and ProQuest. The search terms were program theory, logic model, performance measure/metric/measurement, individual decision making, rational decision making, intuition, bounded theory, goal question metric (GQM), GQM+Strategies, metaphor, and strategic business objective. Subsequent searches looked for allegory and metaphor. Although the focus was on articles from the most recent decade, older foundational articles were also included.

The organization of this literature review begins with an introduction of each of the building blocks to choosing performance measures. These primary concepts are individual decision making, program theory, and performance measurement. This approach was designed to address the purpose of the study, which is to understand experiences the organizational decision makers considered important in shaping their skill in identifying and selecting organizational performance measures. In the literature review, I built a foundation for the knowledge, skill, and insight decision makers require to identify and implement effective organizational performance measures (Matzler et al., 2007).

Individual Decision Making

Leaders and managers in organizations make decisions in order to run their businesses. These decisions may take on different natures, depending on the situation at hand (Khatri & Ng, 2000; Papenhausen, 2006; Tingling & Brydon, 2010). The organization may go through a decision making process to make, inform, or support a decision. To inform, evidence is gathered and tested against the prior knowledge and experience of the decision maker (Franklin, 2012; Merriam et al., 2007; Williams, 2012). Algorithmic approaches, generally based on data (evidence), may be used to make decisions. These approaches are most useful for highly structured problems (Khatri & Ng, 2000).

Rationality. Rational decision making requires the decision maker to know all relevant information on the situation or problem, have the ability to identify all possible alternatives, and to understand all the possible consequences of each alternatives. Cabantous and Gond (2011) found that there are three common features that make rationality elusive. People often assume that rationality is possible, that is, that one can know all the information, conceive of all the possible options, and know all the possible outcomes of those choices. There is a misconception that the various schools of thought on decision making are in opposition; often they are tangential or complementary. The romantic ideals of decision making sometimes get in the way of the practice of decision making in reality in organizations (Cabantous & Gond, 2011). Other misconceptions interfere with this ideal. Decision makers do not always have known objectives that can be articulated clearly enough to enable decision making to occur (Basili & Weiss, 1984; Choong, 2013; Frisk et al., 2014). They rely on suboptimal information with constraints imposed, real or artificial, that limit the available options.

By gathering different perspectives and involving others in the decision process, they can mitigate the lack of information, lack of options, and limited visibility into the likely consequences (Frisk et al., 2014). Even outside rational decision making, a decision maker can be deliberate and disciplined by collecting relevant information, generating alternatives, examining consequences, and choosing optimal alternatives (Kalantari, 2010). Schwarber (2005) also includes identification of the risks and mitigation as part of the rational decision making process.

Bounded rationality. Frisk, Lindgren, and Mathiassen (2014) seek to understand how information technology managers can evaluate alternatives in their space by looking at both tangible data and intangibles such as sentiment. They describe decision making as a “process by which conflicts are resolved among individuals with competing interests” (p. 444). These intangibles fall into bounded rationality (Kalantari, 2010). Because all the options and consequences cannot be known, bounded rationality results in satisficing (that is, making the best decision one can with the available information). When required to satisfice, a decision maker must either adjust his objectives or his alternatives (Kalantari, 2010). The knowledge and skill of a decision maker is critical in determining when and how to make such adjustments.

Another factor that influences bounded reality decision making is the system of beliefs held by the decision maker. These values may limit the decision maker’s field of vision and affect selective perception (Robbins & Judge, 2011), influencing his interpretation of data (evidence) and impacting his choices. In this case, it may not be the availability of information, options, or knowledge of consequences, but the decision maker’s ability to perceive them through the lenses of his values (Steptoe-Warren et al., 2011). Awareness of his system of belief is essential to his perception.

Intuition and data-driven decision making. Intuition has been demonstrated to be more effective when making decisions on poorly structured problems or problems with a high degree of uncertainty or lack of information (Tingling & Brydon, 2010). There are some instances where the decision making process is executed not to make the decision, but to support a decision that has already been made. In this supporting situation, the purpose of going through the process may be to use evidence to lend legitimacy to a decision that has already been made (Baba & HakemZadeh, 2012; Tingling & Brydon, 2010). For routine decisions, data and evidence are effective (Franklin, 2013; Papenhausen, 2006); however, for non-routine, strategic-level decision processes, characterized by "novelty, complexity, and open-endedness…and only a vague idea of what that solution might be" (Papenhausen, 2006, p. 158; Williams, 2012), intuition may be a more effective basis of decision making.

The use of the term *irrational decision making*, that is, intuition, does not refer to illogic or lack of sanity. Rather, it refers to a decision made without all relevant data and based on judgment and personal knowledge/experience, sub-consciously, rather than on looking at data or following the rational decision process. Non-rational is not the same as irrational (Kalantari, 2010). The use of intuition is important when exhaustive information is not available or when there is a "need for quick decisions, … to cope with demands created by complex market forces, and [provide] the assumed benefits of applying deeply held knowledge" (Weaver, 2014, p. 113).

Rational thinking leverages established patterns, whereas experience and intuition breed creativity (Weaver, 2014). Matzler, Bailom, and Mooradian (2007) define intuition as "a highly complex and highly developed form of reasoning that is based on years of experience and learning, and on facts, patterns, concepts, procedures, and abstractions stored in one's head" (p. 14). Robbins and Judge (2011) define intuition as "an unconscious process created from distilled experience" (p. 178), while Williams (2012) defines it as an "inductive skill, seeing the big picture, and looking at the whole problem rather than its discrete parts" (pp. 48-49). In highly volatile, complex, unstable situations, intuition synthesis is useful. In stable or mildly unstable situations, caution (in using intuition) should be used—implying data-driven decisions tend to be a better choice (Khatri & Ng, 2000). The common theme in these various definitions is that intuition is formed through the decision maker's experiences, reflection and internalization of those experiences such that they become a tacit part of the decision maker's thought processes.

Decision models. A decision model is a structured approach to follow when making a decision. One example is the rational decision-making model (Robbins & Judge, 2011). It guides a decision maker to articulate the problem; identify alternatives, specifying measurement criteria for each, and evaluate the likelihood of each alternative happening; compare alternatives and select the one with the highest expected value; and implement it (Cabantous & Gond, 2011; Franklin, 2013). The rational decision-making process is assumed to be sequential and non-iterative, but in reality iterative execution of the various steps may be required as new information is made available. Rational decision making assumes all required information is available at the point when each step is executed and that the decision maker understands clearly the consequences stemming from each step in the process and from the alternatives being considered. It also assumes the decision maker has a clear, well-articulated, well-understood objective for the decision being made. Any of these assumptions are likely to be false and undermine the decision process (Franklin, 2013). Franklin proposes the model as a five-pointed decision star, which allows each point in the process to be revisited iteratively, as needed (Franklin, 2013). The ability to revisit the steps in the process can be used to mitigate the weaknesses in the assumptions in the traditional rational decision making process.

Skills and competencies of the decision maker. Competency is defined as the "skill that an individual and thus the organization possesses that enables it to perform activities" (Steptoe-Warren, Howat, & Hume, 2011, p. 241), suggesting that decision makers require certain competencies to make good decisions. The authors identify the following core competencies for strategic thinking and decision making: technical, business, knowledge management, leadership, social, and intrapersonal competencies. The decision maker may exercise these competencies within a frame.

A frame is a way of understanding that guides reasoning and enables one to use a simpler information model for problem solving in complex situations (Franklin, 2013). The way a decision maker frames a problem has a significant impact on the solution, so a decision maker must have the ability to frame a decision objective, either for himself or a team, in a way that clearly articulates the need. How individuals frame decision situations will reflect their mental models and reflect the ways they find most effective to understanding the environment (Robbins & Judge, 2011).

Decision makers are typically organizational leaders who have richer experiences and amounts of relevant knowledge not commonly available to less experienced people—or those lower in the organization (Khatri & Ng, 2000; Papenhausen, 2006; Simon, Kumar, Schoeman, Moffat, & Power, 2011; Weaver, 2014). These decisions makers may also have more of this relevant knowledge in memory and related in more complex ways, allowing them to make connections not visible to others (Franklin, 2013; Steptoe-Warren et al., 2011). This rich, interconnected knowledge is a strong source of competency in the decision maker. A key component of strategic thinking seems related to this rich, complex knowledge base. Strategic thinking requires “absorptive capacity or the ability to recognize relevant new information and patterns in order to synthesize that information toward useful results” (Weaver, 2014, p. 112). Shared experiences are also a source of building rich, interconnected memories and knowledge. The types of shared experiences common among those who share generational demographics also influences strategic decisions (Papenhausen, 2006).

Papenhausen (2006) also discusses personality and traits as influencing a decision maker’s processes. Another trait these decision makers often display is that of being boundary spanners. Steptoe-Warren et al. (2011) define the boundary spanner as one who "perform[s] roles involving management, suppliers, and customers [with] access to relevant external information that may aid decision making" (p. 240).

Decision makers need to collaborate to get the information they lack, to validate their own knowledge, to broaden their perspective of alternatives, to gain commitment, and to identify shortcomings (Schwarber, 2005). Collaboration also has the benefit of being a means of training future decision makers. Emerging leaders learn these skills and others to grow into strategic thinkers. Steptoe-Warren et al. (2011) describe the strategic thinkers and strategic decision makers as the “people at the top of the organization who have overall responsibility for managing the organization and making decisions as to the strategic direction of the organization” (p. 238). They describe this type of thinking as novel and flexible in a way that allows them to deal with ambiguity. Weaver (2014) describes strategic thinking as a skill that develops over time by experiencing it, by doing it; rather than being a skill one can learn by hearing about it. This relates to the generational perspective offered by Papenhausen (2006).

Communicating decisions. Communication of the measures and the relationships between the measures and the organizational objectives has been shown to be important (Humphreys & Trotman, 2011; Kaplan & Norton, 1996; Kasperskaya & Tayles, 2013; Morard et al., 2012; Olsson & Runeson, 2001; Theriou et al., 2004; Wongrassamee et al., 2003; Wu, 2005). One way of effectively communicating this complexity is using metaphors. In business, metaphors are often used to effectively communicate complex concepts, enabling leaders to gain insight from analysis of measures for decision making (Weaver, 2015).

Zaltman (1996) developed a technique for eliciting the metaphors latent in an organization. A metaphor is a representation of one thing, generally a complex concept, in terms of another simpler concept. Like models, metaphors hide complexity that may be unnecessary when seeking to understand and make decisions. They are frequently expressed visually rather than verbally and it is important to understand their implied meanings (Zaltman, 1996). This study reports on the experiences of the interview participants showing the impact of this communication skill on choosing effective measures.

Program Theory

Program theory provides the next building block: the logic model. By articulating program theory precisely in a logic model, a program manager can identify the capabilities and expected outcomes of a program (Rossi et al., 2004). This makes outcome information available to build the goals in the goal question metric (GQM) paradigm (described below) and align the goals to the outcomes (objectives) in the program theory (Basili & Weiss, 1984). Although the words *theory* and *logic* are generally used in their essential forms, the terms have interesting connotations in the discussion of program theory and program logic (Monroe et al., 2005). They define them as, "*theory* refers to the practitioners' knowledge and intuition of what works," while "*logic* refers to the logical connections among the program's [components]" (p. 61, emphasis theirs).

Program theory has been called by different names over the course of a discussion of program evaluation that started in the early 1960s. Terms like outcomes hierarchies, theory-of-action, theory-based evaluation, and program logic are also used in the literature (Rogers, Petrosino, Huebner, & Hacsi, 2000). Although the terms are different, the concepts are not notably distinct and usage tends to be based on the communities in which the discussions occur.

Benefits. One promise of program theory is to enable understanding of whether programs do or do not work. A program theory does not explain *why* a program works or does not, but will contribute to the ability of organizational leaders to clearly state planned actions and intended outcomes. In this way, they articulate what they seek to accomplish and can measure more effectively to determine the degree to which they have achieved it (Rogers et al., 2000). The ability to attribute certain outcomes to the program in a causal relationship is another promise. Drawing out the program theory allows the organization to articulate what is being done, identify and perhaps quantify the expected outcomes, and establish measurement that will demonstrate the degree to which the outcomes are achieved. Because the program theory is organized as causal chains, the interdependencies among measures would also be visible (Rogers et al., 2000).

The program theory describes what is delivered by the program, who is impacted, and the desired or actual outcomes (Brousselle & Champagne, 2011). It explicitly describes the assumptions about resources and activities and how these are expected to lead to intended outcomes (McLaughlin & Jordan, 2010; Rogers et al., 2000) and allows the decision maker to clearly identify the driving relationships in the program. One benefit of articulating program theory centers on the idea of complexity. Another benefit of articulating an organization's program theory is that the staff are able to construct shared knowledge about the program and to make the tacit explicit. This may enable them to identify the common components of their work and simplify them through common understanding (Rogers et al., 2000).

Skill and experience come into play when a decision maker is faced with a need to either simplify or drive to more complexity. Knowing when to choose either option is described as an art (Rey et al., 2012). This illustrates the importance of understanding the program intent, considering complexity, and simplifying or digging for more details to clearly articulate the program.

Rey et al. (2012) cite another seminal researcher in their discussion of complexity. According to Patton, “in [the] face of complexity, the first task is to identify clear, specific and measurable goals … Everything seems complex until you do a logic model” (Patton, 2011, p. 6, as cited by Rey et al., 2012, p. 81). This highlights the importance of learning to draw logic models with a keen understanding of the level of precision required for the intended purpose. Rey et al. (2012) describe the benefits of doing so as a direct benefit to stakeholders, enabling explicit understanding of their actions and intent, and allowing greater visibility into the strengths and weaknesses of the program. Identifying the program components that are under the stakeholder’s control and those that are not is another important benefit to the organization. A final benefit is that, by explicitly identifying the actions and the interactions, the organization has an opportunity to refine and simplify its processes.

Creation of program theory. Articulating the theory and challenging assumptions also enables the modeler to clarify the connections among the components (Monroe et al., 2005). Acquiring information from the program’s practitioners allows the modeler to probe for both explicit and implicit objectives, ensuring that the theory captures all of what they want to accomplish (Brousselle & Champagne, 2011; Rey et al., 2012; Rossi et al., 2004). When evaluators create or articulate the theory, it is often necessary for them to unpack the information the practitioners provide and to articulate and challenge the assumptions inherent in what they find. Analyzing actual practice against existing program theory allows evaluators and practitioners to highlight the ways theory and practice differ and to make corrections.

Whether capturing information during the development of a program or documenting a program already in place, there are key things the modeler needs to do and essential questions to ask (Monroe et al., 2005). These include identifying the essential goals; articulating the inputs, actions, and desired outcomes; and explicating the connections. The actions might be considered its organizational capabilities. These are “a firm's capacity to deploy resources, usually in combination, using organizational processes…that are firm-specific and are developed over time” (Warren, 2000, p. 52). They describe what the organization is doing (Brousselle & Champagne, 2011) and why.

How is the program expected to achieve that objective (Rey et al., 2012)? Why does the organization believe that the inputs and actions are likely to enable them to achieve their objectives? Theriou et al. (2004) stress the importance of the linkage between the strategy and the measures. A strategy map, associating the actions required to deliver a defined measure, is used to visualize the linkages between the strategy and the measures (Wongrassamee et al., 2013), providing managers with a clear understanding of the relationships between strategy and the measures being generated in the organization. This linkage is an important factor in effective use of the measures.

How will they monitor and measure the health of the program (Savaya & Waysman, 2005)? There is ample opportunity for measurement of the connections among the various inputs, actions, and outcomes (Monroe et al., 2005). Discussions below of the balanced scorecard (BSC) and the relationships drawn between strategy and the performance measurement system used in an organization address this question.

Logic models. McLaughlin and Jordan (2010) describe the logic model as a tool that acknowledges the assumptions and environment in which a program operates and describes how the program will work within that context. Taylor-Powell and Henert describe the logic model as a "graphic representation of a program showing the intended relationships between investments and results" (2008, p. 4). Under either definition, a logic model documenting the program theory can be used as part of the development of a program, to implement a program, or to provide after-the-fact understanding of what is being done. It is common to document the logic model in preparation for a program evaluation activity (Rogers et al., 2000; Rossi et al., 2004). Regardless, the logic model should be acquired or documented as a first step in program evaluation activities.

The model might be created by the organization's practitioners or by a professional program evaluator. Information informing the creation of the logic model may be drawn from literature, from interviews with key informants in the organization, from the causal mechanism (perhaps from reverse engineering a system used to deliver the program), from program documentation, and from the modeler's observations of program activities (Rogers et al., 2000).

The program logic is about the connections among the components in the program's logic model. Those components are inputs (also called resources), activities (associated specifically with outputs), and outcomes (also called goals or objectives; Brousselle & Champagne, 2011; Rey et al., 2012; Rogers et al., 2000). Resources may be human or material: financial means, equipment, and skilled personnel, including alliances or partnerships with other organizations, for example (McLaughlin & Jordan, 2010).

Activities, perhaps expressed as organizational capabilities (Warren, 2000), are the things the organization does that produce value or impact (the outputs). Rey et al. (2012) included a table in their case study to show influencing factors, both external and internal. Of the internal factors, they identified organizational factors and other factors that have particular impact, which might represent risk or opportunity, on the interventions (activities) being defined. McLaughlin and Jordan (2010) name these types of factors ‘mediating factors;’ they influence the production of the outputs and may emerge over time. The modeler might identify these as risks and determine appropriate mitigation strategies to deal with them, should they occur. Understanding the components of a logic model represents key knowledge for a decision maker. The ability to design or assess the logic model influences the decision maker’s ability to align measures to the program objectives (Savaya & Waysman, 2005; Steptoe-Warren et al., 2011; Van der Stede, Chow, & Lin, 2006).

The outputs themselves are the product or service provided by the program, whether the recipient is internal or an ultimate customer of the program. From these outputs, it is expected that the desired outcomes will result (Brousselle & Champagne, 2011; Monroe et al., 2005; Rey et al., 2012). The outcomes are the desired objectives of the program. They might be short-, intermediate-, or long-term and may occur in close proximity in time to the delivery of the program or be a delayed outcome (McLaughlin & Jordan, 2010; Rossi et al., 2004; Taylor-Powell & Henert, 2008).

The intended outcomes may ‘fan in,’ where more than one short-term outcome may culminate in one mid-term; and multiple mid-term outcomes may culminate in one long-term outcome (Rogers et al., 2000). Outcomes may be such things as gaining awareness or knowledge, acquisition of a skill or ability to do something, or a transformational change in behaviors and practices. The outcomes may be intended or unintended (which would not be documented, presumably). Taylor-Powell and Henert (2008) also describe the ultimate, long-term outcome as the ‘impact’ of the program. McLaughlin and Jordan (2010) provide steps to build a logic model, as do Taylor-Power and Henert (2008), whose work is a teaching curriculum. Understanding the component parts and interrelationships allows decision makers to align their measures to their organizational objectives with clear causal linkage (Monroe et al., 2005).

Logic analysis. Logic analysis is an evaluation of program theory. This evaluation depends upon the knowledge of the program practitioners and the evaluator (or modeler) and uses the literature and other scientific knowledge to test the rationality of the program theory. Additionally, this analysis enables the modeler to identify possible alternative actions to achieve the stated objectives (Brousselle & Champagne, 2011; Rey et al., 2012; Rossi et al., 2004).

Direct logic analysis assesses whether the design of the intervention (action) is feasible and likely to achieve its purpose (Brousselle & Champagne, 2011). Reverse logic analysis is used to assess which interventions (actions) are most likely to achieve the stated purpose. Its focus is to identify alternatives, increasing the likelihood of a successful achievement of the desired outcome. The steps in the process of conducting logic analysis are to build the logic model, to develop conceptual framework (direct or reverse), and to evaluate the program theory, for which a participative approach is recommended (Brousselle & Champagne, 2011).

Logic analysis allows the modeler to test a program's theory before entering more deeply into the evaluation process. If there is an existing documented logic model, a modeler may find that what is documented in the logic model is not what is being done. Perhaps the program’s practitioners deviated inadvertently or determined that the design was flawed and made corrections in practice (Brousselle & Champagne, 2011). Logic analysis is useful as described above for reverse logic analysis to test whether the designed intervention is a practicable way to achieve the desired result. Rey et al. (2012), put it this way,

> The aim of logic analysis is to identify the best ways to get where we want to go, that is, to achieve the desired effects. Logic analysis will identify (a) the important characteristics the interventions must have to achieve the effects and (b) the critical conditions required to facilitate the implementation and produce the effects. (p. 63)

Challenges. There are challenges associated with program theory and an organization's ability to realize the promised value. For the practitioners, it "is not that they lack understanding of the program's details but that they do not easily articulate why the dissected elements of the program achieve the program's goals" (Monroe et al., 2005, p. 57). The practitioners' ability to see and comprehend the impact of the cause and effect of the program may be limited. Additionally, the program practitioners may not have the knowledge or skill to develop appropriate measures to assess their outcomes. Even when they are able to identify and develop useful measures, those executing the program may not have the time or the tools necessary to collect data, develop analytical models, and deliver clear, actionable information for decision making (Rogers et al., 2000).

Jääskeläinen and Laihonen (2013) discuss the challenges of measuring performance in knowledge intensive environments. Performance measurement has been studied extensively in the manufacturing and information technology spaces, but the ability to apply quantitative measures of value to information and knowledge work and performance is less well-studied. It is, in part, this dearth of study that prompts the subject study of this paper.

Performance Measurement

While there are some approaches and frameworks within which to build measures for assessing organizational performance, they do not appear to be widely used in practical application (Hedge & Teachout, 2000). Performance measures should be reliable and consistent. They should accurately reflect the reality that they measure. They should make sense to both the analysts who produce them and the decision-makers who consume and use them. Inasmuch as the reality that they measure is predictable, the measures themselves should be predictable (Hedge & Teachout, 2000).

The optimum measure set decision (OMSD) model was designed to enable managers to select an optimum set of measures for their purpose (Bhatti et al., 2009). To measure, you identify *what* is to be measured and the interesting attributes to measure. Both internal and external attributes can be defined as measures. Internal attributes are characteristics of something that are inherently about that thing, while external attributes are about the relationships between that thing and the surrounding environment (Bhatti et al., 2009). The OMSD model may provide an approach to evaluate candidate measures for their usefulness in an overall performance measurement framework. Other criteria may also be used for organizing candidate measures.

Three general classes of criteria might be used to organize candidate measures: those measuring the acceptability of the measures to the analysts and decision-makers, those dealing with the ability of the organization to take action based on the measures, and those applying to the willingness of decision-makers to use them in the decision process (Hedge & Teachout, 2000). Discussions about the BSC and the many extensions and augmentations applied to it by various researchers have included analysis of the relationship between the various components of these models (Humphreys & Trotman, 2011; Kaplan & Norton, 1996; Wongrassamee et al., 2003). In another perspective, Hedge and Teachout (2000) suggest that the acceptability of measures and the practicality of applying them in the organization be assessed in addition to the theoretical and mechanical correctness of the measures.

With the criteria to organize measures, other criteria are available to select from within that organizing structure. Bhatti et al. (2009) identified seven criteria used to select measures from a candidate pool: feasibility, availability of personnel, availability of tools, disruptiveness of data collection, the personal preferences of the decision makers, and the ease of interpretation and presentation. They grouped these criteria into five factors: collection time, cost, value, type, and repetition (Bhatti et al., 2009). Gencel, Petersen, Mughal, and Iqbal (2013) call out two criteria for selecting measures: the cost of producing the measure and the priority of achieving the goal. Considering the measures from the perspective of these criteria provides decision makers with additional richness from which to make informed metric selection decisions.

One example of a performance measurement framework that facilitates a reflection of reality and acceptability of measures is the GQM model (Basili & Weiss, 1984; Mendonça & Basili, 2000; Mendonça et al., 1998). Another is the BSC (Humphreys & Trotman, 2011; Kaplan & Norton, 1996; Wongrassamee et al., 2003). Both models allow the decision maker to assign measures within the context of the objectives they address.

Measurement frameworks. Mendonça, Basili, Bhandari, and Dawson (1998) define a measurement framework as "a set of related metrics, data collection mechanisms, and data uses inside a software organization" (p. 484). To serve the purpose of this study, this definition is modified slightly to apply the concept not only to a software organization, but also to the business organization supported by a software organization. Thus modified, a measurement framework is a set of related measures, data collection mechanisms, and data used to support a business. The qualities of a measurement framework as defined by Mendonça and Basili (2000) are soundness, completeness, leanness, and consistency. These qualities speak to the relationship of the measures in the framework to their ability to enable users to achieve their business objectives effectively and efficiently. Decision makers may not use the term measurement framework but might be more likely to know or refer to the concept as a performance measurement system.

All three focus areas—decision making, program theory, and performance measurement—intersect in the need to have and produce appropriate information to enable leadership decisions. This information is often expressed in the form of measures. There does not appear to be a consistent usage of the terms *metric* and *measure* in the literature. Choong (2013) writes that a measure is "a whole number, expressed either in monetary (financial) form... dimension form...or unit form" (p. 113), while a "metric is more precise than a measure because the former is based on a standard unit of measurement...the metric must be specially developed based on a performance objective that is relevant to the stakeholders" (p. 113). Hanson et al. define a metric as "a verifiable measure that is stated in quantitative terms and forms the basis of a feedback loop" (2011, p. 1091). The term *measure* will be used in this study to mean a defined unit, either quantitative or qualitative, used to express the size, amount, or degree of something, while *metric* will be used to express the standard of measurement. In the formulation of a performance measurement system, the use of *SMART objectives* is desirable.

The balanced scorecard. The balanced scorecard (BSC) is a concept developed by Kaplan and Norton in 1992 (Kaplan & Norton, 1996). It was intended to provide additional richness, beyond financial measures, for organizations to measure performance. The new perspectives were those of the customer, the business processes, and organizational learning and growth. Measures in these perspectives are intended to address organizational capabilities and intangible assets (Kaplan & Norton, 1996).

In the context of the balanced scorecard, the term *balanced* refers to the consideration given to both long- and short-term objectives, financial and nonfinancial measures, leading and lagging indicators, and external and internal performance perspectives (Deem et al., 2010). Perlman (2013) found a direct relationship between measures of organizational learning and growth and financial measures. This supports the idea of the relationship between learning, production efficiency, and quality. Perlman found additional relationships among various factors such as customer service and profit, growth in sales by using path analysis on the various performance measures and the balanced scorecard.

The leading indicators of the BSC, those measures that hint at likely longer-term results, are considered to be organizational learning, customer satisfaction, and the internal business processes. The lagging indicators (the longer-term results) are those measuring financial performance (Wongrassamee et al., 2003). The original relationships in the BSC were such that organizational learning and growth influenced process measures and process measures influenced customer satisfaction. Customer satisfaction then impacted the financial measures (Morard et al., 2012). More recently, Perlman's (2013) research found causal relationships from learning and growth to all three of the others: internal processes, customer satisfaction, and financials. Internal processes were also shown to influence financials and customer satisfaction directly. Finally, customer satisfaction was shown to directly influence financials. All of these relationships show the importance of identifying the right measures for each of the BSC factors, because they have either direct or indirect implications on customer satisfaction and financial performance.

Introducing another lens through which to view the BSC, Wu (2005) asks questions about intellectual capital management from the perspectives of human capital, organizational capital, and customer capital. Wu asserts that, “the strategic objectives of BSC not only lead to the creation and formation of strategic intellectual capital, but also affect the content of measurement, valuation, management, and reporting of strategic intellectual capital, and eventually create the maximized value for companies” (Wu, 2005, pp. 269-270). This speaks to the importance of ensuring that the measures in the BSC are validly linked to the business objectives.

The increasing importance of intangible assets to an organization's success (Theriou et al., 2004) impacted by intellectual capital, suggests relationships organizational leaders may need to measure. It is in acquisition and development of intellectual capital that organizational learning is manifested. “This capacity for enabling organizational learning at the executive level—strategic learning—is what distinguishes the balanced scorecard, making it invaluable for those who wish to create a strategic management system” (Kaplan & Norton, 1996, p. 85).

BSC weaknesses. Akkermans and van Oorschot (2005) point out weaknesses in the balanced scorecard approach. In its original form it did not provide a way to review and update the measures to assure continued relevance of each measure. It provides no guidance to enable a decision-maker to distinguish between what *can* be measured and what *should* be measured. In addition, decision-makers often make assumptions about causality that may not, in fact, bear out. While causality is assumed between strategic objectives and BSC measures (Kaplan & Norton, 1996), establishing causal models in for a BSC in a complex business environment can be problematic.

Kasperskaya and Tayles (2013) found that causal models may be more difficult to develop in more dynamic environments. The more complex and uncertain the environment is, the more difficult it is to identify all the variables impacting the situation. However, imperfect causal models can still provide valuable information to support organizational learning and enable improvements to be made in organizational performance measurement. Even with the difficulties of creating complete causal maps from a mathematical and statistical perspective, they are still useful for communicating understanding through the organization. They enable leaders to communicate the connections between the measures and the objectives the organization seeks to achieve to managers and practitioners (Kasperskaya & Tayles, 2013).

Kasperskaya and Tayles (2013) found that the complexity in the causal relationships among the measures and business objectives is also volatile. Time, environmental conditions, and the variables involved in assumptions in play for any given strategy add to this volatility and complexity. Measures may be established that seem to them to be related and causal, but are not, after statistical analysis is conducted, found to be correlated. Along with the complexity in the causal relationships themselves, the feedback loops also have such complexity and, when unrecognized, may confound predictability. One aspect of the volatility of the time dimension with respect to causality is that of delay between business action and outcome, further contributing to unpredictability (Kasperskaya & Tayles, 2013). Thus, measures, even when carefully selected, must be statistically tested to ensure they give meaningful, reliable information.

The ability to bridge between financial and nonfinancial fields extends to the idea of bridging between the highest levels of the organization and the lowest levels of the organization. The accumulation of lower level measures to produce the higher level measures introduces another aspect of complexity that is difficult to manage. Akkermans and van Oorschot mention another weakness of the BSC. While the balanced scorecard illuminates how the organization is doing in terms of the four primary measurement areas, it does not provide information to help the decision maker understand what competitors are doing. This weakness illustrates additional knowledge and skill decision makers need to assess and select organizational performance measures (2005).

The dynamics of the real world have a direct impact on how we choose to measure performance within our organization. Price variability and function are being eclipsed by matters of service and other intangible contributors to revenue (Bazett et al., 2005). Kaplan and Norton

(1996) stress the importance of the feedback loop. In order to understand the various relationships among the contributing measures and for the organization to learn, this feedback loop must be effectively in place (Senge, 1990). The feedback is intended to address the unpredicted and unintended consequences of the strategy and the measurement of the strategy, as well as to enable the organization to review and correct assumptions that may have been made in the formulation of the strategy. This feedback and organizational learning, strategic learning, is believed to be important, in the current study, to the notion of how organizational decision-makers learn what measures are effective.

Organizational learning of any kind involves reassessing assumptions. The explicit statement of assumptions and review using the information gained from a feedback loop is one way in which this kind of organizational learning can be influenced (Kaplan & Norton, 1996; Senge, 1990). If a strategy's assumptions have internal contradictions, then the strategy will also (Senge, 1990). Organizational process execution measures, together with business results and customer satisfaction feedback, are all considered during the review and adjustment of the business improvement strategy (Wongrassamee et al., 2003). But, it is not only in the operational execution of the business strategy that organizational learning occurs.

Organizational learning also occurs during the development of a balanced scorecard framework (Kaplan & Norton, 1996). When the relationships between the strategy (the actions the organization takes) and the outcome measures are discussed, there is potential for strategic learning (Kasperskaya & Tayles, 2013). Thus, care should be taken, for when assumptions are made about the relationships between strategy and outcome measures, the discussions necessary for strategic learning may not happen.

Although many organizations attempt to apply the balanced scorecard for performance measurement, the actions that are assumed to drive certain aspects of performance may not always exist in a causal relationship (Akkermans & van Oorschot, 2005; Kasperskaya & Tayles, 2013). It is desirable to validate the causality of the chosen measures with respect to the desired outcomes. The formulation of strategy and the measurement of the execution of that strategy, when based on data that lacks sufficient context, may produce a rigid strategy. Enabling organizational learning with good feedback and analysis of performance measures promotes the development of a strategy that is flexible and which can respond to environmental conditions and validation or correction of assumptions in a timely, fluid way. A rigid strategy does not have this characteristic (Kasperskaya & Tayles, 2013). To address this and other shortcomings of the BSC models, various extensions have been offered.

BSC + analytical hierarchy process. The analytic hierarchy process (AHP) is an analysis process used in complex decision making. The AHP approach is used to compare the interactions of the measures with each other in a pairwise comparison. The purpose of this pairwise comparison is to identify the consistency of the measures with respect to each other and to identify to a decision-maker where measures are inconsistent (Theriou et al., 2004).

Theriou et al. (2004) juxtapose BSC with AHP to create a framework to facilitate the organization’s ability to define measurable linkages between its strategies and its measures. These linkages are important input for strategic planning and performance measurement. This suggests that an understanding of the AHP would be beneficial to decision-makers in defining the linkages which are so critical to successful implementation of BSC. The advantages of using the analytic hierarchy process as a tool for implementing the balanced scorecard include its ability to deal with both quantitative and qualitative assessments, multiple inputs, and subjectivity. In addition, it enables improved consistency and judgment, performance assessment, and results in a single composite performance measure (Theriou et al., 2004).

BSC + EFQM excellence model. The European foundation for quality management (EFQM) excellence model is intended to enable performance management by providing understanding of an organization's leadership, resources, and process capabilities as well as a perspective of customer, employee, and societal satisfaction and business results (Wongrassamee et al., 2003). Wongrassamee et al. identified weaknesses in the balanced scorecard the EFQM excellence model is expected to address. These include identification of key objectives for the organization's success, strategies and plans to achieve that success, level of performance required for those plans, rewards (or penalties) for achieving these plans, and the information necessary to enable achievement and learning. Because of its focus on resources, people, customers, and society, this model can help managers identify change and growth opportunities to maximize the satisfaction of their stakeholders (Wongrassamee et al., 2003).

BSC + structural equation modeling. Structural equation modeling (SEM) is a statistical modeling technique using several statistical methods to fit data to known constructs. Morard, Stancu, and Christophe (2012) developed a framework to allow them to bridge the balanced scorecard with SEM. The resulting framework improves integration and communication. It highlights certain measures, frames organizational information in a way that is conducive to understanding and formulating strategy, and makes explicit the relationship between the strategy and results visible in the organization. This BSC extension might allow an organization to see how unrecognized combinations of measures can be explained or framed in unexpected ways to produce insight.

BSC + strategic intellectual capital. Use of the balanced scorecard can, as found in a study by Wu (2005), lead to increased strategic intellectual capital (SIC). SIC is the intellectual capital of the organization that is driven by the objectives of the BSC. It is composed of the intellectual capital derived from customers, processes, innovation, humans, IT, and organizational culture. The perspectives of the balanced scorecard were found to strengthen the management of intellectual capital. Wu defined SIC as a model and found that the BSC and SIC models are complementary (2005). The concept of SIC, in particular the human intellectual capital, speaks to the knowledge of decision makers. This study, in exploring the experiences of the decision makers, may illuminate how this intellectual capital is developed, perhaps driven by the measures of the BSC.

BSC extensions summary. These extensions to the BSC—the AHP, EFQM excellence model, the SEM, and the SIC—are an indication that the BSC itself is a sound foundation on which to build, but that the design for the fully architected building is not yet complete. I've selected and provided the literature on each of these models to provide glimpses into the additional richness for measuring organizational performance. Exploring each of these is expected to provide a foundation from which to hear the insight and experience of the study participants.

BSC ROI. In addition to having too many measures or relying on too few, many companies have failed to realize the benefits desired from the balanced scorecard because they have continued to rely only on historical financial data rather than making the transition to a balanced scorecard (Deem et al., 2010). Organizational culture plays a significant role in the effectiveness of adopting and using the balanced scorecard effectively. In Deem's et al. study, organizational culture is described in terms of how the people in an organization behave, how they teach this belief system to new employees and others who interact with the organization, and how they interact with their environment given the assumptions in play at any given time (2010). Perhaps understanding the organizational culture and how it impacts measurement and the organization's response to measurement is another skill needed by an adept decision maker to choose organizational performance measures.

Schalken and van Vliet (2007) suggest the use of an iterative qualitative/quantitative cycle to assess and explain the usefulness of measures. Bhatti et al. (2009) found that expert judgment is required to identify the right measures, to avoid the temptation to use too many, or to rely heavily on too few. Lack of this expert judgment in organizations is one of the problems that cause performance measurement to give poor return for the investment. The term *metric ROI* is used by Gencel et al. (2013) to refer to "the contribution of metrics in fulfilling the information needs of the stakeholders" (p. 2). The V-GQM validation method (discussed below) was developed to help ensure that measures developed using the GQM method achieve their intended purpose (Olsson & Runeson, 2001). The V-GQM process includes steps to state the goals, define questions that need to be answered in order to achieve the goals, derive measures (information) needed to answer the questions, gather data to generate the measures and assess the outcomes. Then, based on the outcome analysis, the validity of the measures and the questions is assessed. Answering the question, are they useful for the intended purpose? The goals are also refined based on the insight gained from the outcome analysis (Olsson & Runeson, 2001).

While it represents a complex environment, the balanced scorecard itself has the benefit of simplicity. The basic premise is easy to understand and the BSC enables decision-makers to bridge between financial and nonfinancial measures. However, the simplicity may be misleading. At the highest level of the organization, there may be very few measures, but the difficulty lies in identifying the right set of measures and how to derive them (Akkermans & van Oorschot, 2005). *Common measures bias* is the inappropriate preference or importance assigned to measures that are common between organizations to the detriment of other measures which are unique within different areas of the organization. Avoiding the common measures bias is a challenge when selecting the right measures at the highest levels of the organization. When attempting to assess the organization across disparate business areas, the measures that are unique within the disparate areas are difficult to derive in an aggregate measure at a higher level (Humphreys & Trotman, 2011).

One aid to choosing the right measures is to consider the coherence among the measures. Do they align or contradict each other? It is not just the question of what to measure, but the target values the organization desires to achieve and in what timeframe that matters (Akkermans & van Oorschot, 2005). Akkermans and van Oorschot (2005) advocate use of causal modeling to assess the relationships horizontal and hierarchical among the measures on the BSC to explain the level of complexity visible in the measures. Based on their study findings, they suggest the use of system dynamics is beneficial in assessing the validity and usefulness of the BSC. This speaks directly to the basic question of the current study. Studying the system dynamics associated with the BSC measures may be one way in which organizational decision makers learn what works and what does not work with respect to measurement.

A particular difficulty lies in measuring intangible assets like intellectual capital. There is a distinction to be made between an attribute of something being undetectable versus being unmeasurable. Indirect resources are those that "capture a perception or attitude of key players in the team that is not directly amenable to management influence" and, like motivation or creativity, are difficult to measure, but they are detectable (Warren, 2000, p. 51). Morale and reputation, for example, can be assessed using staff surveys or qualitative methods, which might produce results that can be coded and quantified. Special resources may be necessary to bring this type of assessment skill into greater prominence in the organization. Even when such indirect resources are detected and measured, those are just the first steps in enabling an organization to manage them. Intangible resources, Warren (2000) asserts, are effectively managed using leadership skills, while direct resources are better managed with typical management skill.

Linkages. Münch et al. (2013) discuss the need to identify and link organizational objectives and strategies across an entire organization, as opposed to having isolated strategies and objectives in silos within an organization. The relationships between the goals of the organization and the measures used to determine progress toward those objectives need to be clearly articulated (Münch, Fagerhold, Kettunen, Pagels, & Partanen, 2013). The finding of the common measures bias related to the effectiveness of the balanced scorecard demonstrates the importance of explicit linkages between measures and strategy (Humphreys & Trotman, 2011).

Absence of these linkages may result in diminished decision-making quality. Kaplan and Norton (1996) describes a strategic management system assuming that we have the explicit (and causal) linkages between measures and objectives. As part of managing the strategy, the organizational leaders are expected to communicate the strategy to the organization. However, a criticism of the balanced scorecard is that when the strategy is not communicated clearly and effectively to the organization the scorecard itself is not as effective as it might be otherwise (Kaplan & Norton, 1996).

Common measures bias, a simplifying strategy, is a risk when there is incomplete information and these strategy-measure relationships are not fully understood and communicated. Basically, the Humphreys and Trotman study found that both incomplete information about the linkages between strategy and measures, as well as failure to deliver information about the strategy, result in the common measures bias. They sought to understand what factors impacted or even eliminated the common measures bias: providing strategy information, how much, and with what linkage to the measures. Managers who do not have sufficient information relating the measures to the strategy are likely to use them incorrectly or ineffectively (Humphreys & Trotman, 2011). That is not to say that the measures are, in themselves, ineffective; rather that they may not be used to best effect.

The goal question metric paradigm. The goal question metric (GQM) paradigm is "a mechanism for defining measurement in a purposeful way" (Mendonça et al., 1998). This model that provides a clear line of sight between the goals and measures in a technical environment, perhaps providing a way to make the effective application of the measures more explicit. The GQM paradigm was developed in the early 1980s as an approach for the structured development of measures of performance measurement, enabling the identification and implementation of measures in the information technology space (Basili & Weiss, 1984).

GQM has been applied in a limited way in the business environment (Becker & Bostelman, 1999). Building upon GQM and the work of Becker and Bostelman, further development of a model to apply those concepts to measurement of business strategy success may enable more effective organizational performance measurement. Additional application in the business environment has been in the development and use of the GQM+Strategies model, discussed below. One of the difficulties with the GQM approach is that decision makers may not know what their goals or objectives are, or may not know them at a level that can be articulated in a SMART (specific, measurable, achievable, relevant, and time-bound) way (Boyd, 2005;

Markovic & Kowalkiewicz, 2008). SMART objectives, as defined by Peter F. Drucker (1954), are “specific, measurable, achievable, relevant, and time bound” (as cited by Markovic & Kowalkiewicz, 2008, p. 332). In such cases, collaborative teamwork can be used to articulate the goals.

Shull, Seaman, and Zelkowitz (2006) review Basili’s work in an essay—glossing over how goals in the GQM model are identified, while illustrating the difficulty of describing precisely how the things we need to measure should be identified and how the measures should be defined. Shull et al. echo the exploration visible in the work by Mashiko and Basili (1997) and Mendonça et al., (1998) of application of the GQM in IT software development, but not in business meaning or outcome measurement from the business perspective. Becker and Bostelman (1999) discuss the intersection of the balanced scorecard and the GQM model. It is in the intersection of the concepts of performance measurement systems that one begins to see the end-to-end connection between the business objectives in the key performance measures of the balanced scored card and in the data necessary to derive the measures in the GQM model.

One of the strengths of GQM is that it seeks to identify what the decision maker needs to know—not what measure to use, but what a measure should make understood to the decision maker (Boyd, 2005). Analyzing these measures in a bottom-up approach and connecting them within a GQM model ensures that the existing measures are considered and their usefulness is understood. This enables the practitioners to account for the current state of their environment and to determine whether all the existing measures are still required, explicitly connecting them to the organization objectives to ensure value (Boyd, 2005). In other usage, when they are already using measures, practitioners may elect to apply the GQM in a top-down approach. While this allows them to look at the organization from a more strategic perspective, such an approach may result in missing important insight to be gained by examining existing measures (Boyd, 2005).

Either a bottom-up or top-down approach, carefully applied, will allow the organization to cull measures that are no longer useful in the face of changing organizational objectives, environmental conditions, or technical capabilities (Boyd, 2005). Regardless of the method used to identify desired measures, one study found that organizations that found success often started with a more modest set of rigorously defined measures. Proving the value of the initial set, these organizations empowered their people to both act on and provide feedback to improve the measures (Boyd, 2005). Perhaps an adept decision maker requires an understanding of a tool such as the GQM as a means to maintain a parsimonious (minimal, but sufficient) set of measures.

GQM-decision support framework for metric selection. The GQM-DSFMS is an extension to the GQM by Gencel, Petersen, Mughal, and Iqbal (2013). A primary value of the GQM-DSFMS is to enable practitioners to identify and select appropriate measures with traceability between the measure and the organizational objectives they address (Gencel, Petersen, Mughal, & Iqbal, 2013). This model calls for a parsimonious set of measures to provide a clear line of sight for decision makers to both the cost and the value of the measures.

GQM+strategies. The original GQM+Strategies method concept was published in 2007 as a white paper by Basili, Heindrich, Lindvall, Münch, Regardie, Rombach et al. (Mandić & Basili, 2010). The GQM+Strategies approach enables traceability not only between measures and the organizational objectives they support, but extends the linkage to include the strategies used to achieve those objectives (Münch et al., 2013). By bringing the strategy into clear view, this method enables clarification, harmonization, alignment of the goals and strategies, as well as the ability to monitor the strategy's deployment in the organization. It communicates information about the strategy to the organization as well as enabling feedback from the organization. GQM+Strategies is a concept which "integrates goal-oriented measurement in the alignment process and therefore allows to manage, control, analyze, and change goals and strategies based on data" (Münch et al., 2013, p. 2). As with any organizational strategy, the artifacts developed using the GQM+ Strategies approach will continually evolve with the business strategy. Periodic review and update enable this evolution (Münch et al., 2013).

The objective of Sarcia's (2010) research study was to identify the assumptions necessary to apply the GQM+Strategies approach, the extent to which it is exportable to other domains, whether non-software development personnel can easily apply it, and whether it is convenient to apply it to non-software development domains. Sarcia found that familiarity with the basic GQM approach is important when applying the GQM+Strategies approach and that application in domains other than software development, such as the Italian Air Force in this study, is difficult when practitioners do not have prior GQM knowledge or experience (Sarcia, 2010). Sarcia's research may identify another area of knowledge that the adept decision maker needs to identify and select performance measures, as it explicates concerns about the applicability of the GQM+Strategies approach to different environments.

Literature Summary

Leaders make situationally-sensitive decisions to run their businesses (Khatri & Ng, 2000; Papenhausen, 2006; Tingling & Brydon, 2010) using evidence gathered and tested against their prior knowledge and experience (Franklin, 2012; Merriam et al., 2007; Williams, 2012). Cabantous and Gond (2011) found three common features that make rational decision making elusive. People assume rationality is possible—that they *can* know all information, identify all options, and identify all possible outcomes. In addition to lacking some of this knowledge, decision makers do not always have objectives that can be articulated clearly enough to enable decision making (Basili & Weiss, 1984; Choong, 2013; Frisk, Lindgren, & Mathiassen, 2014) and they rely on suboptimal information with constraints imposed, real or artificial, that limit the available options.

Owing to the difficulty in describing or quantifying intangibles, decision making surrounding them falls more readily into bounded rationality (Frisk, Lindgren, & Mathiassen, 2014; Kalantari, 2010). Because all the options and consequences cannot be known, bounded rationality results in satisficing (Kalantari, 2010). In addition, the decision maker's system of beliefs may limit her field of vision and affect selective perception (Robbins & Judge, 2011). Sometimes rationality and bounded rationality (data-driven decision making) is not appropriate. Intuition has been demonstrated to be more effective when making decisions on poorly structured problems or those lacking information or involving high degrees of uncertainty (Tingling & Brydon, 2010).

Decision making processes are executed to make a decision, to inform a decision, or to support a decision that has already been made (Baba & HakemZadeh, 2012; Tingling & Brydon, 2010). Intuition is formed by the decision maker's experiences, reflection, and internalization of those experiences (Khatri & Ng, 2000, Matzler et al., 2007; Robbins & Judge, 2011; Weaver, 2014; Williams, 2012), whereas rational thinking tends to confirm established patterns (Weaver, 2014). For non-routine, strategic decisions characterized by vagueness, intuition may be a more effective basis of decision making (Papenhausen, 2006; Williams, 2012). Such intuition assumes certain competencies.

Competency is defined as "skill that an individual and thus the organization possesses that enables it to perform activities" (Steptoe-Warren et al., 2011, p. 241). Framing is one of the competencies required of a decision maker. The way a decision maker frames a problem impacts the solution, requiring him to have the ability to frame a decision objective in a way that clearly articulates the need (Franklin, 2013; Robbins & Judge, 2011). Decision makers typically have richer experiences and larger amounts of relevant knowledge not commonly available to less experienced people—or those lower in the organization (Khatri & Ng, 2000; Papenhausen, 2006; Simon, Kumar, Schoeman, Moffat, & Power, 2011; Weaver, 2014). They may also have more of this relevant knowledge in memory and related in more complex ways, allowing them to make connections not visible to others (Franklin, 2013; Steptoe-Warren et al., 2011). This rich, interconnected knowledge is a strong source of competency in the decision maker.

Decision makers need to collaborate to get information they lack, to validate knowledge, to broaden their perspective of alternatives, to gain commitment, and to identify shortcomings (Schwarber, 2005; Steptoe-Warren et al., 2011). Communication of measures and the relationships between the measures and objectives has been shown to be important (Humphreys & Trotman, 2011; Kaplan & Norton, 1996; Kasperskaya & Tayles, 2013; Morard et al., 2012; Olsson & Runeson, 2001; Theriou et al., 2004; Wongrassamee et al., 2003; Wu, 2005).

By communicating program theory precisely in a logic model, a program manager identifies and aligns the capabilities and expected outcomes of a program (Basili & Weiss, 1984; Monroe et al., 2005; Rogers et al., 2000; Rossi et al., 2004). By articulating what they seek to accomplish, they can identify common components and simplify objectives—learning when to simplify and when to add complexity (Rey et al., 2012; Rogers et al., 2000)—to measure their achievements more effectively. Because the program theory is organized as causal chains, the interdependencies among measures would also be visible (Rogers et al., 2000). It explicitly describes the assumptions about resources and activities and how these are expected to lead to intended outcomes (McLaughlin & Jordan, 2010; Rogers et al., 2000).

A logic model is an illustration of program theory, showing how a program works under a given environment and assumptions (McLaughlin & Jordan, 2010; Taylor-Powell & Henert, 2008). The program logic is about the connections among the program's components. Those components include resources, activities, and outcomes/goals or objectives (Brousselle & Champagne, 2011; McLaughlin & Jordan, 2010; Rey et al., 2012; Rogers et al., 2000). The ability to design or assess the logic model influences the decision maker’s ability to align measures to the program objectives (Savaya & Waysman, 2005; Steptoe-Warren et al., 2011; Van der Stede, Chow, & Lin, 2006).

There are some challenges for developing program theory. Practitioners cannot always say why the components of the program theory work or do not work. Their ability to see and comprehend cause and effect in the program may be limited and they may not have the knowledge or skill to develop appropriate measures to assess their outcomes (Monroe et al., 2005). They may not have the time or the tools necessary to collect data; develop analytical models; and deliver clear, actionable information for decision making (Rogers et al., 2000).

Hedge and Teachout (2000) identified three classes of criteria to assess candidate measures: acceptability, actionability, and usability. Bhatti et al. (2009) identified seven measure selection criteria: feasibility, availability of personnel, availability of tools, disruptiveness of data collection, the personal preferences of the decision makers, and the ease of interpretation and presentation grouped into five factors: collection time, cost, value, type, and repetition. Gencel et al. (2013) call out two criteria for selecting measures: the cost of producing the measure and the priority of achieving the goal.

A measurement framework is a set of related measures, data collection mechanisms, and data used to support a business (Mendonça et al., 1998). The desired qualities of a measurement framework are soundness, completeness, leanness, and consistency (Mendonça & Basili, 2000). One example of a measurement framework, the BSC, was developed by Kaplan and Norton in 1992 to provide new perspectives (customer, the business processes, and learning and growth) to address organizational capabilities and intangible assets (Kaplan & Norton, 1996).

In its original form the BSC did not provide review, update, and assurance of continued relevance of each measure (Akkermans & van Oorschot, 2005). Decision makers assume causality, when it may not exist (Akkermans & van Oorschot, 2005). However, causality is assumed in the BSC (Kaplan & Norton, 1996). The dynamics of the real world have a direct impact on how we measure performance (Bazett et al., 2005), whether in the BSC, GQM, or other measurement frameworks. One benefit of effective measurement framework use is to facilitate organizational learning. Such learning occurs during BSC development (Kaplan & Norton, 1996; Kasperskaya & Tayles, 2013) and Kaplan and Norton (1996) stress the importance feedback to enable this organizational, strategic learning (Kaplan & Norton, 1996; Senge, 1990; Wongrassamee et al., 2003; Wu, 2005).

Metric ROI is used by Gencel et al. to refer to “the contribution of metrics in fulfilling the information needs of the stakeholders” (2013, p. 2). Organizations may fail to realize ROI because of having too many measures or relying on too few, or continuing to rely only on historical financial data rather the BSC (Deem et al., 2010). Organizational culture plays a significant role in the effectiveness of adopting and using the balanced scorecard effectively

(Deem et al., 2010). Understanding the insight delivered by a performance measurement framework is another challenge. Schalken and van Vliet (2007) suggest the use of an iterative qualitative/quantitative cycle to assess and explain the usefulness of the measures. Bhatti et al. (2009) found that expert judgment is required to identify the right measures, to avoid the temptation to use too many, or to rely heavily on too few. Lack of this expert judgment in organizations is one of the problems that cause performance measurement to give poor return for the investment.

V-GQM validation helps practitioners using the GQM method develop measures that achieve their intended purpose (Olsson & Runeson, 2001). Avoiding common measures bias is a challenge to selecting the right measures (Humphreys & Trotman, 2011). One aid to choosing the right measures is considering coherence among the measures (Akkermans & van Oorschot, 2005). They advocate use of causal modeling to assess the relationships horizontal and hierarchical among the BSC measures the findings of their study suggest that the use of system dynamics is beneficial in assessing the validity and usefulness of the BSC.

Münch et al. (2013) discuss the need to identify and link organizational objectives and strategies across an entire organization. Kaplan and Norton (1996) describe a strategic management system assuming explicit linkages between measures and objectives. The discovery of the common measures bias related to the effectiveness of the BSC demonstrates the importance of explicit strategy – measure linkages. Incomplete strategy - measure linkage information (or failure to deliver information about the strategy) both result in the common measures bias, resulting in diminished decision-making quality (Humphreys & Trotman, 2011). When the strategy is not communicated clearly and effectively to the organization the scorecard itself is not as effective as it might be otherwise (Kaplan & Norton, 1996).

GQM is “a mechanism for defining measurement in a purposeful way” (Mendonça et al., 1998). One difficulty with GQM is that decision makers may not know what their goals or objectives are (Boyd, 2005; Markovic & Kowalkiewicz, 2008). When the objectives are known, the GQM provides a clear line of sight between the goals and measures in a technical environment. Two types of measures that may be generated using the GQM are process and product measures. It is in the intersection of the concepts of performance measurement systems that one begins to see the end-to-end connection between the business objectives in the key performance measures of the balanced scored card and in the data necessary to derive the measures in the GQM model. One of the strengths of GQM is that it seeks to identify the insight a measure provides to the decision maker (Boyd, 2005).

The original GQM+Strategies method concept was published in 2007 (Mandić & Basili, 2010). This approach enables traceability not only between measures and the organizational objectives they support, but extends the linkage to include the strategies used to achieve those objectives (Münch et al., 2013). Sarcia (2010) found that familiarity with the basic GQM approach is important when applying the approach and that application in domains other than software development is difficult when practitioners do not have prior GQM knowledge or experience.

Leaders make decisions to run their businesses (Khatri & Ng, 2000; Papenhausen, 2006; Tingling & Brydon, 2010). They formulate strategy (Humphreys & Trotman, 2011; Kaplan & Norton, 1996). They design plans to deliver value and consider the outcomes they seek (Basili & Weiss, 1984; Monroe et al., 2005; Rogers et al., 2000; Rossi et al., 2004). They measure their progress in achieving their business objectives (Mendonça et al., 1998). They make decisions about continuing or changing their business programs and practices (Kaplan & Norton, 1996;

Senge, 1990; Wongrassamee et al., 2003; Wu, 2005). In all of these activities, their prior experience comes into play. This study will build on the body of knowledge presented in this literature review and extend it by exploring the experiences that form decision makers, enabling them to do these things.

Methodology

Mixed methods research (MMR) is defined as "research in which the investigator collects, analyzes, mixes, and draws inferences from both quantitative and qualitative data in a single study or program of inquiry" (Cameron, 2011, p. 96). The premise of MMR is that the combination of the qualitative and quantitative approaches is essential to understanding the research question under consideration. MMR designs allow the researcher to combine qualitative and quantitative analysis techniques, collecting and analyzing both qualitative and quantitative data to deliver a more comprehensive exploration of the phenomenon under study (Cameron, 2011; Creswell, 2012).

This study used a mixed method, exploratory sequential research design (Creswell, 2012). Qualitative and quantitative approaches are not mutually exclusive and opposed. They exist on a continuum rather than as opposing concepts (Cameron, 2011; Creswell, 2014). Cameron (2011) asserts that qualitative data can be analyzed quantitatively and quantitative data can be analyzed qualitatively. Exploratory sequential design, in particular, is an MMR design in which a qualitative study is conducted to identify themes present in the phenomenon under study.

Those themes are then used to direct the development of the next phase of study during which a quantitative measure of understanding is sought (Creswell, 2012). Saldaña writes about coding in mixed methods studies, saying, "major codes or even significant quotes from participant interviews might serve as stimuli for writing specific survey instrument items" (2013, p. 63). In the research design of this study, triangulation of the findings (Creswell, 2014) of the literature review, the interview findings, and the survey findings were used to integrate the data and report the nature and degree of the life, work, and educational experiences that contribute to the formation of decision makers who identify and select what they consider to be effective organizational performance measures.

The study research questions are being examined using an MMR approach for two reasons. First, the business and academic values of the research are equally important to the researcher. Conducting qualitative research to develop understanding of the life, work, and educational experiences from which decision makers learn to choose organizational performance measures has inherent value in both perspectives. Adding the quantitative assessment provides information that is expected to be actionable in a business perspective (Miles, Huberman, & Saldana, 2014). Second, the exploration of the development of knowledge or skill (epistemology) with the qualitative study followed by the analysis of the occurrences of such knowledge and skill within a business environment provides a more complete picture of the ontology (Cameron, 2011). The quantitative portion of the study was expected to enrich the qualitative findings, whether by supporting or contradicting them (Miles et al., 2014).

This method allowed me to explore both the stories of the participants' experiences in the formation of their individual decision making and ability to identify and select organizational performance measures, as well as to explore the degree to which those experiences are shared among the population of process engineering community at the company. The findings from both studies have been assessed in the context of the skill and knowledge suggested in the literature.

The essential research question in the qualitative phase is, what are the life, work, and educational experiences that contributed to the ability of the organization's decision makers to choose effective organizational performance measures. In the quantitative phase, the research questions sought to identify and quantify the importance of the constructs represented within the qualitative data and to understand how those constructs are impacted by various dimensions within the respondent community.

Design of the Qualitative Phase

I conducted a basic qualitative interpretive study (Lichtman, 2013) using one-on-one interviews of purposefully-selected (Creswell, 2012; Creswell, 2014; Miles et al., 2014) organizational decision makers to explore the life, work, and educational experiences that have enabled them to identify effective measures of organizational performance to aid their decision making. The decision makers were expected to “articulate [and] share ideas comfortably” (Creswell, 2012, p. 218), and to share rich, meaningful experiences (Patton, 1990) that have contributed to their success. I explored the research question by interviewing eleven executive process owners, using semi-structured (guided) interviews. The executives were selected based on the roles they play with respect to organizational business processes.

Several strengths of the basic qualitative design made it useful for this study. Using interview questions that allowed the participant to discuss and elaborate on answers and that allowed me to probe for meaning enabled the collection of more focused data. The stories the participants shared provided rich understanding and direction for analysis. Lichtman (2013) discusses the use of a basis qualitative design when the researcher wants to understand the participants’ perspective of a phenomenon—in this case, the phenomenon is the learning experience of the participant. At the same time, the analysis of the interview findings required disciplined documentation of the steps and analytical thought processes. The purpose of understanding the formation of these decision makers makes the basic qualitative design appropriate to the research task.

Ethics. Neither interview participants nor survey respondents received incentives for their involvement in this study. The nature of the information I sought was not sensitive, nor was any information of a sensitive nature encountered or reported. While it was possible that a participant's life, work, and educational experiences could have involved personal stories beyond the scope of the information sought (unexpected richness), this was encountered only in ways that did not pose an information-sensitivity or identity risk for the participants. Information in the participant stories was de-identified for analysis and reporting (Davis, 2003).

Proper handling and destruction of interview audio recordings is assured following the publication of the initial research, that is, this dissertation study. A study disclosure statement, including the ethical behavior to be practiced, was included in the interview protocol, as well as in the preface to the online survey. Participants were drawn from one particular company and the research questions and interview protocol did not seek company intellectual property. None was encountered and no sensitive intellectual property was disclosed, either in the conduct or analysis of the research or in is published study (Creswell, 2012; Lichtman, 2013). The targeted subject matter is not sensitive and participants are not a protected or vulnerable population, so the Institutional Review Board (IRB) proceedings were conducted as an expedited review.

Interview protocol. In individual interviews, participants were invited to share the life, work, and educational experiences they felt shaped their ability to choose organizational performance measures. The IRB approved the interview protocol, which included primary topics of interest to spur conversation (Creswell, 2012; Lichtman, 2013; Miles et al., 2014), such as process complexity, organizational performance, and past experience with well- or poorly-chosen measures. See the IRB documents in Appendix A and the interview protocol in Appendix B. It includes guiding questions with clarifying questions to prompt further conversation if needed. Basic opening questions sought to elicit conversation about the participant's background; to introduce the researcher, establish rapport, and tell why the interview and study may matter to the participant; to find out about the actual experience of the participant; and to ask what advice the participant might give a protégé or emerging leader regarding selection of measures.

Interview perspective. Roulston (2010) discusses the neo-positivist perspective, describing an interview in which the interviewer is in a more neutral role and takes care not to introduce bias in the questions or conversation. Although the focus of this study was to understand the stories of the participants, rather than to develop an understanding together, my perspective and involvement were not conducive to such a perspective. Therefore, I approached the interviews from a constructivist perspective, where the interviewer and the participant together construct meaning during the interview process (Brinkman & Kvale, 2015; Creswell, 2012). In order to select participants with whom to construct this understanding, I focused selection on aspects of process complexity. Literature describing process complexity is presented here, to provide clarity into my participant-selection criteria and perspective.

Process complexity. Assessing the complexity of the processes used in a business is an important part of an organization's ability to manage its processes. Process complexity may be described in terms of the degree to which people involved in the process can understand or explain their process to others (Cardoso, 2008). Complexity measures are used to assess the difficulty to be expected in understanding the process (Laue & Gruhn, 2006). Complexity may vary based on how much routine, variety, and interdependence there is among the tasks involved in the process (Schäfermeyer, Rosenkranz, & Holten, 2012). The objectives these business processes deliver and the environments in which they are executed are often complex, making it difficult to reduce or eliminate that complexity in the process measures. The processes must be designed to address this complexity (Schäfermeyer et al., 2012), which results in implications for the decision maker. More information and perhaps more decision-making experience may be required for making decisions about the process.

Process complexity impacts the organization's ability to standardize processes. The more complex the process, the more effort is required to standardize it, while at the same time, the less amenable to standardization it is (Schäfermeyer et al., 2012) and the more likely it is to generate error (Cheng & Prabhu, 2008). As part of measuring complexity, both Laue and Gruhn (2006) and Cheng and Prabhu (2008) consider the cognitive weight of the process to be a factor of its complexity. By analyzing the structures in the process as patterns and assigning cognitive weights to the individual patterns, the organization can assess the understandability of the patterns by themselves, then as a whole.

Factors or dimensions of complexity describing these patterns include the number of activities, control-flow complexity, and nesting depth. Nesting depth is a measure of the decision points in a process (Laue & Gruhn, 2006). Cardoso (2008) seems to express all these concepts as simplicity, then adds consistency, automation, and the notions that measures must be additive and interoperable. Rather than using the term cognitive weight, Cheng and Prabhu (2008) use understandability, then call out maintainability (which is impacted by simplicity) and size (which is, at least in part, number of activities). The number of factors or dimensions suggested by various research supports Cordoso's (2008) position that process complexity is not practically summed up in a single measure. He focused on control-flow complexity, which was also mentioned by Laue and Gruhn (2006), but identified three other perspectives to consider: activity complexity, data-flow complexity, and resource complexity. All of these attributes of complexity influence the measures that a process owner might select.

The levels of detail discussed by Cheng and Prabhu (2008), Laue and Gruhn (2006), and Schäfermeyer et al. (2012), are more precise than is required for the purpose of this study. To select the study participants, process complexity will be assessed based most nearly on Cordoso’s (2008) perspectives. The organization in which the study will be conducted uses common industry terms for addressing dimensionality: people, process, technology, and information. These align roughly to the resource complexity, activity complexity, data-flow complexity, and control-flow complexity, respectively (although an argument might be made to align aspects of resource complexity and data-flow complexity to technology also).

Based on this review of process complexity literature, the criteria for selecting qualitative phase participants are as follows. The ideal participant is the owner of a process which spans two or more organizational business units, involves eleven or more people and three or more automated systems, and consists of eleven or more significant activities, as defined by the APQC Process Classification Framework (American Productivity & Quality Center [APQC], 2015). Participant selection will be facilitated through recommendations made by a leader in the company’s data and analytics office.

Participants. Considering a proposed set of candidate decision makers, as well as his own knowledge of the company and the study’s purpose, the company leader recommended fourteen participants for consideration for the qualitative phase of this study. This is reflective of a purposive reputational case selection (Miles et al., 2014). The criteria for selecting the participants was twofold: their willingness to participate in the study and their responsibility as the owner of a process of moderate to complex nature. Willing participants were selected on the condition that they are the owners of processes that meet moderate or complex level complexity criteria: 1) Number of resources involved in the process (0-10 within a single organization, simple; 11-20 in a single or no more than two organizational units, moderate; and 21 or more spanning 2 or more organizational units, complex). 2) Number of activities executed in the process (0-10, simple; 11-20, moderate; and 21 or more, complex). 3) Number of systems involved in the process (0-2, simple; 3-5, moderate; and 6 or more, complex).

Although I did not have direct knowledge of the quality or complexity of each potential participant’s knowledge or experience with regard to decision making and identification and selection of organizational performance measures, all eleven participants were owners of complex processes, spanning 21 or more resources, 21 or more activities, and 6 or more systems. This selection approach assumed that the participants in positions of process ownership for moderate or complex processes exhibited characteristics necessary to the skill and knowledge of interest for this study. For the purpose of this research design, a business process owner, informally referred to as simply *process owner*, is defined as the organizational executive who is accountable for the functioning of the process and delivery of the product or service provided by the business process.

Each participant was assigned an identifier, P_01 through P_11, in no particular order. Some participants represented more than one business area, with representation from each of the following business areas: banking, insurance, investment management, marketing, human resources, information technology, data and analytics, and cross-functional areas. It was desirable to have more than one participant from each major business area to observe whether there were similar experiences by area.

I had access to the participants and permission to request their participation (Creswell, 2012), and each was free to participate or not as they choose, without pressure of any kind. Although contingency plans were made to deal with an insufficient number of participants by using snowball sampling, it was not necessary. Eleven of the fourteen individuals originally invited agreed to participate in the study and were able to complete the interview. Of the three who did not participate, two did not respond to the invitation and the last was interested, but had no available schedule time open for an interview appointment.

Data collection. I performed the transcription and analytical activity during transcription (Brinkmann & Kvale, 2015; Miles et al., 2014). The source of the data was audio recordings and written notes from one-on-one interviews of participants identified in a purposeful sample of owners of moderate to complex business processes. The participants were interviewed individually for two reasons: scheduling simplicity and logistics. The process owners have significant demands on their time and are located in various parts of the company campus. The likelihood of arranging timely interviews was increased and confidentiality was assured by conducting individual conversations.

Additionally, the convenience to the participant was increased by individual interviews conducted at the location of their choice. In each case, the interview was conducted in the office of the participant. Two of the interviews (P_02 and P_04) were conducted in informal, conversational settings. In the other nine interviews, I sat with the participant over a table in each of their offices. I attempted to arrange the seating so that we were at angles to each other, rather than facing directly across the tables; however, in several cases, the participants invited me to sit first and then selected the placement they preferred. Because I was interviewing in a setting where I had established credibility, there was little or no awkwardness in the engagements.

Data capture. Transcription for the purpose of qualitative analysis requires transparency into the researcher's paradigms and theoretical foundation. The correctness and understandability of the interview transcript are impacted by the decisions made by the researcher during transcription (Brinkmann & Kvale, 2015; Miles et al., 2014; Skukauskaite, 2012). I chose to transcribe verbatim, allowing for omission of repeated words and verbal pauses. The interview transcription was influenced by my perspectives and experience. Where I recognized these, I explicitly disclosure them for transparency. In addition to my perspective, I also examined any assumptions I was making, and validated or corrected these assumptions if possible. (Skukauskaite, 2014). Given my combined business and academic perspectives, I approached the interviews in this study as co-constructions rather than being positioned with the interviewees as strictly a providers of information.

Along with their other stated perspectives and assumptions, during the process of analyzing and interview interaction, my theoretical grounding shaped my transcription decisions (Skukauskaite, 2014). Because the act of transcribing required me to understand theory and my own perspectives and assumptions, and apply that foundational knowledge as I made transcription decisions, the transcription itself was an analytical activity (Skukauskaite, 2014). As a result, there was more to transcribing the interviews for the purpose of conducting qualitative analysis than just recording the verbal interaction of the interviews in written form. The analysis of the interviews did not begin with reading the transcript.

I performed analysis in the production of the transcript itself. As the act of doing transcription was inherently an analysis activity, I produced the interview transcripts myself. I captured the conversation of each interview in a distinct audio recording as well as in typed and handwritten interviewer notes. Taking the notes did not seem to impede the meaningful exchange of information or make the interview participants uncomfortable during those interviews where I used it. However, it quickly became apparent that the richness available from the audio recordings was not significantly increased by the typed notes and I discontinued them completely after the sixth interview. I transcribed the interview audio recordings using distinct fonts to indicate the different voices of the interviewer and participant (Miles et al., 2014; Skukauskaite, 2012).

Transcription verbatim rather than by inference was important because trying to force the interview dialog into a grammatically correct sentence would have hidden signs, signals, and evidence of nonverbal components of the interaction and the possibly altered meanings they may indicate. For example, the use of air quotes or a sarcastic or clearly self-deprecating tone can invert the meaning of the spoken word. When nonverbal communication such as repeated words, verbal pauses, and other elements of the interaction are not captured, the resulting transcript may be misleading (Skukauskaite, 2012). Initial transcriptions were as close to verbatim as I was able to make them, however, I did go back and remove repeated words, verbal pauses to aid my continued analysis. There were a few instances where I inserted comments inline in the transcript to indicate that the participant took a long pause before responding to a question or probe. Most notably, this occurred when I asked about what education, in hindsight, they would have benefitted from and when I asked about their definition of an effective measure.

For the purpose of this study, *unexpected richness* refers to information provided by the interviewee, but not explicitly sought with the designed interview protocol. Unexpected richness encountered during the interview interaction is hoped-for, but not expected because of the guided nature of the interview protocol. However, such unexpected richness was included in the analysis wherever possible (Skukauskaite, 2014). There were several responses provided in the interviews that strayed beyond the specific information I sought. One such conversation led into the decisions made based on effective and non-effective measures. Another led into employee behaviors in response to effective and non-effective measures. The discussion of those findings is not included in this study, except as a call for potential future research.

It is also appropriate to show the nonlinear nature of the conversation in an interview transcript. There may be times when an interview participant returns and revisits a previously discussed question, adding richness in detail or making corrections for that matter. Such nonlinear behavior in the conversation is interesting and important in analyzing the interview (Skukauskaite, 2012). There were two significant instances of nonlinear response. In both cases, after the discussion appeared to be concluded and I asked if the interview participant had any questions for me, two of the participants circled back to items of particular interest to them. In one case, it was to focus on the importance of reflection (P_06) and in the other, on the importance of organizational complexity in measurement (P_09). In both cases, the follow-on discussion was extensive and clearly of strong significance to the participants.

Reflection and reflexivity. After each interview, I recorded observations, thoughts, and impressions and reflected on them while conducting transcription. I included my recorded content when I did the initial coding to begin the analysis and seek meaningful codes. I sought meaning and made connections in these reflections, by considering the basic interrogative questions surrounding each thought expressed in the interview—who, what, when, where, and why (Saldaña, 2013). By taking the time to do this with each interview, I was able to build a clearer picture of the participants' stories and of things that mattered to them—especially across disparate business interests. This activity was directly useful in the qualitative data preparation and analysis, and in the formulation and articulation of the findings and conclusions (Brinkmann & Kvale, 2015; Miles et al., 2014; Saldaña, 2013).

Data preparation. As I conducted the interviews, I iteratively analyzed and coded the transcripts and interview notes for each interview. "Coding is a heuristic – a method of discovery that hopefully stimulates your *thinking* about the data" (Saldaña, 2013, pp. 39-40, emphasis his). Thus inspired and using reference material and initial coding, I generated a coding frame within which to understand the information I collected in the interview process and I identified themes and concepts as the collected content matured. I used provisional coding based on literature and my prior knowledge and amended it as analysis continued (Saldaña, 2013).

Modes of work experience can be measured in three ways: using time-based measures, using amount based measures, and using type measures. These three task modes and measurement modes compose a framework depicted in a three-by-three matrix where the rows signify the task mode and the columns represent the measurement modes (Quinones et al., 1995). I assessed the interview data to determine the fitness of the work experience framework for analysis of the participants' work experience. The focus of the interview questions was on the experiences of the participants in learning to choose measures, but none of the interviews touched on the nature and type of measures that were selected. Although I was prepared to do analysis on the work experience through this lens, it was not relevant in the executed experience.

While the primary focus was on identifying the experiences important to the participants' formation in choosing effective measures, the individual stories they told were paramount. As I focused on the identification of codes, themes, and concepts, I was also alert to the holistic sense of these stories (Lichtman, 2013). I used these codes, themes, and concepts to construct the coding frame.

> A coding frame is the guiding conceptual scheme for a research study…it contains the definitions of concepts and categories that mediate the translation of raw data…[and] the rules used to single out the observations associated with them [the concepts] in raw data. (Benaquisto, 2008, p. 89)

Use of a common coding scheme between this future research as well as this current research will enable findings to be compared meaningfully (Benaquisto, 2008).

Creswell (2012) presents a model of the coding process through which one builds a coding frame. It includes the following steps, which will be used to construct the coding frame for this study:

1) Begin with the raw text of the transcript, which may be comprised of many pages of text. Start by reading the textual data.
2) Divide the text into logical segments of information, narrowing down many pages into segments. In alignment with Creswell's segments, analyze the transcribed interview interactions using the concept of message units. Along with the message units specifically focused on the words used, pay special attention to nonverbal communication which may indicate emphasis, inversion of meaning, or deeper richness in meaning (Skukauskaite, 2012).
3) Label the segments of information with codes. The target is 30 to 40 codes. I attempted to use the framework established by Hedge and Teachout (2000) as an initial coding scheme for work experience. I took care to remain open to work experience that did not map cleanly into the framework, to avoid inappropriate adherence. It quickly became apparent that the framework was not well aligned the study participants' experiences. Once I determined this, I inductively derived the coding for the interview analysis to develop the questionnaire for the survey (Benaquisto, 2008).
4) Reduce the overlap and redundancy of the codes-to about 20 codes; and

5) Collapse the codes into themes-ideally 5 to 7 themes. The coding process allowed me to organize the data by categorizing according to a reduced set of labels (Creswell, 2014). Coding used terms in the vernacular of the participants, with standardization to common data and analytic terminology from the various colloquial language of the participants. (Creswell, 2014). I found 48 meaningful codes, aligned to 5 themes.

Data analysis. Although analysis actually began with the creation of the interview transcripts, it continued through coding and into an iterative process concurrent with the interview process. I did conventional textual analysis of the transcribed interviews (Lichtman, 2013) using a spreadsheet to record the coding process for each interview transcript. No electronic or automated means of coding or identification of themes or concepts (Basit, 2003) was used. As the set of interviews grew, I analyzed the text, discovered and showed relationships among the codes, and built a coding frame to illustrate these relationships. Although categorization based on the main themes identified in the literature review and the concepts of work, life, and educational experience was used as a starting point, the coding frame was constructed from the contents of the interviews.

Using the concept map, I reflected on the codes, identified themes, and discussed them in the context of the findings of relevant literature in decision making, program theory, and organizational performance measurement. Additionally, I consulted with my dissertation committee for guidance and to ensure a rational analysis. In this way, I articulated how the information discovered in the interviews related to the theoretical foundation presented in the literature review. As part of the process of coding, identifying themes, and drawing connections, I explicitly showed my work, exhibiting the connections in written form as they were developed.

Methods of verification/trustworthiness. I transcribed the interview audio recordings and, after coding and identifying themes and concepts, verified the accuracy of the findings with reflection, by associating the findings from the research to the relevant literature, and by member checking (Lichtman, 2013) with the original interview participants. In addition to the research approach described with transparency to this point, trustworthiness was tested by collaborating with another analyst to independently review the data and analysis documentation, and discussing the rationality of the findings. Note that this review was conducted using data that had been de-identified for the privacy of the participants.

The interview findings were related back to the framework of literature presented in the literature review. In this way, the findings are anchored to individual decision making, program theory, and performance measurement concepts and provide a foundation upon which the reliability of the findings may be trusted (Lichtman, 2013). The outcomes of this qualitative research informed the creation of a survey instrument to collect data about how many practitioners in the company's process engineering community shared the same types of experiences.

Guidelines for the qualitative phase of the study. The AERA standards were used to guide the development, execution, analysis, and presentation of the qualitative analysis and findings of this study. Inasmuch as was useful, I provided rich description when describing the interactions with the interview participants and the findings (AERA, 2006). In addition to the AERA standards, I leveraged insight from the 5Ps framework in the formation and execution of this study.

Cameron (2011) presents the 5Ps framework, a starter kit for mixed methods researchers, by identifying the 5Ps: paradigms, pragmatism, praxis, proficiency, and publishing. A *paradigm* is “a way of looking at the world” (p. 100). *Pragmatism* refers to the likelihood of successfully applying the findings in practical terms, while *praxis* refers to “the practical application of theory” (p. 102). In this research study, I have approached the interview conversations from a business perspective (pragmatic, paradigm). While the interview protocol and data collection rigor adheres to an academic standard (praxis), much of the conversation is guided by business experience (proficiency).

I followed this qualitative research and analysis with a quantitative study to determine the nature of the occurrences of the experiences discovered in the qualitative study. This survey approach is appropriate to describe the trends of experience in the population. The survey was developed, informed by the themes in experience that were identified in the qualitative study. A simple cross-sectional survey design was employed to examine the experiences of the process owners at a single point in time (Creswell, 2012). The IRB reviewed and approved the survey design in an amendment to the original expedited review conducted for the qualitative phase.

Design of the Quantitative Phase

The qualitative findings, codes and themes, were used to inform the initial development of the survey instrument of the quantitative phase of the study. Subsequent refinement of the instrument resulted in reorganization of the items and provided a basis upon which the answers to the quantitative research questions may be answered. The research questions for this phase of the study are

(1) What constructs represent the important content of experience, knowledge and skill, and what constructs encapsulate the concept of the effective measures?

(2) How are those constructs impacted by various dimensions within the respondent community.

To answer the first question, principal components analysis was used to extract components (constructs) from the 55 EKS variables and the 23 measure variables. The factor means were compared to determine the relative importance of the EKS factors. For the second quantitative research question, one-way ANOVA (for the individual importance of the constructs) and MANOVA (for the collective importance) was used to determine how the group means vary.

The effective measure data was collected, primarily to provide context in which to understand the EKS data. In asking what experience, knowledge, and skill are important to the respondents in learning to choose effective measures, an assumption was made that the respondents knew what an *effective measure* was. This information was collected to provide a basis for composing a comprehensive definition and description of effective measures. Although it may appear that there is a relationship of some kind between them, the hypothesis was tested using linear regression to determine whether there was, in fact, a linear relationship between the EKS constructs and the measure constructs.

It was hypothesized that constructs might be found in the data as outlined in Appendix D: for the EKS items, Collaboration, Knowledge Development, Experience with Measures, Mentors, and Technique; for the measure items, Effective Measures and Good Measure Definition (H1). Further, it is hypothesized that the EKS and measure constructs will not be directly related (H2). The nature of the relationship is thought to be between the condition that a practitioner possesses the EKS characteristics and produces effective measures. However, this study is not examining or assessing actual measures for effectiveness, rather, it is exploring what an effective measure means. No relationship is hypothesized between EKS constructs and measure constructs. See descriptions of the EKS and measure items in the code book in Appendix E.

Finally, it was hypothesized that the importance levels of the constructs will not vary across the dimensional attributes by which they are analyzed (H3): age groups, gender, process complexity groups, and decision-making longevity groups. This is expected to bear out in individual analysis for each construct as well as multivariate analysis across the whole set of EKS constructs.

Population. The quantitative study population was comprised of the process engineering community at the company. There were 188 practitioners of process engineering in the population. The survey was applied to the entire population. The process engineering community population is responsible for processes of simple, moderate, and complex natures as described for interview participant selection. The study population exists in an organization that typically employs college graduates in the practitioner roles. This level of education was anticipated, but not assumed.

Data collection. Data collection for the quantitative phase of the study was conducted using a questionnaire. The questionnaire was administered using Survey Monkey following introduction of the study in a group meeting of the process engineering community. I included basic classifying questions to analyze the results by the complexity of the process for which they were responsible; number of years as a decision maker; age range and gender of the respondent.

Survey instrument. I developed an original instrument for a cross-sectional survey design (see Appendix C). This design was useful to explore the cross-sectional perspective of the survey respondents at a single point in time (Creswell, 2012). It was an appropriate tool to query practitioners about the current state of their life, work, and educational experiences and the degree to which those experiences appear in the organization. Analysis of the resulting data produced a description of the rates of incidence across the population of the various kinds of experiences that complex-process owners (in the qualitative phase) found important for the development of their ability to choose effective measures.

Reliability and validity. I created, piloted, and tested the survey instrument. In the pilot, the statements were assessed by members of the population for clarity, singularity, conciseness, neutrality, absence of jargon or language inappropriate to the population, mutually exclusive responses, balanced responses, alignment of questions and responses, and applicability of the questions to the population (Creswell, 2012). Then, the survey was administered to the population.

The survey was composed two sets of statements. In section one, each EKS survey item named a potential characteristic of the respondent. These items consisted of characteristics a respondent might consider important about their experience, knowledge, or skill in learning to choose effective performance measures. For this set of items, respondents were asked to apply a Likert rating, indicating the level of importance of the item in influencing the respondent’s ability to identify and use performance measures.

In section two, each survey item named a potential characteristic of an effective measure. These items consisted of characteristics the respondents might consider to describe what an effective measure is to one extent or another. For this set, the Likert ratings indicated, from the respondent’s perspective, the extent to which each statement describes an effective measure.

The two sections of the survey were tested for reliability. Cronbach’s alpha ranges from zero to one, with values closer to one being very good (Cronk, 2012). Reliability analysis values demonstrate the internal consistency of the items analyzed, that is, that they make logical sense as a set. The Cronbach's alpha for the first set, survey questions 1-55, was .947. for the second set, effective measures, Cronbach's alpha was .820. Running reliability analysis on the comprehensive set of 78 items returned a Cronbach's alpha of .949.

Data analysis. The research questions in the quantitative portion of the study address the constructs represented in the data (EKS and measure), the relationship among them, and the variation in importance of the constructs across the dimensional groups. To determine the constructs that are represented in the data, principal component analysis (PCA) was conducted. PCA will be used to determine if correlations among variables are consistent with the hypothesized components and to determine the underlying experiences, knowledge, and skill associated to them. To address the relationships among the constructs, linear regression was conducted on the EKS components (as independent variables) with respect to the measure components (as the dependent variables). For the final question, regarding the relative importance of the components across groups, one-way ANOVA was used for the independent assessment and MANOVA used for the collective assessment.

Descriptive analysis. I assessed the distribution of the responses for each of the survey variables, including mean, median, and mode; range, standard deviation, and variance. I identified the characteristics that were, on average, deemed very important and compared those to the characteristics the interview participants identified, based on the number of responses, as important. As part of the analysis, I examined the correlations among the experience variables as well as among the measure variables. In particular, I looked for correlations among the experience characteristics identified as candidate variables for each candidate independent factor: those focused around concepts of collaboration, experience with measures, mentors/mentoring, knowledge and development, and analysis technique.

I looked for correlations among the measure characteristics identified as candidate variables for each candidate dependent factor: effective measure and good measure definition. Then, I examined the patterns in the data. I ran PCA on the candidate factors to show whether the proposed patterns of the independent variable characteristics behave, collectively, in a meaningful way (Tabachnick & Fidell, 2013).

Exploratory factor analysis is used to develop a theory about latent processes. Variables are carefully and specifically analyzed to reveal underlying processes. Among other things, it is used to summarize patterns of correlations among several variables and to provide an operational definition for an underlying process (Tabachnick & Fidell, 2013). Focusing on my research questions, this would enable me to see how I might identify someone who will choose good measures, based on their experience, knowledge, and skill or develop those skills in emerging decision makers.

The data was examined by groups. Both MANOVA and one-way ANOVA were used to determine whether there were differences in the importance of the discovered factors between gender groups (male, female, declined), age groups (30s, 40s, 50s, 60+), process complexity groups (simple, moderate, or complex), and decision-making tenure. The following hypotheses were tested for each viable factor.

H_1: the importance of the factor does not vary based on the respondent's gender group.

H_2: the importance of the factor does not vary based on the complexity of the process in which the respondent is involved.

H_3: the importance of the factor does not vary based on the age group of the respondent.

H_4: the importance of the factor does not vary based on the decision-making tenure group of the respondent.

The initial research question from the qualitative phase was, what are the life, work, and educational experiences that influenced the decision maker’s ability to choose effective performance measures? Next in my analysis of the quantitative survey results, I looked at correlations among the survey variables and the responses related to the original research question of how leaders learn to choose organizational performance measures.

Assumptions

It was assumed that the identification of the 188 members of the process engineering community was accurate. The list was provided by the community leaders. It was further assumed that all members of the community had roles that involved performance measurement to some degree. Finally, it was assumed that, as requested in the invitation, the survey respondents did not forward the survey to others outside the identified population or take the survey multiple times. As the survey was anonymous, there was no way to verify this.

Qualitative Findings

After conducting interviews of eleven executive process owners at the company, I extracted the concepts from the transcribed conversations and organized them around five major themes (Creswell, 2012; Saldaña, 2013) life experience, education experience, work experience, skills and knowledge, and effective measures. Within each section there was a rich collection of concepts from which to draw a robust picture of the experiences that enabled these process owners to learn to choose organizational performance measures. As the interviews progressed, it became apparent that there is no single or common understanding among the participants of what an *organizational performance measure* is, whether it includes employee performance measures or whether those are something distinct. Therefore, for the purposes of this study, the term organizational performance measure has been used in a more general capacity, intended to include any of the performance measures relevant to the process owners.

In order to make sense of much of the interview content, an understanding of the company's organizational structure, in general terms, is necessary. I'll use the terms company, organization, and business area as follows: (1) the company is composed of organizations, (2) an organization is composed of business areas, and (3) process owners are assigned in a particular business area. Each of these terms, company, organization, and business area refer to a common way to group people and activities necessary to do specific portions of the company's business. The interview participants were selected from the population of process owners at the company. With the advocacy of a member of the company's leadership team, I selected participants from the following organizations: banking, data and analytics, financial planning, investments, IT operations, life insurance, marketing, process engineering, property and casualty insurance, research, and vendor management.

Because of organizational complexity, there were some participants who represented multiple business areas. For example, one was in data and analytics for the property and casualty business area, and so, represented experience for both areas. Processes owned in the banking, property and casualty insurance, life insurance, and investments organizations are primarily focused around providing products and services to the company's customers. I'll refer to their activities and groups as *product-focused processes* and *product-focused organizations*. Other organizations such as marketing, research, data and analytics, IT operations, process engineering, and vendor management support the product-delivery organizations. I'll refer to their activities and groups as *support processes* and *support organizations*.

The findings are organized using five themes that were influenced by the questions asked during the interviews. I interviewed the participants separately, for scheduling convenience and identity protection. I asked each participant to describe his or her current role, the path (life, education, and career choices and experiences) that led them to the current position, and the formal education he or she had and the impact he or she felt it had on developing their skill and knowledge in choosing performance measures. Probe questions were guided by the responses the participants gave to these questions. I probed more deeply to understand the participant's direct involvement in identifying measure, as distinguished from being a project sponsor responding to measures identified by a team. I also probed more deeply about education that the participant, in hindsight, felt would have benefited them in identifying and using organizational performance measures. The probing question about desired education, in particular, generated lively conversation in almost every interview.

As a result of the general form of the semi-structured interview, the themes around which I analyzed and will discuss the findings align to the following high-level topics: life experience, educational experience, work experiences, knowledge and skill, and effective measure definition. I will call out concepts that were common among the participants and highlight interesting, unique experiences that impacted some of the participants. After discussing the concepts within each of the five themes, I will re-introduce the major theories explored in the literature review, highlight the skills implied or expressed as necessary to put those theories to practical use in an organization, and then compare the experiences, skill, and knowledge of my study participants with the skills necessary for the foundational theory.

Finally, because the meaningfulness of the study is predicated on the assumption that the participants understand what an 'effective measure' is, I asked each participant what they considered this concept to encompass. As a group, the composite definition and description they provided for an effective measure aligned well to assumptions about knowledge and skill required in the various foundational theories discussed earlier in the paper. Following from my participants' experiences, skill, and knowledge, as well as the theory, I will discuss the ideas raised by my participants about the composition of effective measures and descriptive information they deemed needful. I will align this to theory about decision making, program theory, and performance measurement frameworks to provide a context in which the effective measure content may rest.

Life Experiences

My objective in asking the participants about their life experiences was to draw out those things that, for many, are foundational in their personalities, in their approach to life and to the experiences they have, and that influence their attitudes toward learning. My thought was that understanding these types of experiences might illuminate distinguishing marks of an individual who would be more likely to develop the ability to choose organizational performance measures well. I will illustrate each item in this section by providing insight directly from the participants' interviews, whether to illustrate commonly held experiences or illuminate unique experiences.

Organizational culture. The first set of experiences revolve around the organizational culture of the various groups the participants have been involved in over time. Some experiences are from the company and others are past involvements in the participant's experience. All of these were thought, by the participant, to have influenced the development of their performance measurement knowledge and abilities.

Having background in command and control environments as well as open collaboration environments. Participant P_06 spoke of the difficulty of developing more open collaboration among the people involved in developing data and analytic capabilities, including measures. This participant encouraged and actively mentored people reporting directly in the collaborative art.

> At first it was uncomfortable for them because the [company] culture is a command-and-control. … If you're looking for me to have all the answers, we failed, because I don't have all the answers. I give you intent. I give you what I know. We can test it, but I need you guys to bring your experience, your skill sets to the table and help us solve to this and then go out to other resources that you know are doing this already and figure out what it is that they have done, both what worked well and what didn't work well and bring that back in. (P_06)

Other participants mentioned collaboration skills as necessary, but did not discuss them in particular connection to the development of the analytic capabilities.

Having experience in organizations with a strong learning culture. Learning organizations are described in Senge's "The Fifth Discipline" (1990). He states, "we learn best from experience but we never directly experience the consequences of many of our most important decisions" (p. 23) which may limit our ability to learn in full context from our experiences. An experience one participant had in an organization with a learning culture was gaining an explicit understanding of the practice of failing, failing fast, learning fast, and moving on. In that organization, this participant had an experience that puts the best face on Senge's learning statement above, by ensuring that the participant took time to reflect on what caused the failure and learn from it, so as not to repeat the failure.

> So, it was just a nurturing, learning culture and they always said, you're always going to make mistakes, but make certain…it's only a mistake if you don't learn something from it and you don't apply it. Because [you] can learn something but then go to the same thing over and over and continue to fail. It's not a mistake if you learn from it and you applied and you shared it. The big thing was share, share, share so others can learn from your challenges and opportunities. (P_06)

Another participant stressed the importance of organizational learning related to individual learning. This participant shared that, "I spent my career building new things.… In most cases, there's not a defined measurement system around what you should measure. So you're creating a vision of what you want to accomplish" (P_10). The message from that was that as an individual learns by doing, propagation of that learning to the others in the organization is not optional if the organization as a whole is to create and innovate.

The participant continued, a

> company [might speak] Greek and you speak Latin…and so, you come as a new thing and you're trying to talk in a different way…. You have to figure out how you measure things in a way that people can understand, while also making sure that, hey, what I really intend to measure is something different, because this is different. But if I can't get folks to agree on this, I'll never get them here. (P_10)

It's the leader's responsibility to articulate the vision (Northouse, 2013) and propagate that vision throughout the organization. P_10 echoes this, saying that helping the organization understand the measures, what they're called, what they mean, and how they should be used to impact organizational behavior is part of that.

Human behavior. The next set of experiences revolve around human behavior in general. These things happen in work environment, in homes, churches, and schools. Sometimes, they even happen in personal relationships among friends. I'll briefly discuss how these experiences influenced some of the study's interview participants.

Being able to control for 'gaming' behavior when designing metrics. Gaming behavior is described by one participant as driving behaviors that are different than those intended—or even wrong behaviors that do not. P_03 described it this way, "we want to make sure that we have measures that balance out each other so that we are not driving the wrong behaviors." Once we discover these different or wrong behaviors, typically during a review of the measures, we would then take those measures off the table or change them to mitigate the undesirable behaviors. Another participant considered the possibility of gaming the measures as part of the selection process.

P_11 had the perspective that an effective measure,

> has to be a measure that can't be 'gamed,' for lack of a better way to say it. So I've seen measures that measured things that then drives a human behavior to do things that make the measure green [that is, 'good'] all the time. And I don't like measures that can be gamed….and I'm not trying to say they're dishonest. (P_11)

This participant felt that in most instances, the people were just striving to meet expectations, rather than to mislead. In this perspective, it is important to design measures that are detected in system performance and captured in business activities in a way that people do not have the ability to impact, except by exhibiting the desired behaviors.

Being able to predict unexpected consequences of measuring. Once participant had an experience early in his work career in which he was expected to assess multiple employee measurement systems in order to design a single, consolidated performance measurement framework through which all the organization's information needs could be delivered. This participant found that managers using the different existing systems had inconsistent understandings of the measures used in their systems. In attempting to bring the existing systems into alignment, he also needed to understand the behaviors being driven by those different ways of understanding the measures.

Learning what consequences were being driven by the different ways of understanding and, in effect, retraining those managers to a common understanding of the measures and their meanings was an important part of being successful at his assigned task. Some managers' understandings and usage of the measures drove negative behaviors in their employees, while other managers' understandings drove desirable behaviors. This was a strong source of learning for this participant.

"Sometimes it was just the number of metrics is overwhelming, because then, [they have] too many metrics, they're trying to meet them all. And they can't. They don't understand the trade-offs" (P_03). Sometimes, what might look like gaming was just someone trying to do the right thing, but not really knowing how, it was perception rather than intention. And there were also times when

> metrics that were driving conflicting behavior… depending on the manager, on what goal they were to meet, or what's important to their management chain, right, it could be driving them toward one particular behavior that is not necessary balanced by different behavior. (P_03)

Considering the behavior that we intend to drive in the organization by taking certain actions, P_10 expressed the position that we tend to expect people to behave in a certain way. For example, say you have a rule or guideline that tells you,

> If I know A, then do B. Most people won't do B. Most people know A. Like [the concept that people should] save more for retirement. You'd probably be hard-pressed to find anyone who says, hey, I'm totally not saving for, I don't want to save more for retirement. That's where everyone knows what they should do, but most people don't do anything about it. And there's a whole range of reasons why. So if you go in there and say I'm going to measure this. If you're going to measure people who do B—those people are actually doing something. The folks you really need to touch are the folks who aren't and understanding why they're not. So understanding your actual way of measuring in a pure quantitative way will drive wrong behaviors if you're not careful. (P_10)

In recognizing situations where we are expecting certain behaviors, assuming people will respond in a rational way based on information provided, for example, we may be able to identify instances where undesirable consequences are likely from the measures we are considering. We can use both the understanding of the difference in understanding and complex interaction of the things we measure (P_03) as well as the unpredictable behavior of the person we are attempting to influence (P_10) as case studies to learn how to anticipate unexpected responses to measures and measuring.

Relationships. Then next set of findings focused on the relationships among the decision makers, their other professional colleagues, and the wider supporting organization. Personal networks, understanding one's value relative to the rest of the organization and being able to see one's perspective relative to the others' were all important concepts for the interview participants.

Having strong personal networks among professional colleagues. Strong personal networks and the ability to find complementary knowledge and skill, and to collaborate effectively are considered an important part of learning to identify and use performance measures. One participant discussed reliance on others to augment personal skills, saying, "we involve a lot of people from [HR] to help us. I'm not a performance management expert, I'm a practitioner. I've practiced a lot, but I'm not schooled, necessarily … in developing performance processes, so I rely heavily on them" (P_04). The participant added that, in developing strong professional networks,

> you should work in such a way that people seek you out right, and how you do that work, you should have the kind of relationships that, if you need help, you know there are people you can call that will just say yes… They won't ask what you need or why, they'll just say yes. And you should know who would call you. On both sides of that relationship, you actually know who those people are. You're actively building relationships that bring that. That's sort of the unconditional help (P_04)

P_04 called this the person's *personal brand*. P_09 also spoke of establishing this kind of reputation within a professional network, including the importance in maintaining personal and professional networks for having entrée to certain types of experience, "I had to work, … but through relationships, to even get back into this program." The participant was part of a rotational training program that was interrupted by circumstances. Because of the strong professional and personal relationships this participant had with others in the organization, it was possible to resume the program and re-enter the development cycle.

Other professional relationships were of a mentoring nature.

> I've had mentors along the way that groomed me who said, you need to look at other aspects of leadership qualities and things like that. … My mentor when I came out of college, he gave me enough rope to hang myself. Whatever I wanted to do, he would just direct me. …[another,] my boss for the last 8-9 years certainly mentored me a lot. And the softer skills, relationship building. so, I was a technologist. It was about technology, not about people. But ultimately, [he] supported me. (P_11)

Knowing your own value/having a clear image of your own value. Along with the implications on personal and professional relationships and networking, P_04's concept of personal brand plays into each individual's self-image:

> if there's a disconnect between what *you think* your brand is, what you *want it to* be, right? and *what others think it is*… if others don't see you that way, right or wrong, fair or unfair, you can't have it as part of your personal brand if others don't believe it. (P_04)

This self-image is important when working across organizational areas within a company. Another participant described it this way,

> [the] lesson I learned [was] to really stand up for what I believed in and not feel like I had to back down just because somebody was at a higher level than me. … I know what I bring to the table. I was hired for a certain expertise and I sure as heck expect to be used for that expertise. (P_05)

This perspective allows the participant to identify and support the value of the measures to be used—as well as the insight derived from them and the decisions made based upon them.

Another participant, P_06 had experience in collaborative decision, standing in for his leader when his leader was unable to participate. The experience was a challenging growth experience, because it required the participant to demonstrate the courage of his knowledge in a way he had not been called to do before. He was required to “speak to the hierarchy” (Chaleff, 2009). In working with a group, each member of which formally outranked him, he was in a position to respectfully disagree and explain the position. The remarkable part of the story, from my researcher’s perspective, was not that he had the experience, but what followed.

After the difficult interaction of disagreeing with, basically, everyone else in the meeting, he cleared his calendar for the rest of the day and reflected on what had happened, what he had learned. In his words,

> I left the room, I called [my admin], and I said, ‘clear my schedule.’ Because this was like a $50 million investment, right? and because in that moment, you’re reading the audience, where is the audience going, what’s the political landscape, what’s the mood of the room, right? Why are they making this big, large decision? … and just trying to take all these dynamics in play and say, are you going to take the stand or not?
>
> And so, after that meeting, … I was worn out—completely, stressed about it. Turned out we did make that decision, but I went home for the day, collected my thoughts… what did I just learn in that moment? (P_06)

In light of the other experience and insight this participant offered, it was, perhaps not so remarkable that he chose to reflect and understand the learning that happened as a result, but it illuminated a driving desire on his part to make sure that no experience, no learning possibility, was unexamined.

Finally, P_11 has the perspective that learning is, “about how I become a better person.” This participant talked of a former company CEO who said something to the effect that, “the day you stop learning, you may as well quit.” For P_11, this became a key way of thinking. He continued, “And so, for me, it’s about how can I constantly learn and how can I constantly be of more value. For me, just the academic part of certificates, diplomas, I don't care. I'm just more about how can I get better as a person, right? And how do people see me?" (P_11).

Being able/willing to see the other's point of view. As a final thought on relationships, our willingness and ability to look for and consider the other person's point of view is considered to be important in how organizational performance measures might be designed and used. P_04 described it this way,

> I have a point of view, but I understand yours, too. And I can understand it, and sometimes agree with that and sometimes disagree with it, but I understand why you think about it that way. I think that's good. What I see sometimes, not just in business, but in life. Of people like, they refuse to accept that the way you see something could possibly be right. But, like it's right for them. But you don't have to agree with it. … one of my skills is that I'm able to see an issue from many different points of view. (P_04)

This willingness may be an important aspect of developing well-designed, related measures. It seems that the development of measures, especially those that describe the health of connections between processes owned by different business areas, will be impacted when leaders have or do not have this perspective.

Values. The next theme in the interview concepts centered on values, of importance, of ambiguity, of reflection, and of ethics. These were concepts that were deeply ingrained in the participants, rather than knowledge or skill they could learn or develop, these concepts represented more of who they were, as individuals.

Being able to filter signal from noise; the important from the unimportant. P_01 discussed the ability to differentiate important facts or concepts from those that were either not important or which were at a level of precision that was not relevant to a particular decision. Junior people, in particular, may have difficulty clearly delineating this importance. Additionally, the concept of importance may often be a value judgment, rather than a mathematical calculation. Experience in and exposure to decision making is important to developing this skill. Even among those who have more experience to measures and have had responsibility for making decisions, the challenge of filtering signal from noise exists. Another participant, P_03, talked of the sheer number and complexity of the measures, saying

> they're trying to meet them all and they can't. They don't understand the trade-offs. … engagement with leaders, okay, and understanding their priorities, what they're focusing on, …helped me understand, because you can measure a lot of things, but what is it that is most important? (P_03)

This participant felt that it was engagement with the leaders and learning their priorities that would enable the other, less experienced practitioners to learn to distinguish the important information.

Being comfortable with ambiguity, uncertainty. Almost a sibling-concept to signal-to-noise detection, P_01 discussed the leader's comfort level with uncertainty and ambiguity. When determining what to measure, especially when proxies are required, the leader's comfort with uncertainty is essential. This includes the ability to accept that a measure may not describe exactly what needs to be measured, but is "close enough," in the absence of precisely the right measure. Another participant put it this way, "I think that part of what I think has made me successful at [the company] and just in general is, I'm not uncomfortable in unknown situations" (P_02). Outside of financial measures, the participants were in general agreement that the ability to accept ambiguity and uncertainty is a factor of maturity in leadership and decision making.

> Maybe it's mileage or maturity or whatever you want to call it. I can very easily live in that dynamic tension that I can't attempt to put everything that matters on a spreadsheet for you. I know for some people, that can be a little bit difficult. (P_04)

Having a habit of reflection. Three participants spoke about specifically about reflection. "As a leader I spend a lot of time reflecting on … why am I the way I am? And being comfortable with myself so I can explain how I react to other folks" (P_02). This participant used reflection as a means to predict reactions, not only for [him/herself] but also the reactions of others. Although the participant did not say it in so many words, it aligns with the concept of seeing from the other's perspective. Another participant, focusing on teaching the skill across the business area, called it "the pause," saying, "my biggest role is to make certain that from the leadership all the way through, we pause, we anticipate, we make certain that we have the right skills at the right time to work on the right things" (P_06). This particular habit was learned from life experience.

> My mom was just an amazing individual [with the ability] to break things down. So, as myself and my siblings were growing up, we would encounter things where, okay, people say stuff and we think we have a general understanding of what that meant, but she would always pause and take time. She'd say, do you really understand what that means? And … she'd give her interpretation or her viewpoint to help us break it down and digest it and understand it or she'd say here's my understanding, but I want you to go get more information about this, this, and this to bring that back so you have an understanding. I think from watching her do that over and over and over for 17 years, that shaped my approach. (P_06)

As a final thought on reflection, P_09 talked of reflection in discussing the selection of a formal education focus. In developing the focus of the Master's degree work, P_09 spoke of reflecting on the energy and enjoyment of taking certain classes, even though the classes were not in the participant's original educational focus area. It was this reflection that led to a significant change in disciplines for the degree program. Once again, engaging in reflection helped a participant make a decision that was proven, over time, to be sound.

Having a strong work ethic. In our discussions about the path that brought each participant to their current position, there was not always specific mention of having a strong work ethic. When not specifically mentioned, it became apparent that it was an unspoken assumption. In addition, none of the participants said they had envisioned being in positions like the ones they are currently in. Each expressed openness to opportunity and tended to have mentors and people advising or directing them, but none expressed the ambition to be a complex process owner at a Fortune 200 Financial Services company, for example.

I'll present just a few examples of the participants' beliefs that a strong work ethic is essential.

> I never thought I'd be in the job like I have today. I certainly never aspired, necessarily, that I would have the level of responsibility that I have today. But, I always had a strong work ethic, probably instilled mostly by my mom. And I was a paper boy when I was in middle school and high school. I worked at McDonalds when I was eligible and was finally 16 and could get a real job. I always laugh, but I tell people that my work ethic was largely shaped by McDonald's. (P_04)

There are aspects of one's educational and work experiences, in alignment with a strong work ethic, in the development of one's ability to choose measures effectively. As part of education within the workplace, one participant discussed performance.

> We got ranked and after the first year of about 27 students, I got the highest bonus, I was ranked number one. But, it was because of my education and [because I] worked my tail off. But, I had a phenomenal toolkit. There's no way I could have been that effective had I not had it. (P_09)

Finally, looking at the work ethic in terms of willingness, ability, and knowledge, P_11 said it this way.

> If I knew how to hire someone, to measure the ability of a person to logically think like technology works, they have a passion for this stuff and they have a high work ethic, I could guarantee you they'd be successful. (P_11)

In this statement, the participant expresses an understanding of independent and dependent variables in an individual's performance that may play into the idea of the leading and lagging performance indicators needed for organizational performance.

Understanding ethical presentation of measures. The concept of ethical presentation of measures refers to the fact that statistics, while true, may be presented in an unethical way—a way that misleads the reader to make an inference or gain an incorrect understanding. Another perspective on having a strong ethical mooring is expressed by P_05. In doing a study while in a work-study job in college, this participant was told that the 'purist' perspective of reporting the statistics (ethical statistical reporting) was not, necessarily, practical in delivering study results to some customers. The participant learned the ethical lesson of when and how to push back when people ask you to 'spin' measure results. The participant has applied this particularly strong experiential learning to presenting findings ever since.

Two participants also stressed 'remembering humility' as a significant factor from their life experience in learning how to choose performance measures, particularly because it reminded them that they do not know all, and do not expect themselves to know all that must be known. It reminded them to seek out and collaborate with those who have knowledge and skill they lack (P_01, P_11).

Education Experiences

This section will include discussion about formal, informal, and non-formal educational experiences (Merriam et al., 2007). I will introduce concepts participants learned from their formal education, focusing especially on the idea of learning *how to learn* and *how to think,* which were topics that many of the participants dwelled on during the interviews. Another area of discussion during the interviews was desired education. Given the positions these participants are in now and the education, life, and work experience they have, I asked them about what education they would like to have had. This was useful in the study because it helped me realize that the idea of life-long learning was a necessary part of the conversation for learning to choose organizational performance measures.

Formal education. "Formal education is highly institutionalized, bureaucratic, curriculum driven, and formally recognized with grades, diplomas, or certificates" (Merriam et al., 2007). The next set of findings are related to the formal education of the participants.

Having formal education (all, bachelors). In several of the interview conversations, it was apparent that the subject matter of the participants' undergraduate degrees was not considered particularly relevant to the work they have done in their careers. At the same time, they acknowledged its importance in helping them learn to think in a helpful way. One participant said,

> the focus of my undergraduate education was really around teaching you to think and solve problems. …[the] intent wasn't mine, but the school was very much focused on your thought process, because anyone can memorize facts, regurgitate facts, and answer you know, multiple choice questions and you walk out and forget it, but that doesn't actually teach you how to think. (P_10)

In this participant's experience, a primary value of the formal, undergraduate education was not the subject matter, but the way of thinking. I asked another participant to talk to me a little bit more about gaining knowledge and the value the participant placed on it, regardless of the formality of the training. That participant responded,

> For me, it is, again, about how I become a better person. … it's about how can I constantly learn and how can I constantly be of more value? For me, just the academic part of certificates, diplomas, I don't care. I'm just more about how can I get better as a person, right? (P_11)

Having master's level formal education. For the Master's level, too, the participants were more about having learned a new way of thinking, of becoming a better learner, than they were about the subject matter they studied. "I think the biggest benefit was less about the specific things I learned in those classes or programs and more about being a learner and having learning agility over time (P_03). P_05 discussed master's level education, the focus of which was on statistics. This provided a foundation for measuring and understanding what's important to measure, in terms of relevance and significance, in particular. Although not a formal master's program, P_06 was in a professional rotational program that provided master's level education. In that program,

> every six months you did a different type of role in finance. You also took a class that you got graded on. So, in essence, 70% of your performance was how did you do on the job and 30% was how did you do in this class that you took. (P_06)

P_07's MBA was in general management. In addition, this participant also engaged in rotational training at an early employer. That program

> was 2-1/2 years. Every six months you took a different job in finance, but somewhere in the company. … The class was taught in the evenings and as part of the class, it was just like any other graduate-level course, but it was just class. It wasn't a full load. … in essence, think of it as a graduate school-level class where you did case studies. There would be homework to turn in, you took tests, you took exams, you got a grade. (P_07)

One other participant discussed their master's work and the impact it had on their holistic understanding.

> I completed an MBA, Masters of business administration and there was some measurement, right? And there was focus on operations measurement…. I did take quite a [few] financial and accounting classes that gave me a deeper understanding of financials and there was a good component of strategy. It was more of a strategic MBA program, so it gave me more understanding of strategic measures and strategic planning. (P_08)

This participant felt that the strategic perspective was especially important in how [he] developed the knowledge and skill to identify and use performance measures.

Having post-graduate formal education. Only one of the participants had engaged in post-graduate work. P_05 discussed the circumstances surrounding that experience. I drew two primary concepts from this discussion. First, this participant expressed a strong self-image, a clear sense of self and identify. The decisions the participant made about the post-graduate work was influenced greatly—or perhaps the sense of self was developed as part of those educational experiences. Certainly, there was learning going on that was not about the subject matter—again, the recurring theme when the participants discussed formal education—but about the ancillary lessons. Second, it requires great courage to break with the expectations of others to do the right thing, whatever one conceives that to be. This courage seemed to be the primary gift the participant received in the post-graduate formal education.

Nonformal/structured learning. Nonformal learning is often short term in comparison with few formal learning and does not generally have the structured, prerequisites. They do typically have a well-structured curriculum delivered in a controlled setting by a facilitator (Merriam et al., 2007). Nonformal education is also delivered in civic environments, as well as by churches and service organizations. This is the class of learning delivered by many business organizations. The next set of findings can be described as nonformal learning experiences.

Having participated in rotational training opportunities. I've discussed professional rotational programs in previous sections, tangential to the points being developed. This section is focused specifically on the rotational program and its role in preparing an employee for the work at a particular organization. Such a program might be part of employee development. As such, a rotational training is periodic rotation from one business area or specialization to another in order to gain a range of knowledge and experience relevant to the employment experience.

P_03 participated in rotations through several areas: actuary, claims, analytics, marketing, data management, and underwriting. Another participant was at a company with a strong learning culture.

> When you came in, [it was like an] intern program … You have the technical, you get the framework, the policies, but you're able to practice that and fail and fail fast, learn fast, and move on. And so they were nurturing in that way. And when you did make a mistake, they would say, ok. Well, that was an expensive college course. What did you learn from this? … What would you do differently? And how [would] you share that information with your peers so they won't make the same mistake as you did doing that process? (P_06)

Another participant talked about experience in a retail industry, where it was important for all the employees to share a common understanding of the business, its practices, and be able to communicate those effectively to others. "I went through a management rotational program, management trainee program. Ultimately, they were preparing you to go out and be a district manager" (P_09). In each case where a participant was involved in rotational training, it was from an employer where the specific knowledge and skill needs of the employment was being addressed. These programs addressed a chief shortcoming of formal education for these participants, which was the lack of specific focus on the job or career needs the person may actually have.

Certifications like six sigma black belt. In the financial services industry, including insurance, banking, and investment lines of business, there are many certifications relevant to the specific business and products that are available to the company’s customers. Several of the participants had insurance, banking, and investment certifications that, like rotational training, were specific to the job and career needs they had. Other certifications, like process engineering black belt, is focused on support organizations and processes. Two participants identified the black belt training as significant for their development of measuring knowledge and skill.

> How do I make sure I have the right data and measurability built into [a process] so I can see what’s causing that to not perform as needed? …Then we have the whole [view] from what you design it, … measurability, then I go work with the IT partners, leveraging our business managers, to get all the requirements, and actually [get] code developed tested, prototype it, and then ultimately optimize it into full-scale launch. So we own it from the moment that the strategy’s set from design to monitor and improve or continuously improve or optimize. (P_06)

This is not the certification, but points to the need for knowledge of process engineering or sufficient knowledge to collaborate effectively with those experts. “We’re not the process owners. We’re working with the process owners to be able to define those experiences end-to-end processes. We come in with recommendations on measurability” (P_06). Another participant was in a business area focused on process engineering, in which the majority of the company’s process engineers are assigned. “I have various process [engineering] certifications like black belt, master black belt, stuff like that” (P_07). In this case, education and expertise in the subject was necessary to manage the business area effectively.

Self-directed/unstructured learning. Informal learning is the unstructured, self-directed learning, in everyday life. The next set of findings focuses on the types of learning that are not designed, structured, or delivered in a facilitated manner. Many of a business' on-the-job training experiences fall into this category.

Being an agile, continual learner with a growth mindset. The ability to learn, rather than just the subject matter one has mastered, is the primary focus for many of the participants. I asked the participants, as a follow-up question to some of their stories illustrating the importance of understanding how they learned, rather than what they learned, "are there some of those experiences for which there is no substitute to just living? Is there a danger in unearned knowledge?" One participant talked about how the formal education laid a foundation that enables a student to learn how to learn, at the same time that it introduced a foundation of subject-matter content. This participant talked also about content that might actually be beyond the student at the time they take undergraduate classes.

> I would say while you may not learn it, like I say, the class just exposes you to it and the importance of it so that you can continue to develop in that particular area, right? So, you are not going to be an expert or by any means, you know, a subject matter expert or knowledgeable about that particular [area] just by taking one or two classes. But, it would help shape your thinking in terms of your continuous learning. (P_03)

This sentiment was echoed when P_04 shared, "the biggest benefit [of formal education] was less about the specific things I learned in those classes or programs and more about being a learner and having learning agility over time." The idea was that learning agility, that formal learning structured the participants' thinking, ways of thinking, problem solving methods, and analytical thinking…that learning agility and the capacity to learn prepares them for any new content they encounter. Another participant spoke of it in terms of guidance received from a mentor.

> One of the people that I worked for very early in my career, who's still a mentor to this day—he's retired—but he told me, … my career advice to you would be—he helped me—is, never stop learning, never stop growing. If the company needs you to do something, do it. You'll be better off for it. (P_07)

A person's learning agility also plays out in how the learn to anticipate and respond to not only new situations and knowledge, but also to new leaders.

> I've been on the other end of organizational realignment, so it's forced me to constantly adapt to how I view, how I communicate, how I approach things, I'm almost constantly in motion. What worked here doesn't work here, so it's about looking at different frameworks. So if you're looking at my advice to most folks starting out, do a lot of different things and be highly adaptable because that forces you to think and approach things in a different way. It makes you more valuable because there are plenty of people who think linearly who have spent 20 years doing the same thing. (P_10)

Being an experiential learner. The participants found learning agility to be a strong characteristic for those who are experiential learners. It was interesting to me that so many of the participants volunteered the term "experiential learner." The company has strong requirements for people being hired into leadership positions to have formal education, but in every case, the participants felt that the experiential learning was significantly more valuable for them when it came to learning how to identify, choose, and use organizational performance measures. One participant shared,

> I would say those classes in college were just a foundation. it's really my work experience, it's learning from other people, it's learning from actually trying something and seeing whether or not it works or doesn't work. That's the real learning experience and because I've been here such a long time and you know, been involved in so many different areas, seen so many different metrics. You just learn from that. (P_03)

Another felt that the rotational education they received on the job had the most impact, because of its tight focus on the job at hand, rather than as a general educational foundation. That learning cycle included learning "the techniques, learning the framework, learning the methodologies, learning the rules… you get to go practice that over and over… practice that and fail and fail fast, learn fast, and move on" (P_06). The life and work experiences another participant had were self-described as more impactful the formal educational experiences. The availability of a rotational training program at an early employer aligned strongly with this participant's natural learning preferences. The high level of engagement in the rotational training impacted this participant heavily as well, but P_09 also described [his] master's level work saying, "I checked the box on the undergrad. I went through graduate school and I LEARNED."

A couple of the participants talked around the concepts of theory and applied theory.

> Stats 101 was like 300 people. They didn't make it [interesting, useful]. I'm an experiential learner. If they just would have done it in an applied way, I would have loved it, but the fact that they grilled the mechanics into you, it was painful… (P_10)

P_11's formal education, which was highly technical in nature, had no focus at all on measurement. Neither did the informal education P_11 engaged in. The participant considered such measurement to be a skill and behavior learned by people as they engage in business and other work environments. "It's something that you learn over time as a leader" (P_11).

In considering the participants who self-identified as experiential learners, I was not left with any impression on whether they esteemed or disdained formal education, in general, but I was left with a definite impression that the experiential learners did not find a great deal of value in *their* formal education, in particular, unless it was explicitly tied to their work area, e.g., an actuary who studied actuarial science, a researcher who studied statistics. The experiential learners tended to be working in business areas unrelated to their undergraduate, and in some cases, their graduate formal education.

Desired education. In a follow-up question to the formal education discussions, I asked participants to think about, given their current positions and responsibilities, what formal education they might have benefitted from having. Several of them identified data science, in particular. Although the discipline was not available for many of them during the time they would have been engaged in formal education, they felt it to be a highly desirable skill for those who can engage now.

They felt it applied strongly to finding, testing, and understanding measures. P_03 expressed the thought that formal development in creativity and storytelling would have been of benefit. Several of the participants talked about the need to be able to present complex material in a simple way, illustrating with a story or metaphor. Having some formal training in storytelling was conjectured to be of value.

P_09 had opportunities to get additional certifications around the same time as completing the formal education, later regretting having chosen not pursue those opportunities. However, it was not the missed opportunity for *certification* that the participant regretted, but the deeper knowledge that would have been gained by doing the preparation for those certifications. This deeper knowledge would have been an additional tool in the toolkit used to choose organizational measures.

Work Experiences

The next section of findings from the interviews focus on the work experiences, focusing on various breadth of experience described by the participants. There was general agreement that a breadth of experience was needed to develop a robust ability to identify and use performance measures. The experience did not have to be across years of work, but had a several foci: access to a wide range of data, access to business leaders, access to projects in a wide range of business areas, access to strategic level projects (implying broad scope), being personally accountable for organizational performance, and having a mentor.

Access to a broad range of data early in your career. A couple of the participants came up through career paths that started with data analysis. In such roles, they had exposure to a broad range of data, including financials, human resource data, marketing and sales data, as well as insurance and actuarial data. “So, the benefit I got … from being an actuary is that I got to look at a lot of data” (P_03). Sometimes, the value of such access is not realized or recognized until later in one’s career, but another participant recognized the value of that access, even while it was happening.

> What I’ve had is access, right? … information is king, right? And in a lot of situations, information is highly guarded and junior people may not get access to a lot of information… getting clearances and approvals to access that information, it’s a difficult thing. (P_08)

In this case, the participant was aware of the value of the opportunity to look at the organization and understand it through the richness of the data.

Access to business leaders early in your career. Not only data stored in databases is of value. Other participants talked about the value of data that was shared by exposure to business leaders during their formative years. One participant,

> had the opportunity to interact with leaders across [the organization] at a very early stage. I mean, within a year or two, I am speaking to [an organizational] president, okay? And that engagement with leaders, okay, and understanding their priorities, what they’re focusing on, okay, helped me understand—because you can measure a lot of things, but what is it that is most important? (P_03)

Just as P_08 had access to data, access to leaders was also part of the experience.

> What leaders have provided me is access to interesting problems or access to the data or access to the question, right? Like, here’s what’s happening, here’s the situation we’re facing. Go figure it out, right? or go get data so we can figure it out. So, the access to those higher-level problems or bigger problems is what’s help me develop that skill set. (P_08)

Access to wide variety of project assignments early in your career. Add to the broad range of data and access to business leaders, a variety of interesting projects and you provide yet another facet to the experiential learning and development of the emerging performance measurement professional.

> The first part of my career was as an actuary in pricing. then after different rotations through multiple areas, I got to see performance metrics. I was in claims at one point in time doing analytics and I was helping with metrics … learning the operational metrics was part of it. I went to underwriting in one of my rotations. I've learned a little bit about what they look at, you know, what changes they're making, and what data do they look at to help them decide on their underwriting decisions. Then I came back and I did data management and now I get into really understanding the data piece of it. (P_03)

This pattern of a wide range of experiences was echoed by another participant.

> So the first about 10 years or so of my career was all in property and casualty and pretty focused on claims, property claims. It's interesting because at that point in time, at least in [that business area], specialization was very rewarded. Well, then, the winds kind of started to change a little bit and then we wanted more people with broader skills. So I started doing lots of other, different things inside of [that business area] including making a complete career path change from claims into what was then called policy service. Back then, that was somewhat radical. I mean, you either worked in claims your whole life, or you worked in policy service your whole life, or you worked in underwriting your whole life. Not a lot of people went between those, but now it seems like it's not that big a deal. But, yeah, I worked in, the only departments I didn't work directly in [in that business area] were probably like finance and actuary. (P_04)

P_07 felt that the broad range of experiences are what made [him] an attractive candidate for the current position. "If I hadn't had those [a broad range of] experiences, like what I said earlier, this opportunity wouldn't have arrived" (P_07). As a data analyst, P_08 had a wide range of job assignments in banking organizations, within the business, HR, and customer service functions of those organizations. Access to both the business problems and questions as well as the leaders and the data in those assignments is something that P_08 considered essential in developing the skill and knowledge to choose good organizational performance measures.

Another participant told a story of wide-ranging experience with a different flair. Early in [his] career, expertise in mainframe work made it possible to do 'temporary duty' in different business areas. Although this participant was in IT, the various temporary duty assignments were in the property and casualty area, the life area, and the bank area. Later, when the participant made the career pivot from mainframe to the client-server environment, the same types of opportunities became available.

> So, I didn’t trade units, I didn’t change managers. Basically, it was like your day job over here, but I’m going to relieve you of most of your duties, go over there on a sabbatical for 8 months and write code for these guys, because I had the background to do it. And then when I was done writing code I came back and re-immersed into the mainframe team….
>
> A year or two later when PCs hit the world and we got into the whole client-server model and we started building applications on the desktop I again got loaned out (this time for about 6 months). … One of the things it gave me was a lot of different experiences… I did that actually, 3 times in the early 90s while I was a mainframe system programmer. (P_11)

Access to strategic level projects early in your career. Another aspect of breadth that was valued by participants was not only a breadth of project experience, but also an exposure to projects at varying levels of visibility in the company. Having an opportunity to work on projects that had a broader vision in the company enables a person to begin seeing and thinking at a ‘system level’ of thinking. This was considered by one participant to be a critical part of [his] formation.

> Probably my best experience in that space was when I was in a corporate strategy group, in a different organization from [the company]. I was given the task to develop a balanced scorecard for the business. So I went through the scorecard methodology, I read the books. (P_08)

By learning the concepts of the balanced scorecard, the participant learned of balancing measures, of trailing and leading indicators, of outcome measures and diagnostics.

> Most of your financial metrics are not a leading indicator of anything, right? So, that was kind of an “aha” for me, but you know you not only measure that, you have to measure other things. So, other things included people, you know, how are people doing? If you don’t have happy employees who are productively engaged with their work, the financials are not going to look good a few years out, right? So, what are the right things you need to measure about your employees and your people to know that the system is good, right, and it’s performing a stable way. (P_08)

Being accountable for the measures. In a couple of stories, participants acknowledged that, for them, the concepts of measure and organizational performance did not truly solidify until they became responsible for the performance of a business area or product line.

> When I finally owned my own P&L and it wasn't as accounting for it or measuring it from a financial lens, is when I paused to think a lot of metrics that we're using were the wrong metrics—or they were the right metrics for a period of time, but they needed to evolve to something else, because that's where the real world happens. (P_06)

In the position of responsibility, an organizational leader would have measures to watch on the dashboard. In order for those measures to be useful, the leader needs to understand 'so what, who cares, and now what' with respect to the measures. Until this participant became accountable, [his] understanding was limited about what to do because that number had a certain value, or when its trend line showed a particular behavior. Part of that education was to learn what to do when the trend has a certain shape or slope, whether it is moving in the expected direction or not, whether it is moving in a desirable direction, but at too high a rate of change.

Once responsible for the business area, the participant had a need to explain the behavior of any measure or set of measures and understand whether and how they functioned as an explainable unit and what the movement of that explainable unit means in the complex form. It was at that point that a great deal of foundational knowledge, learned from formal education as well as past work experience crystalized and the participant was able to leverage it to add value. Another perspective on the measurements focused on the usability of the full range of measures used by any particular business area or process. Sometimes,

> we focus too much on admiring the problem with a lot of metrics versus getting the right metrics that say, now I can anticipate—these measures allow me to anticipate and get in front it before it happens, or to sit back and react in the most effective way. it wasn't until you actually got in and owned a P&L and you get that practical end-to-end understanding of what really matters to the consumer, what matters to the people there who make it happen every day. (P_06)

Another perspective focused on the reliability of the measures and how they were used.

> So we report on those metrics and we have a process and it has to be auditable and traceable and statistically significant, all those kinds of things. So that's the reporting piece which is probably [the] mechanical aspect… We also review and provide guidance and advice based on what we see with all the measures and metrics we are responsible for. (P_08)

Having a mentor. There were some participants who had specific mentors, both formal and informal, and others who just had exposure to organizational leaders. In all three cases, the participants talked about their own ability and practice in leveraging the mentoring or exposure to learn as much as possible. One participant said,

> I haven't had a whole lot of hands-on mentorship to be honest, like people who are helping me and holding my hand. I haven't had a whole lot of that. Perhaps, if I had had more that, it would've taken less time.… But, what I've had is access. (P_08)

Another participant had informal mentorship, saying, "I was a technologist. It was about technology not about people … my boss for the last 8-9 years certainly mentored me a lot [in] the softer skills, relationship building" (P_11). This participant's mentor recognized that the participant needed to learn the softer skills required for leadership of people in addition to the skills required for management of computer technology. However, none of the participants discussed mentoring about how to assess the performance of the organization, in particular, but were focused on inspiration and motivation of the people who follow you as a leader.

Knowledge and Skill

The next set of findings is focused on the knowledge and skills identified by the various participants as being important to learning to identify and use organizational performance measures. The knowledge is focused around ways of thinking (structured, systems thinking, process thinking, creativity and storytelling), scientific or mathematical knowledge (STEM skills, statistics, causal analysis, financial modeling, and data collection methods), and business knowledge (benchmarking, foundational business knowledge learning techniques, measurement frameworks and methodologies). The skills are focused around soft skills (collaboration, consulting, giving effective feedback, leadership and mentoring, observation and conversational skills, asking good questions, reflection and teaching skills), and more technical skills (computational skills, flexing between levels of precision, forming and testing hypotheses, hiding complexity, dealing with assumptions and patterns, and understanding organizational complexity).

Knowledge. The next section presents the areas of knowledge deemed important by the interview participants for their development in learning to choose organizational performance measures. From understanding how to use data, to collect and leverage it in rules, benchmarking, and in models such as financial models, the decision maker's familiarity with handling data is of interest. Ways of thinking are another focal point, including process and systems thinking, creativity and innovation. The other point made by many of the interview participants clusters knowledge of technical competence and such things as statistics, statistical significance, measurement frameworks and other science, technology, engineering, and math skills.

Benchmarking (industry and internal). Any discussion of measurement is incomplete if you have no basis by which to determine if improvement has happened. In many businesses, this assessment is accomplished by comparing the organizational performance measures to either past performance measures or to industry benchmarks. As one participant explained, for business areas new to measuring and performance measurement frameworks, it is not unusual to look outside the organization for such comparisons. "We looked at such industry benchmarks to understand our efficiency and our effectiveness" (P_02). In other cases, the organization simply had not been able to measure anything in the 'old way of doing things' that could be a basis of comparison later.

One organization underwent a major transformation and found it was extremely difficult to identify and produce measures to determine whether they had actually improved their business position by doing so. One participant described it this way,

> First of all, in transformation—we have whole new processes, we have a whole new organizational design, we have no baseline, and, oh, a lot of things that we had no baseline, that we had never captured before, so how can we actually measure?" (P_03)

In discussing "effective measures," P_07 said,

> I would also look at, are there things, from a benchmarking perspective? If I had no idea [internally], are there other companies in the same industry or field that I'm in and how are they measuring things? What's on their scorecard at the top of the house? What is, if it's a publicly traded company, what's in their annual report? What is in the analyst's reports? That would give me some indication of what would be an effective measure, all assuming that we're in the same industry. Are we trying to achieve the same thing? (P_07)

Another participant describes the challenge in another part of the company by explaining that they do not have the internal history, sometimes calling for detailed data 20 and 30 years back, to accommodate the financial cycles, necessary to do baselining. In benchmarking, as in pattern recognition, discussed later, understanding the types of financial cycles and the behaviors you're looking for is important experiential knowledge.

> That kind of detailed … information, it's hard to get industry data on. [In other areas], there's a lot of platforms where you can go out and buy and get into consortiums to get industry data… So we'll do studies with companies, third parties who will provide information and they'll give us some of those insights. But, those are probably more recent, where we're starting to get some of that, those consortiums on those products. (P_09)

In information technology,

> over the years, there have been benchmarks done. You benchmark yourself against industry. We use Gartner data [a research group which provides industry-specific content] and other industry data, saying on average people who run IT shops look like this, so we're taking data to try and compare, what do we look like in comparison? (P_11)

From this participant's perspective, when a company is out there on the 'bleeding edge,' it makes benchmarking more difficult, depending on what they are trying to compare. The idea, then, is to take the innovative nature of something and find something more tangible to measure that still tells the story about the innovative technology.

> The intangible things about bleeding edge and technology and creativity—yes, it's really hard. But what it comes down to [is] how many people to support how much infrastructure, regardless of what's running on that infrastructure? That's a little more tangible, right? Pretty much black and white. It's how many servers you've got; how many people you've got. (P_11)

Broad, foundational business knowledge. In line with the breadth of project experience, range of strategic projects, and access to experienced business people, participants identified the foundational business knowledge that a person has as a factor in identifying what should be measured. The breadth of experience and access were considered by these participants to be the means by which this broad, foundational business knowledge is most effectively acquired. Formal education was acknowledged, but putting it in the context of specific business problems was a non-negotiable element in their views.

One participant put it this way. "Because I've been in different parts of the company, all those interactions helped build, you know kind of, my knowledge base for that" (P_03). For another, it had to do with exposure to the very detailed levels of business knowledge and constructing those into higher levels of knowledge.

> Initially I was in very granular roles where I managed very specific portions of the business, which led me to become familiar with that portion of the business, right? But, when you are deep down in the details you don't have visibility for how the whole system works, right? So, large businesses like [this company] are large complex systems and your junior years in the organization are probably deep into one small area of the business. That's good as a formative years of business experience, but that doesn't allow you to think about performance metrics, overall. That doesn't allow you to understand how the whole system is stable and how the whole system succeeds or not succeed, right? … What allowed me to cross that threshold was having positions where I could see the enterprise more broadly, right? So, strategy roles. (P_08)

P_09 spoke of the broad range of business knowledge obtained from the various formal education, rotational training, and on-the-job training the participant had. That broad range of knowledge reaped multiple benefits. The primary message from the story P_09 shared was that, not only did this breadth of business knowledge enable additional training, it opened the door to more opportunities, while providing the tools to exceed expectations in those opportunities.

> A lot of them [other students in the rotational training program] had focused on pure investments during their graduate school, where ours was more on business finance … if you look at investments there's a lot of things related to investment theory, diversification principles, different measurements of performance. Think about investing in equities. When you come over into business finance, [you need to know how] you value this particular project, this oil rig, or whatever it may be; getting down [to] fundamental tools for understanding components [to assess how] an individual division's performing and how to decompose that. So it was more like financial statement analysis/ business analysis and I had things in my tool kit that I had an advantage over some of the students coming in from some of these tier 1 school and I was given all the top projects. (P_09)

Causal analysis. As part of the discussions about integrated measures and the measure review and refresh process, causal analysis or statistical significance can be assessed for existing measures. From these analyses, the measures might be tuned, discontinued, or augmented. One participant identified causal analysis as their desired state. "Right now we are still in the early stages of just making sure that we are collecting the right data and that the data makes sense … Until we're comfortable with that, there's no [point in] doing more advanced analysis" (P_03).

Similarly, P_10 says it this way, "we have not done it yet for innovation … we still need to get to a point where we can measure value before we can attribute value. We're measuring value of the unknown" (P_10). These two participants are dealing with focus areas that are soft or undefined; innovative and creative. These things are difficult to measure in part because there is little consensus on what constitutes innovation or creativity. P_03 is of the view that one will look for "signs" that creativity has happened and, perhaps, measure those.

P_03's situation involves being in the early stages of discovering what the organization's new measures look like, collecting data, and beginning to analyze it statistically. Causal analysis is desirable in these areas, but is considered to be a state of maturity for which the company's skills are still emerging. In other areas of the company where data has been collected and analyzed longer, causal analysis is more often becoming a part of standard practice. Skill and knowledge around those topics are other areas of interest for desired learning to aid the goal of finding ways to effectively assess innovation and creativity.

Creativity, storytelling/innovation. P_03 has a need to understand creativity and the role it plays in influencing business success. Similarly, P_10 has a need to quantify innovation and the benefit gained by the company's development of innovative ways of thinking and doing business. P_03 pondered the value of quantifying creativity by identifying objective signs of it—not measuring the creativity itself, but by measuring some proxy result of its having taken place.

> It's not as precise as we always want it to be, but we have to understand it enough to accept that, okay, if there's the presence of these things and there's enough of presence, okay, then that means there's a lot of creativity… there's a difference between presence of something versus a list of things [signs] that, if we do them, it [creativity] will happen. (P_03)

These participants can measure the things their organizations do to facilitate the possibility of creativity and of innovation by providing an atmosphere and culture in which they can flourish. Actions taken to create a creativity or innovative culture can be measured and then, perhaps, be correlated with creative work happening in that environment.

Another opportunity for creativity and innovation lies in partnering with other organizations. Each organization may hold part of the solution, one may provide an infrastructure in which a new idea can be implemented and another may come to the table with ideas of new or different things it needs to be able to do.

> If we live in a world where every time we go to a vendor [he] says, hmm, 'we've got some pieces, but we might need to do a little work to make what you're trying to do successful' … more often than not, we're pushing our vendors to create things for us that help us deliver things we're trying to deliver. To me that's another way of measuring [relationships]… We're not completely bleeding edge, but we're way out there. In most cases, it's not easy to find technology in the world that does exactly what we want. (P_11)

The term *bleeding edge* refers to the extremely early adoption or development of new technology. When organizations are early adopters of new technology, there are often painful consequences. However, in some cases, as described above, there is not a more mature technology which suffices to fit the need. This participant sees the company as a whetstone that is sharpening the sword, compelling innovation and creativity by way of the capabilities the company is collaborating with its vendors to create.

Data collection methods. Some of the participants more closely aligned to the data and analytics business areas spoke of the mechanics of measurement, of the need to have high quality data with which to calculate measures. In a way similar to the chain of custody for data in research and the ability of the researcher in following that data through analysis to findings, to discussion, to conclusions, the people involved in data and analytics in the company require certification that the data they are using is of bona fide quality and lineage.

P_02 discussed the need for knowledge and continual awareness of data collection methods, including new development in technology that might produce efficiencies as time goes on. Additionally, this participant stressed a need for ease of data collection, expressing the data in a raw form so that the business might generate additional insight by slicing it in many different ways, and making it easy to tune the measures. In order to make data available at all, the data collection method may need to be designed in a way that would make participation fun, influencing participation, and making people want to provide data.

Additionally, in business, access to data comes at a cost. For the good of the business and its customers, it is necessary to demonstrate the value of collecting data, formulating information, and delivering insight to the decision makers. Sometimes these decision makers are the customers themselves, other times decision makers are executives and other employees within the company.

> [Our business area], historically, has not invested into data and analytics. … I went to [my boss] and told him, you're never going to achieve the actionable insights that you need for your organization unless we invest. So we [increased project spending] …, and so with that huge increase in investment, [my boss] and my peers are asking, 'what are we getting for it?' I'm constantly telling [my direct reports], 'with great investment comes great responsibility.'… We've got to articulate the 'so what' and the value creation to the [customer], to the employees, and to the [company]. (P_06)

In this participant's view, because data collection in the company is the lion's share of data and analytics, demonstrating the value of the investment in data and analytics is of particular interest. It is evidenced by the company's ability to produce actionable insight and in the efficiency and effectiveness of the data collection methods.

Financial models. Understanding the business model, including the complexity of the business organization, is critical to being able to formulate and use financial models. There are sometimes cases where the organizational structure and the functions within a business are managed in a way that makes certain aspects of the financial modeling more difficult, if not impossible to do. Learning how to structure the organization so that the financials can be monitored and assessed effectively is an important endeavor (P_09). Having an understanding of financial models, as well as the organizational complexity and data and analytics practices is crucial to successfully implement some of the financial models.

Learning techniques, measurement frameworks, rules/methodologies. As a way of learning and growing, P_08 indicated that the access itself, to leaders, to data, to a broad range of business problems was, in itself, "a great learning opportunity" (P_08).

> [You asked,] what has shaped me from how I think about measures and information and I'd say frameworks for that. So, that little team I described for you that I worked for at [a large bank] that was 'the magic?' I quickly learned—so you start as an analytical person or a finance guy. Excel is your friend. … And you thought, boy, I can do anything in Excel. But, … I started to learn the power of using mass-scale infrastructure and MIS. So,

> I learned how to build anything in Excel and worked it, and ran jobs that would deliver account-level profitability and run it every night on every account we booked with all kinds of detailed assumptions and it would be at your fingertips on your screen the next morning. So I went through a period of about five years where I learned to really build those platforms and got a taste for, and got an appreciation for, scalable financial MIS. (P_09)

This type of experience and appreciation enables P_09 to be more effective when providing information requirements, collaborating with IT to build data systems, and designing measurement delivery solutions.

Process thinking. The subject of measures cannot be viewed exclusively through a data and information lens. The aspects of people and process are inextricably intertwined. The business leader and decision maker who understands the role in the wider context is advantaged over one who does not.

> Once the strategy has been defined and set, we take that strategy statement, that strategy intent, and we take it as how do you design that actual experience, right, to the moment to how do you design the end-to-end processes that bring those experiences to life consistently, every single time. How do you embed the right measures into those end-to-end processes so you can measure the health of that process, delivered consistently defined by this, every single time? (P_06)

When the decision maker is aware of and has insight into the roles and processes that are interrelated to his or her processes, especially if the decision maker has played roles in any of those interrelated processes, the decision maker is better equipped to understand how end-to-end logic—process thinking—may be implemented well.

> Prior to coming to [the company] two years and nine months ago, I hadn’t done a job like this one in 11 or 12 years. … But, you know, I had lived it, had breathed it, had applied process thinking to other types of jobs, but not this type of more program type role.… that’s kind of the hallmark of my career. (P_07)

The successes this participant has found, including helping to raise the bar in the quality of the company’s process measures, demonstrate the advantage of having such multi-disciplinary experience and process thinking.

Statistics, statistical significance. The company requires the ability to measure things that count, but sometimes measures things that do not. A chief outcome of this study may be a better understanding of why this happens and how the company might prevent it. The understanding of statistical analysis and identifying those measures that have statistical significance is part of this understanding. One participant marveled about the amazing number of questions that can be answered with statistical data modeling.

> I have a pretty good statistics foundation, statistical modeling and statistical analysis foundation from engineering, plus a little bit from the MBA… So we report on those metrics and we have a process and it has to be auditable and traceable and statistically significant, all those kinds of things. So that's the reporting piece which is probably [the] mechanical aspect. (P_08)

By looking at statistical significance, this participant felt that the company could make headway in its objective to stop measuring things that don't count and that are not moving the organization toward its desired state.

STEM (science, technology, engineering, and mathematics) skills. While several participants mentioned STEM skills and the benefit they expect to see from employees who are strong in those disciplines, they also acknowledge that those skills alone are not sufficient.

> You have these whiz-kid individuals back in finance or accounting or whatever doing a lot of this mathematical genius stuff, but as soon as you put those metrics and things out there and your assumptions, they're outdated unless you really bring that practical expertise into it to help you sit back and say, is this a good metric or not? (P_06)

Addressing the topic of collaboration skills during measure development, P_06 related,

> I do look for individual that have the skills, more mathematical skills, I'll lean on them to help me bring more of an objective view into that, more of the engineering, mathematical type of skills, logic, thinking that kind of helps shape that, but then I will test it with my individuals that are not necessarily as mathematical or engineering, what have you. Because I want to see how they respond to that metric and can they see themselves in that metric? Can they see how they move that metric, and if not, to your point, it can be the most over-engineered set of metrics, but I'm not getting the outcome needed because there's some disconnect between the two. (P_06)

Balance is relevant in identifying and choosing the measures, as well as for assessing the measures for consumability, usability, and usefulness.

Another participant agreed that the ability to work effectively with performance measures is not exclusive to people with a STEM background.

> I think what we've typically found is, people that have some sort of quantitative background... start with college degree. Whether it's an engineering or a business degree are the ones that typically, it's an easier transition, not to say that if you were a liberal arts major you couldn't do it, but typically if you look at people that are doing this type of work, it's one of those, more of a quantitative background. (P_07)

But, another participant was interested in seeing more people with foundational knowledge in STEM, to promote more rigorous training in deep analysis and ways of thinking.

> So I really think STEM careers and getting more people to get into STEM careers so they can productively work in those environments, that's becoming increasingly important. …[it's] the way of thinking, yes, and the learning to identify patterns, right? For example, someone explains to me how a tool works or how a certain algorithm works and I understand the logic and I understand how I can use it for business purposes. I don't have to get into the minutia of how it works, because I've seen that before somewhere, somehow during my education years. Versus a person may not have that they may be more insecure in front of that technology algorithm approach and they need to go deeper and analyze the whole thing, that slows down decisions, right? So, I think that science or technology or engineering background, that's been very useful in my later career stages, but that's kind of education-wise. (P_08)

Structured/systems thinking. The concept of systems thinking was high on several participants' list of important characteristics. Some referred to it as 'end-to-end' thinking, while others talked of 'process thinking,' which is related, but distinct. P_02 spoke of it as designing the end-to-end process and the business interactions with the individual business areas so that individual priorities are visible, understood and that the measures for the whole take that into account. Even contracts and agreements, using systems thinking, would be designed for the individual areas to account for both the internal priorities and the end-to-end priorities.

Insight into the end-to-end process design will also inform how each business area might be measured, allowing the perspective to be transitioned from an *internal focus* of measuring performance to what that participant referred to as a *self-as-part-of-focus*. This refers to seeing how an individual's personal striving for success may be ‘good’ or ‘bad’ or perceived as good or bad for the larger group or organization. Another pair of perspectives dealt with understanding one’s span of control or context boundaries within the organization.

> But, … they’ve also had to understand, outside of the data components, they’ve had to think a little bit in end-to-end terms. Where does something start? Where does something end? … where to start something and how to harvest what I do upstream [that] influences what happens downstream. (P_07)

> So, when I had a strategy role, I had to get familiar with the entirety of the business. here’s [one business area], here’s [another]. here’s how [the first] makes money, here’s how the [other] makes money, here is the [customer] dynamic, like, how we acquire [customers] and how [we] retain [customers] and how many do you need to acquire to keep the system growing or in balance. That sense of how the entirety of how the system works requires you to play a role in a broad exposure type of function. (P_08)

Finally, P_11 talked about the need for employees to consider, analyze, and understand very complex things. This participant considered the ability to think in a logical, “complex, stringing things together” way.

> There are different jobs in the world that require different levels of aptitude. It’s the one thing that I think, initiative and passion can probably be groomed in your upbringing. Aptitude, different people are born with different levels of aptitude. I know some people that I think, holy smoke, I don’t know how they think like they think. Then I know some people who don’t have a very logical-minded aptitude, but who are extremely creative-thinking people. So, I think there are different jobs in the world for different aptitudes. In our world, in the technology world, it’s a logical world, a complex, stringing-things-together world. If I knew how to hire someone, to measure the ability of a person to logically think like technology works, they have a passion for this stuff and they have a high work ethic, I could guarantee you they’d be successful. (P_11)

For this participant, the ability to think in this way plays into the ability to determine how to put measures in place that allow the organization to determine whether it is meeting its objectives. Especially in IT, systems are developed in components that are then assembled to deliver a larger, complex capability. People need to think in terms of components and interrelated components in order to deliver such systems. Providing the ability to measure the effectiveness and efficiency of each component and then to measure the success of the assembled system is part of that, analogous to measuring such things in complex human processes.

Skill. This portion of the findings focus on interpersonal skills, like collaboration, observing, teaching, influencing, and consulting. These focus on how we elicit and construct understanding together. How we test and use what we learn using these interpersonal skills is demonstrated as we ask good questions, form hypotheses and test them, recognize patterns and understand how organizational complexity impacts those patterns and the behavior of related measures. Skill is needed to effectively communicate the knowledge we have constructed—hiding complexity to express ideas simply and, finally, speaking at the appropriate level of precision for the information consumer.

Collaboration and influencing skills. In a process similar to a qualitative research effort to identify the things that are happening in a particular environment, setting, or person's life, a business person may be called on to take a qualitative research approach to discovering the business requirements for an organization. This includes the ability to determine how the business strategy is envisioned, describing it in rich language that can be then understood in terms that one might measure. One participant, stressed the importance of her skill in interviewing business stakeholders, employees, and listening to the voice of the customers and employees.

Listening to the employee or the customer means more to this participant than just hearing the words they say. It means understanding and internalizing them so that the things that are most important to those individual may be given the importance they require and so that the business can focus on meeting the needs they express. By being able to interview and elicit the person's needs, to listen effectively to their input, and translate that into rich, clear business requirements, the business' ability to measure those needs is also improved.

For another participant also, influence had a definite place in the toolbox.

> My biggest role is to make certain that from the leadership all the way through, we pause, we anticipate, we make certain that we have the right skills at the right time to work on the right things. Then I make certain that if we have to take a shift in how we do the work…. In the past we've done agile teams just with the IT group, but we're not fully business agile this point because here's the things that we're missing. … We need to build these type of skills, but also build these types of processes and different ways of doing the work that allows us to be more effective and efficient. So, not only am I anticipating for my team, but I'm also anticipating for the broader [organization] and how we need this shift to different business frameworks and also how we bring different skills across [the organization] to help us get to the strategy. (P_06)

Another participant focused on the collaboration skills.

> One of the steps is a stakeholder analysis... I'm going to work on understanding or improving this particular process, okay? Well, who are the stakeholders that touch this and impact it? Now, let me think about what that is. (P_07)

This participant also expressed a second slant on playing an influencing role.

> Later in my career, … I remember talking to my wife about [the idea that] I don't necessarily want to be CEO of a company or the founder of a company, but what I would like to do whatever the role is, is kind of to have a seat at the table on the leadership team. Like whatever that role, it would be satisfying. (P_07)

P_09 shared the idea that, in learning about measures, we often have to deal with a confounding organizational structure. Profit centers may not particularly care about expense centers, so measures around expenses may not influence change or management decisions effectively in the profit centers. The ability of the business leader and decision maker to influence the choices and vision of the various business centers, especially in helping them view the end-to-end value chain for the organization, is a strong asset. Another participant expressed the need for strong collaboration and influencing skills this way,

> For my domain, I'm accountable [for] setting performance measures at the macro level.… no individual makes any one decision around here. We tend to 'committee

> approve' everything. But, I will say that my job is to assess performance targets. And in our decision framework, … I'm a heavy influencer into those. (P_10)

Consulting skills. Along with soft skills like collaboration and influencing are other skills that can be categorized under the heading *consulting skills*. It may not, necessarily, be the consulting skills, specifically, but the understanding that consultants are often granted, as a part of their consultancy, access to a wide range of data and access to business leaders.

> An example, [from] when I was management consultant. When you come in and work for consulting firm charging several million dollars for a project, you will have access. Because the organization has a vested interest in giving this group of consultants everything they need to go figure out the problem. So, we had lots of access to information. (P_08)

The soft skills necessary for success in consultancy are called into play when dealing with the need to negotiate and cross over organizational boundaries to understand the interrelated processes and the interactive measures needed to understand end-to-end systems.

Flexing between levels of precision. P_01 discussed the need for measurement practitioners to be able, or perhaps willing, to express measures a varying levels of precision. This participant felt that the ability to express directionally correct in measures, rather than only precisely correct measures, was important when delivering information to decision makers. Decision makers at higher levels expressed the feeling that sometimes the practitioners try to be too precise. There seemed also to be a mixing of the concepts of imprecision and aggregation, with one participant expressing the thought that, at times, decision makers might be better served by directionally correct information than by waiting for precision which cannot be delivered.

> [Sometimes,] I want to measure whether I won every battle, … I've lost the war though, because I wasn't really looking at the big picture of the things that really matter to other individuals … in the enterprise or taking that further out toward the people element … What are we missing? What do we gain?" (P_06)

Forming and testing hypotheses to explain outcomes. In order to determine what to measure when the necessary measures are not designed into processes and systems as part of the original designs—or where no such design is suitable, there is a need to hypothesize what is happening in any given environment, one data and analytics process owner felt that the practitioner's skill in developing and testing hypotheses was critical. This skill enables them to mine data in order to discover what it might have to tell about the customer behavior, process performance, or other subjects under study. When focusing on the concept of data mining, such experimentation aligns with a research study that will analyze data to determine whether the hypothesis bear out. This is distinctly different from designing processes and systems with an understanding of the desired outcomes and the data that might be provided in the design to enable measurement of those outcomes (P_01).

Giving effective feedback. Also related to strong collaborative and influencing skills, the ability to give good feedback was identified by a couple of participants as a necessary skill. If you start from the premise that giving feedback is intended to enable the receiver of the feedback to assess and take action on some matter needing attention, then the feedback may be considered a measure (or assessment) of the receiver's original behavior or actions. This puts a qualitative face on the idea of the measures this study is exploring.

P_02 shared some thoughts about an effort to collect information about employee sentiment about their work on any given day. The employee could click on the company's internal home page on a 'smiley' or 'frowny' face to indicate how they were feeling about their work.

> The thought process was that, like when you log on, you see your department is frowny-faced, right, and [the company] is smiley-faced, right? and you're smiley-faced. And you've like, well, wait a minute, that's not an accurate depiction of how I feel, right? I'm now more motivated to go in and share my feedback, right, to have it be more representational of how I feel, right? You're [feeling] frowny faced and the data is, the data does not represent that, right, it says that everybody's happy and you're really not happy, right? (P_02)

This type of condition might influence the employee to register their feelings about being ‘frowny-faced.’

Hiding complexity to present findings simply. This skill aligns with the ability to flex between levels of precision. When communicating findings ‘up’ in an organization, the ability to hide complexity and express the findings simply is considered critical by people in a position to receive those findings. They want to know the ‘answer’ rather than seeing the practitioner ‘show their work” (P_01) While the receiver of the information may press for more details in areas of interest, they value the ability of the practitioner to present the simplified findings in a way that clearly identifies the ‘so what.’ When developing and using measures, this participant considered it important for the users to be able to understand what the measure was telling them and then to clearly identifying why it mattered to the success of the customer or the business.

Interviewing and observation skills. There may be times when collaboration takes the form of interviewing and observation rather than the more typical interactive exchanges that occur in business. P_02 identified such skills being needed to develop good measures.

> How we train our process engineers here on change management and communications is a big part it [learning what needs to be measured]. It’s one thing to be technically brilliant. It’s another thing to be able to articulate what you were trying to do and why, it’s another to bring others along, in order to get things done, right? (P_02)

Another participant agreed that effective collaboration depends on the ability to communicate what information is needed and ask for it effectively.

> And absolutely they are both are important, right? Also it’s recognizing that particularly here, we have resources here to help. if you need help understanding what change management or what you need to communicate is, we’ve got resources here, full-time resources that can help, that can be part of the team, just like just like any SME [subject-matter expert] would. And how you would bring them into the fold to help get that done?” (P_07)

Those participants were joined by a third, who agreed and added a focus on observation, being able to effectively see what is happening.

> I think the pattern recognition is something that requires time. And, again, the only way you accelerate pattern recognition is, perhaps, having you be in a position where you can see what's happening, right? Because if you're too deep down in the organization, you may not see what, you may your details, but you may not see the whole picture. (P_08)

Knowing the right questions to ask. Strongly related to interviewing skills is the ability to ask the right question. This is essential for understanding a problem at hand and enabling an analyst to, first, determine if he or she understands a problem correctly and sufficiently, and if so, to break it down into solvable pieces.

> I think we spent a lot of time … chasing the wrong questions. Another thing—I think I do this well, but I'm sure I'm guilty of it too—sometimes we ask questions and spin up a lot of people to answer the question. And I wonder, when we know the answer to this question, what will be do? Is it interesting or is it actionable, right? … it's not only do we ask the right question, are we asking the right question is the flavor wrong? it's more, will the answer really matter?" (P_04)

This aligns also to the comments of this and another participant who both stressed the idea that it is a poor practice to generate measures to answer questions of intellectual curiosity, but which serve no other defined purpose (P_01, P_04).

Another participant spoke of a long-time practice of keeping a log. A researcher might refer to this as a research journal. In preparing for an engagement to develop requirements or design a new process, the participant would do homework to prepare for the encounters, identify questions and be prepared to stimulate conversation using those questions. Additionally, the participant would reflect on the conversation and refine the questions for future encounters. In this manner, the participant would have a way to follow through on the questions, answers, and reasoning that led to certain requirements and design decisions (P_07). The participant shared that,

> We have resources here to help. if you need help understanding what change management or what you need to communicate is, we've got resources here, full-time resources that can help, that can be part of the team, just like just like any SME would. (P_07)

Mentoring skill. One participant shared a perspective on the mix of experiences that contributed to [his] learning. “[In] almost everything that you do, because you’re learning—what, 70% is exposure, 20% is mentoring, and 10% is the classroom” (P_06). The participant acknowledged that the importance of the classroom (and by that, the participant was referring to formal and sometimes informal education) would vary based on the focus of an individual and the practice or discipline in which they are employed. Of interest also was the expressed belief that mentoring made a larger contribution to the participant’s learning how to choose organizational performance measures.

Another participant took a more general slant when discussing the importance of mentoring. The focus in this participant’s business area was on the use of coaching to influence and fine-tune a practitioner’s skills. Coaching and mentoring differ, in this participant’s perspective as follows. Coaching is task- and performance-oriented. It is about helping an individual execute a task to a higher level of quality. Mentoring is person-oriented. It is about helping that individual broaden and deepen, to become more well-rounded in all the characteristics, skills, ways of thinking necessary to be successful in a particular environment.

> I’m a big proponent of …. I think about it almost as, mentoring can take many [forms]…when you hear the word mentoring it can mean many things… from a process [engineering] perspective, I think the concept of coaching is important, no matter what. And so, one of the things that we do promote and we have a formal structure around is coaching. (P_07)

Focusing on the development of the whole person, the selection of a mentor is considered by some to be essential while others shared that it would have been nice to have one. By virtue of the positions each of the study’s interview participants held, I consider each to be successful. Still, one participant spoke of mentorship in this way.

> In my case, right? I haven’t had a whole lot of hands-on mentorship to be honest, like people who are helping me and holding my hand. I haven’t had a whole lot of that. Perhaps, if I had had more that, it would’ve taken less time, right? (P_08)

P_11 shared a perspective of mentoring that requires a clear measure of humility. In choosing who and how to mentor, this participant viewed it as an essential responsibility to help protégés find their way, to navigate political waters, and to interact effectively above their current organizational levels.

> As a leader, if I feel like, say something happened to me tomorrow and I needed to go away for two months. If I was worried about this organization running for two months without me, then I haven't done my job making sure I have the right leaders underneath me to run it and make the right decisions. If you've got that kind of mindset, then I think you have not built and mentored the team that you need. (P_11)

Recognizing and using patterns effectively. Several participants mentioned the concept of being able to see, recognize, and use patterns effectively in making decisions and running their businesses. They also discussed the ways and times when it was appropriate to recognize deviation from a pattern and when that divergence was a cause for concern.

> If you have a stable environment, then you have much confidence in terms of your metrics, right, especially over a long period of time. However, things do change and you have to be able to recognize [when] you're in a state where it is significantly different, or you're heading into the state where it's significantly different, you need to be able to adjust.… We look at three different components [types of deviation from an established pattern], the gradual, the cyclical short-term, and then random. (P_03)

The ability to recognize patterns and learn to use them effectively was thought to be a skill that required life and work experience. This is especially true in the financial sector, where economic cycles might be decades long. A student can be exposed to the concepts and taught about patterns that are already part of the economic landscape, but the ability to recognize new cycles is one that is considered to be learned by experience, not by formal education (P_09). Another participant concurred.

> I think the pattern recognition is something that requires time. … The only way you accelerate pattern recognition is, perhaps, having you be in a position where you can see what's happening, right? Because if you're too deep down in the organization, you may not see what, you may see details, but you may not see the whole picture. I think the role of leaders in getting people to become better pattern recognizers is sharing with them what's happening. (P_08)

Reflection and reflexivity. *Reflection* is the practice of thinking about an experience or new piece of information and determining how it fits in one's mental models, in one's frame of reference. *Reflexivity* is applying the insight derived from reflection to change one's interactions or behaviors with respect to the new experience or information. One participant focused on the "pause," which represents a point of reflection in the participant's way of thinking. In considering one's business functions,

> you had to pause and say, you're going to constantly look into the rearview mirror to measure that, and see how that translates into the future, but most of it is, you're looking at, how do I identify the leading indicators to know that I'm heading into the right direction, versus lagging. (P_06)

Reflection in one business area is focused on listening to customer feedback and determining how it should influence management of their business processes. In this process, the participant's business area took the feedback, reflected on it, and determined the appropriate actions to take with respect to what they learned (the scorecard measures themselves) and the feedback about those measures.

> They hear a lot of the ground truth and feedback and we have an opportunity before we publish the scorecard to talk about it as a team as well as with the broader community. …We review the scorecard and after that is when we publish it. (P_07)

For another participant, the discussion about reflection focused on the decision to redirect the educational focus in a completely new direction, toward finance.

> I took my first finance course in my core curriculum and I reflected on all of the things that I truly enjoyed in my prior four years and they were all analytical in nature. It wasn't the sales aspect of my job or the marketing…, it was all anything that was more financially oriented or analytical. … So, I completely switched careers, right? Went from marketing sales over into finance and 17 years later, I never looked back. (P_09)

Teaching skills. Teaching skills were not mentioned in so many words, but there were frequent references in the interview conversations about helping people learn or understand, or helping people to use measures correctly.

> I had this focus group in which we randomly picked directors who didn't necessarily know each other, okay? And they came in, they looked at the same thing, and they interpreted it very different, okay? And they learned from each other a lot of times as well. So that just meant we were producing a lot of numbers, but we really didn't educate and train people enough on how to use these numbers. (P_03)

P_05 has teaching experience, during and after graduate school, both in the classroom and online. Although we discussed the experience, there was no clear indication that the teaching experience impacted the participant's ability to choose organizational performance measures. However, that skill impacted the participant's ability to collaborate with others who had requirements to put measures in place. The participant considers helping others understand the important aspects of defining measures and executing the measurements to be a significant part of the job responsibility.

Understanding organizational complexity and its impact on measurement. Although only one participant mentioned organizational complexity specifically, the importance placed on it was unmistakable. The discussion called to mind the importance of defining problems sufficiently and then breaking them down into component pieces that can be analyzed and addressed more effectively—those analytical problem solving skills, certainly, but also the ability to identify the real problems impacting the organization. This participant spoke of the complexity of the organizational structure, not specific to the company, but as is true to some degree for many companies. Difficulties exist where the organizational structure does not align cleanly with the way financial measures are calculated and assembled.

The primary message the participant was communicating was not limited to the organizational structure, but could easily be applied to process complexity, to complexity in technical and information architectures, or even to the complexity on a single individual's thinking processes. The takeaway, from this participant's perspective was to make careful analysis to decompose that complexity as much as possible to enable sound measurement (P_09).

Effective Measures

As a final question in each interview conversation, I asked the participants to share with me their perspectives on what constitutes an *effective measure*. Based on their responses, I aligned the common perceptions to the literature on balanced scorecard, program theory, goal-question-metric approach, and performance management, composing a comprehensive view of the concept of an effective measure. There were several perspectives offered, with two prevailing themes: what an effective measure is and the contextual information required for a measure to be useful. In addition to having contextual information, one participant also made it 'real' at the individual level. "[By] meaningful, I'm thinking about performance measures, that's why I said, measuring and being measured. So, if someone's measuring me, but I do not agree with the measurement by which I'm being measured, then it's not useful" (P_05). In this way, the participant identified a necessary connection between the meaning and usage of the measure and its meaningfulness to the person being measured.

An effective measure <u>is</u>…. An effective measure is one that is actionable. Four of the eleven participants explicitly named this characteristic (P_04, P_05, P_06, P_09). Although there are some measures generated strictly based on regulatory law, a measure defined at the organization's discretion will provide actionable insight that is "not overwhelming, to where, now, that's all you do is spend your time monitoring instead of actually *doing* things" (P_03). A measure is considered effective if it can be used directly to make a decision or is used as a factor in another measure which is.

An effective measure is one that is continually measured over time and moves over time. "An effective measure … it has to move" (P_03). Seven of the participants mentioned this dynamic (P_01, P_02, P_05, P_08, P_09, P_10, P_11). Once a measure ceases to show movement, it becomes inert (constant) and ineffective in driving behavior change or decisioning (P_02).

Unless one is describing an object, process, or condition in the organization which *can* be influenced or controlled, generating a measure for it should be carefully considered. One criterion in selecting an effective measure should be to understand explicit actions the organization can take to move the measure. Although only one participant (P_01) explicitly called this characteristic out in conversation, it seemed to be implied or assumed by many other participants. The themes of the conversations revolved primarily around managing and decision making, actions which imply that the measures can be used to impact other things the organization cares about.

Another characteristic of an effective measure is that it has been used over time and, through that use, a business objective reached. The review of a measure over time refreshes its use and reconfirms its value. “You put [the tested measure] out for the larger group, you continue to monitor it, and you’re going to continue to tweak it and refine it” (P_03). P_05 addressed the concept of reviewing measures to ensure that those being measured understand and agree with the measures and have an opportunity to provide feedback about the usefulness of the measure. Since measuring drives behavior, reviewing and refreshing measures is important. Obsolete measures may be entrenching behaviors the organization wants to grow past (P_06). Finally, the review allows the organization to collect information about what works well, and how well. The review/refresh process includes feedback from the customers for whom they are producing the measures. Those customers collect data about what is working and how well, and to make sure the organization is still using the right measures (P_07).

A measure that is an assessment of the right thing, whether it can be measured directly or by measuring a sign, of some kind, that stands in proxy. That is, “what are the things that, at a high-level, [are] important to you. We want the signs that you’re looking for. … We have to accept the fact there are some things you can’t measure objectively” (P_03). Other times, no proxy is needed, and then effective measures are those that “measure the right thing and that they measure it accurately… [they are] discrete and actually measuring the thing you want to measure” (P_04).

Repeatability and reproducibility when generating measures are a signal of reliability and quality. There may be regulatory, contractual, and procedural requirements in organizations that require measures to be reproducible to demonstrate fidelity. For example, if two different people follow the procedure to calculate the measure, they would get the same answer and if one repeatedly extracted data out of the same system, it would deliver the same data every time (P_07). This would make the measures auditable (P_08).

An effective measure is simple or can be expressed simply (P_05, P_07). Simple measures, even if they are not those that are ultimately desired, create trust, momentum, and potentially enable the organization to grow into desired measures (P_10). Some understanding of simplicity relates to the clarity of the connection between the measure and the strategic intent for which it is designed. “If anything you're doing doesn't contribute to that simple intent, don't do it” (P_06).

Effective measures are calculated correctly, tested, and demonstrated to work as designed.

> Before you actually put it into production to where people using it, you have to test it, okay? then, once you’ve tested and [see they] are driving the right behaviors and so forth for small sample, then you put [them] out for the larger group, you continue to monitor it, and you’re going to continue to tweak it and refine it. (P_03)

An example of this is when measures, while technically correct, do not reflect the spirit of the concept that needs to be measured. In some cases, the technically-correct measure drives wrong behavior. “When we went out and talked to the business, one of the things we heard was, [our business area] just seems kind of slow, right? … What? Like we’re intellectually slow?” (P_02). A measure was being applied that started the clock for their response time long before a task was presented to the business area for action. The measure was technically correct, calculated correctly, but misrepresented the response time for that business area. In this case, the measure did not actually work as intended, though it worked as designed.

A complete definition of an "effective measure" includes…. Well defined measures must be balanced when viewed in context with other measures. Analysis of effective measures includes a well-defined rationale for balancing possibly opposing objectives and deciding, among multiple measures, which to focus on. An effective measure

> has to be balanced. So, we’re not talking about one particular metric, but a set of metrics. You can’t just go with one, you have to have a set. Because by just following one, you could take one, could take it to the extreme and not understand the implications of that on other aspects of your processes or your business. (P_03)

As an example, another participant described the balance between product sales and the health of the organization overall. So balance has to be provided between measures of product movement and other aspects of organizational health, such as employee satisfaction and process efficiencies.

> As a manufacturer your goal in life is to “move the metal,” right, move as much product as possible, but you also want a healthy dealer franchise, right? to make sure they’re in place for the long run, to serve your customers in the end. (P_09)

The identification of related measures that act in concert (including for triangulation) is another characteristic of a well-defined effective measure. This might be illustrated in a conceptual model or diagram showing the related measures. The relationships should be defined to the extent that consumers know “they don’t have so many other influences that you can move around and not be the thing that you actually care about. That may require a set of measures” (P_04). Being able to assess a measure set and understand the more complex story it tells will help justify the cost of developing and managing the measures.

Effective measures are produced in a timely manner.

> Timeliness and quality, okay? So there are some inherent trade-offs to that. It doesn’t mean there’s always a tradeoff. Sometimes there are actual things that you can do to improve both, to move both in the same direction, but a lot of times there are tradeoffs and you have to recognize that you can’t just follow one and abandon the other, okay? (P_03)

P_03 stressed the idea that there are times when decision makers must choose between improving the performance in one dynamic, while allowing another, competing measure fall. This is when business conditions, environmental factors, the needs of the customer balanced with needs of the organization, and other judgment calls come into play. Referring back to the discussion of intuition versus data-driven decision making, there are some times when the measures themselves cannot tell the whole story.

Effective measures need to be defined with accompanying information explicitly describing the behavior they are designed to drive. This may include negative behaviors that they may drive and ways to mitigate that negative behavior. These behaviors include intended behaviors, driven by design as well as possible unintended consequences. The behavior of the measure itself, including variance over time, seasonal variance, expected trends, and factors influencing-the behavior of the measure should be considered when measures are designed and put into operational use. As the measures “should signal some sort of action or behavior so that you can affect that” (P_03), you should know ahead of time so that you can determine whether that intended outcome is being realized.

A well-formed definition of a measure will also include explicitly defined context P_01, P_02. P_06, P_07). This context may consist of the process in which the source data is created or managed, the process in which the measure is created or leveraged, the intended usage, the various influencers (moderators impacting the measure), and a description of the environment being measures or in which the measure is leveraged for action. The environment in which the measures is created should include well-defined information enabling the business to implement an auditable data collection mechanism.

Along with definition and context, a formally agreed-upon usage of the measure may be included in the description of an effective measure (P_02, P_03, P_05, P_07, P_09). This might include materials used for teaching consumers about the proper meaning, context, and usage of the measure and insight generated from it. By including this information, the overall value of the measure will be clearly articulated.

An effective measure, especially in context with other measures that enable implementation and management of a desired objective, will also include an explicitly defined intent, the “Commander's intent.” In this way, those who are consuming the measures and taking action on them can remain directionally correct with respect to intended organizational objectives (P_02, P_03, P_05, P_06, P_10).

Well-formed measures include a definition expressed in a business language shared by the measure’s producers and consumers—or in a form in which both producers and consumers can come to understand the measure from a common perspective P_06, P_10). This might include development of a shared glossary of measures. This glossary might include the explicitly defined meaning, that is, an understanding of the essential concept being measured as well as the mechanics and the formula used to derive it. It “has to be understandable—so, simple enough to understand, but not too simple to where it doesn’t clearly say, here’s what you need to do” (P_03).

In addition to the clearly identified behaviors of the measures themselves, that is, the way the numbers are expected to behave, effective measures will also have explicitly identified desired outcomes, business objectives, or needs that are illuminated by the measure. This characteristic was mentioned by all interview participants. Some measures are defined to show that progress is being made to achieving the objectives of a business strategy, while others are designed to provide diagnostic information about the efficiency of the processes used to deliver the business strategy. Understanding the outcomes for each measures is an important part of knowing if it is telling the organization about meeting the objective compared to how efficiently it is meeting the objective.

Good context around an effective measure will include identification of the business questions that can be answered by the measure and demonstrate that the measure has a value-add purpose, rather than just satisfying intellectual curiosity (P_01, P_02, P_05, P_10, P_11). While there are business functions that call for the satisfaction of intellectual curiosity, again, balance is required to ensure that the resources applied to generation and maintenance of measures is supported by the value added to the organization.

Another characteristic of a well-formed effective measure is the identification of the measure type P_02, P_03, P_04, P_06, P_07, P_08, P_09, P_10, P_11). There were three primary types discussed by the study’s interview participants: (1) strategic measures (P_08), (2) outcome measures (also referred to as lagging indicators, output measures, and goal measures), (3) diagnostic measures (also referred to as leading indicators, input measures, and milestones). A final type that was mentioned was a measure used as a proxy for, or a sign of, something currently unmeasurable. This final type was an indicator for such things as creativity and innovation.

> I think the strategic metrics are indicators of whether you're accomplishing your strategy and that's a very high level, right? In this case it's almost on the person accountable for those metrics would likely be someone like a CEO, right? The composition of those metrics into plans and activities then result in lower-level metrics for people in the organization. (P_08)

Finally, an effective measure or set of measures may include suitable presentation or visualization options P_01, P_02, P_05, P_10). When telling a story to enable sound decision making and to communicate the progress of the organization toward strategic objectives, the visualization of the story plays an important role. There are some visualization tools, presentation options that may communicate the information more clearly than others. If this is the case, it may be helpful to include such recommendations when measures are developed.

With this qualitative research and analysis of the life, education, and work experiences of executive process owners, the identification of skills and knowledge they drew from those experiences, and their insight into what effective measures are, I formulated a survey to be conducted with the full population of the process engineering community in the company. The significant themes and concepts discussed above make up the bulk of the survey, which may be found in Appendix C.

Quantitative Findings

The qualitative interview transcripts were assessed and codes were extracted from each interview. These codes were aligned and analyzed to developed themes. The first draft of the survey was composed and organized based on the theoretical foundations of the study and the perspective of the research question. The theoretical foundations were decision making, program theory, and performance measurement. The qualitative research question was, what are experiences, activities, and knowledge that contributed to the decision maker's ability to select organizational performance measures.

Formulation of the Survey

The interview findings in the qualitative findings section were organized according to the discovered themes. The same organizing structure guided the initial formulation of the survey items and the organization of the survey questions. The initial organization scheme for the survey, based on the foundational theory and the research question, was rational.

Survey organization scheme. On further consideration, it seemed that the original organization could introduce a bias in the responses, influencing respondents inappropriately, leading them to a foregone conclusion. Further analysis resulted in a way to frame the survey that would reduce this bias: a better way to frame the survey items, an approach for developing the Likert responses, and an organization of the items that did not introduce such bias.

Survey planning resulted in a formula for stating the survey items, an approach to the Likert responses that would yield sound results, and the formulation of candidate factors as a basis from which to analyze the survey results. In asking the respondent to assess each statement for importance, the formula was to state the item as, "my ability to…," "my knowledge of …," or "my <characteristic>…." The responses were in a five-level Likert scale: very unimportant,

unimportant, moderately important, important, and very important. To these, an option ‘I do not have this characteristic’ was added. Discussion of the consequences of this decision are included with the handling of missing data. Finally, the candidate factors (see Appendix D) provided a way to think about the various characteristics and approach the analysis. These factors were not visible in the survey itself, in which the items were presented simply in alphabetical order.

Survey creation. Survey Monkey was used to create, deliver, and collect responses to the survey with anonymous responses, collecting no email or IP addresses. the survey was organized in four pages: the informed consent, the experience, knowledge, and skill items, the measure items, and the demographics. The items on pages two and three of the survey (EKS and measure items) were all required, and thus produced no missing data, in and of themselves. There were optional questions on the demographics, primarily those involving entry of a masters’ or post-graduate degree focus.

Survey execution. The survey was offered, via a link to the survey in Survey Monkey in an email, to the population being surveyed, for seven days, from Sept 14th to 20th. A reminder email was sent on September 19th and a thank you email on the 21st. Status updates were provided to the business leaders of the population community who facilitated access to the population after day three and on days six and seven.

Survey responses were extracted on days two and six. The first extract was for testing and setup of SPSS and the second for full analysis. Survey responses were extracted from Survey Monkey into an Excel spreadsheet using the web site’s export utility. There were a total of 59 responses, with four incomplete responses. There were two responses on day one, 20 on day two, two on day three, 30 on day six, and five on day seven. The peak days were the days the initial and reminder emails were sent to the population.

SPSS approach. SPSS version 21 was used to analyze the survey responses, generating descriptive statistics, testing for normality (required for factor analysis), assessing Cronbach's alpha, and executing factor analysis. PCA was used to extract factors, regression analysis was used to attempt to identify variables involved in the multicollinearity issues, and MANOVA and one-way ANOVA were used to assess the behavior of the extracted factors by population group.

Data analysis. Of the 59 responses, four were incomplete. The 55 complete responses were grouped by age range: 12 respondents (21.8%) were under 30, 23 (41.8%) were age 31-40, 14 (25.5%) were 41-50, and 6 (10.9%) were over 50. Thirty-nine (70.9%) respondents were male, 15 (27.3%) female, and one declined (1.8%, this was treated as missing data). The process complexity demographic showed 8 respondents with simple processes (14.5%), 15 with moderate process complexity (27.3%), and 32 with complex processes (58.2%). There were three decision tenure ranges, 0-9 years with 15 respondents (27.3%), 10-11 years with 8 respondents (14.5%), and 12 or more years with 32 respondents (58.2%).

The incomplete cases were removed from all analysis (Tabachnick & Fidell, 2013). All 55 experience, knowledge, and skill (EKS) variables were assessed for mean, median, mode, standard deviation, variance, and missing data. There were several cases with "I don't have this characteristic" responses. This value was recorded as a 6 in the data. Including these values in the analysis skews the means, influencing the other statistics unacceptably. These values have been code as missing data. However, for a number of the variables, an unacceptable percentage of the cases are impacted, prevented replacement with the series mean. This impacted financialModels, 11.9% missing; Masters, 13.6%; trainingRotation, 28.8%; postGraduate, 23.7%; and commandControl, 5.1% (Tabachnick & Fidell, 2013). The maximum allowed to be missing for replacement is 5%. To move forward with the analysis so that an unacceptable number of cases will not be omitted from analysis, these variables will be removed from the PCA analysis (Tabachnick & Fidell, 2013).

Assess for normality and outliers. After being treated for missing data, the remaining 50 variables were assessed for normality. With the exception of rightQuestions and visualizeArticulate among the EKS variables and canBeInfluenced among the measure variables, all were normally distributed according to assessments of the kurtosis and skewness variables. Normally distributed variables are desired for factor analysis (Yong & Pearce, 2013), but a solution using non-normal distributions, while degraded, can still have value (Tabachnick & Fidell, 2013). For the purpose of this analysis, these variables have been excluded from the PCA analysis. Outliers (see Tables 1 and 2) were addressed by pulling in the outliers to the lowest value, less .01. There were variables that could not be corrected. These are discussed below in conjunction with the factors sets they impacted. The following EKS variables could not be corrected due to the number of cases impacted, with the number in parenthesis indicating the number of cases affected: workEthic (4), technicalPractitioner (4), clearSelfImage (4), accountability (4), visualizeArticulate (5), and rightQuestions (5).

Table 1

Measure Outliers Pulled In

One outlier			Two outliers	Three or more outliers
timely	balance	measureType	canBeInfluenced	intent (4, >5%)
achieve	relatedMeasures	questions	movesOverTime	not corrected
language	meaning	value	works	
			behavior	

Note: Four+ outliers were not corrected. They represented >5% of the cases

Cronbach's alpha. Cronbach's alpha for the untreated 55 EKS variables was .970 (Tabachnick & Fidell, 2013). Testing reliability for the set that omits the 4 incomplete cases and the 5 variables with unacceptably high percent missing (that is, "I don't have this characteristic" entries) and replacing with means those missing data that are less than 5% (all other values were 1.7% missing), the Cronbach's alpha for the adjusted set was .955 (see Table 3).

Table 2

EKS Outliers Pulled In

One outlier		Two outliers	
statistics	experientialLearning	ethicalPresentation	businessKnowledge
reflection	influencingSkill	patternRecognition	broadRangeOfData
feedback	strategicLevel	interviewingSkills	applyInsight
assumptions	formalEducation	advocacyVisioning	mitigateGaming
selfDirected	businessLeaderAccess	collaborative	hideComplexity
		consultingSkills	hypothesis

Note: Four+ outliers were not corrected. They represented >5% of the cases

Table 3

EKS Reliability Statistics

Cronbach's Alpha	N of Items
.955	50

One variable (rightQuestions) was recommended for removal. It would have improved the Cronbach's alpha to .956, but I elected to retain it as the improvement was small and I was curious about whether it would factor in any meaningful way with the others. In the PCA, it aligned to a non-viable factor and removed.

Assess correlations. The correlations among the 55 EKS variables were assessed, as well as those among the 23 measure variables. Additionally, the correlations between the EKS variables and the measure variables were assessed. The measure variables with the highest number of correlations to EKS variables are recommended for assessment using linear regression for future research.

Multicollinearity among the variables was an issue in the analysis, complicating the factoring process. One of the signals of multicollinearity is high values (above .7) in the correlation matrix (Tabachnick & Fidell, 2013). There were only two correlations over .7 in the matrix, but many more than two variables that produced indications in the factor analysis of multicollinearity. The indications were the determinant (delivered with the correlation matrix in the PCA results) was zero and no factors were extracted. Determining which of the variables were involved in the issue was difficult.

To detect the multicollinearity, a series of linear regressions were conducted. Variables were included as independent variables and one-by-one, the linear regression executed. In statistics, collinearity diagnostics were requested. In the output, the variance inflation factor (VIF) was examined for each combination of dependent and independent variables, which should be less than three. Values above ten certainly indicate multicollinearity between the variables. The survey data set had VIF values between above five and in some cases in the hundreds. It will be essential to eliminate the problematic variables to extract factors. Using the results of the linear regression tests, variables were eliminated from the input to the factor extractions.

Constructs representing EKS items

Research question 2. What constructs represent the important content of experience, knowledge and skill, and what constructs encapsulate the concept of the effective measures? The composition of this exploratory survey was ill-suited to the PCA due to the high volume of variables and the unknown relationships among them. While the correlation matrices showed only modest strength of correlations (most between .3 and .5), there were two above .7. This did not signal the difficulty that occurred when the factor extraction was attempted. Although this unsuitability existed, exploring higher-order groupings among the variables, identifying and eliminating collinear variables, and simplifying the data set is essential to further analysis of this data. Two requirements of factor analysis are that the variables be normally distributed and have no untreated outliers. Another assumption for general factor analysis is that the variables load onto the factors at .7 or above and, at the same time, do not load onto another factor at greater than .32 (Tabachnick & Fidell, 2013; Yong & Pearce, 2013). In this exploratory analysis, primarily to facilitate the initial culling of the potentially unneeded variables, values over .5 and cross-loadings of up to .45 were considered (Osborne & Costello, 2004).

The most serious weakness of the analysis is the poor sample size (de Winter, Dodou, & Wieringa, 2009; Osborne & Costello, 2004; Tabachnick & Fidell, 2013). High loading levels, low numbers of factors, and a large number of variables can still yield a viable exploratory factor analysis solution. Six viable factors were extracted with solid loadings from a large number of variables (50), so it is possible that the factors have some stability (de Winter et al., 2009). Nevertheless, the exploratory factor analysis approach, in particular PCA, is being used to provide insight to cull the data set and improve the survey for future studies of appropriate sample size.

Initial attempts at factor extraction using all 78 variables as input failed due to multicollinearity among the variables, indicated by the determinant value of zero on the correlation matrix. A value greater than .0001 is required for factor extraction (Tabachnick & Fidell, 2013). Subsequent attempts, using the 55 EKS variables in one pass and the 23 measure variables in a second also failed. As problematic variables were identified, they were dropped from the analysis. Factors were extracted and assessed for viability. This assessment included assessment of the eigenvalues for each factor and performing parallel analysis with Monte Carlo simulation to determine whether to retain or discard each factor and evaluating the loadings of each variable to the factor. Although some recommendations are for loadings above .7 on the primary factor and on all other factors at below .3, loadings of .5 are considered strong for exploratory factor analysis (Osborne & Costello, 2004).

The initial extraction used the following approach. The SPSS dimension reduction function was selected. The set of variables to be examined was selected and the options for the extraction were set. For descriptives, univariate descriptives and initial solution statistics were requested. For the correlation matrix, coefficients, significance levels, determinant, and KMO and Bartlett's test of sphericity were requested. For the extraction, the principal components method was selected and the correlation matrix analyzed. The unrotated factor solution and scree plot were displayed. The extraction was initially executed based on eigenvalues greater than one. Finally, 25 iterations were specified for convergence.

The direct oblimin rotation method was requested with rotated solution and loading plots displayed. Scores were not saved as variables. Missing data had been replaced with means (for the 55 EKS variables), but the 'exclude cases pairwise' missing values choice was selected. Output in the coefficient displays were sorted by size, with coefficients smaller than .32 suppressed (Tabachnick & Fidell, 2013).

The correlation matrix was examined, particularly focusing on values over .7 and the determinant, which would indicate multicollinearity. The communalities of the variables were examined to determine whether they were strongly correlated to the factor. Values below .3 indicated variables that were not sufficiently strongly correlated to the factor to be viable. These variables were removed from the analysis and the extraction re-executed.

The Kaiser-Meyer-Olkin Measure of Sampling Adequacy (KMO) and Bartlett's test of sphericity were examined. A KMO test of .5 or above was considered adequate for factor analysis (Yong & Pearce, 2013), with a value above .6 preferred (Tabachnick & Fidell, 2013). A sufficient KMO indicates adequate sample size for factor analysis and a significant Bartlett's test of sphericity (p <.001), indicates that is at least one pair of variables with a significant correlation. Both a KMO greater than .5 and a significant Bartlett's test were required to move forward.

Next, SPSS produced a table containing the total variance explained by each component. The cumulative percent of the extraction sums of squared loadings was considered. Values over 50% were considered good. The parallel analysis was executed to compare the parallel analysis eigenvalues to the eigenvalues produced by the PCA. If the parallel analysis eigenvalue was less than the PCA eigenvalue, the factor was retained, else it was discarded. If the factors extracted by the PCA were discarded, the extraction was re-executed to force the number of factors that were retained.

Table 4

Total Variance Explained - PCA

	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings[a]
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
1	9.814	30.668	30.668	9.814	30.668	30.668	5.603
2	2.619	8.184	38.852	2.619	8.184	38.852	3.682
3	2.094	6.543	45.395	2.094	6.543	45.395	4.029
4	1.851	5.785	51.180	1.851	5.785	51.180	2.024
5	1.655	5.173	56.353	1.655	5.173	56.353	3.639
6	1.456	4.550	60.903	1.456	4.550	60.903	4.322
7	1.265	3.952	64.855	1.265	3.952	64.855	4.297
8	1.154	3.606	68.460	1.154	3.606	68.460	3.915
9	.974	3.044	71.505				
…			(rows 10-31 omitted)				
32	.026	.081	100.000				

Note: Extraction Method: Principal Component Analysis.
a. When components are correlated, sums of squared loadings cannot be added to obtain a total variance.

The pattern matrix showed the cleanest view of the extracted factors, allowing an assessment of cross-loadings as well as identification of the variables that loaded to each factor. It may be that the cross-loadings are also a result of the small sample size (Osborne & Costello, 2004). Any variables that loaded at less than .3 on any factor were removed and the analysis re-executed. For the final PCA, in order to deal with multicollinearity, the set of variables that loaded successfully in the principal axis factoring were used as a starting point and then variables added one at a time to determine whether it introduced multicollinearity. Variables that resulted in a determinant of zero were removed and testing continued.

EKS factors. Variable descriptives were examined and the kurtosis and skewness calculations examined to determine the normality of the distributions of each variable. While normality is desired, it is not absolutely required (Tabachnick & Fidell, 2013). Since the non-normally distributed variables were also impacted by uncorrectable outliers, they were not used in the PCA.

Examination of univariate outliers resulted in the correction outliers on 22 variables. The variables that are not normally distributed (rightQuestions and visualizeArticulate) and the variables with outliers that could not be corrected due to having more than 5% of the cases impacted, are shown in Table 5. These variables were not included in the PCA.

Table 5

Non-normal or Uncorrected EKS Variable Outliers

EKS variable	Skewness	Std. Error of Skewness	Kurtosis	Std. Error of Kurtosis	Uncorrected Outliers
rightQuestions	.514	-2.851	.322	7.246	5
visualizeArticulate	.498	-2.285	.322	4.661	5
dataCollection	.902	-1.123	.322	.074	4
workEthic	1.013	-1.014	.322	-.284	4
accountability	.995	-1.053	.322	.074	4
clearSelfImage	.951	-.850	.322	-.284	4
technicalPractitioner	.911	-.724	.322	-.216	4

Note: confidence interval for mean 95%.

The KMO for the EKS variables being tested for PCA was .616 and the Bartlett's test of sphericity was significant, at p <.001, indicating adequacy of sample size and that there is at least one pair of variables with a significant correlation. See Table 6.

Table 6

EKS Variables KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.616
Bartlett's Test of Sphericity	Approx. Chi-Square	991.014
	df	496
	Sig.	.000

The communalities table showed no variables correlated that were below .3 (Tabachnick & Fidell, 2013). Eight factors were extracted. Factors five and six could not be assigned meaningful names, and so were not carried forward in the analysis, though they are reported in Table 7. Cronbach's alpha, presented in Table 8, was calculated for each of the meaningful EKS factors.

Measure factors. Variable descriptives for the measure factors were examined and the kurtosis and skewness calculations examined to determine the normality of the distributions of each variable. Only canBeInfluenced was not normally distributed. Examination of univariate outliers resulted in the correction outliers on 12 variables. Only one measure variable had uncorrectable outliers. The variables that are not normally distributed and the variables with outliers that could not be corrected due to having more than 5% of the cases impacted, are shown in Table 9. These variables were not included in the PCA.

Table 7

EKS Variables Pattern Matrix[a]

	Component							
EKS Variable	1	2	3	4	5	6	7	8
influencingSkill	.841							
professionalNetworks	.696							
collaborative	.598							
mentors	.524	-.358						
teachingSkills	.474						.367	
feedback	.393					.359		-.326
causalAnalysis		.862						
statistics		.665						
STEMSkills		.545						
benchmarking		.437				.390		
ethicalPresentation			.804					
signalNoise			.713					
assumptions			.557					
organizationalComplexity			.551	.435				
applyInsight	.369		.540					
businessKnowledge				.826				
consultingSkills		.372		-.434				
breadthOfExperience	.322	.384		.394				
hideComplexity					-.756			
agileLearning					-.727			
broadRangeOfData	.399				-.425			
informalEducation						.869		
computerSkill						.611		
businessLeaderAccess						.512		
experientialLearning							.793	
learningCulture					-.393		.678	
formalEducation						.386	.467	.342
ambiguity								-.595
pointOfView				-.348				-.524
levelsOfPrecision			.363					-.522
strategicLevel								-.480
advocacyVisioning	.363				.350		.321	-.404

Note: Extraction Method: Principal Component Analysis. Rotation Method: Oblimin with Kaiser Normalization.[a] a. Rotation converged in 22 iterations.

Table 8

EKS Factors

Factor	Mean	Std Dev	Cronbach's Alpha	Normality: Kurtosis	Normality: Skewness
1 CollaborationFactor	3.8427	.64856	.820	-.559	-.531
2 ComplexityTools	4.1496	.60231	.745	.644	-.692
3 Synthesis	4.1241	.50500	.739	1.248	-.867
4 BusinessKnowledge	4.1028	.58410	.422	-.585	-.152
7 Learning	3.6396	.75748	.639	-.527	.072
8 StrategicThinking	4.0711	.60485	.779	.311	-.755

Note: confidence interval for mean 95%.

Table 9

Non-normal or Uncorrected Measure Variable Outliers

Measure variable	Skewness	Std. Error of Skewness	Kurtosis	Std. Error of Kurtosis	Uncorrected Outliers
canBeInfluenced	.834	-1.316	.322	2.949	0
Intent	1.043	-.690	.322	.074	4

Note: confidence interval for mean 95%.

The KMO for the measure variables being tested for PCA was .680 and the Bartlett's test of sphericity was significant, at p <.001, indicating adequacy of sample size and that there is at least one pair of variables with a significant correlation (see Table 10). The communalities table showed no variables correlated that were below .3 (Tabachnick & Fidell, 2013). Five factors were extracted (see Table 11).

Table 10

Measure Variables KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.680
Bartlett's Test of Sphericity	Approx. Chi-Square	330.034
	Df	153
	Sig.	.000

Table 11

Measure Variables Pattern Matrix

Measure Variable	Component 1	2	3	4	5
behavior	.876				
outcomes	.814				
value	.692				
relatedMeasures	.651				
actionable		.761			
simple		.751			
achieve		.592			
meaning	.451	.589	.352		
presentationVisualization			-.837		
questions			-.710		
language			-.617		.446
measureType			-.596		-.354
movesOverTime				.842	
Context				.713	
Balance				.557	
repeatable					.769
rightThing				.400	.617
auditable		.456			.496

Note: Extraction Method: Principal Component Analysis. Rotation Method: Oblimin with Kaiser Normalization. Rotation converged in 14 iterations.

Cronbach’s alpha, presented in Table 12, was calculated for each of the measure factors.

Table 12

Measure Factors

Factor	Mean	Std Dev	Cronbach's Alpha	Normality (based on K&S)
1 Business Outcome	3.6455	.73863	.820	Normal
2 MeasureUsage	3.6364	.73096	.742	Normal
3 Usability	4.1909	.51587	.683	Normal
4 MeasureContext	3.4970	.64748	.652	Normal
5 Execution	4.497	.42972	.583	Normal

Note: confidence interval for mean 95%.

Relationship between EKS factors and measure factors. Multiple linear regression was conducted to determine whether there is a relationship between the EKS factors and the measure factors.

H_{10}: There is no relationship between the EKS factors and the Measure factors.

H_{1a}: There is a linear relationship between the EKS factors and the Measure factors.

The assumptions for multiple linear regression are a sample size of about 20 cases per independent variable, no multicollinearity among the independent variables, independent variables must be correlated to the dependent variables, no outliers among the variables, and that the independent variables be normally distributed. To test the linear relationships between dependent variables, a scatter plot was generated to allow observation of elliptical patterns (see Figure 1). The Shapiro Wilk tests of normality (see Table 13) showed that some of the measures were not normal. For MeasureUsage, F=.975, 55, p >.05; CollaborationFactor, F=.962, 55, p >.05. However, the Kurtosis and Skewness values (see Table 14) for these factors are well between ±2, indicating normality.

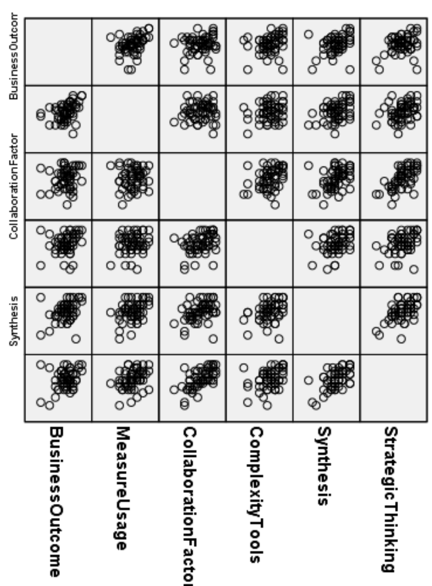

Figure 1. Scatter plot: Linear relationship between independent variables

Table 13

EKS Factors Tests of Normality

Factor	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
BusinessOutcome	.149	55	.004	.944	55	.012
MeasureUsage	.109	55	.155	.975	55	.303
CollaborationFactor	.100	55	.200*	.962	55	.077
ComplexityTools	.134	55	.016	.925	55	.002
Synthesis	.125	55	.032	.942	55	.010
StrategicThinking	.126	55	.030	.956	55	.041

Notes: *. This is a lower bound of the true significance.
a. Lilliefors Significance Correction

Table 14

EKS Factor Descriptive Statistics

Factor	N	Mean	Std. Deviation	Skewness		Kurtosis	
				Statistic	Std. Error	Statistic	Std. Error
BusinessOutcome	55	3.6455	.73863	-.821	.322	1.330	.634
CollaborationFactor	55	4.0181	.64856	-.361	.322	-.573	.634
ComplexityTools	55	4.1496	.60231	-.745	.322	.644	.634
MeasureUsage	55	3.6364	.73096	-.191	.322	-.323	.634
StrategicThinking	55	4.0711	.60485	-.505	.322	.178	.634
Synthesis	55	4.2606	.50500	-.633	.322	.639	.634
Valid N (listwise)	55						

There were no correlations over .7 (no multicollinearity among these variables) and all the variables were correlated. However, none were correlated as high as .3, which is an indicator that the independent variables may not predict the dependent. This is evident in the R^2 value in the model summary (see Table 15).

R^2 for model 1 tells us that 6.7% of the variance in the BusinessOutcome is attributed to change in the independent variables (CollaborationFactor and ComplexityTools). For Measure Usage (dependent) with Synthesis and StrategicThinking (independent), the correlations are greater than .3, indicating that there may be a linear relationship. R^2 for model 2 indicates that the predictor variables (StrategicThinking and Synthesis) account for 15.7% of the variance in the dependent variable (MeasureUsage). Multiple linear regression among the EKS factors and the Measure factors produced no viable model for a predictive relationship. The tolerance and VIF in the Coefficients table (see Table 16) show that there is not multicollinearity among the independent variables.

Table 15

Model Summary[b]

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.259[a]	.067	.031	.72703	.067	1.869	2	52	.165
2	.396[a]	.157	.124	.68409	.157	4.827	2	52	.012

Notes: Model 1: *a*. Predictors: (Constant), ComplexityTools, CollaborationFactor
b. Dependent Variable: BusinessOutcome

Notes: Model 2: *a*. Predictors: (Constant), StrategicThinking, Synthesis
b. Dependent Variable: MeasureUsage

Table 16

EKS Factor Model Coefficients[a]

		Unstandardized Coefficients		Std Coeff			95.0% Confidence Interval for B		Correlations			Collinearity Statistics	
Model		B	Std. Error	Beta	t	Sig.	L B	U B	0-order	Partial	Part	Tolerance	VIF
1	(Constant)	1.105	.820		1.347	.184	-.541	2.751					
	Synthesis	.431	.224	.298	1.922	.060	-.019	.881	.378	.258	.245	.676	1.480
	Strategic Thinking	.171	.187	.141	.912	.366	-.205	.547	.311	.126	.116	.676	1.480

Note: a. Dependent Variable: MeasureUsage

Impact of Demographic Dimensions on Factor Importance

Research question 3. How are those constructs impacted by various dimensions within the respondent community? The survey respondents indicated their perception of the importance of each of the EKS characteristics. The exploratory factor analysis extracted six viable factors for these characteristics. Each factor has a composite importance based on the average of the importance assigned to each of the characteristics composing it. The following analysis will assess whether the importance of each factor independently is impacted by four demographic dimensions: age range, gender, decision-making tenure, and process complexity. Additionally, the linear combination of the six factors will be tested for impact by the same four dimensions. One-way ANOVA was used for the individual assessments and MANOVA was used to assess the linear combination.

Impact of dimensional groups on individual constructs. One-way ANOVA was conducted for the factors with Cronbach's Alpha greater than .7: CollaborationFactor, StrategicThinking, ComplexityTools, Synthesis, BusinessOutcome, and MeasureUsage. For each factor, the following hypothesis sets were tested:

H_1: the importance of the factor does not vary based on the gender group of the respondent.

H_2: the importance of the factor does not vary based on the complexity of the process in which the respondent is involved.

H_3: the importance of the factor does not vary based on the age group of the respondent.

H_4: the importance of the factor does not vary based on the decision-making tenure group of the respondent.

While the Shapiro-Wilk test of normality showed that the EKS factors are not normally distributed (see Table 17), the Kurtosis and Skewness for the factors are well within ±2 (see Table 8). The Normal Q-Q Plots (Figures 2 – 7) show that the observed values align well to the expected norms. The factors will be considered normally distributed for the purposes of this analysis.

Table 17

EKS Factors Test of Normality

	Shapiro-Wilk		
EKS Factor	Statistic	df	Sig.
Business Knowledge	.950	55	.024
Collaboration	.941	55	.009
ComplexityTools	.952	55	.030
Learning	.949	55	.020
Strategic Thinking	.935	55	.005
Synthesis	.937	55	.006

Note: a. Lilliefors Significance Correction

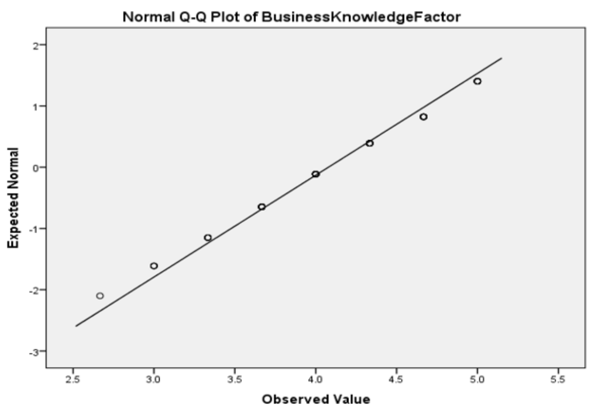

Figure 2. Normal Q-Q Plot, BusinessKnowledge Factor

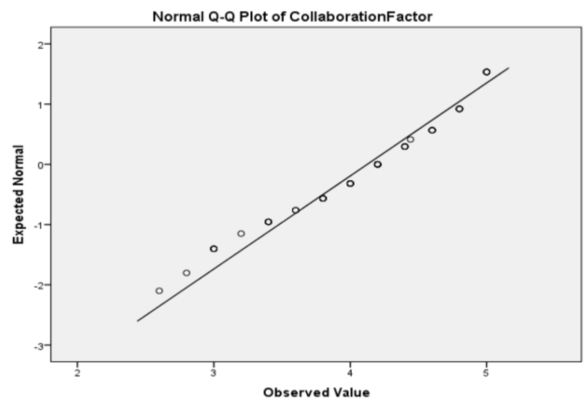

Figure 3. Normal Q-Q Plat, Collaboration Factor

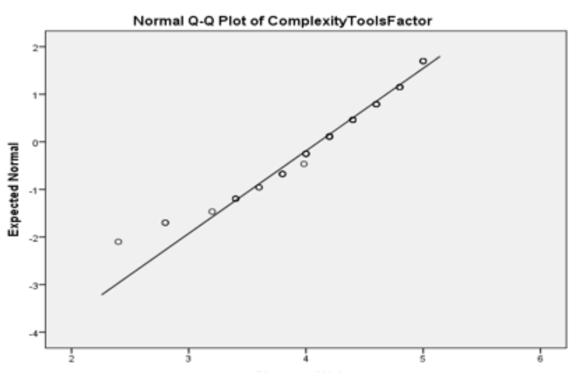

Figure 4. Normal Q-Q Plot, ComplexityTools Factor

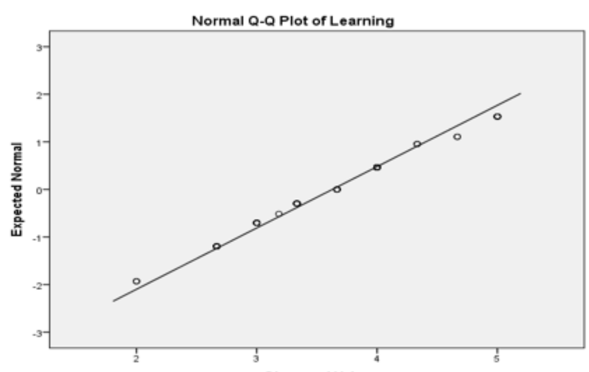

Figure 5. Normal Q-Q Plat, Learning Factor

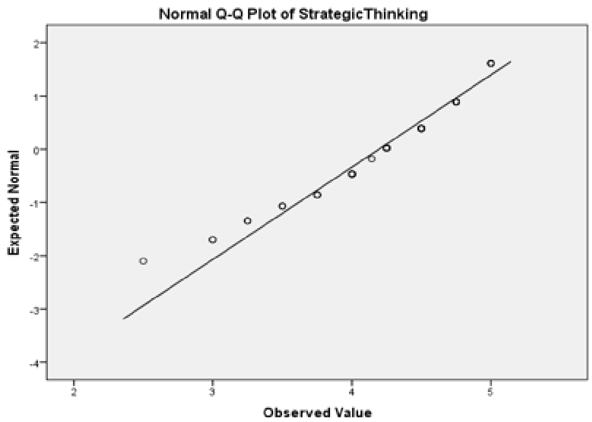

Figure 6. Normal Q-Q Plot, StrategicThinking Factor

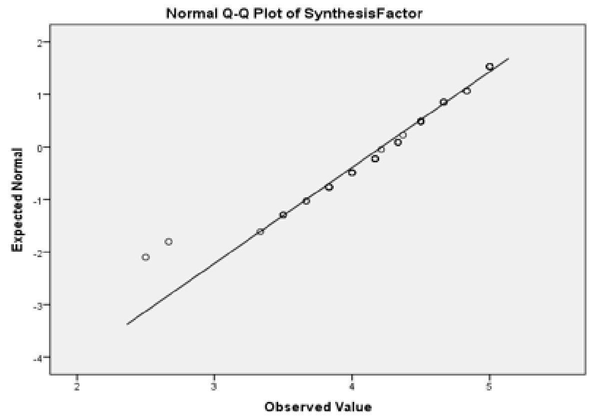

Figure 7. Normal Q-Q Plat, Synthesis Factor

The EKS factors were tested for multivariate outliers using the Mahalanobis distance (see Table 18). This assessment determines if there are unusual combinations among the variables included in the factor and whether the combination of the variables produces outliers in the new variables. The maximum value for the Mahalanobis Distance from the chi-square table for six variables is 22.46. The value for the six factors, 22.17037 is less than 22.46. There are no multivariate outliers among the EKS factors. In case of significant findings, a Scheffe post hoc test, which is robust for unequally sized groups, was requested for all one-way ANOVAs.

Table 18

Mahalanobis' Distance for EKS Factors

Item	N	Range	Minimum	Maximum
Mahalanobis Distance	55	21.72543	.44494	22.17037
Valid N (listwise)	55			

BusinessKnowledge factor. A one-way ANOVA was run to determine if there is a difference in the perceived importance of Business Knowledge between male and female respondents. Levene's test of homogeneity of variances was not significant, $F(1,52) = .028$, $p > .05$ (see Table 19), so we fail to reject the null hypothesis, indicating that there is no difference in the variances. The assumption of homogeneity is validated.

Table 19

Test of Homogeneity of Variances for BusinessKnowledgeFactor for Gender

Levene Statistic	df1	df2	Sig.
.028	1	52	.867

As a result, we can use the ANOVA. The one-way ANOVA was not significant, $F(1) = .156$, $p > .05$ (see Table 20), indicating that there is no difference in the BusinessKnowledge factor among gender groups. The Collaboration importance does not vary by gender groups.

Table 20

ANOVA BusinessKnowledgeFactor

Item	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	.059	1	.059	.156	.694
Within Groups	19.483	52	.375		
Total	19.541	53			

A one-way ANOVA was run to determine if there is a difference in the perceived importance of Business Knowledge between age groups. Three respondent age groups are defined. Group 1 is respondents up to 40, group 2 is those between 41 and 50, and group 3 is those 51 and over. This broke the respondents into three similarly-sized groups (15, 22, and 18, respectively). Levene's test of homogeneity of variances was not significant, $F(1,52) = .822$, $p > .05$ (see Table 21), so we fail to reject the null hypothesis, indicating that there is no difference in the variances. The assumption of homogeneity is validated.

Table 21

Test of Homogeneity of Variances for BusinessKnowledgeFactor for Age group

Levene Statistic	df1	df2	Sig.
.822	3	51	.488

As a result, we can use the ANOVA. The one-way ANOVA was not significant, $F(1) = .069$, $p > .05$ (see Table 22), indicating that there is no difference in the BusinessKnowledge factor among the age groups. The perceived importance of business knowledge does not vary among age groups.

Table 22

ANOVA for BusinessKnowledgeFactor for Age group

Item	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	.079	3	.026	.069	.976
Within Groups	19.468	51	.382		
Total	19.547	54			

A one-way ANOVA was run to determine if there is a difference in the perceived importance of Business Knowledge between process complexity groups. Levene's test of homogeneity of variances was not significant, $F(1,52) = .432$, $p > .05$ (see Table 23), so we fail to reject the null hypothesis, indicating that there is no difference in the variances. The assumption of homogeneity is validated.

Table 23

Test of Homogeneity of Variances for BusinessKnowledgeFactor for processComplexity

Levene Statistic	df1	df2	Sig.
.432	2	52	.651

As a result, we can use the ANOVA. The one-way ANOVA was not significant, $F(1) = .272$, $p > .05$ (see Table 24), indicating that there is no difference in the BusinessKnowledge factor among the process complexity groups. The perceived importance of business knowledge does not vary based on the complexity of the process for which a respondent is responsible.

Table 24

ANOVA for BusinessKnowledgeFactor for processComplexity

Item	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	.202	2	.101	.272	.763
Within Groups	19.345	52	.372		
Total	19.547	54			

A one-way ANOVA was run to determine if there is a difference in the perceived importance of Business Knowledge between decision-making tenure groups. Levene's test of homogeneity of variances was not significant, $F(1,52) = .312$, $p > .05$ (see Table 26), so we fail to reject the null hypothesis, indicating that there is no difference in the variances. The assumption of homogeneity is validated.

Table 25

Test of Homogeneity of Variances for BusinessKnowledgeFactor for Decision-making Tenure

Levene Statistic	df1	df2	Sig.
.312	2	52	.733

As a result, we can use the ANOVA. The one-way ANOVA was not significant, $F(1) = 3.293$, $p > .05$ (see Table 26), indicating that there is no difference in the BusinessKnowledge factor among the decision-making tenure groups. The perceived importance of business knowledge does not vary based on the decision-making experience of the respondent.

Table 26

ANOVA for BusinessKnowledgeFactor for Decision-making Tenure

Item	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	2.197	2	1.099	3.293	.045
Within Groups	17.350	52	.334		
Total	19.547	54			

Collaboration factor. A one-way ANOVA was run to determine if there is a difference in the Collaboration factor between men and women. Levene's test of homogeneity of variances was not significant, $F(1,52) = .902$, $p > .05$ (see Table 27), so we fail to reject the null hypothesis, indicating that there is no difference in the variances. The assumption of homogeneity is validated.

Table 27

Test of Homogeneity of Variances for the CollaborationFactor for Gender

Levene Statistic	df1	df2	Sig.
.902	1	52	.347

As a result, we can use the ANOVA. The one-way ANOVA was not significant, $F(1) = .050$ $p > .05$ (see Table 28), indicating that there is no difference in the CollaborationFactor among the gender groups. The perceived importance of Collaboration does not vary based on gender.

Table 28

ANOVA for the CollaborationFactor for Gender

Item	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	.022	1	.022	.050	.823
Within Groups	22.495	52	.433		
Total	22.517	53			

A one-way ANOVA was run to determine if there is a difference in the Collaboration factor based on process complexity. Levene's test of homogeneity of variances was not significant, $F(2,52) = 2.764$, $p > .05$ (see Table 29), so we fail to reject the null hypothesis, indicating that there is no difference in the variances. The assumption of homogeneity is validated.

Table 29

Test of Homogeneity of Variances for CollaborationFactor for processComplexity

Levene Statistic	df1	df2	Sig.
2.764	2	52	.072

As a result, we can use the ANOVA. The one-way ANOVA was not significant, $F(2) = .385$, $p > .05$ (see Table 30), indicating that there is no difference in the CollaborationFactor among the process complexity groups. The perceived importance of Collaboration does not vary based on process complexity.

Table 30

ANOVA for the CollaborationFactor for processComplexity

Item	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	.307	2	.154	.358	.701
Within Groups	22.317	52	.429		
Total	22.624	54			

A one-way ANOVA was run to determine if there is a difference in the Collaboration Factor based on respondent age group. Levene's test of homogeneity of variances was not significant, $F(3,51) = .942$, $p > .05$ (see Table 31), so we fail to reject the null hypothesis, indicating that there is no difference in the variances. The assumption of homogeneity is validated.

Table 31

Test of Homogeneity of Variances for CollaborationFactor for Age group

Levene Statistic	df1	df2	Sig.
.942	3	51	.427

As a result, we can use the ANOVA. The one-way ANOVA was not significant, $F(3) = 2.369$, $p > .05$ (see Table 32), indicating that there is no difference in the CollaborationFactor among the respondent age groups. The perceived importance of Collaboration does not vary based on age.

Table 32

ANOVA for CollaborationFactor for Age group

Item	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	2.767	3	.922	2.369	.081
Within Groups	19.856	51	.389		
Total	22.624	54			

A one-way ANOVA was run to determine if there is a difference in the Collaboration factor based on respondent decision-making tenure group. Levene's test of homogeneity of variances was not significant, $F(2,52) = 1.44$, $p > .05$ (see Table 33), so we fail to reject the null hypothesis, indicating that there is no difference in the variances. The assumption of homogeneity is validated.

Table 33

Test of Homogeneity of Variances for CollaborationFactor for Decision-making Tenure

Levene Statistic	df1	df2	Sig.
.863	2	52	.428

As a result, we can use the ANOVA. The one-way ANOVA was significant, $F(2) = 3.589$, $p < .05$ (see Table 34), indicating that there is a difference in the Collaboration factor among the respondent decisions-making tenure groups. The perceived importance of Collaboration does vary based on decision-making tenure.

Table 34

ANOVA for CollaborationFactor for Decision-making Tenure

Item	Sum of Squares	Df	Mean Square	F	Sig.
Between Groups	2.744	2	1.372	3.589	.035
Within Groups	19.879	52	.382		
Total	22.624	54			

Because the one-way ANOVA delivered a significant result, the Scheffe post hoc test is examined for the multiple comparisons of the decision-making tenure levels. There are no results showing a significant difference between the rows, but the lowest value produced is between groups one and two (less than ten years' experience and 10 to 12 years' experience (see Table 35). The homogenous subsets output shows the Scheffe test as significant (p <.05; see Table 36) with the Means Plot (Figure 8) showing a marked difference between groups one (m=4.4694, sd=.53247) and two (m=3.8250, sd=.72850; see Table 37). Respondents with less than 10 years' decision-making experience found the collaboration factor significantly more important than did the group with 10-12 years' experience. Neither group was significantly different from the group with 13 or more years' experience.

Table 35

Multiple Comparisons Dependent Variable: CollaborationFactor for Decision-making Tenure

Post hoc test	(I) decision TenureRange	(J) decision TenureRange	Mean Diff (I-J)	Std. Error	Sig.	95% Confidence Interval L Bound	95% Confidence Interval U Bound
Scheffe	1.00	2.00	.64443	.27069	.068	-.0377	1.3266
		3.00	.43193	.19348	.093	-.0556	.9195
	2.00	1.00	-.64443	.27069	.068	-1.3266	.0377
		3.00	-.21250	.24441	.687	-.8284	.4034
	3.00	1.00	-.43193	.19348	.093	-.9195	.0556
		2.00	.21250	.24441	.687	-.4034	.8284

Table 36

CollaborationFactor for decisionTenureRange for Decision-making Tenure

			Subset for alpha = .001
Post Hoc Test	decsionTenureRange	N	1
Scheffe[a,b]	2.00	8	3.8250
	3.00	32	4.0375
	1.00	15	4.4694
	Sig.		.033

Notes: Means for groups in homogeneous subsets are displayed.

a. Uses Harmonic Mean Sample Size = 13.458.

b. The group sizes are unequal. The harmonic mean of the group sizes is used.

Type I error levels are not guaranteed.

Table 37

Descriptives for CollaborationFactor for Decision-making Tenure

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Min	Max
					L Bound	U Bound		
1.00	15	4.4694	.53247	.13748	4.1746	4.7643	3.20	5.00
2.00	8	3.8250	.72850	.25756	3.2160	4.4340	2.60	4.60
3.00	32	4.0375	.62721	.11088	3.8114	4.2636	2.80	5.00
Total	55	4.1244	.64727	.08728	3.9494	4.2994	2.60	5.00

The Means plot shows a marked difference between group one and two.

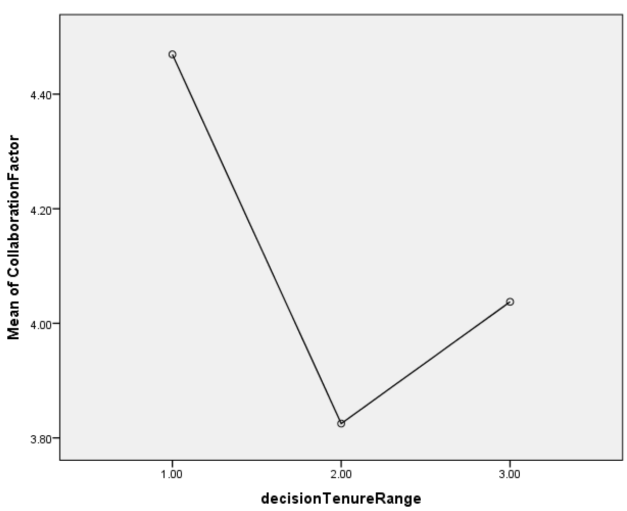

Figure 8. Decision-making Tenure Means Plot

StrategicThinking factor. A one-way ANOVA was run to determine if there is a difference in the StrategicThinking factor between men and women. Levene's test of homogeneity of variances was significant, $F(1,52) = 5.059$, $p < .05$ (see Table 38), so we reject the null hypothesis, indicating that there is a difference in the variances. The assumption of homogeneity is violated.

Table 38

Test of Homogeneity of Variances for StrategicThinking for Gender

Levene Statistic	df1	df2	Sig.
8.048	1	52	.006

As a result, we cannot use the ANOVA. In cases with a non-homogeneity of variances, the Brown-Forsyche robust test of equality of means is used. This test resulted in a non-significant finding, $F(1,47.659) = .574$, $p > .05$ (see Table 39), indicating that there is no difference in the StrategicThinking factor among the gender groups. The perceived importance of Strategic Thinking does not vary based on gender.

Table 39

Robust Tests of Equality of Means for StrategicThinking for Gender

Test	Statistic[a]	df1	df2	Sig.
Welch	.574	1	47.659	.453
Brown-Forsythe	.574	1	47.659	.453

Note: a. Asymptotically F distributed.

A one-way ANOVA was run to determine if there is a difference in the StrategicThinking factor based on process complexity. Levene's test of homogeneity of variances was not significant, $F(2,52) = .292$, $p > .05$ (see Table 40), so we fail to reject the null hypothesis, indicating that there is no difference in the variances. The assumption of homogeneity is validated.

Table 40

Test of Homogeneity of Variances for StrategicThinking for Process Complexity

Levene Statistic	df1	df2	Sig.
.292	2	52	.748

As a result, we can use the ANOVA. The one-way ANOVA was not significant, $F(2) = .385$, $p > .05$ (see Table 41), indicating that there is no difference in the StrategicThinking factor among the process complexity groups. The perceived importance of Strategic Thinking does not vary based on process complexity.

Table 41

ANOVA for StrategicThinking for Process Complexity

Item	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	.262	2	.131	.385	.682
Within Groups	17.699	52	.340		
Total	17.961	54			

A one-way ANOVA was run to determine if there is a difference in the Strategic Thinking factor based the age group of the respondent. Levene's test of homogeneity of variances was not significant, $F(3,51) = .673$, $p > .05$ (see Table 42), so we fail to reject the null hypothesis, indicating that there is no difference in the variances. The assumption of homogeneity is validated.

Table 42

Test of Homogeneity of Variances for StrategicThinking for Age groups

Levene Statistic	df1	df2	Sig.
.673	3	51	.572

As a result, we can use the ANOVA. The ANOVA was not significant, $F(3) = .607$, $p > .05$ (see Table 43), indicating that there is no difference in the StrategicThinking factor among the respondent age groups. Strategic Thinking importance does not vary between age groups.

Table 43

ANOVA for StrategicThinking for Age groups

Item	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	.619	3	.206	.607	.614
Within Groups	17.342	51	.340		
Total	17.961	54			

A one-way ANOVA was run to determine if there is a difference in the Strategic Thinking factor based on respondent decision-making tenure group. Levene's test of homogeneity of variances was not significant, $F(2,52) = .515$, $p > .05$ (see Table 44), so we fail to reject the null hypothesis, indicating that there is no difference in the variances. The assumption of homogeneity is validated.

Table 44

Test of Homogeneity of Variances for StrategicThinking for Decision-making Tenure

Levene Statistic	df1	df2	Sig.
.515	2	52	.601

As a result, we can use the ANOVA. The one-way ANOVA was not significant, $F(2) = 3.088$, $p > .05$ (see Table 45), indicating that there is no difference in the Strategic Thinking factor among the respondent decision-making tenure groups. The perceived importance of Strategic Thinking does not vary based on decision-making tenure.

Table 45

ANOVA for StrategicThinking for Decision-making Tenure

Item	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	1.906	2	.953	3.088	.054
Within Groups	16.055	52	.309		
Total	17.961	54			

ComplexityTools factor. A one-way ANOVA was run to determine if there is a difference in the ComplexityTools factor between men and women. Levene's test of homogeneity of variances was not significant, $F(1,52) = .070$, $p > .05$ (see Table 46), so we fail to reject the null hypothesis, indicating that there is no difference in the variances. The assumption of homogeneity is validated.

Table 46

Test of Homogeneity of Variances for ComplexityToolsFactor for Gender

Levene Statistic	df1	df2	Sig.
.070	1	52	.793

As a result, we can use the ANOVA. The one-way ANOVA was not significant, $F(1) = .447$, $p > .05$ (see Table 47), indicating that there is no difference in the ComplexityTools factor among the gender groups. The importance of Complexity Tools does not vary between gender groups.

Table 47

ANOVA for ComplexityToolsFactor for Gender

Item	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	.152	1	.152	.447	.507
Within Groups	17.661	52	.340		
Total	17.812	53			

A one-way ANOVA was run to determine if there is a difference in the ComplexityTools factor based on process complexity. Levene's test of homogeneity of variances was not significant, $F(2,52) = 3.196$, $p < .05$ (see Table 48), so we reject the null hypothesis, indicating that there is a difference in the variances. The assumption of homogeneity is violated.

Table 48

Test of Homogeneity of Variances for ComplexityToolsFactor for Process Complexity

Levene Statistic	df1	df2	Sig.
3.196	2	52	.049

As a result, we cannot use the ANOVA. The Welch test of equality of means is not significant, $F(2,16.293) = .620$, $p > .05$ (see Table 49), indicating that there is no difference in the importance of the ComplexityToolsFactor between respondents responsible for processes of different complexity. The perceived importance of Complexity Tools does not vary by process complexity.

Table 49

Robust Tests of Equality of Means for ComplexityToolsFactor for Process Complexity

Test	Statistic	df1	df2	Sig.
Welch	.620	2	16.293	.550
Brown-Forsythe	.661	2	12.998	.533

A one-way ANOVA was run to determine if there is a difference in the ComplexityTools factor based on respondent age group. Levene's test of homogeneity of variances was not significant, $F(3,51) = .308$, $p > .05$ (see Table 50), so we fail to reject the null hypothesis, indicating that there is no difference in the variances. The assumption of homogeneity is validated.

Table 50

Test of Homogeneity of Variances for ComplexityToolsFactor for Age groups

Levene Statistic	df1	df2	Sig.
.308	3	51	.819

As a result, we can use the ANOVA. The ANOVA was not significant, $F(3) = 1.106$, $p > .05$ (see Table 51), indicating that there is no difference in the ComplexityTools factor among the respondent age groups. The perceived importance of Complexity Tools does not vary by age.

Table 51

ANOVA for ComplexityToolsFactor for Age groups

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	1.094	3	.365	1.106	.355
Within Groups	16.815	51	.330		
Total	17.910	54			

A one-way ANOVA was run to determine if there is a difference in the Complexity Tools factor based on respondent decision-making tenure group. Levene's test of homogeneity of variances was not significant, $F(2,52) = .104$, $p > .05$ (see Table 52), so we fail to reject the null hypothesis, indicating that there is no difference in the variances. The assumption of homogeneity is validated.

Table 52

Test of Homogeneity of Variances for ComplexityToolsFactor for Decision-making Tenure

Levene Statistic	df1	df2	Sig.
.104	2	52	.901

As a result, we can use the ANOVA. The one-way ANOVA was significant, $F(2) = 4.180$, $p < .05$ (see Table 53), indicating that there is a difference in the Complexity Tools factor among the respondent decision-making tenure groups. The perceived importance of Complexity Tools varies significantly between decision-making tenure groups.

Table 53

ANOVA for ComplexityToolsFactor for Decision-making Tenure

Item	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	2.481	2	1.240	4.180	.021
Within Groups	15.429	52	.297		
Total	17.910	54			

Because there is a significant finding from the one-way ANOVA, the Scheffe post hoc analysis (see Table 54) is examined to determine which of the groups exhibit significant differences in the importance of the complexity tools factor. There is a significant difference in the mean value of the ComplexityToolsFactor between decision-making tenure groups one and three ($p < .05$). Those respondents with less than ten years' decision making tenure considered the complexity tools of more importance (m=4.4533, sd=.56804) than did those with 13 or more years of experience (m=3.9938, sd=.53878; see Table 55).

Table 54

Multiple Comparisons for Dependent Variable: ComplexityToolsFactor

Post Hoc Test	(I) decisionTenure Range	(J) decisionTenure Range	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval L Bound	95% Confidence Interval U Bound
Scheffe	1.00	2.00	.53049	.23847	.094	-.0705	1.1314
		3.00	.45958*	.17045	.033	.0301	.8891
	2.00	1.00	-.53049	.23847	.094	-1.1314	.0705
		3.00	-.07091	.21531	.947	-.6135	.4717
	3.00	1.00	-.45958*	.17045	.033	-.8891	-.0301
		2.00	.07091	.21531	.947	-.4717	.6135

Note: *The mean difference is significant at the 0.05 level.

Table 55

Descriptives for ComplexityToolsFactor

Group	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean Lower Bound	95% Confidence Interval for Mean Upper Bound	Min	Max
1.00	15	4.4533	.56804	.14667	4.1388	4.7679	2.80	5.00
2.00	8	3.9228	.52272	.18481	3.4858	4.3599	2.80	4.60
3.00	32	3.9938	.53878	.09524	3.7995	4.1880	2.40	5.00
Total	55	4.1088	.57590	.07765	3.9531	4.2645	2.40	5.00

Synthesis factor. A one-way ANOVA was run to determine if there is a difference in the Synthesis factor between men and women. Levene's test of homogeneity of variances was significant, $F(1,52) = 4.440$, $p < .05$ (see Table 56), so we reject the null hypothesis, indicating that there is a difference in the variances. The assumption of homogeneity is violated.

Table 56

Test of Homogeneity of Variances for SynthesisFactor for Gender

Levene Statistic	df1	df2	Sig.
4.440	1	52	.040

As a result, we cannot use the ANOVA. The Welch robust test of equivalence of means was not significant, $F(1, 43.815) = .300$, $p > .05$ (see Table 57), indicating that there is no difference in the Synthesis factor among the gender groups. The perceived importance of Synthesis does not vary based on gender.

Table 57

Robust Tests of Equality of Means for SynthesisFactor for Gender

Test	Statistic[a]	df1	df2	Sig.
Welch	.300	1	43.815	.586
Brown-Forsythe	.300	1	43.815	.586

Note: a. Asymptotically F distributed.

A one-way ANOVA was run to determine if there is a difference in the Synthesis factor based on process complexity. Levene's test of homogeneity of variances was not significant, $F(2,52) = .824$, $p > .05$ (see Table 58), so we fail to reject the null hypothesis, indicating that there is no difference in the variances. The assumption of homogeneity is validated.

Table 58

Test of Homogeneity of Variances for the SynthesisFactor for Process Complexity

Levene Statistic	df1	df2	Sig.
.824	2	52	.444

As a result, we can use the ANOVA. The ANOVA was not significant, $F(2) = .044$, $p > .05$ (see Table 59), indicating that there is no difference in the Synthesis factor among the process complexity groups. The importance of Synthesis does not vary between process complexity groups.

Table 59

ANOVA for the SynthesisFactor for Process Complexity

Item	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	.027	2	.014	.044	.957
Within Groups	16.173	52	.311		
Total	16.200	54			

A one-way ANOVA was run to determine if there is a difference in the Synthesis factor based on respondent age group. Levene's test of homogeneity of variances was not significant, $F(3,51) = .128$, $p > .05$ (see Table 60), so we fail to reject the null hypothesis, indicating that there is no difference in the variances. The assumption of homogeneity is validated.

Table 60

Test of Homogeneity of Variances for SynthesisFactor for Age groups

Levene Statistic	df1	df2	Sig.
.128	3	51	.943

As a result, we can use the ANOVA. The one-way ANOVA was not significant, $F(3) = .094$ $p > .05$ (see Table 61), indicating that there is no difference in the Synthesis factor among the respondent age groups. The perceived importance of Synthesis does not vary based on age.

Table 61

ANOVA for the SynthesisFactor for Age Groups

Item	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	.089	3	.030	.094	.963
Within Groups	16.111	51	.316		
Total	16.200	54			

A one-way ANOVA was run to determine if there is a difference in the Synthesis factor based on respondent decision-making tenure group. Levene's test of homogeneity of variances was not significant, $F(2,52) = 2.262$, $p > .05$ (see Table 62), so we fail to reject the null hypothesis, indicating that there is no difference in the variances. The assumption of homogeneity is validated.

Table 62

Test of Homogeneity of Variances for SynthesisFactor for Decision-making Tenure

Levene Statistic	df1	df2	Sig.
2.262	2	52	.114

As a result, we can use the ANOVA. The one-way ANOVA was significant, $F(2) = 4.175$, $p > .05$ (see Table 63), indicating that there is a difference in the BusinessOutcome among the respondent decision-making tenure groups. The perceived importance of Synthesis varies based on decision-making tenure.

Table 63

ANOVA for SynthesisFactor for Decision-making Tenure

Item	Sum of Squares	Df	Mean Square	F	Sig.
Between Groups	2.241	2	1.121	4.175	.021
Within Groups	13.959	52	.268		
Total	16.200	54			

Because the one-way ANOVA indicated a significant result, the Scheffe post hoc test is examined (see Table 64) to determine the groups among which there is a significant difference in the importance of the Synthesis factor. The difference is between groups one and two: those with fewer than 10 years found Synthesis significantly more important (m=4.4469, sd=.48608) than those with 10-12 years' experience (m=3.7917, sd=.79057; see Table 65).

Table 64

Multiple Comparisons for Dependent Variable: SynthesisFactor

Post Hoc Test	(I) decision TenureRange	(J) decision TenureRange	Mean Diff (I-J)	Std. Error	Sig.	95% Conf Interval L Bound	95% Conf Interval U Bound
Scheffe	1.00	2.00	.65527*	.22683	.021	.0837	1.2269
		3.00	.23716	.16213	.350	-.1714	.6457
	2.00	1.00	-.65527*	.22683	.021	-1.2269	-.0837
		3.00	-.41810	.20480	.135	-.9342	.0980
	3.00	1.00	-.23716	.16213	.350	-.6457	.1714
		2.00	.41810	.20480	.135	-.0980	.9342

Note: *The mean difference is significant at the 0.05 level.

Table 65

Descriptives for SynthesisFactor for Decision-making Tenure

Group	N	Mean	Std. Deviation	Std. Error	95% Conf Interval for Mean Lower Bound	95% Conf Interval for Mean Upper Bound	Min	Max
1.00	15	4.4469	.48608	.12550	4.1778	4.7161	3.67	5.00
2.00	8	3.7917	.79057	.27951	3.1307	4.4526	2.50	4.50
3.00	32	4.2098	.44995	.07954	4.0475	4.3720	3.33	5.00
Total	55	4.2136	.54773	.07386	4.0656	4.3617	2.50	5.00

ANOVA summary. The findings of the one-way ANOVA tests demonstrate, for each factor, that the importance of the factor does not vary based on the gender group of the respondent (H), the complexity of the process in which the respondent is involved (H_2), or the age group of the respondent (H_3). However, the importance of three factors did vary based on the decision-making tenure of the respondent (H_4): Synthesis, Collaboration, and Complexity Tools. The stability of the factors is still of concern when determining the meaning of the findings due to the small sample size.

Impact of dimensional groups on the collective set of constructs. MANOVA was executed to determine whether the constructs, collectively, were impacted by the various dimensional groups: age, gender, decision-making tenure, and process complexity. The validation of the assumptions and the test results are presented in the following sections.

Assumptions. The assumptions under which MANOVA is executed are that the test includes two or more dependent variables (scale) and one or more independent variables (categorical with 2 or more levels). The Observations need to be independent. The sample size needs to exceed the number of levels of the independent variable times the number of dependent variables. Although multivariate normality is desirable, if this condition is not met, Pillai's Trace is used. If the multivariate normality condition is met, use Wilk's. The test is sensitive to outliers, so multivariate outliers will be examined. There must be a linear relationship between each pair of dependent variables across each level of independent variable. This is examined by assessing the scatter dot diagram and showing an elliptical shape. Homogeneity of covariance, tested as part of the MANOVA, is also required. Finally, the dependent variables cannot be multicollinear.

There will be six scale, dependent variables and one independent variable for each execution of the test. The test will be executed once for each of age, gender, decision-making tenure, and process complexity. The observations are independent. For sample size, the independent variables have either two or three levels each and there are six dependent variables, so 18 cases would be sufficient for this analysis. There are varying numbers of cases available for this analysis (due to missing data), but in all required analysis there were more than 52 viable cases. Tests for multivariate normality have been shown previously. Test for outliers and multicollinearity, linear relationships will be shown following.

Outliers. Outliers are tested by calculating the Mahalanobis' distance across the set of variables being analyzed. The critical value in the chi-square tables for Mahalanobis' distance for six dependent variables is 22.46 (Tabachnick & Fidell, 2013). The Mahalanobis distance for the six factors being analyzed is 22.170 (see Table 66). There are no multivariate outliers.

Table 66

MANOVA Assumptions, Outliers, Residuals Statistics[a]

Item	Minimum	Maximum	Mean	SD	N
Predicted Value	3.5111	4.7048	4.2545	.21493	55
Std. Predicted Value	-3.459	2.095	.000	1.000	55
Standard Error of Predicted Value	.156	.626	.326	.102	55
Adjusted Predicted Value	3.2888	5.1383	4.2673	.28459	55
Residual	-1.45214	1.86979	.00000	.90207	55
Std. Residual	-1.518	1.954	.000	.943	55
Stud. Residual	-1.642	1.981	-.006	1.006	55
Deleted Residual	-1.79111	2.08285	-.01276	1.03078	55
Stud. Deleted Residual	-1.672	2.045	-.003	1.020	55
Mahal. Distance	.445	22.170	5.891	4.478	55
Cook's Distance	.000	.137	.021	.032	55
Centered Leverage Value	.008	.411	.109	.083	55

Linear relationships. To check for the linear relationship between the dependent variables, assess the multi-scatter plot. The general shape of the intersections between the six dependent variables should be elliptical from lower left to upper right. These patterns are generally visible in Figure 1, shown previously.

Multivariate normality. To determine multivariate normality, assess the Kurtosis and Skewness of the variables and consider the Shapiro-Wilk test of normality (used for fewer than 2000 cases). Number of cases is 55, so use Shapiro-Wilk. The Shapiro-Wilk test of normality indicates none of the factor variables is distributed normally (for each dependent variable, *p* <.05; see Table 13). However, for every factor variable, both Kurtosis and Skewness are between ±2 (see Table 14).

Multicollinearity. To test for multicollinearity, the correlations among the six dependent variables were examined. One correlation is high at .756: strategicThinking X businessKnowledgeFactor (see Table 67). The test is if the correlation is between ±.2 and ±.8 it is acceptable. Correlations below .9 are acceptable (Tabachnick & Fidell, 2013).

Table 67

EKS Factor Correlations

Factor	Row identifier	Strategic Thinking	Compl. Tools Factor	Collab. Factor	Synthesis Factor	Learning	Business Know. Factor
Strategic Thinking	Pearson Cor	1	.435**	.474**	.492**	.472**	.756**
	Sig.(2-tail)		.001	.000	.000	.000	.000
	N	55	55	55	55	55	55
Compl. Tools Factor	Pearson Cor	.435**	1	.404**	.526**	.360**	.542**
	Sig.(2-tail)	.001		.002	.000	.007	.000
	N	55	55	55	55	55	55
Collab. Factor	Pearson Cor	.474**	.404**	1	.551**	.542**	.569**
	Sig.(2-tail)	.000	.002		.000	.000	.000
	N	55	55	55	55	55	55
Synthesis Factor	Pearson Cor	.492**	.526**	.551**	1	.511**	.409**
	Sig.(2-tail)	.000	.000	.000		.000	.002
	N	55	55	55	55	55	55
Learning	Pearson Cor	.472**	.360**	.542**	.511**	1	.527**
	Sig.(2-tail)	.000	.007	.000	.000		.000
	N	55	55	55	55	55	55
Business Know. Factor	Pearson Cor	.756**	.542**	.569**	.409**	.527**	1
	Sig.(2-tail)	.000	.000	.000	.002	.000	
	N	55	55	55	55	55	55

Note: **Correlation is significant at the 0.01 level (2-tailed).

Tests. Dependent variables are the six factors extracted from the EKS variables from the survey data. Ranged values of each factor were generated to enable determination of linear relationships, however, the original version of each factor was used for the MANOVA tests. A cross-tabulation of factors to the levels of the independent variables is provided in Appendix F.

Age Range. The multivariate analysis of variance was requested for a significance level of .05, confidence intervals of 95%. Because the age ranges produced unequal group sizes (12,23,14, and 6; see Table 68) Scheffe is used for post hoc analysis. The dependent variables are BusinessKnowledge, Collaboration, ComplexityTools, Learning, StrategicThinking, and Synthesis. Table 69 shows the descriptive statistics for the dependent variables for age.

Table 68

Between-Subjects Factors, Age

AgeRange	N
3.00	12
4.00	23
5.00	14
6.00	6

Box's test is not significant, $p > .05$, validating the equality of covariances assumption (see Table 70). Levene's test (see Table 71) is not significant for any of the dependent variables, $p > .05$ for each. This indicates that there is homogeneity of variances for all the dependent variables.

Table 69

Descriptive Statistics, EKS Factors by Age

Factor	AgeRange	Mean	Std. Deviation	N
StrategicThinking	3.00	4.1785	.54463	12
	4.00	4.0870	.67676	23
	5.00	4.3393	.47644	14
	6.00	4.2917	.45871	6
	Total	4.1935	.57672	55
ComplexityToolsFactor	3.00	4.2652	.65200	12
	4.00	3.9478	.60066	23
	5.00	4.1714	.44277	14
	6.00	4.2667	.57504	6
	Total	4.1088	.57590	55
CollaborationFactor	3.00	4.3833	.50782	12
	4.00	4.0192	.66148	23
	5.00	3.9000	.70055	14
	6.00	4.5333	.45019	6
	Total	4.1244	.64727	55
SynthesisFactor	3.00	4.2083	.48265	12
	4.00	4.1775	.61286	23
	5.00	4.2381	.54973	14
	6.00	4.3056	.52086	6
	Total	4.2136	.54773	55
Learning	3.00	3.7375	.82606	12
	4.00	3.4928	.80321	23
	5.00	3.5714	.68474	14
	6.00	4.0556	.77220	6
	Total	3.6276	.77558	55
BusinessKnowledge Factor	3.00	4.1389	.57662	12
	4.00	4.0435	.57123	23
	5.00	4.0714	.68161	14
	6.00	4.1111	.72008	6
	Total	4.0788	.60166	55

Table 70

Box's Test of Equality of Covariance Matrices,[a] Age

Box's M	55.275
F	1.035
df1	42
df2	3861.193
Sig.	.410

Notes: a. Design: Intercept + AgeRange

Table 71

Levene's Test of Equality of Error Variances,[a] Age

Factor	F	df1	df2	Sig.
BusinessKnowledgeFactor	.822	3	51	.488
CollaborationFactor	.942	3	51	.427
ComplexityToolsFactor	.308	3	51	.819
Learning	.516	3	51	.673
StrategicThinking	.673	3	51	.572
SynthesisFactor	.128	3	51	.943

Notes: Tests the null hypothesis that the error variance of the dependent variable is equal across groups.

a. Design: Intercept + AgeRange

The test assumptions have been met, so Wilks' Lambda is used (see Table 72). Wilks' Lambda is not significant, p >.05, indicating no difference between the linear combinations of dependent variables based on ageRange. The partial eta squared (.128) indicates that 12.8% of the variability in the linear combination of dependent variables can be explained by age.

Table 72

Multivariate Tests,[a] Age

Effect	Test	Value	F	Hypoth. df	Error df	Sig.	Partial Eta Sq	Noncent. Parameter	Obsvd Power[d]
Intercept	Pillai's Trace	.987	562.137[b]	6.000	46.000	.000	.987	3372.822	1.000
	Wilks' Lambda	.013	562.137[b]	6.000	46.000	.000	.987	3372.822	1.000
	Hotelling's Trc	73.322	562.137[b]	6.000	46.000	.000	.987	3372.822	1.000
	Roy's Lgst Root	73.322	562.137[b]	6.000	46.000	.000	.987	3372.822	1.000
AgeRange	Pillai's Trace	.371	1.128	18.000	144.000	.331	.124	20.308	.753
	Wilks' Lambda	.663	1.136	18.000	130.593	.325	.128	19.202	.717
	Hotelling's Trc	.459	1.140	18.000	134.000	.321	.133	20.521	.755
	Roy's Lgst Root	.307	2.459[c]	6.000	48.000	.037	.235	14.754	.777

Notes: a. Design: Intercept + AgeRange

b. Exact statistic

c. The statistic is an upper bound on F that yields a lower bound on the significance level.

d. Computed using alpha = .05

Gender. The multivariate analysis of variance was requested for a significance level of .05, confidence intervals of 95%. Because the gender group sizes are unequal (39 and 15; see Table 73), Scheffe is used for post hoc analysis. The dependent variables are BusinessKnowledge, Collaboration, ComplexityTools, Learning, StrategicThinking, and Synthesis. Table 74 shows the descriptive statistics for the dependent variables with respect to Gender.

Table 73

Between-Subjects Factors, Gender

Variable	Group	N
Gender	1	39
	2	15

Table 74

Descriptive Statistics, Gender

Factor	Gender	Mean	Std. Deviation	N
StrategicThinking	1	4.1639	.65464	39
	2	4.2667	.33363	15
	Total	4.1924	.58209	54
ComplexityToolsFactor	1	4.0816	.60482	39
	2	4.2000	.51824	15
	Total	4.1145	.57973	54
CollaborationFactor	1	4.1179	.68475	39
	2	4.1628	.57802	15
	Total	4.1304	.65180	54
SynthesisFactor	1	4.1849	.61154	39
	2	4.2580	.35071	15
	Total	4.2052	.54929	54
Learning	1	3.6457	.79277	39
	2	3.5556	.77323	15
	Total	3.6207	.78116	54
BusinessKnowledgeFactor	1	4.0598	.61593	39
	2	4.1333	.60159	15
	Total	4.0802	.60721	54

Box's test is significant, $p < .05$, violating the equality of covariances assumption (see Table 75). Levene's test is significant for Strategic Thinking and for SynthesisFactor, $p < .05$ at

.006 and .040 respectively (see Table 76). The assumption of homogeneity of variances is violated.

Table 75

Box's Test of Equality of Covariance Matrices,[a] Gender

Box's M	44.104
F	1.734
df1	21
df2	2710.792
Sig.	.020

Notes: Tests the null hypothesis that the observed covariance matrices of the dependent variables are equal across groups.

a. Design: Intercept + gender

Table 76

Levene's Test of Equality of Error Variances,[a] gender

Factor	F	df1	df2	Sig.
StrategicThinking	8.048	1	52	.006
ComplexityToolsFactor	.070	1	52	.793
CollaborationFactor	.902	1	52	.347
SynthesisFactor	4.440	1	52	.040
Learning	.051	1	52	.822
BusinessKnowledgeFactor	.028	1	52	.867

Notes: Tests the null hypothesis that the error variance of the dependent variable is equal across groups.

a. Design: Intercept + gender

Because the tests of equality of variance and covariance are violated Pillai's Trace is used, rather than Wilks' Lambda. Pillai's Trace is not significant, $p > .05$ (see Table 77) at .973 indicating that there is no difference between the linear combination of dependent variables based on gender.

Table 77

Multivariate Tests,[a] Gender

Effect		Value	F	Hypoth. df	Error df	Sig.	Partial Eta Sq	Noncent. Parameter	Obsvd Power[c]
Intercept	Pillai's Trace	.986	548.205[b]	6.000	47.000	.000	.986	3289.233	1.000
	Wilks' Lambda	.014	548.205[b]	6.000	47.000	.000	.986	3289.233	1.000
	Hotelling's Trc	69.984	548.205[b]	6.000	47.000	.000	.986	3289.233	1.000
	Roy's Lgst Root	69.984	548.205[b]	6.000	47.000	.000	.986	3289.233	1.000
Gender	Pillai's Trace	.026	.206[b]	6.000	47.000	.973	.026	1.238	.098
	Wilks' Lambda	.974	.206[b]	6.000	47.000	.973	.026	1.238	.098
	Hotelling's Trc	.026	.206[b]	6.000	47.000	.973	.026	1.238	.098
	Roy's Lgst Root	.026	.206[b]	6.000	47.000	.973	.026	1.238	.098

Notes: a. Design: Intercept + gender

b. Exact statistic

c. Computed using alpha = .05

DecisionTenure. The multivariate analysis of variance was requested for a significance level of .05, confidence intervals of 95%. Because the decision-making tenure ranges are not equally sized (15, 8, and 32 respondents; see Table 78), Scheffe post hoc analysis was requested. Table 79 shows the descriptive statistics for the dependent variables.

Box's Test is not significant, *p* >.05 at .409 (see Table 80), indicating that the equality of covariances assumption is met. Levene's test is not significant, for all dependent variables, *p* >.05 (see Table 81), indicating that the homogeneity of variance assumption is met. The Wilks' Lambda test was used.

Table 78

Between-Subjects Factors, decisionTenure

Variable	Group	N
decisionTenureRange	1.00	15
	2.00	8
	3.00	32

Table 79

Descriptive Statistics, decisionTenure

Factor	decisionTenureRange	Mean	Std. Deviation	N
StrategicThinking	1.00	4.3833	.54989	15
	2.00	3.7813	.69997	8
	3.00	4.2076	.52028	32
	Total	4.1935	.57672	55
ComplexityToolsFactor	1.00	4.4533	.56804	15
	2.00	3.9228	.52272	8
	3.00	3.9938	.53878	32
	Total	4.1088	.57590	55
CollaborationFactor	1.00	4.4694	.53247	15
	2.00	3.8250	.72850	8
	3.00	4.0375	.62721	32
	Total	4.1244	.64727	55
SynthesisFactor	1.00	4.4469	.48608	15
	2.00	3.7917	.79057	8
	3.00	4.2098	.44995	32
	Total	4.2136	.54773	55
Learning	1.00	3.8345	.73082	15
	2.00	3.2917	.60257	8
	3.00	3.6146	.82135	32
	Total	3.6276	.77558	55
BusinessKnowledgeFactor	1.00	4.4000	.55205	15
	2.00	3.8750	.66518	8
	3.00	3.9792	.56757	32
	Total	4.0788	.60166	55

Table 80

Box's Test of Equality of Covariance Matrices,[a] decisionTenure

Box's M	59.516
F	1.036
df1	42
df2	1503.540
Sig.	.409

Notes: Tests the null hypothesis that the observed covariance matrices of the dependent variables are equal across groups.

a. Design: Intercept + decisionTenureRange

Table 81

Levene's Test of Equality of Error Variances,[a] decisionTenure

Factor	F	df1	df2	Sig.
StrategicThinking	.515	2	52	.601
ComplexityToolsFactor	.104	2	52	.901
CollaborationFactor	.863	2	52	.428
SynthesisFactor	2.262	2	52	.114
Learning	.375	2	52	.689
BusinessKnowledgeFactor	.312	2	52	.733

Notes: Tests the null hypothesis that the error variance of the dependent variable is equal across groups.

a. Design: Intercept + decisionTenureRange

Wilks' Lambda is not significant, p >.05 (see Table 82), indicating that there is no difference between the linear combination of dependent variables based on decisionTenure.

Table 82

Decision-making tenure Multivariate Tests,[a] decisionTenure

Effect	Test	Value	F	Hypoth. df	Error df	Sig.	Partial Eta Sq	Noncent. Parameter	Obsvd Power[d]
Intercept	Pillai's Trace	.987	605.247[b]	6.000	47.000	.000	.987	3631.480	1.000
	Wilks' Lambda	.013	605.247[b]	6.000	47.000	.000	.987	3631.480	1.000
	Hotelling's Trc	77.266	605.247[b]	6.000	47.000	.000	.987	3631.480	1.000
	Roy's Lgst Root	77.266	605.247[b]	6.000	47.000	.000	.987	3631.480	1.000
Decision Tenure Range	Pillai's Trace	.340	1.638	12.000	96.000	.094	.170	19.659	.810
	Wilks' Lambda	.688	1.610[b]	12.000	94.000	.102	.170	19.320	.800
	Hotelling's Trc	.413	1.581	12.000	92.000	.111	.171	18.978	.790
	Roy's Lgst Root	.249	1.990[c]	6.000	48.000	.086	.199	11.939	.670

Notes: a. Design: Intercept + decisionTenureRange

b. Exact statistic.

c. The statistic is an upper bound on F that yields a lower bound on the significance level.

d. Computed using alpha = .05

Process Complexity. The multivariate analysis of variance was requested for a significance level of .05, confidence intervals of 95%. Because the process complexity groups are not equally sized (8, 15, and 32 respondents; see Table 83), Scheffe post hoc analysis was requested. Table 84 shows the descriptive statistics for the dependent variables.

Table 83

Between-Subjects Factors, processComplexity

Variable	Group	N
ProcessComplexity	1	8
	2	15
	3	32

Table 84

Descriptive Statistics, processComplexity

Factor	Process Complexity	Mean	Std. Deviation	N
StrategicThinking	1	4.3125	.59387	8
	2	4.2500	.50885	15
	3	4.1373	.61184	32
	Total	4.1935	.57672	55
ComplexityToolsFactor	1	3.8750	.90672	8
	2	4.2255	.45961	15
	3	4.1125	.52533	32
	Total	4.1088	.57590	55
CollaborationFactor	1	4.0250	.79597	8
	2	4.2400	.44207	15
	3	4.0950	.69898	32
	Total	4.1244	.64727	55
SynthesisFactor	1	4.2500	.42725	8
	2	4.2333	.44006	15
	3	4.1953	.62693	32
	Total	4.2136	.54773	55
Learning	1	3.5230	.93104	8
	2	3.6889	.64816	15
	3	3.6250	.81099	32
	Total	3.6276	.77558	55
BusinessKnowledgeFactor	1	3.9583	.65314	8
	2	4.0444	.61550	15
	3	4.1250	.59719	32
	Total	4.0788	.60166	55

Box's test of equality was not significant, p >.05 (see Table 85), validating the equality of covariances assumption. However, Levene's test is significant for ComplexityToolsFactor, p

<.05 at .049 (see Table 86). This violates the homogeneity of variances for this dependent variable.

Because the test of equality of variance was violated, Pillai's Trace was used. The test is not significant, *p* >.05 (see Table 87), indicating that there is no difference in the linear combination of dependent variable based on process complexity. The partial eta squared value, .092, indicates that 9.2% of the variability in the linear combination of dependent variables is explained by process complexity.

Table 85

Box's Test of Equality of Covariance Matrices,[a] processComplexity

Box's M	75.800
F	1.320
df1	42
df2	1503.540
Sig.	.084

Notes: Tests the null hypothesis that the observed covariance matrices of the dependent variables are equal across groups.

a. Design: Intercept + processComplexity

Table 86

Levene's Test of Equality of Error Variances,[a] processComplexity

Factor	F	df1	df2	Sig.
StrategicThinking	.292	2	52	.748
ComplexityToolsFactor	3.196	2	52	.049
CollaborationFactor	2.764	2	52	.072
SynthesisFactor	.824	2	52	.444
Learning	.873	2	52	.424
BusinessKnowledgeFactor	.432	2	52	.651

Notes: Tests the null hypothesis that the error variance of the dependent variable is equal across groups.

a. Design: Intercept + processComplexity

MANOVA summary. Although there were differences found in some factors based on decision-making tenure, those differences did not impact the linear combination of those factors.

There is no difference in the importance represented by the linear combinations of dependent variables based on age, gender, decision-making Tenure, or process complexity.

Table 87

Multivariate Tests,[a] processComplexity

Effect		Value	F	Hypoth. df	Error df	Sig.	Partial Eta Sq	Noncent. Parameter	Obsvd Power[d]
Intercept	Pillai's Trace	.985	504.931[b]	6.000	47.000	.000	.985	3029.587	1.000
	Wilks' Lambda	.015	504.931[b]	6.000	47.000	.000	.985	3029.587	1.000
	Hotelling's Trc	64.459	504.931[b]	6.000	47.000	.000	.985	3029.587	1.000
	Roy's Lgst Root	64.459	504.931[b]	6.000	47.000	.000	.985	3029.587	1.000
Process Complexity	Pillai's Trace	.183	.806	12.000	96.000	.643	.092	9.675	.439
	Wilks' Lambda	.825	.791[b]	12.000	94.000	.659	.092	9.489	.429
	Hotelling's Trc	.202	.775	12.000	92.000	.674	.092	9.302	.419
	Roy's Lgst Root	.120	.962[c]	6.000	48.000	.461	.107	5.774	.342

Notes: a. Design: Intercept + processComplexity

b. Exact statistic.

c. The statistic is an upper bound on F that yields a lower bound on the significance level.

d. Computed using alpha = .05

Discussion

The prevailing themes of the qualitative interviews were influencing and collaboration skills; informal, experiential, and rotational learning; and mentoring, pattern recognition, and benchmarking knowledge. The interview participants stressed the influence of a broad range of experience in their development, as well as their exposure to a broad range of mentors and opportunities to mentor others. These things all point to the lived experiences as the most impactful for answering the question of what these decision makers perceived shaped their ability to choose performance measures for their organizations.

Among those who did not practice specific mathematical or statistical work, it was generally agreed that the undergraduate and graduate education was formational and provided the ability to learn, rather than specific knowledge or skill in choosing measures. Those who practiced in the subject area of their undergraduate education, in actuarial science, for example, had a different perspective. There were few who pursued advanced degrees other than MBAs, and in several instances, the reasons they pursued them at all was to broaden their view.

There were several topics that seemed especially important to the interview participant who raised them, but were raised by only one or, at most, two participants. Such topics were the ability to distinguish the important from the less- or unimportant, the ability to hide complexity when communicating information, and the ability to conceive and test hypotheses. These topics were interesting, because although they were raised by few participants, they were deemed highly important by the survey respondents.

The stressed interview topics which appeared in the top ten most important topics, based on the survey responses, were signalNoise (which speaks to distinguishing important information, ranked 3rd in importance), hideComplexity (ranked 7th), and hypotheses (tied for

17th). It was interesting that experiential learning, informal education and rotational training, although mentioned by many of the interview participants as important, were all ranked below 30 by the survey respondents.

When collected into the constructs indicated by the statistical analysis, the individual experience, knowledge and skill characteristics formed factors dealing with complexity tools (statistics, causal analysis, STEM skills, and benchmarking—most important), synthesis (the ability to pull together various pieces of information to make sense or meaning from them), business knowledge (the breadth of exposure discussed by the interview participants), strategic thinking (dealing with ambiguity, precision, perspective), collaboration(influence, networking, collaboration, mentoring and feedback), and learning (experiential and formal education and being part of a learning culture).

The experience, knowledge, and skill characteristics identified in the participant interviews and collectively formed into factors by statistical analysis of the survey responses map cleanly to the literature describing important knowledge and skill for individual decision making, program theory, and performance management. These relationships are outlined in the following discussion.

Individual Decision Making

The nature of decision making varies by situation (Khatri & Ng, 2000; Papenhausen, 2006; Tingling & Brydon, 2010). It is also influenced by an individual's personal characteristics, interpersonal relationships, and professional and organizational interactions, as evidenced in the qualitative findings of this study. The situation and what the decision maker brings to the table, in terms of personal, interpersonal, and organizational characteristics, define a context in which decision making happens.

Personal characteristics. There are some aspects of individual decision making that may be influenced by an individual's personal characteristics such as self-image and comfort with ambiguity. The decision maker's system of beliefs, including his or her self-image plays a part in the lens through which they view the organization (Robbins & Judge, 2011). Findings showed that having a clear self-image was considered important or very important by 76.4% respondents. This impacts their ability to frame situations for problem solving. The decision maker's comfort with ambiguity is complemented when they have a habit of reflection and an agile learning mindset within which to extend their knowledge as ambiguity is resolved over time.

Being comfortable with ambiguity, uncertainty. When making decisions about intangible concepts such as sentiment (Frisk et al., 2014; Kalantari, 2010), leaders may have to satisfice, that is, make the best decision they can with only the information available. For decision makers in highly technical fields, this comfort with ambiguity or uncertainty may be more important when dealing with decisions about bleeding edge technology (P_11), but precisely correct information may be required when dealing with administrative aspects of managing technology. Decision makers do not always have clear-cut questions, allowing for the development of specific and unambiguous measures (Basili & Weiss, 1984; Choong, 2013; Frisk et al., 2014) and the decision maker's ability to accept and use directionally correct information, augmenting with intuition and experience is essential in these ill-defined cases (P_01, P_06). 74.5% of respondents felt being comfortable with ambiguity was important or very important.

Knowing your own value/having a clear image of your own value. A decision maker's confidence in their knowledge and experience is called into play when satisficing becomes necessary. A decision maker who does not have precisely correct information from which to make decisions may need to bring other experiential knowledge into play, including knowledge of risks and how to deal with those (Schwarber, 2005). If the leader does not have confidence in their own knowledge, skill, experience—in essence, the value of their decision making, then their individual decision making skills will be impacted by the absence of complete and precise information for decision making.

Reflection and reflexivity. Having a habit of stopping to pause and reflect on what is known versus assumed, what information is needed to address a particular business decision, and who needs to be involved in the decision making process was called out as essential by more than one interview participant. The community of practice echoed the voice of the leader-decision makers, identifying these themes at a high level of importance. Reflection and the ability to apply insight gained from reflection were rated at the same level of importance. 80% of respondents felt reflection and being able to apply the insight gained from reflection was important or very important.

This perspective supports the point of view discovered in the literature, identifying the reflective practice as one that contributes to sound decision making (Schwarber, 2005; Steptoe-Warren et al., 2011; Papenhausen, 2006; Weaver, 2014). The selection of measures that enable a decision maker to determine the success of a business strategy is strengthened by a focus on strategic thinking and the habit of reflection as part of that strategic thinking.

Being an agile learner in a learning culture with active mentoring. Organizational learning is considered by many researchers to be part of a strong organizational measurement framework (Barrett et al., 2005; Kaplan & Norton, 1996; Senge, 1990), in the form of the learning feedback loop. In order for an organization to learn, the organization's individual members require a growth mindset and a continual learning behavior. Being an agile learner enables such organizational learning. Several of the interview participants discussed the notion of their ability to learn eclipsing the subject matter they had studied in formal education. Their mindsets were essential to their success in identifying the right measures to manage their organizational responsibilities: in continually hearing and considering new information, determining how it fit or did not fit in their existing frameworks, and then incorporating the new information into their decision making models. 61.8% of respondents felt that having an agile learning mindset was important or very important, while 69% considered mentoring important or very important.

Mentors and mentoring, and teaching skills. Part of learning is the importance of engaging in professional networks, which may include having mentors and mentoring others. 38% of respondents ranked teaching skills as important or very important to learning to choose organizational measures. The collaboration within professional networks and interactions with mentors can help the emerging leader learn how to determine when a decision is ‘good enough’ (Kalantari, 2010; Schwarber, 2005). Such a mentor typically has rich, relevant knowledge to share (Khatri & Ng, 2000; Papenhausen, 2006; Simon et al., 2011; Weaver, 2014). The complementary side of having a mentor is, in time, becoming a mentor to emerging leaders. Such mentoring may be seen to go hand-in-hand with teaching skills, which both involve one’s ability to share knowledge effectively, whether passing on the practice or sharing understanding of measures developed by the practice. Mentors, mentoring, and teaching skills, while rated as ‘important’ by the average score in the survey, were low in comparison to the experience, knowledge, and skill considered important to actually identify and use performance measures. It may be that the careful propagation of the knowledge required for the practice is negatively impacted by this relative unimportance.

Interpersonal characteristics. The interpersonal characteristics that may impact a person's individual decision making include their collaboration and influencing skills, interviewing and observational skills, as well as being able to ask the right questions to get the information they need for decision making. Having an agile learning focus and a growth mindset will also impact how they investigate and collect the information necessary for decision making.

Consulting, collaboration, and influencing. When making decisions, good decision makers collaborate to get the information they lack, to reinforce or corroborate information from other sources, or to validate their own knowledge (Schwarber, 2005; Steptoe-Warren et al., 2011). This collaboration may impact how the decision maker frames the problem (Franklin, 2013), thereby potentially changing the approach to making the decision. The importance of these skills was echoed by the survey analysis, which ranked these skills in the top third in terms of their importance in the development of a decision maker. These skills were, on average, among the more important of the skills considered by the survey respondents. 81.8% found collaboration and influencing skills important or very important and 85.5% rated consulting skills similarly. This may balance the relative unimportance of the mentoring, mentors, and teaching skills, if the emerging decision makers are able to participate in the consulting and collaborative activities and see those skills modeled by their more experienced leaders.

In business, strategies are often collaboratively developed. This enables the strategy owners to frame their business problems, identify issues and search for the right information to form a solution. Collaboration ranked high among the skills identified by the interview participants of this study and survey respondents, supporting the development of the leader's collaborative skills as an important part of learning to choose organizational performance measures needed to provide information for decision making.

Interviewing and observation skills and knowing the right questions to ask. Chief among the interviewing and observation skills called out by interview participants was the ability to ask good questions and to listen effectively to the answers. Richness of experiences among the decision makers was an important factor in strong decision making based on the literature review (Khatri & Ng, 2000; Papenhausen, 2006; Simon et al., 2011; Weaver, 2014). The study participants felt that it was not only their own rich experience, but that their ability to recognize and leverage the rich experiences of others also contributed to effective decision making. This was echoed by the 90.9% of survey respondents who rated interviewing and observation skills as important or very important.

Professional and organizational interaction. In addition to personal and interpersonal characteristics, the characteristics that describe an individual's interactions with the wider organization are also interesting to explain how they learned to identify performance measures.

Having strong personal networks among professional colleagues. Organizational experiences, including developing strong personal networks, were mentioned by several interview participants (P_04, P_09, P_11). These networks constitute, in part, the resources these decision makers call on for collaboration in their decision making. Another participant discussed the importance of one's personal brand—the essential value one is known for among one's personal network (P_04). Establishing a reputation as a reliable decision maker, for example, is valuable in being included in collaborations which impact interactions among business areas, for end-to-end process measures. Only 58.1% of survey respondents rated this characteristic as important or very important.

Access to a broad range of data and project assignments, including strategic level projects, early in one's career. For a future decision maker, seeking out job positions which afford a high degree of access to a broad range of data over a broad range of business areas is considered a strong contributor to learning about what matters in the organization. Forming this understanding of what is important is the theme across both access to a broad range of data as well as the wide variety of project assignments. It is not just about what the organization knows, but about how the organization uses that information that makes this type of experience invaluable to the emerging decision maker. This was considered important by five of the interview participants and important or very important by 63.6% (projects), 40% (broad data), and 49% (strategic-level projects) of survey respondents. The survey respondents were, in general, less experienced than the interview participants. This supports the perspective from literature that good decision makers have richer experience in their backgrounds (Khatri & Ng, 2000; Papenhausen, 2006; Simon et al., 2011; Weaver, 2014).

The overarching message from the interview participants about the personal characteristics necessary to identify and use organizational performance measures was that the individual's dedication to using good information, in as complete a form as possible, was essential. This was echoed in the importance assigned to the characteristics by the practitioners in the survey responses. This completeness and quality could be assured by personal agile learning tendencies; by purposely seeking out a rich variety of data, project, and work experiences; and by collaborating with others who have knowledge that one lacks. These perspectives were consistent with the literature on individual decision making. With these sound practices and experiences, a decision maker can also apply program theory to the task of identifying and choosing effective organizational performance measures.

Program Theory (PT)

The logic model from program theory is the second primary building block in identifying organizational performance measures (Monroe et al., 2005; Rossi et al., 2004). Program theory describes what is delivered by a program, who is impacted, the desired outcomes, assumptions about resources and activities, and how these are expected to lead to the desired outcomes (Brousselle & Champagne, 2011; McLaughlin & Jordan, 2010; Rogers et al., 2000). The decision maker's way of thinking is an important capability in developing or using models of program theory. Ways of thinking for the interview participants were formed and tuned in both formal and informal education.

Skills learned in formal and informal education. All of the participants had bachelor's-level formal education and most had master's-level formal education. Only one had doctoral level experience. Many of the participants had content-focused informal education, like Six Sigma Black Belt training or various insurance or investment certifications. The general consensus among the participants was that their way of thinking was the greatest benefit most received from their formal education. Those who had more extensive science, technology, engineering and math (STEM) background expressed the viewpoint that the analytical ways of thinking inherent in those disciplines were particularly beneficial to the understanding of measures and their proper usage. 50% of survey respondents found formal education important or very important in learning to choose organizational measures. The ratings were higher for informal education, with 81.8% rated as important or very important.

Understanding causal relationships in program theory. Three areas of interest from the interviews impact this aspect of program theory: causal analysis, process thinking, and structured system thinking. Several of the interview participants focused strongly on the idea that system thinking was essential in identifying good performance measures. They stressed the idea that one must be able to look at an organization end-to-end, understanding how it interacts with other organizations and how its feedback loops work. One participant talked of causal analysis as a way to test measures that have been put in place to determine whether they are actually significant in the outcomes being measured. 96.3% of survey respondents felt understanding causal relationships was important or very important.

Another participant, along with the first, talked of measuring intangibles like creativity and innovation. These participants speculated about using causal analysis to determine whether a proxy measure, something focused on a *sign* that creativity or innovation is happening, rather than the creativity itself, might be useful. Creativity and innovation were considered important or very important by 69% of survey respondents. This stands to reason, as creativity and innovation are essential in formulating ideas about what to build or what to do, but the process engineering community is focused on how to do those things. Creativity is important in that environment, but in different ways.

Process and systems thinking were two ideas that were discussed by many, if not all the interview participants in one form or another. Process thinking was considered important or very important by 92.7% of survey respondents, while systems thinking was rated so by only 67.2%. This also stands to reason, as the focus of the population being surveyed is process engineering. These interrelated ways of thinking deal with not only the linear execution of activities from a pre-defined start to finish, but also of the layers of disciplines involved, including the people who conduct the activities, the technology they use, and the information they consume and produce. This flows into the concepts of program theory, identifying the situation in which the program operates, the actions we take, as well as identifying the people impacted by the actions (some the actors, some the subjects, and some impacted peripherally). Although the information consumed and produced is not explicitly mentioned in the logic model of program theory, the outcomes suggest possible focal points for development of measures—which require input data, business rules defining the measures, and the output measure. These implied information requirements form the connection point to the next building block, performance measurement frameworks.

Performance Measurement (PM) and Performance Measurement Frameworks

Performance measurement systems include such models as the balanced scorecard (BSC) and the goal, question, metric (GQM) approach. In this discussion, three major factors are considered: first, what does the decision maker know and how do they use that knowledge? Second, what experience does the decision maker have? And third, what techniques does the decision maker use?

Critical skills and knowledge for measuring. There were some broad categories of knowledge and skill identified by the interview participants as they considered how they learned to choose organizational measures. Being able to package information suited to the intended audience is considered essential. Part of being able to identify what is important lies in understanding statistical significance in measures and then being able to express the business significance effectively.

Identifying what is important at the right level of precision, while hiding unneeded complexity. filter signal from noise, that is, the important from the unimportant, was considered an essential skill. The interview participants acknowledged that experience was generally required to do so—being told about such distinctions was not enough. Interacting with more experienced decision makers and understanding their objectives was identified as an important part of this experience. The GQM allows the practitioner to distinguish the important things in a structured approach (Boyd, 2005). 92.7% of survey respondents agreed that understanding how to hide complexity and express ideas simply was important or very important, with 74.5% rating the ability to express information at the right level of precision similarly. While developing the ability to distinguish the essential from the other information, a person would, ideally, also develop the parallel abilities to hide much of the detailed complexity and to present findings simply.

The ability to flex between levels of precision is also likely to be influenced by the recognition of the important or essential at the level at which decisions need to be made. Part of the criteria for identifying the important information is to understand the relationships between the measures and the organizational objectives. This supports the findings in existing research (Humphreys & Trotman, 2011; Kaplan & Norton, 1996; Kasperskaya & Tayles, 2013; Morard et al., 2012; Olsson & Runeson, 2001; Theriou et al., 2004; Wongrassamee et al., 2003; Wu, 2005).

Statistical significance and business significance. Once measures are identified and data collection and analysis enabled, testing for the statistical significance of the measures may lend insight into which measures provide meaningful information to enable decision makers to improve the performance of the organization. Measures that are not statistically relevant to the outcomes they are thought to measure may be eliminated and work reduced, data storage and processing time recovered, and time and attention turned to measures which are truly effective in aiding the management of the organization. 76.3% of survey respondents rated the importance of understanding statistics and statistical significance as important or very important.

Unfortunately, decision makers may assume causality, when it may not exist (Akkermans & van Oorschot, 2005). The perspective of the interview participants supports findings in literature regarding the assumptions made about causality in performance measurement systems.

At the same time, it acknowledges those assumptions and seeks to verify or correct the use of measures which do not, in fact, point to the desired outcomes.

An additional aspect of complexity in the conversation about statistical significance and causality involves organizational complexity. There are challenges in determining the right measures to use and effective ways to filter those measures when dealing with complex organizations. One example of this concern is when measures cross organizational areas, but are devised under inconsistent ways of naming, collecting, recording metadata for, and reporting the measures. This presents a particularly challenging case for the development of the performance measurement framework (Mendonça et al., 1998).

Critical experience and the motivation to measure. There is a difference between knowing about something and knowing how to do something, or being something. Knowing about performance measures and being able to choose them effectively are related, but distinct. One is knowledge and the other skill. Being accountable for measures impacts a decision maker in ways that participating as a practitioner in developing measures does not. Being able to formulate hypotheses and test them is another way in which the practitioner can begin to transition from knowing about performance measurement to being skilled in performance measurement. Knowledge that contributes to the ability to formulate hypotheses concerns recognizing existing patterns of behavior and measurement schemes as well as benchmarking.

Being accountable for the measures. Determining the measures required to describe the success of a particular process or business area was described as a skill for which decision makers may not have a frame of reference, the motivation, or the span of control to do effectively until they are in the position of being accountable for the business area or process—and thereby the supporting measures. These participants perceived the scope of the ‘big picture’ necessary for management of the business area to be one which required actual experience to understand. It could be talked about in formal education, discussed in work experience, but it had to be lived to grow into the full, necessary understanding.

There was no discussion in the literature I reviewed that supported the concerns expressed by these interview participants about the difficulty of being able to see the entirety of the big picture they required. In addition to the ability to see the big picture completely, the decision maker requires the ability to formulate hypotheses about how the components of that picture interact. Echoing this, 80% of survey respondents considered experience being accountable for delivering measures as an important or very important aspect of learning to choose organizational performance measures.

Forming and testing hypotheses to explain outcomes. Participants expected to be able to see the big picture, formulate hypotheses to explain its functional interactions, and then to test those interactions to determine whether the overall objectives of the endeavor were being achieved. 76.3% of survey respondents felt the ability to formulate and test hypotheses was important or very important. One of the issues with devising performance measurements systems to produce such insight is that decision makers may not be able to articulate their goals or objectives with sufficient clarity to identify the measures they need (Boyd, 2005; Markovic & Kowalkiewicz, 2008). By using such tools as the logic model of program theory described above, decision makers may apply a step-wise, structured analytic approach to articulating their objectives. The clear line of sight illustrated in the logic model between what the organization does, who it impacts, and the outcomes it is trying to drive will inform the hypotheses that the decision maker may use to determine the usefulness of the selected measures.

Recognizing and using patterns, as well as using industry and internal benchmarking, effectively. The process complexity may be assessed using the patterns detected in their construction (Cheng & Prabhu, 2008; Schäfermeyer et al., 2012). The patterns visible in trends and the similarity or divergence from examples such as benchmark measures provide insight for the seasoned decision maker that may not be available or understood by the emerging decision maker (Weaver, 2014). 78.2% of survey respondents felt pattern recognition was an important or very important aspect of learning to choose measures. 74.5% considered knowledge of benchmarking similarly. Understanding the patterns present in a process may aid the decision maker in the selection of measures that are more likely to be useful for processes of particular complexity. The value of the measures lies not only in their selection, but in learning how to read the behavior of those measures over time.

Critical techniques when designing and measuring. There were several techniques identified in the interviews that were supported by the survey responses as being important to learning to choose organizational performance measures. The ability to consider unexpected consequences—indeed, the awareness that such things need to be considered—is important. The ability to look at the measure design from another person or business area’s point of view is an integral part of being able to anticipate the consequences of putting measures in place. Then, with the interactions of various processes, business areas, and individuals in place, considering the consequences of putting measures into production, the manner in which those measures are presented to the organization is important.

Unexpected consequences. Being able to predict unexpected consequences of measuring and being able to control for gaming behavior when designing metrics are necessary for the identification and design of good performance measures. Even careful implementation of measures and measuring poses potential risk, as measuring may have unforeseen and undesirable consequences (Deem et al., 2010). Measuring in business area may drive undesirable behaviors in other areas which have unaligned or competing objectives (Azevedo, Carvalho, & Cruz-Machado, 2013; Courty & Marschke, 2003; Richard, Devinney, Yip & Johnson, 2009). This characteristic was not considered important by the majority of survey respondents. 54.5% considered it moderately important or less. This is consistent with the finding that process thinking is considered more important than systems thinking. Looking at consequences of measurement is an outcome, which would be of high interest to systems thinkers, but not to process thinkers due to the focus of their practice.

Interview participants recognized the need to have a broad view of the business, facilitating their ability to see such competing objectives and minimize the possibility of driving such undesirable consequences. Anticipating consequences involves ideating on ways to prevent or mitigate undesirable behaviors that may ensue. Undesirable behaviors, such as gaming may cause programs to fail without business leaders understanding why (Monroe et al., 2005). Important factors of that view are the decision maker’s willingness and ability to consider the perspectives of the other business areas.

Being able/willing to see the other's point of view. Seeing the importance of the objectives of those in other related business areas may require a decision maker to make a concerted effort to understand the point of view of the decision makers and others in that business area (P_02, P_04). The questioning and listening skills discussed above will be leveraged in order to understand the point of view of the other area, as well as the ability to give effective feedback on what has been discussed. This collaborative work is likely to be an essential part of developing sound, company-wide performance measurement frameworks composed of effective, integrated measures. 90.9% of the survey respondents rated this characteristic as important or very important.

Creativity, storytelling/innovation and understanding ethical presentation of measures. While creativity and storytelling are necessary pieces of communicating the insight provided by measures, there is a balancing ethic in how those measures are presented. The insight derived from measures is not always intuitively obvious. Often, decision makers must study the measures and determine the insight that is concealed within them. As this is a matter of judgment and ingenuity, there is also the possibility of bias or errors in interpretation. Is incumbent on those who measure, derive insight, and report on outcomes to ensure ethical presentation of the information which influences the direction of the organization based on the measures (APA, 2009). 85.5% of survey respondents agreed that this was important or very important. One example of deficiency in this area is the common measures bias, which may result in diminished decision-making quality (Humphreys & Trotman, 2011).

Factors

As presented in the findings, the factors discovered using principal component analysis must be considered with prejudice based on the very poor sample size (55), the number of variables (50), and the presence multicollinearity among the variables (clearly present, but not completely quantified). Although the multicollinearity was not visible in the correlation matrices, it was visible in regression testing and it prevented factors from being extracted from the EKS set as a whole, and from the measures set as a whole. Two variables (master’s and post-graduate education) were found to be redundant to the formalEducation variable. Depending on the focus of the inquiry, whether the understanding of the levels of formal education are of most interest, either formalEducation or the two others might be removed for better results.

There is insight to be gained to direct future research in this space, so the following is offered for consideration as the basis for more suitable study conditions. The consistency in the findings of the importance of the factors among gender groups, age groups, process complexity groups, and decision-making tenure provides an encouraging basis on which to conduct further research.

Experience, knowledge, and skill factors. The factors extracted from experience, knowledge and skill variables were named *Business Knowledge*, *Collaboration*, *Complexity Tools*, *Learning*, *Strategic Thinking*, and *Synthesis*. Business Knowledge concerns the practitioners' breadth of business knowledge, project experience, and consulting skill. It points to their ability to recognize and understand what is happening in the organization based on broad experience and ability to interact effectively.

The collaboration factor is composed of items dealing with interactions among the various players involved with performance measures—those identifying requirements, practitioners developing processes and ways to measure them, and those using measures to accomplish their business purpose. Complexity tools are the skills and techniques a practitioner requires to deal with complexity: first, awareness and perspective, then analysis, and then meaning making. The learning factor is composed of the practitioner's preference for experiential learning, having a formal learning foundation, and being an active part of a learning culture. It represents a fertile ground for individual and, collectively, organizational learning.

The strategic thinking factor describes the importance of a practitioner's breadth of experience and span of awareness across the organization as well as their ability to distinguish what is important and to clearly articulate vision. And finally, the synthesis factor deals with the knowledge and skill necessary to consume, analyze, synthesize measures in their precise, detailed form, and, based on knowledge of the audience, package that synthesized understanding in a way that speaks truly to it. These four factors represent the composition of experience, knowledge, and skill initially revealed through qualitative interviews and then supported in quantitative analysis.

Measure factors. The factors extracted from the measure variables were named *Business Outcomes, Measure Usage, Measure Context, Usability,* and *Execution*. Of these, the execution factor was perceived as most important based on the survey responses. This factor is composed of items (measuring the right things, repeatable results, and auditable processes and numbers) that deal with the production of the numbers actually delivered to the decision makers, indicating that it is not in the understanding of the measure, but in the delivery and application that the value may be realized. Usability was the next, most important factor, indicating that measures need to be actionable, simple, achievable, and have meaning that can be clearly understood by the consumers.

The business outcomes factor deals with the ways in which a measure or collection of measures drive behavior and influence outcomes that constitute business value. Understanding the behaviors that the measure assesses and drives, whether the overall business outcomes are achieved, balanced against a clear understanding of the value of those outcomes is important in this factor. Finally, it was acknowledged that an understanding is needed of how to deal with related measures which sometimes compete for attention and periodization when funding questions arise.

Measure context and usage provide information about the ties between the information impacted by the measure and the questions that can be answered by the measure to say whether an outcome has been achieved versus why it was or was not achieved (Basili & Weiss, 1984;

Becker & Bostelman, 1999; Boyd, 2005; Humphreys & Trotman, 2011). Usage addresses the ways in which a measure can be used in a healthy way with respect to achieving the organization's objectives. Although these measures were deemed less important than the execution and usability measures, they were still identified as important.

Tools to handle complexity were perceived as the most important of the experience, knowledge, and skill characteristics, followed by those EKS characteristics needed for synthesis. business knowledge, general as well as industry-specific, and strategic thinking abilities were also rated as very important. The practitioner's ability to collaborate effectively and participate in a learning culture were considered important. Business knowledge is directly applicable in decision making. It enables the identification of options and allows the practitioner to see possible consequences of the choices they make, based on their past experiences. The complexity tools factor, including benchmarking, statistics, causal analysis, and other STEM skills, contributes to the practitioner's ability to test and learn in order to make better decisions. These complexity tools allow the practitioner to execute this learning in modeling environments first, minimizing the impact to the organization, before applying successful models in the workplace.

Strategic thinking and synthesis allow the practitioner to distinguish between situations in which intuition versus data-driven decisions should be used. The learning factor includes aspects of belonging to a learning culture. This implies sharing knowledge to the organization as well as gaining knowledge from the organization. This communication and interaction is necessary for healthy decision making (Humphreys & Trotman, 2011; Kaplan & Norton, 1996; Kasperskaya & Tayles, 2013; Morard et al., 2012; Olsson & Runeson, 2011; Theriou et al., 2004; Wongrassamee et al., 2003; Wu, 2005). Strategic thinking and synthesis is also enable practitioners to develop and leverage skill in program theory. making connections and understanding consequences of actions and ensuring those actions drive the desired outcomes is inherent in developing program theory (Brousselle & Champagne, 2011; McLaughlin & Jordan, 2010; Rey et al., 2012; Rogers et al., 2000).

Limitations

The insight gained through the qualitative portion of the study is presented as a basis for understanding the characteristics of experience, knowledge, and skill that 11 senior decision makers in the company felt influenced their development in choosing organizational performance measures. In that respect the basic answer to the research question is answered. The quantitative portion of the study provided insight into the alignment of the practitioner community with respect to the leadership. There are limitations in the application of the quantitative findings of the study. As has been presented with transparency throughout the discussion, although they provide insight, the results of the quantitative portion of the study cannot be generalized due to the small sample size (de Winter et al., 2009; Tabachnick & Fidell, 2013). The number of items in the survey questionnaire introduced a multicollinearity problem with the data during PCA. The researcher has explained in careful detail the measures that were taken to minimize the risk in presenting these findings, with the expectation that the foundation that has been established will add to the body of knowledge and enable further development in this space.

Recommendations for Future Research

Future research is recommended

(1) To pursue the regression analysis for the candidate sets (see Table 1). This, in addition to other analysis of the current study data is recommended to cull out the

variables which constituted multicollinearity in this study, confounding the extraction of factors.

(2) To explore the conditions under which de Winter, Dodou, and Wieringa (2009) discovered sample sizes less than 50 can yield sound results is also recommended.

(3) Finally, to replicate this study, perhaps among a professional community of process engineering professionals, to achieve the conventionally desired samples sizes for factor analysis.

Conclusion

Qualitative interviews with eleven organizational decision makers yielded a rich body of experience, knowledge, and skills that contribute to the decision makers' learning to choose performance measures in the organization. A cross-sectional survey of process engineering professionals in the organization illuminated those areas deemed of most importance to the practitioners largely responsible for identifying and implementing performance measures for process execution. Most of the tests showed that the importance of the constructs did not vary across the age, gender, and process complexity dimensions. The exceptions were in the decision-making experience dimension with respect to the collaboration, complexity tools, and synthesis constructs. Practitioners with less experience found these constructs significantly more important, indicating perhaps, a greater need for emerging decision makers to have solid guardrails and guidance as they hone their decision making over time.

References

Akkermans, H. A., & van Oorschot, K. E. (2005). Relevance assumed: A case study of balanced scorecard development using system dynamics. *Journal of the Operational Research Society, 56*(8), 931–941. doi:http://dx.doi.org/10.1057/palgrave.jors.2601923

American Educational Research Association (AERA). (2006). Standards for reporting on empirical social science research in AERA publications. *Educational Researcher, 35*(6), 33–40.

American Psychological Association, (2009). *Publication manual of the American Psychological Association* (6th ed.). Washington, DC: Author.

American Productivity & Quality Center (APQC). (2015). *Process Classification Framework.* Retrieved from https://www.apqc.org/

Azevedo, S., Carvalho, H., & Cruz-Machado, V. (2013). Using interpretive structural modeling to identify and rank performance measures. *Baltic Journal of Management, 8*(2), 208–230. doi:10.1108/17465261311310027

Baba, V. V., & HakemZadeh, F. (2012). Toward a theory of evidence based decision making. *Management Decision, 50*(5), 832–867. doi:http://dx.doi.org/10.1108/00251741211227546

Basili, V. R., & Weiss, D. M. (1984). A methodology for collecting valid software engineering data. *IEEE Transactions on Software Engineering, SE-10*(6), 728–738. doi:http://dx.doi.org/10.1109/TSE.1984.5010301

Basit, T. N. (2003). Manual or electronic? The role of coding in qualitative data analysis. *Educational Research, 45*(2), 143–154. doi:10.1080/0013188032000133548

Bazett, M., Bowde, I., Love, J., Street, R., & Wilson, H. (2005). Measuring multichannel effectiveness using the balanced scorecard. *Interactive Marketing, 6*(3), 224–231. doi:http://dx.doi.org/10.1057/palgrave.im.4340289

Becker, S. A., & Bostelman, M. L. (1999). Aligning strategic and project measurement systems. *IEEE Software, 16*(3), 46–51. doi:http://dx.doi.org/10.1109/52.765786

Behn, R. D. (2003). Why measure performance? Different purposes require different measures. *Public Administration Review, 63*(5), 586–606. doi:http://dx.doi.org/10.1111/1540-6210.00322

Benaquisto, L. (2008). Coding frame. In L. M. Given, (Ed.), *The Sage Encyclopedia of Qualitative Research Methods* (pp. 88–89). Thousand Oaks, CA: Sage.

Bhatti, A. M., Abdullah, H. M. & Gencel, C. (2009). A model for selecting an optimum set of measures in software organizations. *EuroSPI 2009, CCIS 42*, 44–56. doi:http://dx.doi.org/10.1007/978-3-642-04133-4_4

Boyd, A. J. (2005). The evolution of goal-based information modelling: Literature review. *Aslib Proceedings, 57*(6), 523–538. doi:http://dx.doi.org/10.1108/00012530510634253

Briand, L. C., Morasca, S., Basili, V. R. (2002). An operational process for goal-driven definition of measures. *IEEE Transactions on Software Engineering*, *28*(12), 1106–1125. doi:http://dx.doi.org/10.1109/TSE.2002.1158285

Brinkmann, S., & Kvale, S. (2015). *InterViews: Learning the craft of qualitative research interviewing* (3rd ed.). Thousand Oaks, CA: SAGE Publications Inc.

Brousselle, A., & Champagne, F. (2011). Program theory evaluation: Logic analysis. *Evaluation and Program Planning, 34*, 69–78. doi:http://dx.doi.org/10.1016/j.evalprogplan.2010.04.001

Buytendijk, F. A. (2007). Challenging conventional wisdom related to defining business metrics: A behavioral approach. *Measuring Business Excellence*, *11*(1), 20–26. doi:http://dx.doi.org/10.1108/13683040710740899

Cabantous, L., & Gond, J. (2011). Rational decision making as performative praxis: Explaining rationality's éternel retour, *Organization Science, 22*(3), 573–586. doi:10.1287/orsc/1100.0534

Cameron, R. (2011). Mixed methods research: The 5Ps framework. *The Electronic Journal of Business Research Methods, 9*(2), 96–108.

Cardoso, J. (2008) Business process control-flow complexity: Metric, evaluation, and validation. *International Journal of Web Services Research, 5*(2), 49–76. doi:http://dx.doi.org/10.4018/jwsr.2008040103

Chaleff, I. (2009). *The courageous follower: Standing up to and for our leaders* (3rd. ed.). San Francisco, CA: Berrett-Koehler.

Cheng, C. Y., & Prabhu, V. (2008). Complexity model for business process analysis. *Proceedings of the 2008 Industrial Engineering Research Conference*.

Choong, K. K. (2013). Understanding the features of performance measurement system: a literature review. *Measuring Business Excellence*, *17*(4), 102–121. doi:10.1108/MBE-05-2012-0031

Courty, P., & Marschke, G. (2003). Dynamics of performance-measurement systems. *Oxford Review of Economy Policy, 19*(2), 268–284. doi:http://dx.doi.org/10.1093/oxrep/19.2.268

Creswell, J. W. (2012). Educational research: Planning conducting and evaluating quantitative and qualitative research (4th ed.). Boston, MA: Pearson Education.

Creswell, J. W. (2014). *Research design: Qualitative, quantitative, and mixed methods approaches*. Thousand Oaks, CA: Sage.

Davis, M. (2003). Professional responsibility: Just following the rules? In J. Rowan & S. Zinach, Jr. (Eds.), *Ethics for the professions* (pp. 62–69). Belmont, CA: Cengage Learning.

De Winter, J. C. F., Dodou, D., & Wieringa, P. A. (2009). Exploratory factor analysis with small sample sizes. *Multivariate Behavioral Research, 44*, 147–181. http://dx.doi.org/10.1080/00273170902794206

Deem, J. W., Barnes, B., Segal, S., & Preziosi, R. (2010). The relationship of organizational culture to balanced scorecard. *SAM Advanced Management Journal, 75*(4), 31–39.

Franceschini, F., Galetto, M., Turina, E. (2013). Techniques for impact evaluation of performance measurement systems. *International Journal of Quality & Reliability Management, 30*(2), 197–220. doi:10.1108/02656711311293599

Franklin, C. L. (2013). Developing expertise in management decision-making. *Academy of Strategic Management Journal, 12*(1), 21–37.

Frisk, J. E., Lindgren, R., & Mathiassen, L. (2014). Design matters for decision makers: Discovering IT investment alternatives. *European Journal of Information Systems, 23*, 442–461. doi:10.1057/ejis.2013.13

Gencel, C., Petersen, K., Mughal, A. A., & Iqbal, M. I. (2013). A decision support framework for metrics selection in goal-based measurement programs: GQM-DSFMS. *Journal of Systems and Software*, *86*(12), 3091–3108. doi:10.1016/j.jss.2013.07.022

Halachmi, A. (2011). Imagined promises versus real challenges to public performance management. *International Journal of Productivity and Performance Management, 60*(1), 24–40. doi:10.1108/17410401111094295

Hammer, M. (2007) The 7 deadly sins of performance measurement [and how to avoid them]. *MIT Sloan Management Review, Spring*, 19–28.

Hanson, J. D., Mclnyk, S. A., & Calantone, R. A. (2011). Defining and measuring alignment in performance management. *International Journal of Operations & Production Management, 31*(10), 1089–1114. doi:10.1108/01443571111172444

Hedge, J. W., & Teachout, M. S. (2000). Exploring the concept of acceptability as a criterion for evaluating performance measures. *Group & Organization Management*, *25*(1), 22–44. Doi:http://dx.doi.org/10.1177/1059601100251003

Humphreys, K. A., & Trotman, K. T (2011). The balanced scorecard: The effect of strategy information on performance evaluation judgments. *Journal of Management Accounting Research, 23,* 81–98. doi:http://dx.doi.org/10.2308/jmar-10085

Jääskeläinen, A., & Laihonen, H. (2013). Overcoming the specific performance measurement challenges of knowledge-intensive organizations. *International Journal of Productivity and Performance Management, 62*(4), 350–363. doi:http://dx.doi.org/10.1108/17410401311329607

Kalantari, B. (2010). Herbert A. Simon on making decisions: Enduring insights and bounded rationality. *Journal of Management History, 16*(4), 509–520. doi:10.1108/17511341011073988

Kaplan, R. S., & Norton, D. P. (1996). Using the balanced scorecard as a strategic management System. *Harvard Business Review, 74*(1), 75–85.

Kasperskaya, Y., & Tayles, M. (2013). The role of causal links in performance measurement models. *Managerial Auditing Journal, 28*(5), 426–443. doi:10.1108/02686901311327209

Khatri, N. & Ng, H. A. (2000). The role of intuition in strategic decision making. Human Relations, 53(1), 57–86. doi:http://dx.doi.org/10.1177/0018726700531004

Laue, R., & Gruhn, V. (2006). "Complexity metrics for business process models," *9th International Conference on Business Information Systems*, Klagenfurt, Austria, 1–12.

Lengacher, D. (2009). Challenges in measuring organizational performance. *Business Intelligence Journal, 14*(3), 18–26.

Lichtman, M. (2013). *Qualitative research in education: A user's guide* (3rd ed.). London, United Kingdom: Sage.

Mandi, V., & Basili, V. (2010). An approach for evaluating business goals. *Tech Report: TR_TOL_2010-2802*. Retrieved from https://www.cs.umd.edu/users/basili/publications/technical/T142.pdf

Markovic, I., & Kowalkiewicz, M. (2008). Linking Business Goals to Process Models in Semantic Business Process Modeling. *12th International IEEE Enterprise Distributed Object Computing Conference*. doi:10.1109/EDOC.2008.43

Mashiko, Y., & Basili, V. R. (1997). Using the GQM paradigm to investigate influential factors for software process improvement. *Journal of Systems Software, 36,* 17–32. doi:http://dx.doi.org/10.1016/0164-1212(95)00194-8

Matzler, K., Bailom, F., & Mooradian, T. A. (2007). Intuitive decision making. *MIT Sloan Management Review, 49*(1), 13–15. Retrieved from http://uiwtx.idm.oclc.org/login?url=http://search.proquest.com.uiwtx.idm.oclc.org/docview/224960930?accountid=7139

McLaughlin, J. A., & Jordan, G. B. (2010). Using Logic Models, In J. S. Wholey, H. P. Hatry, K. E. Newcomer (Eds.), *Handbook of Practical Program Evaluation* (pp. 55–80). San Francisco, CA: Jossey-Bass. doi:http://dx.doi.org/10.1002/9781119171386.ch3

Mendonça, M. G., & Basili, V. R. (2000). Validation of an approach for improving existing measurement frameworks. *IEEE Transactions on Software Engineering, 26*(6), 484–499. doi:http://dx.doi.org/10.1109/32.852739

Mendonça, M. G., Basili, V. R., Bhandari, I. S., & Dawson, J. (1998). An approach to improving existing measurement frameworks. *IBM Systems Journal, 37*(4), 484–501. doi:http://dx.doi.org/10.1147/sj.374.0484

Merriam, S. B., Caffarella, R. S., & Baumgartner, L. M. (2007). *Learning in Adulthood, A Comprehensive Guide* (3rd ed.). San Francisco, CA: Jossey-Bass.

Miles, M. B., Huberman, A. M., & Saldaña, J. (2014). *Qualitative data analysis: A methods sourcebook* (3rd ed.). Thousand Oaks, CA: Sage.

Monroe, M. C., Fleming, M. L., Bowman, R. A., Zimmer, J. F., Marcinkowski, T., Washburn, J., & Mitchell, N. J. (2005). Evaluators as educators: Articulating program theory and building evaluation capacity. *New Directions for Evaluation, 108*, 57–71. doi:http://dx.doi.org/10.1002/ev.171

Morard, B., Stancu, A., & Christophe, J. (2012). Time evolution analysis and forecast of key performance indicators in a balanced scorecard. *Global Conference on Business and Finance Proceedings, 7*(2), 568–581.

Münch, J., Fagerhold, F., Kettunen, P., Pagels, M., Partanen, J. (2013). The effects of GQM+Strategies on organizational alignment. *Proceedings of the DASMA Software Metric Congress (MetriKon 2013)*: Magdeburger Schriften zum Empiriscchen Software Engineering.

Neely, A., Gregory, M., & Platts, K. (2005). Performance measurement systems design: A literature review and research agenda. *International Journal of Operations & Production Management, 25*(12), 1228–1263. doi:10.1108/01443570510633639

Neely, A., Mills, J., Platts, K., Gregory, M., & Richards, H. (1994). Realizing strategy through measurement. *International Journal of Operations & Production Management, 14*(3), 140–152. doi:http://dx.doi.org/10.1108/01443579410058603

Nørreklit, H. (2000). The balance on the balanced scorecard: A critical analysis of some of its assumptions. *Management Accounting Research, 11*, 65–88. doi:http://dx.doi.org/10.1006/mare.1999.0121

Northouse, P. G. (2013). *Leadership: Theory and practice* (6th ed.). Thousand Oaks, CA: Sage.

Offen, R. J., & Jeffrey, R. (1997). Establishing software measurement programs. *IEEE Software, 14*(2), 45–53. doi:http://dx.doi.org/10.1109/52.582974

Olsson, T., & Runeson, P. (2001). V-GQM: A Feed-back approach to validation of a GQM study. In *Software Metrics Symposium, 2001. METRICS 2001. Proceedings. Seventh International* (pp. 236–245). IEEE. doi:http://dx.doi.org/10.1109/METRIC.2001.915532

Osborne, J. W., & Costello, A. B. (2004). Sample size and subject to item ratio in principle components analysis. *Practical Assessment, Research & Evaluation, 9*(11). Retrieved September 25, 2016 from http://PAREonline.net/getvn.asp?v=9&n=11.

Papenhausen, C. (2006). Top managers' generational membership and strategic decision-making. *Journal of Business and Management, 12*(2), 157–168.

Patton, M. Q. (1990). *Qualitative evaluation and research methods* (2nd ed.). Newbury Park, CA: Sage.

Perlman, Y. (2013). Causal relationships in the balanced scorecard: A path analysis approach. *Journal of Management and Strategy, 4*(1), 70–79. doi:http://dx.doi.org/10.5430/jms.v4n1p70

Pun, K. F., & White, A. S. (2005). A performance measurement paradigm for integrating strategy formulation: A review of systems and frameworks. *International Journal of Management Reviews, 7*(1), 49–71. doi:http://dx.doi.org/10.1111/j.1468-2370.2005.00106.x

Quinones, M. A., Ford, J. K., & Teachout, M. S. (1995). The relationship between work experience and job performance: A conceptual and meta-analytic review. *Personnel Psychology, 48*(4), 887–910. doi:http://dx.doi.org/10.1111/j.1744-6570.1995.tb01785.x

Rey, L., Brousselle, A., & Dedobbeleer, N. (2012). Logic analysis: Testing program theory to better evaluate complex interventions. *The Canadian Journal of Program Evaluation, 26*(3), 61–89.

Richard, P. J.; Devinney, T. M.; Yip, G. S.; Johnson, G. (2009). Measuring organizational performance: Towards methodological best practice. *Journal of Management, 35*(3), 718–804. doi:10.1177/0149206308330560

Robbins, S., & Judge, T. (2011). *Organizational behavior* (14th ed.). Upper Saddle River, NJ: Prentice Hall.

Rogers, P., Petrosino, A., Huebner, T. A., & Hacsi T. (2000). Program theory evaluation: Practice, promise, and problems. *New Directions for Evaluation*, *87*, 5–13. doi:http://dx.doi.org/10.1002/ev.1177

Rossi, P., Lipsey, M., & Freeman, H. (2004). *Evaluation: A systematic approach* (7th ed.). Thousand Oaks, CA: Sage.

Roulston, K. (2010). Considering quality in qualitative interviewing. *Qualitative Research, 10*(2), 199–228. doi:10.1177/1468794109356739

Rynes, S. L., Bartunek, J. M., & Daft, R. L. (2001). Across the great divide: Knowledge creation and transfer between practitioners and academics. *Academy of Management Journal, 44*(2), 340–355.

Sarcia, S. A. (2010). Is GQM+ Strategies really applicable as is to non-software development domains? *Proceedings of the 2010 ACM-IEEE International Symposium on Empirical Software Engineering and Measurement*. ACM. doi:http://dx.doi.org/10.1145/1852786.1852844

Saldaña, J. (2013). *The coding manual for qualitative researchers* (2nd ed.). Thousand Oaks, CA: Sage.

Savaya, R., & Waysman, M. (2005). The logic model: A tool for incorporating theory in development and evaluation programs. *Administration in Social Work, 29*(2), 85–103. doi:http://dx.doi.org/10.1300/J147v29n02_06

Schäfermeyer, M., Rosenkranz, C., & Holten, R. (2012). The Impact of Business Process Complexity on Business Process Standardization - An Empirical Study. *Business & Information Systems Engineering*. Published online 2012-08-23. doi:10.1007/s11576-012-0329-z

Schalken, J., & van Vliet, H. (2007). Measuring where it matters: Determining starting points for metric collection. *The Journal of Systems and Software, 81*, 603–615. doi:http://dx.doi.org/10.1016/j.jss.2007.07.041

Schwarber, P. D. (2005). Leaders and the decision-making process. *Management Decision, 43*(7/8), 1086–1092. doi:10.1108/00251740510610099

Senge, P. M. (1990). *The fifth discipline: The art & practice of the learning organization*. New York, NY: Doubleday.

Shull, F., Seaman, C., & Zelkowitz, M. (2006). Victor R. Basili's contributions to software quality. *IEEE Software*, *23*(1), 16–18. http://dx.doi.org/10.1109/MS.2006.33

Simon, A., Kumar, V., Schoeman, P., Moffat, P., & Power, D. (2011). Strategic capabilities and their relationship to organisational success and its measures. *Management Decision, 49*(8), 1305–1326. doi:10.1108/00251741111163133

Skukauskaite, A. (2012). Transparency in transcribing: Making visible theoretical bases impacting knowledge construction from open-ended interview records. Forum Qualitative Sozialforschung/*Forum, Qualitative Social Research, 13*(1). Retrieved from http://nbn-resolving.de/urn:nbn:de:0114-fqs1201146

Skukauskaite, A. (2014). Transcribing as analysis: Logic-in-use in entextualizing interview conversations. In *SAGE research methods cases* (pp. 3–26). London, England: Sage. doi:http://dx.doi.org/10.4135/978144627305014532202

Steptoe-Warren, G., Howat, D., & Hume, I. (2011). Strategic thinking and decision making: Literature review. *Journal of Strategy and Management, 4*(3), 238–250. doi:10.1108/17554351111152261

Sureshchandar, G. S., & Leisten, R. (2006). A framework for evaluating the criticality software metrics: An analytic hierarchy process (AHP) approach. *Measuring Business Excellence, 10*(4), 22–33. doi:10.1108/13683040610719254

Tabachnick, B. G., & Fidell, L. S. (2013). *Using multivariate statistics* (6th ed.). Upper Saddle River, NJ: Pearson Education, Inc.

Taylor-Powell, E., & Henert, E. (2008). *Developing a logic model: Teaching and training guide.* Madison, WI: University of Wisconsin-Extension Cooperative Extension. Retrieved from https://fyi.uwex.edu/programdevelopment/files/2016/03/lmguidecomplete.pdf

Theriou, N. G., Demitriades, E., & Chatzoglou, P. (2004). A proposed framework for integrating the balanced scorecard into the strategic management process. *Operational Research, 4*(2), 147–165. http://dx.doi.org/10.1007/BF02943607

Tingling, P., & Brydon, M. (2010). Is decision-based evidence making necessarily bad? *MIT Sloan Management Review, 51*(4), 71–76. Retrieved from http://uiwtx.idm.oclc.org/login?url=http://search.proquest.com.uiwtx.idm.oclc.org/docview/633072096?accountid=7139

Trkman, P. (2010). The critical success factors of business process management. *International Journal of Information Management, 30,* 125–134. doi:10.1016/j.ijinfomgt.2009.07.003

Van der Stede, W. A., Chow, C. W., & Lin, T. W. (2006). Strategy, Choice of Performance Measures, and Performance. *Behavioral Research in Accounting, 18,* 185–205. doi:http://dx.doi.org/10.2308/bria.2006.18.1.185

Warren, K. (2000). The softer side of strategy dynamics. *Business Strategy Review, 11*(1), 45–58. http://dx.doi.org/10.1111/1467-8616.00128

Weaver, G. J. (2014). Teaching "cause and effect" in business schools: A pathway to improved strategic thinking skills. *Academy of Educational Leadership Journal, 18*(3), 111–119. Retrieved from http://uiwtx.idm.oclc.org/login?url=http://search.proquest.com.uiwtx.idm.oclc.org/docview/1645738655?accountid=7139

Weaver, R. (2015). Metaphors are not just an academic construction; metaphors impact daily decisions by managers and leaders. *Global conference on business and finance proceedings, 10*(2), 151–160.

Williams, K. C. (2012). Business intuition: The mortar among the bricks of analysis. *Journal of Management Policy and Practice, 13*(5), 48–65.

Wongrassamee, S. Gardiner, P. D.; & Simmons, J. E. L. (2003). Performance measurement tools: The balanced scorecard and the EFQM excellence model. *Measuring Business Excellence, 7*(1), 14–29. http://dx.doi.org/10.1108/13683040310466690

Wu, A. (2005). The integration between balanced scorecard and intellectual capital. *Journal of Intellectual Capital, 6*(2) 267–284. http://dx.doi.org/10.1108/14691930510592843

Yauch, C. A. (2011). Measuring agility as a performance outcome. *Journal of Manufacturing Technology Management, 22*(3), 384–404. http://dx.doi.org/10.1108/17410381111112738

Yong, A. G., & Pearce, S. (2013). A beginner's guide to factor analysis: Focusing on exploratory factor analysis. *Tutorials in Quantitative Methods for Psychology, 9*(2), 79–94. http://dx.doi.org/10.20982/tqmp.09.2.p079

Zaltman, G. (1996). Metaphorically speaking. *Marketing Research, 8*(2), 13–20.

Appendices

Appendix A IRB Documents

Initial Approval

UNIVERSITY OF THE INCARNATE WORD

6/8/2016

AnneMarie Hooge
140 Deer Hollow Drive
Boerne, TX 78008-1908

Dear AnneMarie:

Your request to conduct the study titled *How Decision Makers Learn to Choose Measures* was approved by expedited review on 6/8/2016. Your IRB approval number is 16-06-004. Any written communication with potential subjects or subjects must be approved and include the IRB approval number.

Please keep in mind these additional IRB requirements:

- This approval is for one year from the date of the IRB approval.
- Request for continuing review must be completed for projects extending past one year. Use the **IRB Continuation/Completion form**.
- Changes in protocol procedures must be approved by the IRB prior to implementation except when necessary to eliminate apparent immediate hazards to the subjects. Use the **Protocol Revision and Amendment form**.
- Any unanticipated problems involving risks to subjects or others must be reported immediately.

Approved protocols are filed by their number. Please refer to this number when communicating about this protocol.

Approval may be suspended or terminated if there is evidence of a) noncompliance with federal regulations or university policy or b) any aberration from the current, approved protocol.

Congratulations and best wishes for successful completion of your research. If you need any assistance, please contact the UIW IRB representative for your college/school or the Office of Research Development.

Sincerely,

Ana Wandless-Hagendorf, PhD, CPRA

Ana Wandless-Hagendorf, PhD, CPRA
Research Officer
University of the Incarnate Word IRB

Informed Consent – Qualitative Interviews

How decision makers learn to choose organizational performance metrics
Consent to Participate in a Research Study
University of the Incarnate Word

Description of the Study: You are being asked to participate in a research study conducted by PhD student AnneMarie N. Hooge, under the supervision of Dr. Noah Kasraie. The purpose of this study is to understand the life, work, and educational experiences that influence the development of decision makers' ability to choose ways in which to measure organizational performance. The study includes two phases. Phase one is composed of qualitative interviews of 10-12 process owners in your company. Phase two is composed of a survey of approximately 150 process owners in your company. The data collected from Phase one interviews will be used to design the Phase two survey, which will explore how widely and deeply the types of experiences discovered in the interviews are among the population of process owners at the company. You are currently being asked to participate in Phase one of the study, and may be asked to participate in Phase two at a later date.

Study Procedures: If you agree to take part in Phase one, you will be invited to participate in an interview. This interview is designed to take no more than one hour.

Possible Benefits: The possible benefit of this research is adding to the knowledge of decision-making about measurement of effective organization performance evaluation.

Possible Risks: There is a small risk of loss of confidentiality. Because the sample pool is small, there is the possibility that readers could identify you by your responses.

Confidentiality: To minimize the risk of loss of confidentiality, the following procedures will be followed. No information of a sensitive nature will be solicited in the interviews. You will be offered an opportunity to review the interview transcript to ensure that, should your account of your experiences include identifying or sensitive information, it is removed from the reported results. While your name will be associated with the information at the time of the interview, to begin the analysis, a unique identifier will be assigned. The association between your name and the study ID will be used only to enable your review of the interview transcript, should you elect to do so. All further analysis will be done using that study ID. Only the study ID will be used in the reported study. Neither your personally identifying information nor your company name will be used in the study results and report. The relationship between your identity and the surrogate will be maintained separately from other study materials. All data will be kept in secured files, in accord with the standards of the University, Federal regulations, and the American Psychological Association.

Nature of Participation: Participation is voluntary and you have the right to refuse participation without penalty of any kind. You have the right to stop participating at any time, including leaving during the interview, without penalty of any kind. You have the right, at the end of the study, to be informed of the findings of this study.

If you have questions, please ask them at any time. If you have additional questions later or you wish to report a problem that may be related to this study, contact:

AnneMarie N. Hooge	Noah Kasraie, Ph.D.
(210) 913-5350	(210) 829-3133
ahooge@student.uiwtx.edu	kasraie@uiwtx.edu

To contact the University of the Incarnate Word committee that reviews and approves research with human subjects, the Institutional Review Board (IRB), and ask any questions about your rights as a research participant, call: UIW IRB, Office of Research Development (210) 805-3036.

University of the Incarnate Word
IRB Approved
Application No. 16-06-004

If you completely understand the expectations and rights of participants in this study, all of your questions have been answered to your satisfaction, and you are willing to participate in this study please sign and date this consent form in the space provided. To sign this consent form, you must be 18-years-old or older by today's date.

________________________ ________________________

Participant Signature Date Signed

________________________ ________________________

Signature of Person Obtaining Consent Date Signed

Survey Amendment

UNIVERSITY OF THE
INCARNATE WORD

9/13/2016

AnneMarie Hooge
140 Deer Hollow Drive
Boerne, TX 78008-1908

Dear AnneMarie:

Your request for revisions to expedited protocol 16-06-004 was approved. The following revisions to your protocol have been approved:

- Addition of survey instrument
- Addition of consent form for survey instrument

Please keep in mind these additional IRB requirements:

- Request for continuing review must be completed for projects extending past one year. Use the **IRB Continuation/Completion form**.
- Changes in protocol procedures must be approved by the IRB prior to implementation except when necessary to eliminate apparent immediate hazards to the subjects. Use the **Protocol Revision and Amendment form.**
- Any unanticipated problems involving risks to subjects or others must be reported immediately.

Approved protocols are filed by their number. Please refer to this number when communicating about this protocol.

Approval may be suspended or terminated if there is evidence of a) noncompliance with federal regulations or university policy or b) any aberration from the current, approved protocol.

Congratulations and best wishes for successful completion of your research. If you need any assistance, please contact the UIW IRB representative for your college/school or the Office of Research Development.

Sincerely,

Ana Wandless-Hagendorf, Phd, CPRA

Ana Wandless-Hagendorf, PhD, CPRA
Research Officer
University of the Incarnate Word IRB

Appendix B Interview Protocol

Interview Protocol

Process Owner Decision Maker Interview Protocol

Company:

Participant:

Interviewer: AnneMarie N. Hooge

Survey Sections:

1. √ Work Experience / Background
2. √ Educational Experience
3. √ How your work and education experiences apply to performance measurement
4. √ Demographics (no specific questions)

Other Topics Discussed:

Documents Obtained:

Post Interview Comments or Leads:

Process Owner Decision Maker Interview Protocol

Introduction

You have been selected to participate in this research because you have been identified as someone who is involved in decision making in a process ownership role. This research project focuses on the identification of the education, work, and other life experiences that are beneficial in forming decision makers who are able to choose and employ effective performance measures. Some applications of this research will be to formulate mentoring programs and process ownership training to help emerging leaders and decision makers in the skill and knowledge necessary to more effectively, efficiently identify and deploy performance measurement for their processes.

To facilitate note-taking, today's conversation will be audio taped. Only the researcher will be privy to the tape, which will be destroyed upon completion of the research paper.

Your signature is required on the consent form. Essentially, this document states that: (1) all information will be held confidential, (2) your participation is voluntary and you may stop at any time, (3) we do not intend or expect to inflict any harm, and (4) that the interview will be audio taped.

This interview is planned to last approximately one hour. There are several questions to be addressed during that time. Please be prepared for and forgive any interruptions necessary to ensure coverage of the line of questioning.

Thank you for your agreeing to participate.

To answer the questions, think about your experience not just at this company, but across your whole leadership/decision making experience. This research is not about this company, but about the knowledge and experience that go into enabling a leader/decision maker to choose effective performance measures.

A. Work Experience / Background

1. How long have you been …

   _______ in your present position (#of years)?

   _______ at the company (#of years)?

   _______ in positions of leadership/decision making (#of years)?

2. Briefly describe your role (office, committee, classroom, etc.) as it relates to organizational performance assessment.

   Probes: How are you involved in researching, identifying, and validating measures here?

3. Describe the career path that led you to this position.

4. What is your age?

   a. ☐ 30s or younger

   b. ☐ 40s

   c. ☐ 50s

   d. ☐ 60s or older

B. Educational Experience

1. What is your highest level of formal education?

    a. ☐ No formal college degree

    b. ☐ Undergraduate degree, Field of Study ________________________________

    c. ☐ Graduate degree, Field of Study ________________________________

    d. ☐ Post-graduate degree, Field of Study ________________________________

2. What informal education (organizational classes, seminars, conferences) do you have in performance measurement?

    a. ☐ Minimal

    b. ☐ Moderate

    e. ☐ Extensive

3. Describe the impact your formal education has had on your skill and knowledge in choosing performance measures.
   Probe: In hindsight, what formal education do you feel might have benefitted you more?

4. Describe how, in your primary formal educational subject area, performance measures were addressed

   Probe: Was there any specific focus on performance?

C. Your Opinions about how your work, education, and other experiences apply to performance measurement

1. What do you consider to be an "effective measure" (how would you define "effective")?

   Probe: How do you assess the effectiveness of the measure?

2. What factors go into your decision making process when choosing measures or collaborating with your team on developing measures?

   Probe: What skills do you consider most useful in choosing measures?

3. What knowledge and skills in your teams do you consider to be most conducive to developing strong a performance evaluation framework?

4. What criteria do you apply to assess the effectiveness of your measures and to make decisions about discontinuing some or instituting other measures?

Post Interview Comments and/or Observations:

Appendix C Cross-sectional Survey Instrument

List of survey items
How important is each of the following in influencing your ability to identify effective performance measures
1. My ability to ask the right questions 2. My ability to clearly visualize and articulate what success looks like 3. My ability to conceive and test hypotheses to explain outcomes 4. My ability to hide complexity and express ideas simply 5. My ability to identify the important from the unimportant 6. My ability to mitigate "gaming" behavior when designing measures 7. My ability to predict unexpected consequences of decisions 8. My ability to recognize and manage assumptions during collaboration 9. My ability to reflect and apply insight I gain from reflection 10. My ability to think in a structured, "systems" view 11. My ability to think in terms of process 12. My access to a broad range of data early in my career 13. My access to business leaders for mentoring and role modeling early in my career 14. My accountability for measures in my job assignments *(owning a process or P&L, for example)* 15. My agile learning mindset 16. My breadth of experience in project work early in my career 17. My broad business knowledge 18. My clear self-image and confidence in my own value 19. My comfort with ambiguity 20. My consulting skills 21. My creativity and innovative skills 22. My ease in moving between levels of precision 23. My effective feedback during collaboration 24. My experience as a technical practitioner with various measurement frameworks or methodologies 25. My experience in collaborative work environments 26. My experience in command and control organizational environments 27. My experience in organizations with a strong learning culture 28. My exposure to strategic level projects early in my career 29. My focus on the other's point of view during collaboration 30. My formal education 31. My habit of reflection, of pausing to consider factors that impact a given situation or decision 32. My influencing skill during collaboration 33. My informal education *(that is, generally a certificate program, including training delivered by your employer for which they keep a record)* 34. My knowledge of financial models and modeling 35. My leadership skills, especially advocacy and visioning 36. My Master's level formal education 37. My mentoring skills 38. My mentors 39. My observation and interviewing skills 40. My participation in professional work/training rotation programs 41. My pattern recognition skills 42. My Post-graduate level formal education 43. My preference for experiential learning 44. My self-directed, unstructured learning

How important is each of the following in influencing your ability to identify effective performance measures

45. My skill with computers
46. My STEM skills
47. My strong personal and professional networks
48. My strong work ethic
49. My teaching skills
50. My understanding of benchmarking
51. My understanding of causal analysis; my ability to distinguish between correlation and causation
52. My understanding of data collection methods
53. My understanding of statistics, statistical significance
54. My understanding of the ethical presentation of measures *(that is, that statistics, while true, may be presented in an unethical way—a way that misleads either intentionally or unintentionally)*
55. My understanding of the impact of organizational complexity on measurement

In your opinion, to what extent does each of the following statements describe an effective measure.

56. An effective measure is actionable
57. An effective measure is one that describes an object, process, or condition in the organization which can be influenced or controlled
58. An effective measure is one that measures the right thing
59. An effective measure is one that moves over time
60. An effective measure is one that works as designed
61. An effective measure is produced in a timely manner
62. An effective measure is repeatable and reproducible
63. An effective measure is simple or can be expressed simply
64. An effective measure is used to enable the business to achieve its objectives
65. The definition of an effective measure includes a definition expressed in business language shared by the measure's producers and consumers
66. The definition of an effective measure includes a well-defined and auditable data collection mechanism
67. The definition of an effective measure includes a well-defined rationale for balancing possibly opposing objectives
68. The definition of an effective measure includes an explicit description of expected behavior
69. The definition of an effective measure includes an explicit statement of the overall value of the measure
70. The definition of an effective measure includes an explicitly defined context (including, but not limited to process, usage, influencers, environment, completeness)
71. The definition of an effective measure includes explicit identification of related measures that act in concert
72. The definition of an effective measure includes explicit identification of appropriate usage
73. The definition of an effective measure includes explicitly defined commander's intent
74. The definition of an effective measure includes explicitly defined meaning, providing an understanding the essential concept being measured as well as the mechanics/formula to derive it
75. The definition of an effective measure includes explicitly defined desired outcomes, business objectives, or needs that are driven by the measure
76. The definition of an effective measure includes explicitly identified measure type (e.g., diagnostic, outcome, or strategic measures)
77. The definition of an effective measure includes identification of the types of business questions it answers
78. The definition of an effective measure includes recommendations for suitable presentation/visualization options for the measure

Note: This survey is the original work of the study author.

Appendix D Candidate Factors

Candidate Factor	Survey Item (restated)	Variable
Collaboration	My focus on the other's **point of view** during collaboration	pointOfView
	My effective **feedback** during collaboration	feedback
	My experience in **command and control** organizational environments	commandControl
	My experience in **collaborative** work environments	collaborative
	My ability to recognize and manage **assumptions** during collaboration	assumptions
	My **influencing skill** during collaboration	influencingSkill
Knowledge Development	My broad **business knowledge**	businessKnowledge
	My **agile learning** mindset	agileLearning
	My preference for **experiential learning**	experientialLearnin g
	My **formal education**	formalEducation
	My habit of **reflection**, of pausing to consider factors that impact a given situation or decision	Reflection
	My experience in organizations with a strong **learning culture**	learningCulture
	My **Master's** level formal education	Master's
	My participation in professional work/**training rotation** programs	trainingRotation
	My **Post-graduate** level formal education	Post-graduate
	My **informal education** *(that is, generally a certificate program, including training delivered by your employer for which they keep a record)*	informalEducation
	My **clear self-image** and confidence in my own value	clearSelfImage
	My strong **work ethic**	workEthic
	My ability to think in terms of **process**	processThinking
	My **self-directed**, unstructured learning	self-directed
	My **breadth of experience** in project work early in my career	breadthOfExperienc e
	My exposure to **strategic level** projects early in my career	strategicLevel
Experience with Measures	My ability to identify the important from the unimportant [**signal/noise**]	signalNoise
	My ability to predict **unexpected consequences** of decisions	unexpectedConsequ ences
	My understanding of **benchmarking**	Benchmarking
	My understanding of **causal analysis**; my ability to distinguish between correlation and causation	causalAnalysis
	My skill with computers [**computer skill**]	computerSkill
	My knowledge of **financial models** and modeling	financialModels
	My understanding of **data collection** methods	dataCollection
	My ability to **mitigate "gaming"** behavior when designing measures	mitigateGaming
	My understanding of **statistics**, statistical significance	Statistics
	My understanding of the **ethical presentation** of measures *(that is, that statistics, while true, may be presented in an*	ethicalPresentation

	unethical way—a way that misleads either intentionally or unintentionally)	
	My understanding of the impact of **organizational complexity** on measurement	organizational Complexity
	My access to a **broad range of data** early in my career	broadRangeOfData
	My **accountability** for measures in my job assignments *(owning a process or P&L, for example)*	accountability
Mentors	My **creativity** and innovative skills	creativity
	My ability to clearly **visualize and articulate** what success looks like	visualizeArticulate
	My strong personal and **professional networks**	professionalNetwor ks
	My comfort with **ambiguity**	ambiguity
	My leadership skills, especially **advocacy and visioning**	advocacyVisioning
	My **mentoring** skills	mentoring
	My **access to business leaders** for mentoring and role modeling early in my career	businessLeaderAcc ess
	My **mentors**	mentors
Technique	My ability to ask the right questions	rightQuestions
	My consulting skills	consultingSkills
	My ease in moving between levels of precision	levelsOfPrecision
	My ability to conceive and test hypotheses to explain outcomes	Hypotheses
	My ability to hide complexity and express ideas simply	hideComplexity
	My ability to think in a structured, "systems" view [systems thinking]	systemsThinking
	My experience as a technical practitioner with various measurement frameworks or methodologies	technicalPractitione r
	My ability to reflect and apply insight I gain from reflection	applyInsight
	My observation and interviewing skills	interviewingSkills
	My pattern recognition skills	patternRecognition
	My STEM skills	STEMSkills
	My teaching skills	teachingSkills
Effective Measure	An effective measure is **actionable**	Actionable
	An effective measure is one that **moves over time**	movesOverTime
	An effective measure is one that describes an object, process, or condition in the organization which ***can*** **be influenced** or controlled	canBeInfluenced
	An effective measure is used to enable the business to **achieve** its objectives	Achieve
	An effective measure is one that measures the **right thing**	rightThing
	An effective measure is **repeatable** and reproducible	Repeatable
	An effective measure is **simple** or can be expressed simply	Simple
	An effective measure is one that **works** as designed	Works
	An effective measure is produced in a **timely** manner	Timely
Good Measure Definition	The definition of an effective measure includes a well-defined rationale for balancing possibly opposing objectives [**balance**]	Balance
	The definition of an effective measure includes an explicit description of expected **behavior**	Behavior

The definition of an effective measure includes an explicitly defined **context** *(including, but not limited to process, usage, influencers, environment, completeness)*	Context
The definition of an effective measure includes a well-defined and **auditable** data collection mechanism	Auditable
The definition of an effective measure includes explicitly defined commander's **intent**	Intent
The definition of an effective measure includes a definition expressed in business **language** shared by the measure's producers and consumers	Language
The definition of an effective measure includes explicitly defined **meaning**, providing an understanding the essential concept being measured as well as the mechanics/formula to derive it	Meaning
The definition of an effective measure includes explicitly defined desired **outcomes**, business objectives, or needs that are driven by the measure	Outcomes
The definition of an effective measure includes identification of the types of business **questions** it answers	Questions
The definition of an effective measure includes explicit identification of **related measures** that act in concert	relatedMeasures
The definition of an effective measure includes explicitly identified **measure type** (e.g., diagnostic, outcome, or strategic measures)	measureType
The definition of an effective measure includes explicit identification of appropriate **usage**	Usage
The definition of an effective measure includes an explicit statement of the **overall value** of the measure	Value
The definition of an effective measure includes recommendations for suitable **presentation/visualization** options for the measure	Presentation Visualization

Appendix E Code book

All codes are numeric values from 1-6.

Variable	Survey Item	Additional information
accountability	My **accountability** for measures in my job assignments *(owning a process or P&L, for example)*	accountability in an organization is a requirement to justify actions or decisions.
achieve	An effective measure is used to enable the business to **achieve** its objectives	
actionable	An effective measure is **actionable**	The term *actionable* refers to the ability of the consumer of the information to take an appropriate action because of the information.
advocacyVisioning	My leadership skills, especially **advocacy and visioning**	Advocacy is a leadership action intended to influence an action or behavior. Visioning is a leadership action of developing goals or visions (foresight) for the future of the organization.
agileLearning	My **agile learning** mindset	In the perspective of the interview participants, the agile learning mindset is the ability of the practitioner to flex between the many sources and styles of learning, to be in a continual state of learning, open to new ideas and able to test them and determine their consistency with the practitioner's learning style.
ambiguity	My comfort with **ambiguity**	In the perspective of the interview participants, the ability to deal with ambiguity included being able to ideate several possible meanings, provide a strategy that would deal with the viable meanings and plan accordingly.
applyInsight	My ability to reflect and **apply insight** I gain from reflection	Applying insight refers to the ability to realize value from what one has understood.
assumptions	My ability to recognize and manage **assumptions** during collaboration	
auditable	The definition of an effective measure includes a well-	Auditable data collection is a means of assuring the correctness and

Variable	Survey Item	Additional information
	defined and **auditable** data collection mechanism	completeness of the data used to produce a measure
balance	The definition of an effective measure includes a well-defined rationale for **balancing** possibly opposing objectives	This is about making choices when the things being measures come into conflict.
behavior	The definition of an effective measure includes an explicit description of expected **behavior**	This refers to the behavior of the measure itself, rather than the nature of the thing being measured. E.g., is the measure expected to have a slight upward trend? A level trend, a certain shape when a condition of concern is indicated?
benchmarking	My understanding of **benchmarking**	
breadthOfExperience	My **breadth of experience** in project work early in my career	
broadRangeOfData	My access to a **broad range of data** early in my career	
businessKnowledge	My broad **business knowledge**	
businessLeaderAccess	My **access to business leaders** for mentoring and role modeling early in my career	
canBeInfluenced	An effective measure is one that describes an object, process, or condition in the organization which ***can*** **be influenced** or controlled	
causalAnalysis	My understanding of **causal analysis**; my ability to distinguish between correlation and causation	
clearSelfImage	My **clear self-image** and confidence in my own value	
collaborative	My experience in **collaborative** work environments	
commandControl	My experience in **command and control** organizational environments	
computerSkill	My skill with computers [**computer skill**]	
consultingSkills	My **consulting skills**	
context	The definition of an effective measure includes an explicitly defined **context** *(including, but not limited to process, usage, influencers, environment, completeness)*	
creativity	My **creativity** and innovative skills	
dataCollection	My understanding of **data collection** methods	Although the level of rigor may be different, or ensured through different means, this item refers to the care taken in collecting and handling data from its system of record to the ultimate information consumer.

Variable	Survey Item	Additional information
ethicalPresentation	My understanding of the **ethical presentation** of measures *(that is, that statistics, while true, may be presented in an unethical way—a way that misleads either intentionally or unintentionally)*	
experientialLearning	My preference for **experiential learning**	
feedback	My effective **feedback** during collaboration	
financialModels	My knowledge of **financial models** and modeling	
formalEducation	My **formal education**	
hideComplexity	My ability to **hide complexity** and express ideas simply	
hypotheses	My ability to conceive and test **hypotheses** to explain outcomes	
influencingSkill	My **influencing skill** during collaboration	
informalEducation	My **informal education** *(that is, generally a certificate program, including training delivered by your employer for which they keep a record)*	
intent	The definition of an effective measure includes explicitly defined commander's **intent**	"commander's intent" is statement of the overall objective of the leader.
interviewingSkills	My observation and **interviewing skills**	
language	The definition of an effective measure includes a definition expressed in business **language** shared by the measure's producers and consumers	
learningCulture	My experience in organizations with a strong **learning culture**	The learning culture is one that encourages the individual in the culture to increase their knowledge, hone their skills, and improve their performance as a conscious practice.
levelsOfPrecision	My ease in moving between **levels of precision**	
master's	My **Master's** level formal education	
meaning	The definition of an effective measure includes explicitly defined **meaning**, providing an understanding the essential concept being measured as well as the mechanics/formula to derive it	
measureType	The definition of an effective measure includes explicitly identified **measure type** (e.g., diagnostic, outcome, or strategic measures)	
mentoring	My **mentoring** skills	Refers to the practitioner's ability to mentor others. May be related to teaching skills.
mentors	My **mentors**	Refers to the mentors a practitioner has had. May be related to business leader access.
mitigateGaming	My ability to **mitigate** "**gaming**" behavior when designing measures	Refers to the understanding of unexpected consequences of measuring something and preventing (if possible) or dealing

Variable	Survey Item	Additional information
		with the negative behaviors that might result
movesOverTime	An effective measure is one that **moves over time**	Using measures that return only constant values are considered (perhaps only *assumed* to be) less actionable than those on which decisions may be more readily made.
organizationalComplexity	My understanding of the impact of **organizational complexity** on measurement	Refers to the complex interrelationships among business areas of an organization, the ways they deal with communication, funding, and performance measurement.
outcomes	The definition of an effective measure includes explicitly defined desired **outcomes**, business objectives, or needs that are driven by the measure	
patternRecognition	My **pattern recognition** skills	Refers to human pattern recognition, rather than machine pattern recognition, such as is used in data mining.
pointOfView	My focus on the other's **point of view** during collaboration	Perspective
post-graduate	My **Post-graduate** level formal education	Doctoral-level studies
presentationVisualization	The definition of an effective measure includes recommendations for suitable **presentation/visualization** options for the measure	Data visualization is about making the data consumable for the general consumer (e.g., Infographics in USA Today).
processThinking	My ability to think in terms of **process**	Process thinking refers to the practice of considering the activities of the process rather than focusing on the outcomes. Contrast with systems thinking.
professionalNetworks	My strong personal and **professional networks**	
questions	The definition of an effective measure includes identification of the types of business **questions** it answers	May be related to usage
reflection	My habit of **reflection**, of pausing to consider factors that impact a given situation or decision	

Variable	Survey Item	Additional information
relatedMeasures	The definition of an effective measure includes explicit identification of **related measures** that act in concert	May include correlations, causality, or other interaction relationships between the measures themselves or the processes, activities, or behaviors they are intended to measure.
repeatable	An effective measure is **repeatable** and reproducible	This is a quality concept, generally essential during execution of measurement activities. Related to timeliness [timely].
rightQuestions	My ability to ask the **right questions**	Finding the right answer to the wrong question is not helpful and can be, in business, dangerous. This item refers to the ability of the practitioner to identify the right issue to be addressed (the problem, for example, rather than a symptom of the problem).
rightThing	An effective measure is one that measures the **right thing**	Refers to the difficulty, at times, of devising measures that assess exactly the phenomenon, behavior, or performance required, but might measure a proxy in place of the actual thing.
self-directed	My **self-directed**, unstructured learning	Refers to informal education
signalNoise	My ability to identify the important [**signal**] from the unimportant [**noise**]	Or the critically important from the merely important
simple	An effective measure is **simple**	or can be expressed simply
statistics	My understanding of **statistics**, statistical significance	Refers to skill in designing, executing, and/or consuming statistical information.
STEMSkills	My **STEM skills**	Refers to skill in the science, technology, engineering and mathematics disciplines.
strategicLevel	My exposure to **strategic level** projects early in my career	Strategic-level projects are those that span multiple business areas and/or have organization-wide impact
systemsThinking	My ability to think in a structured, "systems" view [**systems thinking**]	Systems thinking considers the components of a system and how they interrelate to deliver overall value to the organization.

Variable	Survey Item	Additional information
teachingSkills	My **teaching skills**	This includes those formally trained to teach in a classroom or those with innate ability to pass on knowledge in a structured, productive way.
technicalPractitioner	My experience as a **technical practitioner** with various measurement frameworks or methodologies	
timely	An effective measure is produced in a **timely** manner	This speaks to the delivery of a measure within a defined required time.
trainingRotation	My participation in professional work/**training rotation** programs	Training rotation programs are non-formal education, generally at business organizations, where a participant rotates through a designed series of roles and job responsibilities for the purpose of learning the business, assessing their fit and liking for a position, and finding a best-fit role.
unexpectedConsequences	My ability to predict **unexpected consequences** of decisions	This speaks to the actions that people might take because something is being measured. It does not necessarily address the desirability or undesirability of those actions.
usage	The definition of an effective measure includes explicit identification of appropriate **usage**	This is about educating the consumer about the proper application of the information. Just as the context and generalizability of an academic study cannot always be applied freely, the use of measures is constrained by the context in which they are defined.
value	The definition of an effective measure includes an explicit statement of the **overall value** of the measure	This is about connecting the measure to the value streams (the series of processes or activities that produce value in an organization) in which it plays a part.
visualizeArticulate	My ability to clearly **visualize and articulate** what success looks like	This is about being able to paint a picture for the followers so that they will recognize successful outcomes and be able to talk about them in ways that will resonate with people who need to understand if the

Variable	Survey Item	Additional information
		organization is accomplishing its objectives.
workEthic	My strong **work ethic**	
works	An effective measure is one that **works** as designed	

Appendix F Factors * grouping variables Crosstabulation

*Factors * Grouping Variables Crosstabulation*

Factor	ageRange					process Complexity				gender			decisionTenure Range			
	3	4	5	6	Total	1	2	3	Total	1	2	Total	1	2	3	Total
StrategicThinking Range	0	3	0	0	3	0	1	2	3	3	0	3	0	1	2	3
	4	7	6	3	20	4	5	11	20	15	5	20	5	4	11	20
	8	13	8	3	32	4	9	19	32	21	10	31	10	3	19	32
Total	12	23	14	6	55	8	15	32	55	39	15	54	15	8	32	55
ComplexityTools Range	1	2	0	0	3	2	0	1	3	3	0	3	1	1	1	3
	3	13	5	2	23	2	7	14	23	15	7	22	2	4	17	23
	8	8	9	4	29	4	8	17	29	21	8	29	12	3	14	29
Total	12	23	14	6	55	8	15	32	55	39	15	54	15	8	32	55
Collaboration Range	0	3	3	0	6	2	0	4	6	5	1	6	0	2	4	6
	2	9	5	1	17	1	8	8	17	11	5	16	3	1	13	17
	10	11	6	5	32	5	7	20	32	23	9	32	12	5	15	32
Total	12	23	14	6	55	8	15	32	55	39	15	54	15	8	32	55
SynthesisRange	0	2	0	0	2	0	0	2	2	2	0	2	0	2	0	2
	5	4	6	2	17	3	5	9	17	13	4	17	4	2	11	17
	7	17	8	4	36	5	10	21	36	24	11	35	11	4	21	36
Total	12	23	14	6	55	8	15	32	55	39	15	54	15	8	32	55
LearningRange	0	2	0	0	2	1	0	1	2	1	1	2	0	0	2	2
	4	6	4	0	14	1	3	10	14	10	4	14	2	5	7	14
	5	12	8	4	29	5	9	15	29	20	8	28	9	3	17	29
	3	3	2	2	10	1	3	6	10	8	2	10	4	0	6	10
Total	12	23	14	6	55	8	15	32	55	39	15	54	15	8	32	55
Business Knowledge Range	1	1	1	1	4	1	1	2	4	3	1	4	0	1	3	4
	6	13	6	2	27	5	7	15	27	20	6	26	6	4	17	27
	5	9	7	3	24	2	7	15	24	16	8	24	9	3	12	24
Total	12	23	14	6	55	8	15	32	55	39	15	54	15	8	32	55

Note: ageRange: 3 (0-30), 4(31-40), 5(41-50), 6(51+); process complexity 1(simple), 2(moderate), 3(complex); gender 1(male), 2(female); decisionTenureRange 1(0-0), 2(10-11), 3(11.1+)