The Impact of Operations Capability on Firm Performance

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Abstract

We propose that a firm's operations capability is manifested through its new product design and development, just-in-time, and quality management efforts. Moreover, we propose that operations capability, so defined, directly and positively impacts firm performance. Survey data was used to independently calibrate and validate a structural equation model linking operations capability, a second order construct, to firm performance. Results provide support for the model and demonstrate a positive relationship between operations capability and firm performance.

Subject Areas: Just-In-Time, Quality Management, New Product Design and Development, Operations Capability, Structural Equation Modeling, Invariant Analysis

1. Introduction

The notion that operations capability plays a vital role in achieving competitive success is widely accepted (e.g., Hammer and Champy 1993, Tan et al. 2004). The manufacturing strategy literature, for example, has emphasized the importance of developing and nurturing manufacturing capabilities as a prelude to achieving long-term, sustainable competitive success (e.g., Roth and Miller, 1992, Hayes and Pisano, 1996). This involves not only strengthening internal capabilities but working with suppliers and customers to take advantage of their technologies and capabilities, for example, by involving strategic suppliers early in new product design and development efforts (Ragatz et al., 1997, Tan, 2001).

Interest in operations capability and its influence on competitive advantage and performance have generated a large research stream within the operations strategy literature (e.g., Flynn and Flynn, 2004, Tan et al., 2004). The impetus for this research lies in the resource based view of the firm, which has emerged as a theoretical framework for analyzing the sources and sustainability of competitive success (Barney, 1991, Grant, 1991). It argues that competitive advantage is created by firms acquiring and utilizing resources in an inimitable manner due to the specialization of assets and implicit knowledge and skills (Barney, 1991). This enables the firm to translate process knowledge into unique operations capabilities that create superior competitive advantage. Prior research has demonstrated that firms in the same market segment that use similar functional strategies can exhibit substantial differences in performance levels (Cool and Schendel, 1988). These differences can be attributed to how firms manage the development of their distinctive competencies (Lawless et al., 1989). For example, when Toyota emerged as the most cost efficient manufacturer in the automotive industry, many competitors attempted but failed to replicate Toyota's success. Similarly in the retail and air transportation sectors, with the exception of a few companies such as Tesco and Ryanair in the U.K., few companies have been able to replicate Wal-Mart's and Southwest Airlines' success in the U.S. The resources firms such as Toyota and Wal-Mart have utilized are by no means unique. However, how they have been leveraged is the key to the successes they have yielded.

The literature on operations capability has focused on identifying the dimensions of organizational success that can be attributed to manufacturing, how capabilities evolve over time, and how they impact a firm's performance. Manufacturing strategies based on cost, delivery, quality, and flexibility have for many years been touted as supporting corporate objectives (e.g., Leong et al., 1990). Different schools of thought have also emerged regarding the number of capabilities a firm can successfully emphasize. Some suggest that firms must choose between capabilities in making strategy and resource allocation decisions (Skinner, 1969), while others advocate that firms must necessarily develop multiple capabilities to respond to increasing competition (e.g., Nakane, 1986, Ferdows and De Meyer, 1990). The content of operations capability, however, has not received much attention from prior studies. Part of the reason is the multi-faceted nature of operations capability. The current study builds on existing literature by examining how operations capabilities manifest themselves in terms of initiatives firms use to achieve high levels of competitiveness. Much of the existing literature focuses on capability as an 'output', focusing on dimensions of manufacturing performance or metrics at which firms excel. Little discussion exists however of how specifically this is accomplished. We posit that operations capability is the result of a strategic commitment to new product development, quality improvement and waste elimination strategies such as Just-in-Time (JIT). Excellence on dimensions of performance such as cost, quality, delivery, and flexibility is the result of systems that focus organizational resources on product and process improvements. In other words, we examine capability from an ‘input’ perspective. For example, JIT can be characterized as a company’s focus on reducing lot sizes and setup times, etc., as opposed to the traditional characterization of inventory reduction. This perspective is useful to firms as they invest in manufacturing practices to develop high levels of operations capability. Specifically, we explore the multi-dimensional and higher order nature of operations capability. A secondary objective of this study is to validate our position by empirically examining the relationship between operations capability and firm performance.

2. Literature Review

2.1. Nature of Operations Capability

While there appears to be a broad consensus that operations capability refers to a firm’s leveraging of its manufacturing function to support organizational success, differences exist in how it is defined. It has for example been characterized as tasks that a firm can do well (Skinner, 1969), internally developed activities that a firm can do better than its competitors (Hayes and Pisano, 1996), stocks of strategic assets accumulated through time and which cannot be easily imitated, acquired, or substituted (Dierickx and Cool, 1989), or an ability to compete on certain dimensions (Safizadeh et al., 2000). Operations capability is sometimes used synonymously with competitive priority. However, competitive priorities reflect manufacturing dimensions on which a firm *needs* to excel at to be competitive (Roth and Van de Velde, 1991), to develop and enhance a plant’s position in the marketplace (Boyer and Lewis, 2002), or that management considers to be important (Safizadeh et al., 2000), rather than those on which it *does* excel. Lack of discrimination also exists between operations capability and manufacturing outcome, the former referring to actionable competencies and the latter to results (Corbett and Van Wassenhove, 1993), and between operations capability and manufacturing competence, the degree to which manufacturing excellence supports a firm's broader strategic goals (Cleveland et al., 1989). Relationships between these terms are summarized in figure 1. Competitive priorities define the dimensions of operations capability necessary for success. These in turn drive manufacturing outcomes, providing support for corporate objectives or manufacturing competence.

Insert Figure 1

Two elements can be observed within the operations capability literature, (1) identification of the dimensions of capability, and relationships between the dimensions and performance, and (2) identification of how capabilities evolve. Several dimensions of capability have been identified as crucial to an organization's long term success. In particular, there is theoretical support for the importance of cost, quality, flexibility, and delivery (e.g., Schmenner and Swink, 1998, Ward et al., 1998). Others have also suggested that innovation (e.g., Hall and Nakane, 1990, Leong et al., 1990), and organizational culture (Hall and Nakane, 1990) may be important elements of manufacturing strategy. Swink and Hegarty (1998) distinguished between capabilities pertinent to maintaining steady state versus those pertinent to growth in the context of product differentiation. They suggested that in addition to innovation, the ability to improve efficiency and productivity, and to expand to encompass new products and/or technologies, are core growth capabilities. In contrast core steady state capabilities are those related to leveraging management's insights into process capability and performance, regulating and directing processes, and switching between manufacturing states at low or no cost. The first and third of these have parallels with quality and flexibility respectively.

Several studies have attempted to empirically validate relationships among individual capabilities and with performance (e.g. White, 1996). Moreover, several shed light on the ongoing debate as to whether capabilities must be traded off or whether they can coexist. Early work suggested it was unreasonable for a plant to simultaneously excel on multiple dimensions, thus tradeoffs must be made in developing capabilities (e.g., Hayes and Wheelwright, 1984, Garvin, 1993, Skinner, 1969). However, this view has also been interpreted as laying the basis for prioritizing between capabilities as opposed to saying that they cannot be developed in tandem (Hayes and Wheelwright, 1984). While limited empirical support for the tradeoff model exists (Boyer and Lewis, 2002, Safizadeh et al., 2002, Ward et al., 1998), much of the recent work questions the notion that firms cannot simultaneously excel at multiple capabilities (e.g., Corbett and Van Wassenhove, 1993, Garvin, 1993, Hayes and Pisano, 1996). The cumulative model (Nakane, 1986) suggests that multiple capabilities can coexist and should be developed in a particular sequence, the development of quality capability being followed by development of capabilities in dependability, cost, and flexibility. The sand cone theory (Ferdows and De Meyer, 1990) suggests that this sequential development of multiple capabilities is the key to lasting improvements in performance. Several studies provide empirical support for the cumulative model, demonstrating that high and low performing firms differ in the number of capabilities they possess (e.g., Flynn and Flynn, 2004, Noble, 1995, Roth and Miller, 1992). However, while acknowledging the co-existence of multiple capabilities, a recent study found no evidence that differences in performance can be attributed to the sequence in which capabilities were developed (Corbett and Claridge, 2002). While the two paradigms may appear to be in conflict, a third paradigm, the integrative model, suggests they may be complementary (Schmenner and Swink 1998). Specifically, it suggests that when a plant is close to the limits of its asset structure, focus is required in making choices regarding the ongoing development of capabilities. In contrast, when a plant is not limited by existing assets, potential exists to develop multiple capabilities.

2.2. Content of Operations Capability

Several actionable dimensions of operations capability consistent with the definitions of Skinner (1969) and Hayes and Pisano (1996) have been identified. Hayes and Pisano (1996) advocated taking advantage of improvement programs such as just-in-time (JIT) or total quality management (TQM). A similar prescription was suggested by Roth and Miller (1992) who identified five areas relevant to the development of capability; total factor resource improvements, quality management programs, advanced manufacturing process technology, information systems, and restructuring. The application of quality improvement methods, advanced process technology, integrated information systems, as well as enhanced product development and production control processes, were also identified as important elements in the plans of Japanese, European, and North American firms (De Meyer et al., 1989). Narasimhan and Jayaram (1998) identified supply management, process improvement and information systems as enablers of capability development. The latter study apart however, little empirical evidence exists to validate the underlying content of operations capability, or its relationship with performance. Tan et al. (2004) proposed a three-factor model of operations capability. Their results provided support for the proposition that underlying a firm's capability are efforts to improve quality using traditional total quality management methods, processes consistent with the just-in-time philosophy, and product development.

It is evident that several initiatives or programs, either under the control of manufacturing or over which manufacturing has significant influence, drive the attainment of manufacturing excellence. These include new product development processes, improvements in processes aimed at quality and productivity, and process control. Consistent with capability being task or activity based (Skinner, 1969, Hayes and Pisano, 1996) it is these that we refer to as operations capabilities when describing operations capability from an input perspective. Operations capabilities are in turn enabled by investments and initiatives typically driven by high level corporate decision making. These, while impacting operations capabilities, have broader implications, and may be motivated by factors other than developing manufacturing excellence. Such investments include those in advanced technology, information technology, and broader organizational change. The focus of this paper is on the operations capabilities themselves rather than their enablers. These capabilities are important since they not only impact the ability to introduce products and compete in different markets and segments but reflect the internally developed infrastructure that drives sustainable success (Hayes and Pisano, 1996). It is this competitive advantage that others have referred to as inimitable capability (e.g., Barney 1991). Based on this rationale and building on the model proposed by Tan et al. (2004), we conclude that there are three critical elements of operations capability; new product design and development, just-in-time and quality management.

3. Elements of Operations Capability

3.1. New Product Design and Development Capability

With the increasing importance of customer focus, and pressure being put on product life cycles by competition, rapid and innovative product development has emerged as a major focus of many organizations. It is the ability of firms to rapidly sense and respond to market signals that provides them with a competitive edge. New product development is however inherently costly and risky, particularly when new technology is involved. This creates opportunities for firms that effectively manage development processes, whether via internal capabilities or collaborative efforts with suppliers (e.g., Ragatz et al., 1997, Tan, 2001). The literature identifies several elements of product development processes that drive competitive advantage. For example, part reduction and standardization, concurrent engineering, the use of cross-functional teams, vendor management, and empowerment, are all related to reductions in development cycle times (e.g., Griffin, 1997, Zirger and Hartley, 1996). Concurrent engineering is also associated with improvements in product quality and reductions in both development time and cost (Hoedemaker et al., 1999, Standish et al., 1994, Wheelwright and Clark, 1992). Toyota Motor Corporation realized a 60% reduction in development costs on new car programs that they attributed to the use of cross-functional teams (Chase et al., 1998). Several studies have found that concurrent engineering also facilitates external integration with suppliers and customers (Langowitz, 1988, Millson et al., 1992). Quality function deployment and value analysis/engineering are also associated with enhancements in product development processes.

3.2. Just-In-Time Capability

The elements and impact of just-in-time capability are well documented. Monden (1983) for example described just-in-time practices based on the Toyota Production System. These included product simplification and standardization, simplified and efficient material flow, setup time reduction, preventive maintenance, improved quality, and commitment to continuous improvement. Lee and Ebrahimpour (1984) concluded that top management support, cooperation from the labor force, good process design and effective supplier relationships are also important just-in-time practices. The results of these efforts can be observed in terms of reductions in inventory and increases in inventory turnover, and improved product quality and throughput (e.g., Fullerton and McWaters, 2001, Nakamura et al., 1998).

3.3. *Quality Management Capability*

An extensive literature exists on how quality management efforts can be used to impact a firm's success (e.g., Ahire et al., 1996, Anderson et al., 1995, Flynn et al., 1995b). Corporate leadership, senior management commitment to a quality strategy, and a customer focus are, for example, key drivers of any quality effort. They provide the basis for efforts to design products and processes and monitor system performance consistent with achieving high levels of quality. They also are drivers of the infrastructure that must develop the human resource side of quality management. While not all quality improvement efforts are successful (e.g., Easton and Jarrell 1998, Hendricks and Singhal, 1997), there is ample evidence to suggest that customer satisfaction (Anderson et al., 1995), product quality (Ahire et al., 1996, Dow et al., 1999), as well as broader measures of manufacturing performance (Flynn et al., 1995a, Samson and Terziovski, 1999) are positively impacted by quality management programs. Not only can strategic quality management affect performance, so can the effective deployment of quality tools, such as process improvement, statistical process control, and quality training (Kannan et al., 1999).

4. Research Model

We posit that a firm's competitive position is enhanced by actions it takes to develop and execute a strategy based on superior product development, quality focus, and adoption of just-in-time manufacturing. While these elements of capability have been suggested previously, the relationship between capability and performance has yet to be tested. Moreover, unlike prior empirical studies of operations capability, we explore how these capabilities are achieved rather than their outcomes. Specifically, we propose

Proposition 1: Operations capability is a second order construct comprised of three interrelated facets; new product design and development capability, just-in-time capability, and quality management capability.

The elements of operations capability are operationalized similar to the approach used in Tan et al. (2004). New product design and development capability, for example, is operationalized by a firm's commitment to modular design of parts, early supplier involvement, concurrent engineering, simplification of parts, standardization of parts, and value analysis/engineering. Just-in-time capability is operationalized by an organization's commitment to reducing lot sizes and setup times, maintaining process integrity using preventive maintenance, increasing delivery frequencies, and reducing inventory to free up capital and expose manufacturing/scheduling problems. Quality management capability is operationalized by an organization's commitment to maintaining process integrity using statistical process control, designing quality into the product, process improvement, training of employees in quality management and control, empowering operators to correct quality problems, and senior management communicating quality goals to the organization. Further, we propose

Proposition 2: Operations capability positively affects firm performance

As the literature suggests, each proposed facet of capability has a direct and positive impact on both manufacturing and broader measures of business performance (e.g., Anderson et al., 1995, Fullerton and McWatters, 2001, Tan, 2001, Wheelwright and Clark, 1992). Firms no longer rely solely on financial performance measures such as earnings per share or return on investment. Increasingly, strategic objectives and metrics are described in terms of customer satisfaction, quality, and market share, instead of or in addition to traditional financial measures (e.g., Kaplan and Norton, 1992). Given an increasingly competitive marketplace, performance must necessarily be defined and measured on multiple dimensions, both financial and non-financial. We therefore operationalize performance in terms of market share, return on assets, overall product quality, overall competitive position, and overall customer service levels.

Propositions 1 and 2 can be represented by a second order structural equation model (Figure 2). The four measurement models, NPDD, JIT, QLT and PERF, denote the new product design and development, just-in-time, quality management, and performance constructs respectively. δ and ε represent error variances for the measured variables and ζ represents error variances for the measurement models. λ represents the first order factor loadings, γ the second order factor loadings, and β the structural parameter denoting the impact of operations capability on firm performance.

Insert Figure 2

5. Survey Methodology

A survey instrument was developed based on the items described above. Five point Likert scales (1 = low, 5 = high) asked how important each of the dimensions of new product design and development, just-in-time, and quality management capability were in the reporting firm's activities, and how the firm performed relative to major competitors (Table 1). Two pretests were conducted to assess the content validity of the survey instrument, and where necessary, modifications made to the questionnaire. Target respondents were identified from membership lists of the Institute for Supply Management (ISM) and the Association for Operations Management (APICS). To increase the likelihood that respondents would be familiar with their firm's strategic goals and operations, the membership lists were pre-screened for only senior supply and operations managers of manufacturing firms. To further ensure that the survey was administered accurately and consistent with the goals of the research, it was administered by a professional firm. Standard mail survey procedures were used (Dillman, 1999). Specifically, surveys were mailed to the 5,470 respondents followed by two follow-up reminders, each two weeks apart. The survey was conducted in three phases, and the last survey was received in mid-2000. A total of 527 useable surveys were returned, yielding a response rate comparable to that of prior studies that used similar membership mailing lists (e.g., Fawcett and Magnan, 2001).

To test for the homogeneity of the samples derived from the two membership lists, t-tests were carried out on responses to a number of randomly selected questions from each sample as well as the number of employees and annual sales. Results indicated no statistically significant differences in mean responses, thereby enabling the two samples to be combined. To test for non-response bias, sample data was separated into two groups based on return date, late arriving surveys considered representative of non-respondents (Lambert and Harrington, 1990). t-tests were again carried out on responses to a number of randomly selected questions items and the number of employees, and annual sales. No statistically significant differences in mean responses were observed, indicating the absence of non-response bias. Harman's single-factor test was used to test for common method variance (Podsakoff et al. 2003). If common method variance is a serious problem, either a single factor will emerge or a general factor will account for a large amount of the variance in the data. Principal components factor analysis of the data yielded nine factors, each with eigen values greater than 1.0, with no one factor accounting for more than 15% of the total variance. We concluded that common method variance was not a concern.

Insert Table 1

6. Statistical Analysis

Much of the existing structural modeling research relies on a single sample to test a proposed research model and ignores the need to further validate the proposed theory with a second sample. This validation is critical however when, as is common practice, the proposed model has been re-specified and an alternate model accepted (Hoyle, 1995). When a model fits a sample, it implies only that the model provides a plausible representation of the structure that produced the observed data. Ideally, a re-specified model should be validated using data separate from that used to calibrate the original model. Since the sample size in this study was sufficiently large, the data was randomly divided into two sub-groups. The calibration sample (264 observations) was used to test the measurement models and explore the structural relationships among the latent variables. The validation sample (263 observations) was then used to validate the proposed structural equation model. Table 1 presents descriptive statistics of the observed indicators for the four constructs in each sample. The risk exists with survey data that responses may be influenced by the status and background of the target respondents, in this case senior supply and operations managers. They may tend to focus more on measures of manufacturing rather than financial performance, and have access to better information on these rather than other metrics. This underscores the importance of using a composite measure of performance as used in this research instead of a single observed indicator. However, correlation of performance measures with data acquired from the Dunn and Bradstreet database, Standard and Poor publications and company financial reports was statistically significant ($p < 0.05$) suggesting the absence of bias.

A two-step structural equation modeling approach was used to analyze the calibration sample (Anderson and Gerbing, 1988). This approach assesses the validity of the structural model independently of the measurement models. Measurement models address the reliability and validity of observed variables in measuring latent variables, and provide an assessment of convergent and discriminant validity (Schumacker and Lomax, 1996). The structural equation model specifies relationships among latent variables and describes the amount of explained and unexplained variance in the model. This provides an assessment of predictive validity (Byrne, 1998). Analysis was carried out with LISREL-SIMPLIS 8.72 using the maximum likelihood estimation method (Jöreskog and Sörbom, 1993). After testing the individual measurement models, the second order structural model was tested to assess whether operations capability can be adequately measured by the three proposed constructs (proposition 1). Finally, the impact of operations capability on firm performance was tested (proposition 2). To validate the analysis, multiple-group analysis was used to investigate whether the second order structural equation model is invariant across the two samples. Model invariance examines whether a model, when applied to multiple samples, has the same number of latent variables with the same indicators and specification of fixed and free parameters in the matrices of factor loadings, structural parameters, and measurement errors (Bollen, 1989).

6.1. Analysis of Measurement Models ($\eta_1, \eta_2, \eta_3, \eta_4$)

Analysis of the new product design and development (NPDD) measurement model indicated a correlation between supplier involvement (Q1B) and simplification of parts (Q1D). Tan et al. (2004) suggested that involving key suppliers early in product design activities may adversely impact simplification efforts. Suppliers may, for example, propose using component parts that utilize new technologies and materials. While this may enhance product quality, it may also slow down the development process. An error covariance term was thus added linking the two variables[1]. Similarly, error covariance terms were added to link standardization of parts (Q1E) with part simplification (Q1D) and value analysis/engineering (Q1F). Value analysis/ engineering can increase part standardization by simplifying product and component design

[1] While allowing error terms to correlate can improve model fit, it is appropriate to do so only if there is a theoretical basis to support the corresponding correlations (Byrne, 1998).

while improving performance. The revised model and its corresponding fit indices are shown in figure 3. Standardized factor loadings range from 0.71 to 0.85, and exhibit the expected positive sign. Table 2 presents a list of widely used goodness of fit criteria and their corresponding acceptable values. Values for commonly used goodness of fit indices suggest the NPDD measurement model fits the sample data well.

Insert Figure 3

Insert Table 2

As indicated by analysis of the just-in-time measurement model (JIT), error covariance terms were added to link reducing setup time (Q2B) with reducing lot size (Q2A), preventive maintenance (Q2C), and reducing inventory to expose production and scheduling problems (Q2F). The underlying premise of the just-in-time philosophy is that inventory hides scheduling, production and other problems. Just-in-time manufacturers using small lot sizes to reduce cycle inventory must significantly improve their ability in the area of rapid changeover. Preventive maintenance is also critical to ensure that machinery and equipment operate smoothly despite frequent setups for mixed-model production. The revised model is shown in figure 3. Standardized factor loadings range from 0.53 to 0.82, and exhibit the expected positive sign and magnitude. Values for goodness of fit indices again suggest that the model fits the sample data.

Analysis of the quality management measurement model (QLT) suggested that process improvement (Q3C) is correlated with designing quality into the product (Q3B) and statistical process control (Q3A). Process improvements not only enhance a firm’s ability to design quality into the product, but one manifestation of process improvement is the use of statistical process control techniques. Error covariance terms were thus added to the model (Figure 3). Standardized factor loadings range from 0.51 to 0.85, and goodness of fit index values again suggest good model fit. Similarly, factor loadings exhibit the expected positive sign. Examination of un-standardized solutions of all three measurement models suggests that all parameter estimates are both reasonable and statistically significant, and that all standard errors are of acceptable magnitude.

Initial analysis of the firm performance (PERF) measurement model suggested that market share (Q4A) is correlated with return on assets (Q4B) and overall competitive position (Q4D). As market share increases, return on assets is expected to improve as a result of increased sales, profitability, and growth opportunities. Increasing market share also strengthens a firm's position in the marketplace which in turn creates further opportunity for consolidation and growth. Conversely, as a firm loses market share, profits and return on assets can be expected to decline, adversely affecting competitiveness. The model was modified to reflect these relationships by adding corresponding error covariance terms. The modified performance measurement model, with standardized factor loadings ranging from 0.45 to 0.77, fit the calibration sample data well (Figure 3).

6.2. Second Order Operations capability Model (ξ_1, η_1, η_2, η_3)

A second order factor model is one in which correlations among first order factors can be represented by a single factor, and in which the higher order factor is hypothesized to explain all covariance among its first order constituents. Since operations capability has been shown previously to be adequately measured by new product design and development, just-in-time and quality management capabilities (Tan et al., 2004), it is logical to extend the model to test operations capability as a second order factor model (Figure 4). Single headed arrows from the second order factor (CAP) to each of the first order factors (NPDD, JIT, QLT) represent freely estimated regression paths or second order factor loadings ($\gamma_{1,1}$, $\gamma_{2,1}$, $\gamma_{3,1}$). Standardized factor loadings exhibit the expected positive sign and reasonable magnitude, and values of goodness of fit indices suggest the model fit the data well. All the three path coefficients are statistically significant. The standardized factor loadings of new product design and development ($\gamma_{1,1}$), just-in-time capability ($\gamma_{2,1}$), and quality management ($\gamma_{3,1}$), are 0.71, 0.87, 0.75 respectively. Given these observations, it appears that operations capability can be adequately represented by the three latent variables, providing initial support for proposition 1.

Insert Figure 4

6.3. Structural Equation Model – ($\beta_{4,1}$)

The saturated structural equation model was examined to determine whether estimated parameters agree with *a priori* specified positive signs and size, and whether the strengths of the relationships are statistically significant and sufficiently large (Figure 5). Goodness of fit indices suggest that the model fits the data well. The standardized structural parameter ($\beta_{4,1}$ = 0.42) exhibits the expected positive sign and is of reasonable magnitude. Moreover, its significance provides support for proposition 2 that operations capability positively affects firm performance.

Insert Figure 5

6.4. Testing for Invariance across Calibration and Validation Samples

To validate the structural equation model, model invariance analysis was carried out by using the validation sample to verify the structural model and relationships depicted in figure 2. A baseline structural equation confirmatory factor analysis model was established using the validation sample (Figure 6). An identical set of indicators, error covariance terms, and structural relationships as depicted in figures 3 and 5, were used in developing the model. All model specifications are identical for both groups since the main goal of a cross-validation application is to determine whether the final model derived from the calibration sample can be replicated across the validation sample (Byrne, 1998). Model fit indices suggest the model fits the validation sample well, confirming that operations capability can be adequately measured by the proposed three-factor, second order structural equation model. The standardized operations capability path coefficients ($\gamma_{1,1}$ = 0.66, $\gamma_{2,1}$ = 0.73, $\gamma_{3,1}$ = 0.85) and the standardized structural parameter ($\beta_{4,1}$ = 0.49) again exhibit the expected positive sign and are of reasonable magnitude.

Insert Figure 6

To compare whether the calibration and validation baseline models are invariant, we first estimate both models simultaneously without imposing the equality constraints (Byrne 1998). The goodness-of-fit indices, which reflect the simultaneous estimation of the model for both the calibration and validation samples, show that $\chi^2_{df=459}$ = 880.60, NFI = 0.95, RFI = 0.94, and NNFI, CFI and IFI all equal 0.97. The value of GFI is 0.88. This model is used as a benchmark against which to establish the tenability of imposed equality constraints. Next, we estimate the most restrictive model by imposing equality constraints on the error covariance terms, factor loadings, and structural paths across the two groups. The most restrictive model and its corresponding goodness of fit indices are shown in figure 7. Although the value of $\Delta\chi^2_{df=33}$ = 40.24 is only marginally insignificant[2], the values of NFI, NNFI, CFI, IFI, and RFI remained unchanged after the equality constraints were imposed. We can thus conclude that the model in figure 7 is invariant across the calibration and validation samples. This analysis provides

[2] $\Delta\chi^2$ = 920.84 – 880.60 = 40.24; Δdf = 492 – 459 = 33 (10 error covariance terms + 23 factor loadings + 4 structural paths – 4 fixed paths = 33)

additional support for representing operations capability as a second order construct, and for the proposition that operations capability positively affects performance. The most restrictive invariant model in figure 7 shows that quality management capability has the greatest impact on operations capability ($\gamma_{3,1}$ = 0.83), followed by just-in-time ($\gamma_{2,1}$ = 0.76) and new product design and development capability (standardized $\gamma_{1,1}$ = 0.69). The structural parameter ($\beta_{4,1}$ = 0.46) verifies that operations capability positively impacts performance.

Insert Figure 7

7. Discussion and Managerial Implications

Support for proposition 1 is consistent with the results of Tan et al. (2004), suggesting that firms need to build capability in the areas of quality management, new product design and development, and just-in-time. It does not however preclude there being other dimensions of capability. This is consistent with the literature that suggests that improvement programs are at the core of the content of operations capability but that capability also reflects broader efforts to improve productivity firm wide (e.g., de Meyer et al., 1989, Roth and Miller, 1992). What distinguishes quality, just in time, and product development however is that not only do they have roots in the operations domain, they represent direct efforts to improve operations performance as opposed to factors such as the enhancement of information technology and changes in organizational structure. These enablers cut across the organization in addition to facilitating improvements within operations. Examination of their role in facilitating the development of operations capability represents a logical extension of the current study,

The global model (Figure 7) suggests that quality management capability has the largest impact on operations capability followed by just-in-time and new product design and development capabilities. The implication is that while the relative importance of each varies, potential benefit exists from building capabilities in all three areas. Moreover, it should be noted that given inherent relationships between the three, not only can improvements in one area be expected to result in improvements in others, failure to develop in one area may hinder efforts elsewhere. The observation that all three dimensions of capability have positive and significant coefficients is consistent with a firm being able to simultaneously possess multiple capabilities. While the results do not explicitly address the issue of the development sequence, the fact that quality management has the greatest individual impact may be an indication that it has had the longest time to develop. This is consistent with the contention of the sand cone theory that quality capability should be developed first.

While it is widely accepted that operations capability positively affects firm performance, this study provides empirical support for this relationship. As a firm improves its operations capability, it enhances its overall competitive position and ability to achieve customer satisfaction. This translates into pricing flexibility and faster diffusion of new products, allowing the firm to increase market share and improve financial and market performance. The implication is that the development of operations capability is a key to not only improving manufacturing related performance, but broader measures of financial and market based performance. However, the standardized structural parameter (Figure 7, $\beta_{4,1} = 0.50$) suggests that operations capability as defined here does not fully explain all variation in performance. This is again consistent with other factors such as managing the supply chain and developing and implementing integrated information systems, being related dimensions of capability. It should be noted that the results do not allow judgments to be made about the relative contribution of individual dimensions of capability to performance. This would, for example, provide insight into how organizations should deploy scarce resources across the three dimensions of capability and whether in fact it is necessary to do so to enhance business performance. The focus of this study however was on the relationship between capability as a multi-dimensional construct and performance. The literature on quality management, just in time, and product development, have amply demonstrated the relationship between each individually and performance. Moreover, prior studies have demonstrated the relative importance to performance of combinations of the three (e.g., Flynn et al., 1995, Nakamura et al., 1997).

8. Conclusion

While operations capability has been researched extensively, little empirical evidence exists of its content. This study confirms case and anecdotal evidence that a firm's operations capability, when viewed from an input, activity based perspective, is multifaceted. While results suggest that quality management capability has the greatest individual influence on operations capability followed by just-in-time, and new product design and development capabilities, this should not be interpreted as quality management being more important than others. Rather, it suggests that to achieve operations capability, an organization must develop capabilities in all three areas concurrently to achieve long term, sustainable competitive advantage. Results also provide support for the proposition that operations capability positively impacts performance. This is consistent with findings in the literature that emphasize the importance of developing and nurturing operations capabilities as a means to achieving long term, sustainable competitive success. This implicitly provides support for the notion that firms should develop multiple capabilities, and refutes the notion that firms cannot simultaneously excel on multiple dimensions of capability.

The results are also significant in that they demonstrate that operations capability is positively related to a comprehensive measure of both internal and market oriented performance. This is important for a number of reasons. Prior research has focused on measures of financial or manufacturing performance. This has precluded exploration of the impact of capability on a firm's ability to position itself in the marketplace. The results here suggest that by positively impacting performance that reflects competitive position and customer service levels, superior operations capability may provide the firm with leverage in the marketplace. This may enable it to, for example, adopt more aggressive pricing strategies, achieve more rapid market penetration with new products, or respond more rapidly to changes in customer preferences. These in turn drive market share and return on assets, reinforcing the cycle of performance improvement. The results also underscore the importance of just-in-time capability. It is generally recognized that new product design and development, and quality management capabilities are essential to compete effectively. To the extent that just-in-time capability is a reflection of an orientation towards leanness, it demonstrates that leanness is an important aspect of operations capability. This corresponds with the experiences of companies like Dell Inc., that have restructured and/or focused on waste reduction in response to fierce competition.

From a methodological perspective, a significant contribution of this study has been the use of multiple samples to calibrate and validate a structural model. The use of structural equation modeling has become commonplace in the operations literature in recent years. However, the results of many of the studies to use this methodology are compromised by the fact that models have been re-specified but tested using the same data used to develop the original model. The use of multiple samples in this study provides evidence of the robustness of the results. The study is not however without its limitations. We have relied upon information collected from a single respondent from each organization and assumed that they have the knowledge of their firms' operations necessary to make reasonable judgments on the issues of interest. Moreover, despite using two professional organizations to develop the sampling frame and achieving a response rate similar to that obtained in several similar studies, it was lower than others in this domain. While steps were taken to mitigate the impact of these factors, one cannot overlook the potential bias attributable and thus the ability to generalize from the results.

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Table 1: Descriptive Statistics of Survey Items

Constructs	Calibration Sample (n=264) Mean	Calibration Sample (n=264) Std Error	Validation Sample (n=263) Mean	Validation Sample (n=263) Std Error
1. New Product Design and Development Capability (NPDD, η_1)				
(A) Modular design of parts, $\lambda_{1,1}$	3.09	.078	3.02	.080
(B) Early Supplier Involvement, $\lambda_{2,1}$	3.33	.070	3.38	.076
(C) Use of concurrent engineering, $\lambda_{3,1}$	3.18	.071	3.16	.076
(D) Simplification of component parts, $\lambda_{4,1}$	3.31	.071	3.25	.080
(E) Standardization of component parts, $\lambda_{5,1}$	3.58	.067	3.63	.077
(F) Use of Value Analysis/Value Engineering, $\lambda_{6,1}$	3.06	.070	2.97	.074
2. Just-In-Time Capability (JIT, η_2)				
(A) Reduce lot size, $\lambda_{7,2}$	3.26	.076	3.20	.078
(B) Reduce setup time, $\lambda_{8,2}$	3.56	.082	3.54	.078
(C) Preventive Maintenance, $\lambda_{9,2}$	3.48	.072	3.43	.070
(D) Increase delivery frequencies, $\lambda_{10,2}$	3.42	.074	3.46	.068
(E) Reduce inventory to free up capital investment, $\lambda_{11,2}$	4.09	.066	4.12	.067
(F) Reduce inventory to expose mfg/scheduling problems, $\lambda_{12,2}$	3.41	.079	3.40	.078
3. Quality Management Capability (QLT, η_3)				
(A) Statistical process control, $\lambda_{13,3}$	3.23	.075	3.23	.079
(B) Design quality into the product, $\lambda_{14,3}$	4.03	.064	4.01	.067
(C) Process improvement (modification of process), $\lambda_{15,3}$	3.88	.062	3.91	.064
(D) Employee training in quality management and control, $\lambda_{16,3}$	3.83	.063	3.84	.068
(E) Empower shop operators to correct quality problems, $\lambda_{17,3}$	3.73	.068	3.70	.069
(F) Top management communication of quality goals, $\lambda_{18,3}$	3.94	.062	3.89	.069
4. Firm Performance (PERF, η_4)				
(A) Market share, $\lambda_{20,4}$	3.71	.061	3.77	.059
(B) Return on assets, $\lambda_{21,4}$	3.55	.056	3.56	.054
(C) Overall product quality, $\lambda_{22,4}$	4.25	.043	4.17	.045
(D) Overall competitive position, $\lambda_{23,4}$	3.94	.050	3.98	.050
(E) Overall customer service levels, $\lambda_{24,4}$	4.08	.049	3.95	.049

Note: Respondents were asked how important the practices/tools were in their firm's activities (1 = low importance, 5 = high importance), and the levels of performance relative to that of major competitors (1 = low performance, 5 = high performance).

Table 2: Goodness-of Fit Criteria *

Goodness-of-Fit Index	Acceptable Level	Comment
χ^2/degrees of freedom	≤ 3.0	χ^2 is sensitive to sample size and departure from multivariate normality assumption. Large sample size (>200) tends to result in significant χ^2 statistics. Non significant χ^2 p-value implies the data fit the hypothesized model.
χ^2 p-value	Non significant	
Root Mean Square Error of Approximation (RMSEA)	≤ 0.05	RMSEA ≤ 0.05 indicates a good model fit.
p-value for Test of Close Fit	≥ 0.50	A very narrow confidence interval argues for good precision of the RMSEA value.
Expected Cross-Validation Index (ECVI)	Compares to alternative models	Measures the discrepancy between the fitted covariance matrix and the expected covariance matrix in another sample of equal size.
Independence Akaike's Information Criterion (AIC)	Compares to alternative models	Measures the extent to which estimates will cross-validate in future samples. Smaller value is desirable.
Independence Bozdogan's Consistent Version of AIC (CAIC)	Compares to alternative models	Measures the extent to which estimated parameters will cross-validate in future samples. CAIC considers sample size. Smaller value is desirable.
Standardized Root Mean Square Residual (RMSR)	≤ 0.05	Measures the average discrepancy between the sample observed and hypothesized correlation matrix. Can be interpreted as the average error of the correlation explained by the model.
Goodness of Fit Index (GFI)	≥ 0.90	Indexes the relative amount of the observed variance and covariance accounted for by a model.
Adjusted GFI (AGFI)	≥ 0.80	GFI adjusted for degrees of freedom.
Parsimony GFI (PGFI)	≥ 0.50	Addresses the issue of parsimony in SEM.
Normed Fit Index (NFI)	≥ 0.90	Compares a proposed model with a null (independence) model. It tends to underestimate fit in small samples.
Non-Normed Fit Index (NNFI)	≥ 0.90	Compares the lack of fit of a target model to the lack of fit of a baseline model.
Parsimony NFI (PNFI)	-	Addresses the issue of parsimony.
Comparative Fit Index (CFI)	≥ 0.90	Revised NFI that takes sample size into account.
Incremental Fit Index (IFI)	Value close to 1	Addresses parsimony and sample size issues that were known to be associated with NFI. Similar to NFI, except that degrees of freedom are taken into account.
Relative Fit Index (RFI)	Value close to 1	Equivalent to CFI in most SEM applications.
Critical N (CN)	≥ 200	Focuses directly on the adequacy of sample size (rather than model fit) that would be sufficient to yield an adequate model fit.

* Source: Hoyle (1995); Byrne (1998); Raykov & Marcoulides (2000).

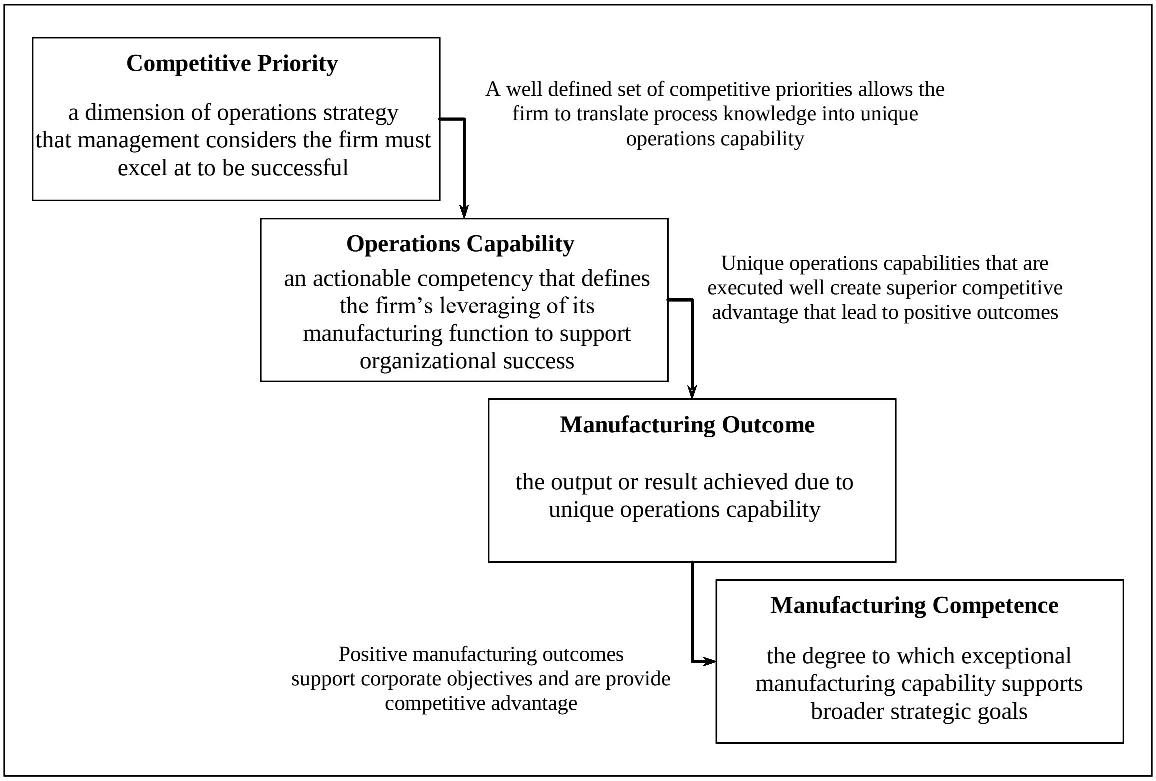


Figure 1: Relationship between Characterizations of Operations Capability

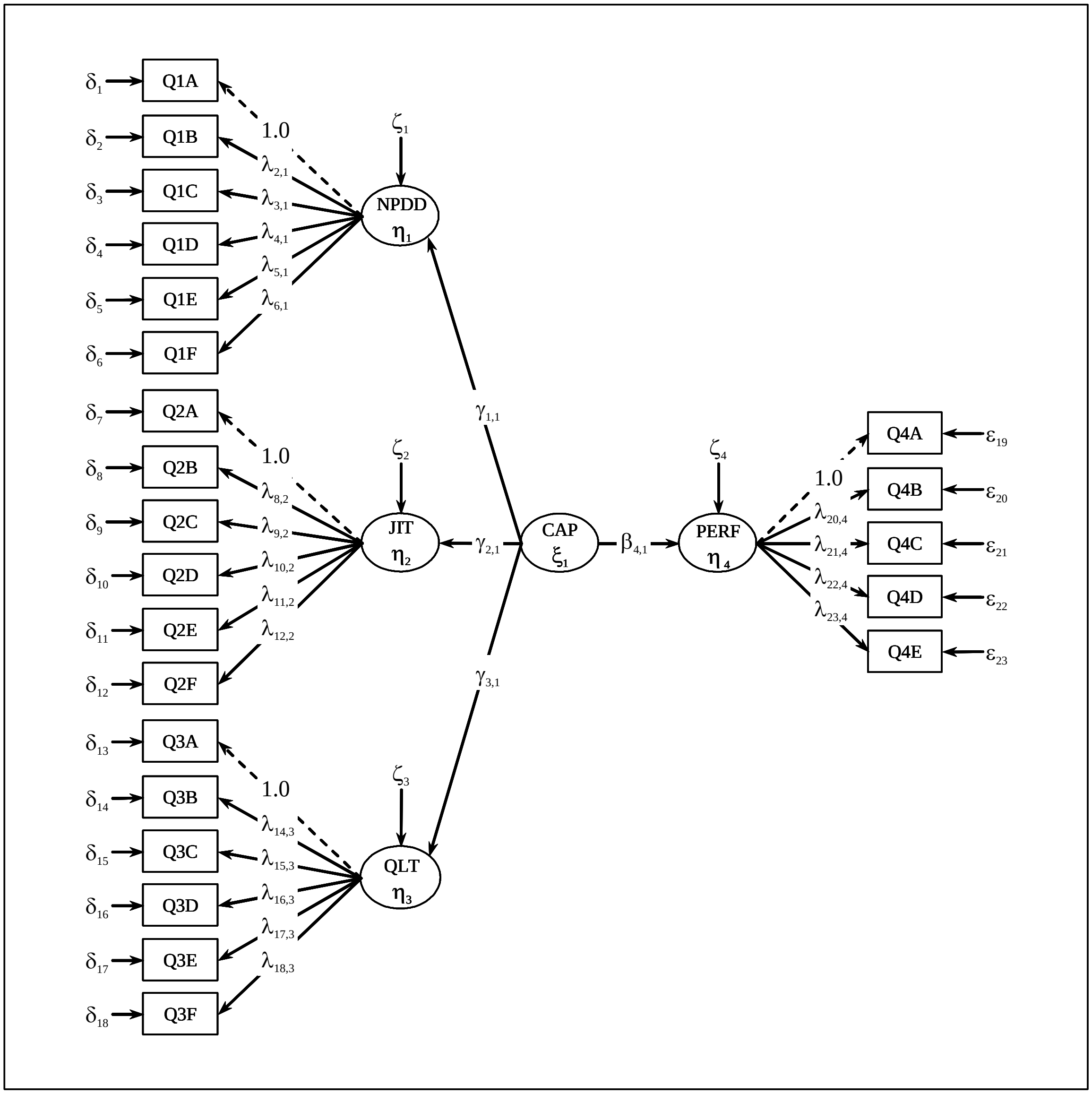
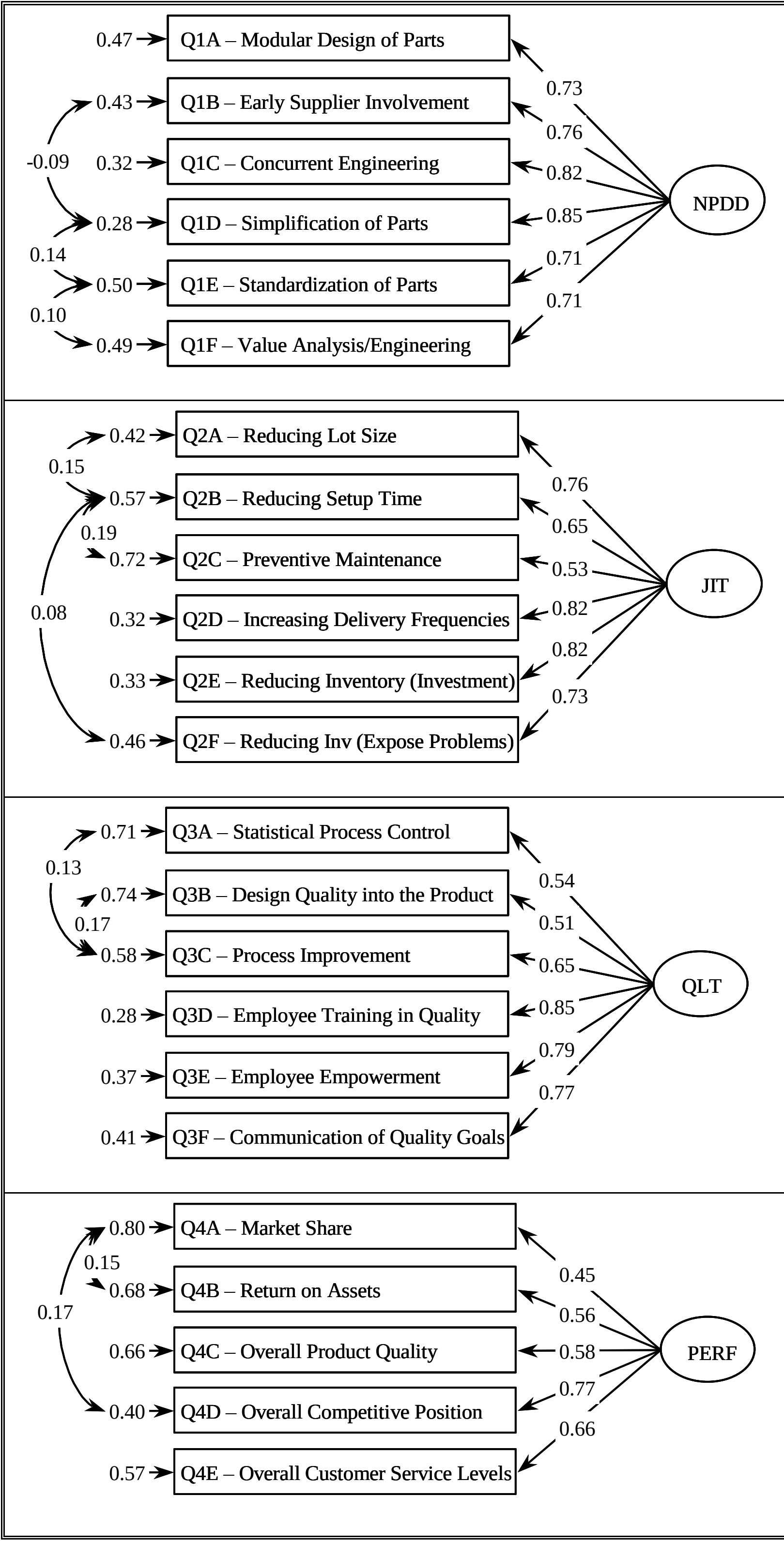
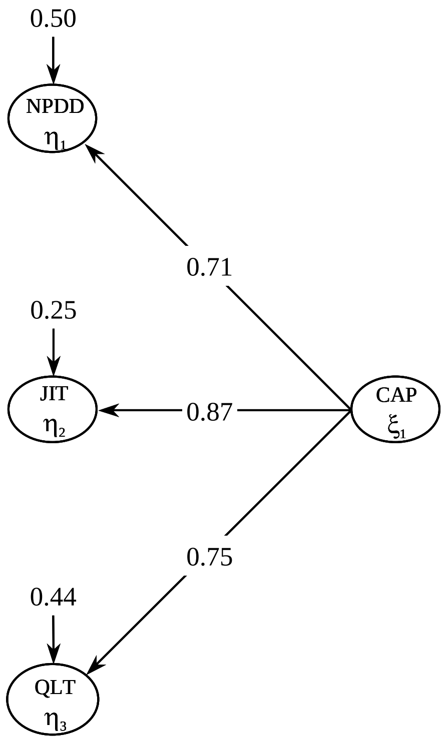


Figure 2: Operations Capability Model



	NPDD	JIT	QLT	PERF
χ^2	11.01	3.93	9.00	2.81
df	6	6	7	3
χ^2/df	1.835	0.655	1.286	0.937
χ^2 p-value	0.088	0.686	0.253	0.422
RMSEA	0.056	0.000	0.033	0.000
NFI	0.99	0.99	0.99	0.99
NNFI	0.98	1.00	0.99	1.00
CFI	0.99	1.00	1.00	1.00
IFI	0.99	1.00	1.00	1.00
RFI	0.97	0.99	0.97	0.97

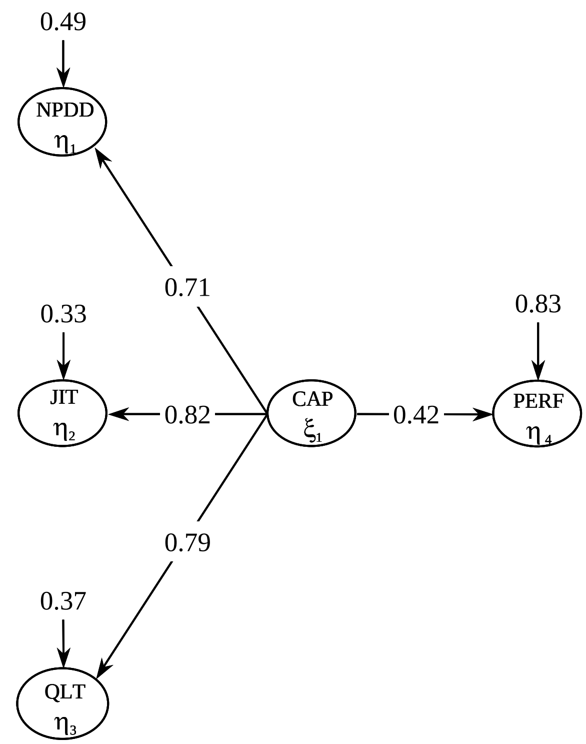
Figure 3: Measurement Models and Fit Indices – Calibration Sample



Fit Indices

χ^2	259.37
df	124
χ^2/df	2.092
χ^2 p-value	0.000
RMSEA	0.064
NFI	0.90
NNFI	0.93
CFI	0.95
IFI	0.95
RFI	0.88

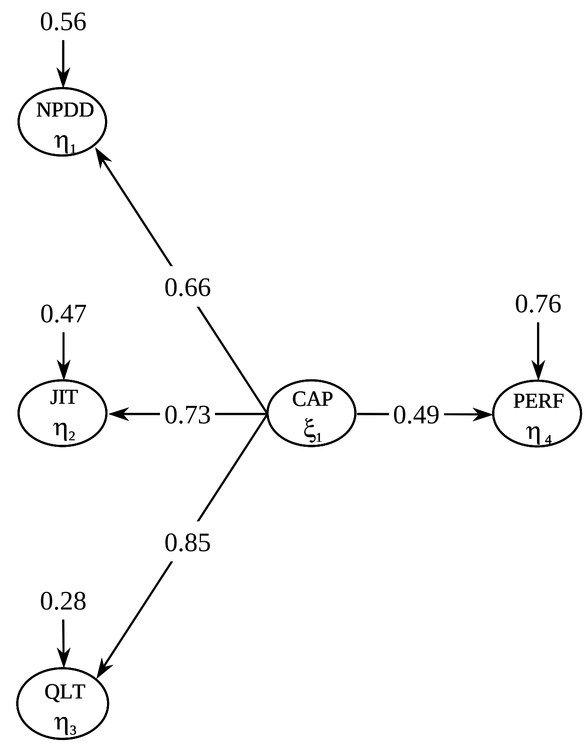
Figure 4: Operations Capability Model – Calibration Sample



Fit Indices

χ^2	383.41
df	216
χ^2/df	1.775
χ^2 p-value	0.000
RMSEA	0.054
NFI	0.95
NNFI	0.97
CFI	0.98
IFI	0.98
RFI	0.95

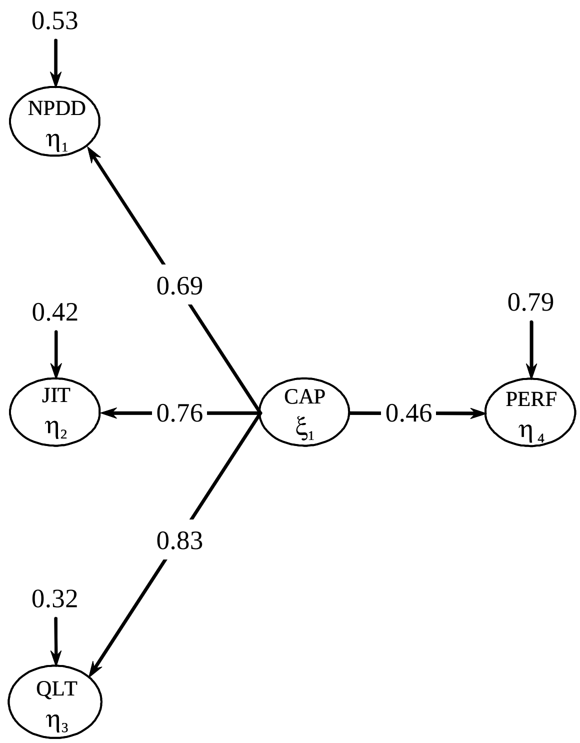
Figure 5: Operations Capability Model – Calibration Model



Fit Indices

χ^2	455.72
df	216
χ^2/df	2.110
χ^2 p-value	0.000
RMSEA	0.065
NFI	0.95
NNFI	0.97
CFI	0.97
IFI	0.97
RFI	0.94

Figure 6: Operations Capability Model – Validation



Global Goodness of Fit Statistics	
χ^2	920.84
df	492
χ^2/df	1.872
χ^2 p-value	0.000
RMSEA	0.058
NFI	0.95
NNFI	0.97
CFI	0.97
IFI	0.97
RFI	0.94

Group Goodness of Fit Statistics	
Contribution to χ^2	427.78
% Contribution to χ^2	46.87
RMR	0.098
Standardized RMR	0.078
GFI	0.88

Figure 7: Invariant Model with Equality Constraints Imposed