The efficient use of enterprise information for strategic advantage: A data envelopment analysis

Elliot Bendoly a,1,2, Eve D. Rosenzweig a,1,*, Jeff K. Stratman b,1,3

a Goizueta Business School, Emory University, 1300 Clifton Road, Atlanta, GA 30322-2710, United States
b David Eccles School of Business, University of Utah, 1645 East Campus Center Dr., Salt Lake City, UT 84112-9304, United States

ARTICLE INFO

Article history:
Received 31 July 2007
Received in revised form 11 November 2008
Accepted 13 November 2008
Available online 21 November 2008

Keywords:
Operations strategy
Enterprise systems
Data envelopment analysis

ABSTRACT

A majority of manufacturers make use of some form of enterprise systems (ES), yet on average, the financial impact of ES adoption is essentially neutral. We propose that in an ES environment of easy information access, competitive success depends, in part, on the policies regulating enterprise information use. To explore this proposition, we examine the efficient use of different types of enterprise information in the realization of strategic performance. Efficient firms will devote fewer resources to information use to achieve the same strategic performance as less efficient firms.

We employ data envelopment analysis (DEA) using data collected from Enterprise Resource Planning (ERP) system adopters at two different points in time in order to calculate a measure of efficient information use. This information efficiency metric is validated as a strong predictor of Compustat profitability. Additional analyses suggest that the most efficient users of information tend to emphasize information related to operational excellence. Regardless of information emphasis, however, efficient manufacturers – in contrast to their less efficient counterparts – were more likely to exhibit a better match between the most emphasized type of information and the corresponding dimension of strategic performance.

© 2008 Elsevier B.V. All rights reserved.

1. Introduction

Today’s managers rely more than ever before on management information systems to provide them with the business data needed to make critical decisions. The prevalence of enterprise systems – MetaGroup (2004) estimate that 400 of the Fortune 500 firms have adopted Enterprise Resource Planning (ERP) systems – has ensured that many managers have access to up-to-the-minute data on all aspects of their enterprises. Yet the long-term financial performance of the average firm with an enterprise system is not greatly different from that of firms without such technological support (Hendricks et al., 2007).

We define an enterprise system as an integrated planning and resource management system that coordinates information across all enterprise functions. Thus, an enterprise system encompasses more than core ERP functionality. By 2002, some form of integrated supply chain management (SCM), customer relationship management (CRM), and product lifecycle management (PLM) functionality was common among enterprise system users either through in-house development or software upgrades from major ERP vendors such as SAP (Bendoly and Jacobs, 2005).

In this study, we posit that having access to a vast amount of managerial information (e.g., product development timelines, customer feedback, resource status, etc.)
does not by itself provide a competitive advantage. Since
managerial time is a finite resource, a performance frontier
may place bounds on the total amount of information that
can be readily accessed and utilized in making decisions
(Schmenner and Swink, 1998; Vastag, 2000). Thus, using
data envelopment analysis (DEA), we examine the ways in
which the manufacturer places differential emphasis on
the “use” of various types of enterprise information (as
opposed to its mere availability) in the realization of its
strategy impacts its performance. Our DEA approach
allows us to measure the efficiency of information use,
as we analyze data collected on enterprise information use
by manufacturers, matched with strategic performance
data collected from the same firms 3 years later. The
resulting DEA efficiency metric is found to be a strong
predictor of Compustat profitability, attesting to its
managerial importance.

The next section develops our research hypotheses. Section 3 provides a description of our sample and the
methods used to construct and verify the empirical
measures employed in the study. Section 4 presents the
analyses and results of our hypotheses tests. We conclude
with a discussion of the theoretical and managerial
implications of our results, study limitations, and sugges-
tions for future research.

2. Hypothesis development

In this section we present the conceptual framework
and definitions relevant to our research model and develop
the logic behind the study hypotheses.

2.1. Definitions and conceptual framework

A key premise of this research is that different strategies
call for the use of (or emphasis on) different types of
information available from the enterprise system, and
result in strategic performance along various dimensions.
We define emphasis on a particular type of enterprise
information as the allocation of finite managerial attention
predominantly on a specific set of information (as made
available through a manufacturer’s enterprise system).
Strategic performance represents key performance indica-
tors that define a manufacturer’s strategic effectiveness.
Building on these two terms, we define efficiency of
information use as the efficiency with which strategic
performance is realized through an emphasis on enterprise
information. Efficient manufacturers spend fewer manage-
rial resources on information use to achieve the same level
of strategic performance as less efficient manufacturers.

We employ a common framework of competitive
strategies to categorize different types of enterprise
information use and strategic performance. Treacy and
Wiersema (1993) specify three basic strategies, or what
they refer to as value disciplines: operational excellence
(e.g., McDonald’s), customer intimacy (e.g., Lowe’s), and
product leadership (e.g., Intel). Market leaders, according
to Treacy and Wiersema (1993), typically excel at one of
these three value disciplines, and tend to meet industry
standards in the other two. Manufacturers that pursue the
first approach – operational excellence – strive for cost-
effective, rapid, and reliable fulfillment of order require-
ments. With the customer intimacy value discipline, the
emphasis shifts to the development of close customer
relationships; manufacturers attempt to increasingly tailor
products and services to fine-tuned market niches. Finally,
product leadership captures the manufacturer’s ability to
rapidly develop and deploy state-of-the-art products and
Corresponding Services.

2.2. The efficient use of enterprise information and
profitability

In the context of this research, information use is tightly
coupled with the technology that provides access to such
information. The technical limitations of the enterprise
system – as well as resource constraints on managerial
time devoted to information search (e.g., accessing,
understanding, transforming, and consolidating the infor-
mation) – place bounds on how effectively information use
can be converted into strategic results (Bendoly and
Cotteleer, 2008). In effect, a performance frontier develops
that represents a variety of information-use policies that
most aptly leverage the available enterprise information
(Schmenner and Swink, 1998; Vastag, 2000).

Fig. 1 provides a representation of such a performance
frontier. Points A, B and C represent efficient manufac-
turers that predominantly focus on operational excellence,
customer intimacy, and product leadership information,
respectively, to achieve relatively high levels of strategic

Fig. 1. The efficient use of enterprise information.
performance. Efficient manufacturers attain relatively high levels of outputs without excessive investments in inputs (Schmenner and Swink, 1998).

Positioning along the performance frontier between these “extreme” points – for example, between points A and B – is feasible (and quite likely) as well. With specific reference to the information-use items we study here (see Section 3.1.1), such a manufacturer would be one that makes effective, appropriate, and regular reference to ERP-stored machine maintenance schedules when attempting to understand customer feedback regarding order fulfillment issues, while not affording excess time studying reports of product design changes that might not impact such feedback.

Points D, E and F in Fig. 1 represent inefficient manufacturers (as do all manufacturers positioned off the performance frontier). Although these manufacturers may achieve the same level of strategic performance as their efficient counterparts (A, B, and C, respectively), they do so by expending more resources on the respective types of enterprise information. One likely scenario is that such manufacturers – and more generally, any inefficient manufacturer – may invest in enterprise systems without making corresponding substantive, infrastructural-related changes to the use of information (Roth and Miller, 1992).

Or perhaps for those inefficient manufacturers positioned somewhere between points D and E, and returning to our order fulfillment example above, the issue is that customer feedback is misinterpreted such that problems associated with order fulfillment are routinely misdiagnosed as product-design related. In this scenario, manufacturers fail to pinpoint the specific domain(s) of data critical to assessment, and instead are bogged down in information that does not improve intelligence or subsequent decision-making.

Scenarios of inefficiency such as these are generally characterized by haphazard attempts to make sense of large quantities of information provided by enterprise systems (Bendoly, 2003), which can be both highly costly and uninformative, if not misleading and strategically detrimental. Furthermore, such real costs can dampen or derail financial success, even if manufacturers are able to ultimately eek out strategic performance benefits. Thus, we expect efficient manufacturers to be more profitable than their less efficient counterparts. This leads us to our first hypothesis:

**H1.** Efficient information use is associated with profitability.

### 2.3. Characteristics of efficient manufacturers

If efficient information use is indeed a key driver of profitability, then it is of interest to uncover the characteristics of such efficient manufacturers. We posit that it is the differences in the use of various types of enterprise information – and not strength on any particular dimension of strategic performance – that primarily determines efficiency. It is well documented that no single strategy or value discipline consistently leads to greater profitability or is easier to achieve (e.g., Epstein and Westbrook, 2001; Kaplan and Norton, 2000; Miller and Roth, 1994; Porter, 1985; Slater et al., 1997; Treacy and Wiersema, 1993). In the context of our study, this implies that a manufacturer does not necessarily have to exhibit strength on a certain strategic performance dimension (versus others) to be considered efficient or “best-in-class.” Thus, to facilitate understanding of the key characteristics of efficient manufacturers, we offer the following hypothesis:

**H2a.** No single dimension of strategic performance dominates the manufacturers positioned on the performance frontier.

Market-leading manufacturers with an operational excellence focus “have built their operations around information systems that emphasize integration and low-cost transaction-processing” (Treacy and Wiersema, 1993:87). These characteristics are fundamental to enterprise systems. Enterprise systems were developed to rationalize and automate enterprise-wide transaction processing through the use of a single integrated database. All of the firm’s transactional data is updated in real-time and stored centrally, allowing for coordinated planning across functional areas (Bancroft et al., 1998). ERP users are essentially forced to make use of operational excellence information in the course of processing day-to-day business transactions. Several studies have found that ERP adoption enhances strategic performance in operational excellence in areas such as on-time deliveries (McAfee, 2002) and lead times (Cottelee and Bendoly, 2006). Information-use policies that focus managerial attention on customer lead times and order handling requirements facilitate these results.

Furthermore, a successful outcome in any of the three value disciplines relies on effective execution. Strategic performance in customer intimacy involves satisfying the customer, which is facilitated by the use of operational excellence information to ensure that customer expectations in terms of order fulfillment are met. Similarly, strategic performance in product leadership involves the on-time, speedy delivery of new products meeting quality specifications, which requires a foundation of operational excellence information to achieve.

In summary, enterprise systems make use of transactions that rely on a foundation of operational excellence information in order to conduct any enterprise business. Therefore, information-use policies must include a sufficient level of attention to operational excellence information, regardless of the chosen value discipline, in order to effectively navigate the transactional structure of the enterprise system. In contrast, information-use policies that de-emphasize operational excellence information work against the structure of the enterprise system, making it more difficult to realize a benefit from the technology. This observation leads to the following hypothesis:

**H2b.** Operational excellence information use dominates the manufacturers positioned on the performance frontier.
Although the logic supporting Hypothesis 2b suggests that the technical capabilities of enterprise systems reward a manufacturer’s use of operational excellence information, it does not necessarily follow that an emphasis on the customer intimacy or product leadership information types cannot add value. The notion that firms might benefit by aligning their use of enterprise information with the strategic needs of their organizations is not new (c.f. Bendoly and Jacobs, 2005). While we expect operational excellence information use to dominate among efficient enterprise system users, manufacturers on the performance frontier that emphasize other types of information (e.g., points B or C in Fig. 1) are expected to show evidence of superior strategic performance corresponding to the selected type of information use.

For those manufacturers pursuing customer intimacy, the key is to invest in technologies that facilitate the collection, integration, and analysis of customer-related information from various sources (Treacy and Wiersema, 1993). For manufacturing firms, strategic performance in customer intimacy involves maintaining ties with customers and surpassing their expectations through a focus on sales data, customer feedback, and post-delivery service requirements. The enterprise system database provides a single point of access to customer data, allowing for responsive customer service. CRM modules collect additional information related to long-term customer relationship-building (Katz, 2002; Suresh, 2004) and facilitate customer intimacy by providing decision-support tools that analyze customer behaviors and preferences across multiple product lines over time.

In terms of product leadership, enterprise systems are needed to facilitate the design and development of desirable new products and corresponding services at a pace that is consistent with or exceeds market expectations. Benchmarking studies of effective new product development (NPD) practices highlight a centralized technological infrastructure that helps “coordinate, communicate, collaborate, and control product development” (Brown, 2005: 11) as a key success factor for businesses based on innovation. A focus on information related to product specifications, and in particular product development timelines, is consistent with these prescriptions, and should enhance strategic performance in product leadership.

Such manufacturers demonstrate efficient selection of, access to, and use of key clusters of information especially relevant to the realization of performance along that particular strategic dimension. Alternatively, manufacturers devoting costly excess attention to distracting information and insufficient attention to essential information, embodied by a “mismatch” between the most emphasized type of information and dimension of strategic performance, are expected, on average, to fall short of the frontier. Accordingly, we hypothesize that:

H2c. Relative to inefficient manufacturers, efficient manufacturers will exhibit a better match between the most emphasized type of information and the corresponding dimension of strategic performance.

3. Research design and methodology

In the subsections that follow, we describe the various sources of data used to operationalize the measures, confirm measurement reliability and validity, and provide an overview of the sample used in the analysis. We also specify the DEA model. The flowchart presented in Fig. 2 represents the timing and variety of data collection activities utilized in developing our understanding of the research context.

3.1. Overview of field studies

Section 3.1.1 provides details of the first field study used to collect data on enterprise information use, while Section 3.1.2 relates how data on strategic performance was collected in the second field study.

3.1.1. Field study #1: information use

The construction of the set of survey items used in assessing enterprise information use – and ultimately in creating multi-item enterprise information use scales – began with an examination of messages generated over a period of 7 months by the Certified Production and Inventory Managers (CPIM) discussion list server, hosted by the American Production and Inventory Control Society (APICS). The participating subscribers represented a total of 374 firms. These messages were screened to exclude certification exam questions/responses, non-work related social correspondence, and all other discussions not associated with real-work inquiries and debates originated by the CPIMs themselves. Descriptive analysis based on keyword content was then performed to further limit our attention to messages that dealt specifically with enterprise system data access. In total, this distinguished 716 relevant messages.

Initially, several generalized types of information (e.g., order-handling requirements) were delineated from the discussions. Twenty-one Likert-type questions related to the accessed use of such information were then formed and screened for effectiveness by a group of experts, consisting of the eight most active participants to the list server. These eight CPIMs had contributed a total of 16.9% of the 716 messages considered and held positions in a range of industries, including Machine Tools, Electrical Components, Instrumentation, and Manufacturing Consulting.

The eight individuals were asked to provide personal assessments with regard to the fraction of CPIMs they felt would have a high level of knowledge regarding the questions. They were also asked to assess the average response to each “usage” question. Items for which CPIMs were expected to generally have limited knowledge, or for which usage was deemed either compulsory in most tactical planning decisions or irrelevant to all but a few isolated decision-making scenarios, were deleted. This vetting was important to ensure both face validity in the items as well as usage-variance critical in analysis. We also note that information use is well within the realm of management control, a typical expectation regarding the interpretation of inputs in DEA analysis. (c.f. Charnes et al., 1978; Metters et al., 1999; Narasimhan et al., 2005).
The final set of questions for the survey instrument includes nine items, each of which can be mapped to one of the three values disciplines discussed in Section 2. Items are measured on a 7-point Likert scale in response to the question: "How often do you access the following data from your Enterprise Resource Planning system in making tactical decisions?" \(^4\)

Use of information relevant to operational excellence \((x_o)\):
- Resource status (e.g., scheduled maintenance)
- Lead time quotations to customers
- Order handling requirements

Use of information relevant to customer intimacy \((x_c)\):
- Customer post-delivery contract items
- Customer feedback
- Sales promotion data

Use of information relevant to product leadership \((x_p)\):
- Product specifications
- Product development timelines
- Notes on design changes

Responses to these items were collected from a post-Y2K survey of U.S. manufacturers equipped with functioning enterprise systems. The initial target population consisted of 607 manufacturers in industrial sectors that ranged from chemical processing to high tech, with contact information provided by the APICS Education and Research Foundation. We collected completed surveys from 178 of these 607 manufacturers, yielding a response rate of 29.3\% (178/607). The unit of analysis is the firm.

### 3.1.2. Field study #2: strategic performance

Data relating to strategic performance was collected in a separate survey administered to the same respondents from the same manufacturing organizations 3 years later. One benefit of pairing earlier measures of enterprise information use with later strategic performance evaluations is the reduced risk of halo effects traditionally associated with common source bias in empirical studies (Hoover, 2001; Podsakoff and Organ, 1986). A second benefit of this particular sequence of data collection allows for a stronger, though not absolute, ability to draw causal interpretations regarding the relationship between the DEA model inputs of enterprise information use and outputs of strategic performance as described below in Section 3.3.

In developing the strategic performance items, we drew on performance metric compilations utilized in practice as well as on those commonly appearing in the academic literature (see Bendoly et al., 2007 for an overview of academic studies). With respect to practitioner-oriented compilations, we gleaned performance metrics consistent with the operational excellence value discipline primarily from the Supply Chain Council's (SCC) supply-chain operations reference (SCOR) model. Customer- and Design-Chain metric libraries – a SCC developmental effort at the time of this field study – were instrumental with regard to the identification and consideration of representative items for our customer intimacy and product leadership performance categories, respectively.

In keeping with Churchill's (1979) well-established item and scale development process, we reviewed operations management studies in which concepts analogous to those outlined by the SCC metrics libraries had been examined. In doing so, we ensured content validity across the pool of strategic performance items to be included in the field study. To facilitate measurement purification – and to ultimately group metrics into multi-item performance scales targeted at the operational excellence, customer intimacy, and product leadership value disciplines – we conducted a multi-phase manual sorting procedure characteristic of other contemporary studies (c.f. Menor and Roth, 2003; Moore and Benbasat, 1991; Stratman and Roth, 2002). That is, the proposed items were iteratively subjected to two independent rounds of Q-sorting, the first of which employed three expert practitioners or "judges," and the second of which employed seven judges. The results of this full Q-sort process, in turn, determined the set of strategic performance items to be included in the field study survey.

We collected responses to these strategic performance items – along with items not directly related to this paper, as the study was part of a larger research project (see Bendoly et al., 2007) – by means of a web-based survey. Because of the broader scope of this second field study, and on account of the performance-related nature of the survey questions, we supplemented the first field study APICS target population with manufacturing members of the SCC, which resulted in a target population of 759 manufacturers.

\(^4\) All information usage items are measured on a 7-point Likert scale (‘1’ never access such information when making decisions; ‘4’ access such information for about half of the decision-making that takes place; ‘7’ always access such information when making decisions).
and a response rate of 15.5% (118/759). The final set of items comprising the three strategic performance scales, also utilized in Bendoly et al. (2007), is measured on a 5-point Likert scale ranging from ‘1’ strongly disagree to ‘5’ strongly agree in response to the question: “To what extent do you agree with the following statements about your manufacturing business unit’s performance?”

Strategic performance in operational excellence ($y_0$)
- We pursue process standardization
- We are known in the marketplace for our conformance quality
- We are known for our on-time delivery performance
- We are known for our speedy deliveries
- We continually pursue price reductions

Strategic performance in customer intimacy ($y_c$)
- We consistently surpass customer expectations
- We are more effective at attracting new customers than competitors
- We encourage our sales force to maintain ties with our customers
- Relative to other firms in our industry, we are better able to accommodate customer preferences
- We make extensive use of customer data when developing marketing plans
- We provide customers a broad range of offerings to ensure their specific needs are filled
- Relative to other firms in our industry, the annual number of solutions we propose to existing clients is high
- We target niche markets

Strategic performance in product leadership ($y_p$)
- We are known in the marketplace for the performance quality of our products
- Our products are known for their features and functions
- Our design team keeps up with recent advances in the field
- The number of times our patents are cited by external parties is high
- We are always the first to deliver a new product/service to market

3.2. Research database

The combined dataset derived from matching complete input ($n = 178$) and output ($n = 118$) item responses from the two surveys included a total of 63 records, which represents 10.4% of the first field study target population. Manufacturers in the industrial machinery industry provided 22% of the 63 records. The other most prevalent sources were the chemical (13%), electronics (11%), transportation equipment (11%), and precision instrumentation (11%) industries. Tests for non-response bias along industry and other demographic information available (e.g., number of employees) showed no significant differences between the combined sample ($n = 63$) and either of the field study target populations.

3.2.1. Scale reliability and validity

Using the combined sample ($n = 63$), we demonstrate that the enterprise information use and strategic performance scales to be used in the DEA model are both reliable and valid. The variables $x_{o}$, $x_{c}$, and $x_{p}$ represent scales measuring the level of emphasis placed on operational excellence, customer intimacy, and product leadership information use, respectively. Similarly, $y_{o}$, $y_{c}$, and $y_{p}$ are scales measuring strategic performance along the value disciplines of operational excellence, customer intimacy, and product leadership, respectively. We note that a simple average of the scale items was used to form single composite information use and strategic performance scale variables pertaining to each respective value discipline.

The confirmatory factor analysis (CFA) results for all proposed scales yielded Bentler–Bonett Non-Normed Fit Index (NNFI) and Tucker–Lewis Index (TLI) values of .90 or greater, and Root Mean Square Error of Approximation (RMSEA) values below 0.05, thus meeting the generally accepted criteria for unidimensionality (Sharma et al., 2005); see Appendix A for individual path loadings and evidence of convergent validity.

To establish discriminant validity, we assessed a series of chi-square ($\chi^2$) difference tests between nested CFA models for all construct pairs (Ahire et al., 1996). Because all $\chi^2$ differences are statistically significant ($p \leq .05$), we conclude that the scales represent distinct constructs.

Finally, we calculated Cronbach’s alpha ($\alpha$) levels to assess scale reliability. These results – which indicate that our composite scale variables suffer from minimal measurement error and are, therefore, reliable – along with additional descriptive statistics, are presented in Table 1.

3.2.2. Compustat profitability

In order to ensure that the DEA-derived efficiency levels (described below in Section 3.3) have some practical meaning, and to ultimately assess Hypothesis 1, we test for the association of these efficiency levels with an objective, secondary-source profitability metric using correlation and regression analyses. Specifically, we utilize Compustat profitability data (profits/sales) averaged over a two-year period, with the starting year coinciding with the collection of our strategic performance data. This profitability data was matched to all manufacturers for which we had complete field data with respect to enterprise information use and strategic performance (i.e., the 63-unit sample).

3.2.3. Control variables

We control for industrial sector membership and organization size in the regression analyses that test Hypothesis 1, as prior research suggests these two factors may influence financial performance (see, for example, Cool and Schendel, 1987; Gaimon, 1997). Following Bendoly et al. (2007), we use two-digit SIC codes to parsimoniously classify the firms into one of three broad
manufacturers feel their processes can be described as extreme formalization. These effects. The first control captures the percentage of a formalization to ‘5’

Hypothesis 1 also includes two variables to control for performance of information technology investments (see Chen et al., 2006; Chen and Zhu, 2004; Shafer and Byrd, 2000). For this reason, our test of Hypothesis 1 also includes two variables to control for these effects. The first control captures the percentage of a firm’s products classified in the mature phase of the product lifecycle. The second measure the extent to which manufacturers feel their processes can be described as formalized, with response choices ranging from ‘1’ little formalization to ‘5’ extreme formalization.

3.3. The DEA model and efficient information use

In the context of this research, the use of DEA enables us to evaluate the relative efficiency of each of our 63 manufacturers in terms of how they use enterprise information in the realization of strategic performance. As with our theoretical model, DEA is a boundary method that estimates relative efficiency in terms of what the top manufacturers have actually been able to achieve. We note that prior research has employed DEA to assess the performance of information technology investments (see Chen et al., 2006; Chen and Zhu, 2004; Shafer and Byrd, 2000; Shao and Lin, 2002).

In formulating our model, we follow the CCR (Charnes et al., 1978) DEA methodology used by authors such as Narasimhan et al. (2005) and Verma and Sinha (2002). The constant returns to scale CCR model is appropriate, as all ERP adopters essentially face the same economies of scale related to information use. While large, geographically diverse and complex enterprises may face higher installation costs, ERP systems, once installed, should provide essentially identical access to and ability to process enterprise data.

For each DMU (i.e., the decision-making units, or empirical observations, used in the analysis), \( m \), of the 63 records being evaluated (\( M \)), the following model applies:

\[
\text{Max } E_m = \sum_{k=1}^{K} v_k y_{km}
\]

s.t. \( \sum_{j=1}^{J} u_j x_{jm} = 1 \)

\( \sum_{k=1}^{K} v_k y_{ji} - \sum_{j=1}^{J} u_j x_{ji} \leq 0 \quad \forall i \in M \)

\( u_j, v_k \geq 0 \quad \forall k \in K, j \in J \)

For unit \( m \), \( x_{jm} \) represents the value of input factor \( j \) and applies to all input variables in set \( J \) (i.e., the three enterprise information use variables corresponding to operational excellence, customer intimacy, and product leadership, respectively). Similarly, \( y_{km} \) represents the value of output factor \( k \) and applies to all output variables in set \( K \) (i.e., the three strategic performance variables). In this scheme, “efficiency” is defined as the ratio of a DMU’s weighted sum of inputs used in pursuing a weighted sum of output performance. To that end, \( u_j \) and \( v_k \) represent the weights assigned to each input and output variable, respectively, in an attempt to maximize the apparent efficiency of any DMU while ensuring that efficiency of other DMUs does not exceed the conceptual ceiling of 100% relative efficiency. This weight-determining constrained maximization is performed for each DMU to allow for efficiency comparisons across the sample of 63 manufacturers.

Efficiency scores may not be estimated correctly if the sample does not contain a sufficient number of DMUs. Rules-of-thumb suggest that the number of DMUs must be greater than the product of the number of inputs and outputs (Soteriou and Zenios, 1998), or three times the sum of inputs and outputs (Chen and Zhu, 2004). Our sample of 63 DMUs easily exceeds the number of 9 or 18 DMUs, respectively, recommended by the two rules-of-thumb.

---

**Table 1**

Descriptive statistics for information use and strategic performance scales.

<table>
<thead>
<tr>
<th>Information use</th>
<th>Strategic performance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average (SD)</td>
<td>x_0 [0.84]^a</td>
</tr>
<tr>
<td>Use of information relevant to operational excellence</td>
<td>x_0 [0.84]^a</td>
</tr>
<tr>
<td>Use of information relevant to customer intimacy</td>
<td>x_c [0.82]</td>
</tr>
<tr>
<td>Use of information relevant to product leadership</td>
<td>y_p [0.77]</td>
</tr>
<tr>
<td>Strategic operational excellence performance</td>
<td>y_p [0.77]</td>
</tr>
<tr>
<td>Strategic customer intimacy performance</td>
<td>y_c [0.75]</td>
</tr>
<tr>
<td>Strategic product leadership performance</td>
<td>y_p [0.77]</td>
</tr>
</tbody>
</table>

---

**Notes:**
- The Cronbach’s \( \alpha \) values associated with each scale are provided in brackets along the diagonal.
- Pearson correlation is significant at the 0.01 level (2-tailed).
- * Pearson correlation is significant at the 0.05 level (2-tailed).
- ** Pearson correlation is significant at the 0.001 level (2-tailed).

---

5 Approximately how many employees, in full-time equivalents (FTEs), does your organization currently employ? Item measured on a 7-point scale (‘1’ under 250; ‘2’ 250–500; ‘3’ over 500–1000; ‘4’ over 1000–2000; ‘5’ over 2000–4000; ‘6’ over 4000–8000; ‘7’ over 8000).

6 What is your current annual sales volume in U.S. dollars? Item measured on a 7-point scale (‘1’ under $50 million; ‘2’ $50 million to $100 million; ‘3’ over $100 million to $200 million; ‘4’ over $200 million to $400 million; ‘5’ over $400 million to $800 million; ‘6’ over $800 million to $1.6 billion; ‘7’ over $1.6 billion).
<table>
<thead>
<tr>
<th>DMU reference #</th>
<th>Relative efficiency</th>
<th>“Dominant” strategic performance</th>
<th>“Dominant” information use</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>OE</td>
<td>OE</td>
</tr>
<tr>
<td>2</td>
<td>1</td>
<td>PL</td>
<td>PL</td>
</tr>
<tr>
<td>3</td>
<td>1</td>
<td>CI</td>
<td>OE</td>
</tr>
<tr>
<td>4</td>
<td>1</td>
<td>OE</td>
<td>OE</td>
</tr>
<tr>
<td>5</td>
<td>1</td>
<td>CI</td>
<td>CI</td>
</tr>
<tr>
<td>6</td>
<td>1</td>
<td>OE</td>
<td>OE</td>
</tr>
<tr>
<td>7</td>
<td>1</td>
<td>CI</td>
<td>CI</td>
</tr>
<tr>
<td>8</td>
<td>1</td>
<td>PL</td>
<td>PL</td>
</tr>
<tr>
<td>9</td>
<td>1</td>
<td>PL</td>
<td>OE</td>
</tr>
<tr>
<td>10</td>
<td>1</td>
<td>CI</td>
<td>CI</td>
</tr>
<tr>
<td>11</td>
<td>1</td>
<td>OE</td>
<td>OE</td>
</tr>
<tr>
<td>12</td>
<td>1</td>
<td>PL</td>
<td>PL</td>
</tr>
<tr>
<td>13</td>
<td>1</td>
<td>PL</td>
<td>PL</td>
</tr>
<tr>
<td>14</td>
<td>1</td>
<td>CI</td>
<td>CI</td>
</tr>
<tr>
<td>15</td>
<td>1</td>
<td>PL</td>
<td>PL</td>
</tr>
<tr>
<td>16</td>
<td>1</td>
<td>OE</td>
<td>OE</td>
</tr>
<tr>
<td>17</td>
<td>1</td>
<td>CI</td>
<td>CI</td>
</tr>
<tr>
<td>18</td>
<td>1</td>
<td>OE</td>
<td>OE</td>
</tr>
<tr>
<td>19</td>
<td>1</td>
<td>CI</td>
<td>CI</td>
</tr>
<tr>
<td>20</td>
<td>1</td>
<td>OE</td>
<td>OE</td>
</tr>
<tr>
<td>21</td>
<td>1</td>
<td>PL</td>
<td>PL</td>
</tr>
<tr>
<td>22</td>
<td>1</td>
<td>PL</td>
<td>OE</td>
</tr>
<tr>
<td>23</td>
<td>1</td>
<td>OE</td>
<td>OE</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>DMU reference #</th>
<th>Relative efficiency</th>
<th>“Dominant” strategic performance</th>
<th>“Dominant” information use</th>
</tr>
</thead>
<tbody>
<tr>
<td>24</td>
<td>0.99</td>
<td>OE</td>
<td>PL</td>
</tr>
<tr>
<td>25</td>
<td>0.98</td>
<td>CI</td>
<td>CI</td>
</tr>
<tr>
<td>26</td>
<td>0.98</td>
<td>CI</td>
<td>CI</td>
</tr>
<tr>
<td>27</td>
<td>0.97</td>
<td>OE</td>
<td>OE</td>
</tr>
<tr>
<td>28</td>
<td>0.97</td>
<td>PL</td>
<td>OE</td>
</tr>
<tr>
<td>29</td>
<td>0.96</td>
<td>OE</td>
<td>OE</td>
</tr>
<tr>
<td>30</td>
<td>0.96</td>
<td>CI</td>
<td>CI</td>
</tr>
<tr>
<td>31</td>
<td>0.96</td>
<td>PL</td>
<td>PL</td>
</tr>
<tr>
<td>32</td>
<td>0.93</td>
<td>CI</td>
<td>PL</td>
</tr>
<tr>
<td>33</td>
<td>0.92</td>
<td>PL</td>
<td>PL</td>
</tr>
<tr>
<td>34</td>
<td>0.91</td>
<td>OE</td>
<td>CI</td>
</tr>
<tr>
<td>35</td>
<td>0.89</td>
<td>OE</td>
<td>OE</td>
</tr>
<tr>
<td>36</td>
<td>0.89</td>
<td>PL</td>
<td>CI</td>
</tr>
<tr>
<td>37</td>
<td>0.88</td>
<td>CI</td>
<td>CI</td>
</tr>
<tr>
<td>38</td>
<td>0.88</td>
<td>OE</td>
<td>OE</td>
</tr>
<tr>
<td>39</td>
<td>0.87</td>
<td>CI</td>
<td>PL</td>
</tr>
<tr>
<td>40</td>
<td>0.87</td>
<td>PL</td>
<td>PL</td>
</tr>
<tr>
<td>41</td>
<td>0.86</td>
<td>OE</td>
<td>CI</td>
</tr>
<tr>
<td>42</td>
<td>0.86</td>
<td>OE</td>
<td>PL</td>
</tr>
<tr>
<td>43</td>
<td>0.85</td>
<td>CI</td>
<td>CI</td>
</tr>
<tr>
<td>44</td>
<td>0.83</td>
<td>PL</td>
<td>CI</td>
</tr>
<tr>
<td>45</td>
<td>0.82</td>
<td>CI</td>
<td>OE</td>
</tr>
<tr>
<td>46</td>
<td>0.81</td>
<td>OE</td>
<td>CI</td>
</tr>
</tbody>
</table>

On frontier (n = 23)

Off frontier (n = 40)

Notes: (1) “Dominant” strategic performance refers to the dimension of strategic performance that the DMU scored highest on. (2) “Dominant” information use refers to the type of enterprise information use on which the DMU reported the most activity. (3) OE = operational excellence; CI = customer intimacy; PL = product leadership.
4. Results

The results for the DEA runs on our database of 63 records are given in Table 2, and visualized in Fig. 3 (in analogy to the conceptual depiction presented earlier in Fig. 1). This table also presents a snapshot of how the DMUs on and off the performance frontier are roughly oriented with regards to relative emphasis in the use of specific enterprise information and strategic performance. For example, DMU #1 in Table 2 is an efficient manufacturer (efficiency score = 1.00) emphasizing operational excellence information use. Of the three strategic performance variables, this DMU reports its highest score along operational excellence, consistent with its emphasis in information use.

Prior to a more comprehensive interpretation of the DEA results, we conducted a check of criterion validity for our DEA-derived measure of efficiency. The Compustat profitability data showed statistically significant, positive Pearson and Spearman rank correlations with the derived efficiency levels ($p < 0.05$). The fact that the DEA-based efficiencies, driven by perceptual survey data, correlate well with secondary-source, objective data is striking and encouraging of the interpretability of these efficiencies for use in further analysis.

4.1. Effect of efficient information use on profitability

We use ordinary least squares (OLS) regression analysis to test Hypothesis 1, which posits a relationship between efficient information use and profitability. We note that the manufacturing industrial sector membership dummy variable is not explicitly included in the Table 3 results because it is designated as the comparison or “reference group” for analysis. In addition, we analyze the model hierarchically in the sense that we first assess the effects of the control variables on profitability (block 1), then consider the incremental effect of our efficiency metric (block 2).

Table 3 shows that the DEA-based efficiency value is a strong predictor of profitability ($\beta = 18.043$; $p \leq .001$), with the block 2 regression showing a significant increase in explained variance (from 10.1% to 28.7%) over the block 1 regression that only includes the control variables. Of the controls, only annual sales and the percentage of products in the mature phase of the product lifecycle are significant; however, the regression coefficients of these controls are much lower than that of the information efficiency metric.

The strength and positive direction of the efficiency effect provide fundamental support to our first hypothesis. As an additional test of the effectiveness of our chosen metric of efficiency, in lieu of related input–output interaction terms capturing a similar concept, we compare our DEA model approach to the more commonly applied moderated multiple regression (MMR) analysis approach in terms of explaining profitability in Appendix B.

4.2. Examining characteristics of efficient manufacturers

Recall that Hypotheses 2a, 2b, and 2c investigate the characteristics of efficient manufacturers. In order to evaluate these three hypotheses, we divided the sample

<table>
<thead>
<tr>
<th>Independent variables</th>
<th>Block-1</th>
<th></th>
<th>Block-2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Unstdzd Betas</td>
<td>t</td>
<td>Sig.</td>
</tr>
<tr>
<td>Constant</td>
<td>31.474</td>
<td>2.922</td>
<td>0.004</td>
</tr>
<tr>
<td>1. Organization size (ln employees)</td>
<td>$-$0.014</td>
<td>$-$0.191</td>
<td>0.441</td>
</tr>
<tr>
<td>2. Annual sales (ln $k$)</td>
<td>0.213</td>
<td>3.254</td>
<td>0.000</td>
</tr>
<tr>
<td>3. Processing industrial sector membership</td>
<td>$-$0.389</td>
<td>$-$0.211</td>
<td>0.397</td>
</tr>
<tr>
<td>4. High-tech industrial sector membership</td>
<td>0.475</td>
<td>0.990</td>
<td>0.172</td>
</tr>
<tr>
<td>5. Percentage Prods – mature stage PLC</td>
<td>0.376</td>
<td>2.305</td>
<td>0.043</td>
</tr>
<tr>
<td>6. Extent of process formalization</td>
<td>0.022</td>
<td>0.360</td>
<td>0.299</td>
</tr>
<tr>
<td>7. Efficiency</td>
<td>18.043</td>
<td>4.883</td>
<td>0.000</td>
</tr>
<tr>
<td>$R^2 = 0.101$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(adj. $R^2) = (0.060)$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>n = 63</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
into two subsets: DMUs positioned on the performance frontier (efficiency \( \approx 1.00; n = 23 \)), and off the performance frontier (efficiency \( < 1.00; n = 40 \)); see Table 2 for sample details.

To test Hypotheses 2a and 2b, we need to examine the extent to which differences exist in strategic performance and enterprise information use emphasis for those manufacturers positioned on the performance frontier. In carrying out these tests, we conduct ANOVAs and report the resulting average standardized enterprise information use and strategic performance values for each subset of DMUs in Table 4. (Although not part of the tests for Hypotheses 2a and 2b, Table 4 includes the average standardized values associated with the off-frontier DMUs for completeness.)

The average standardized values for \( y_o, y_c, \) and \( y_p \) for on-frontier DMUs are \(.14, .09, \) and \(.10 \), respectively. As expected, no distinction was observed among these strategic performance variables \( (p = .205) \) (nor for those off-frontier \( (p = .711) \), although not explicitly hypothesized). Thus, Hypothesis 2a is supported.

The ANOVA test results showed particularly interesting results for the average enterprise information use levels with respect to on-frontier DMUs. The average standardized values for \( x_o, x_c, \) and \( x_p \) for on-frontier DMUs are \(.28, .06, \) and \(.07 \), respectively. Thus, DMUs on the performance frontier appear, on average, to use information relevant to operational excellence significantly more than information relevant to customer intimacy and product leadership \( (p = .002) \). In fact, on account of the standardized nature of the variables, the \( x_o \) value of \(.28 \) for on-frontier DMUs – coupled with the near-zero values of \(.06 \) and \(.07 \) for \( x_c \) and \( x_p \), respectively – clearly demonstrates that the use of information relevant to operational excellence is most strongly associated with efficiency for these DMUs. These results support Hypothesis 2b.

Hypothesis 2c posited that efficient manufacturers are more likely to have performed best on the dimension of strategic performance corresponding to its enterprise information emphasis/focus than inefficient manufacturers. To test this hypothesis, we return to the information contained in Table 2. That is, for each DMU in Table 2, we assess the extent to which the enterprise information type with the highest emphasis (i.e., highest value in \( x_o, x_c \), or \( x_p \)) matches the dimension of strategic performance with the highest score (i.e., highest value in \( y_o, y_c \), or \( y_p \)).

With three enterprise information types and three strategic performance dimensions, there are nine possible combinations, only three of which represent a match (e.g., a DMU placing the most emphasis on operational excellence information and having highest strategic performance related to operational excellence). By chance, matching would be expected to occur 33% of the time.

Eighty-seven percent of the DMUs on the performance frontier score the highest on the strategic performance dimension consistent with their emphasis in enterprise information use (i.e., 20 matches out of 23 opportunities for a match). This result is significantly \( (p \leq .001) \) greater than would be expected to occur by chance, based on a test of equal proportions. Forty-five percent of the off-frontier DMUs are similarly matched (i.e., 18 matches out of 40 opportunities for a match), which is not significantly \( (p = .148) \) greater than would be expected by chance. Using a binomial test of equality of proportions, the matching exhibited by on-frontier DMUs is significantly greater than that of the off-frontier DMUs \( (p \leq .01) \). These basic comparisons, therefore, provide support for Hypothesis 2c.

5. Conclusions

Using data collected from ERP users at two points in time, we empirically explore the relationship between the efficient use of enterprise information in the realization of strategic performance and Compustat profitability. In doing so, we first develop measures of enterprise information use and strategic performance in the context of Treacy and Wiersema’s (1993) operational excellence, customer intimacy, and product leadership value disciplines. Utilizing DEA, we then construct an efficiency metric comprised of these measures. Our DEA-derived efficiency metric is a strong predictor of Compustat profitability, which suggests a clear link between the information-use policies defined by the manufacturers positioned on the performance frontier and the bottom line.

To gain a deeper understanding of the drivers of efficient information use and, ultimately, profitability, we go on to decompose our efficiency metric. We find that
manufacturers on the performance frontier show no significant differences in strength along the strategic performance variables. However, efficient manufacturers, on average, do tend to place significantly more emphasis on operational excellence information than on customer intimacy or product leadership information. Efficient manufacturers are also significantly more likely to demonstrate superior strategic performance that corresponds to the most emphasized type of enterprise information. These findings have important implications for both theory and practice.

5.1. Theoretical and managerial implications

This study provides insights on how organizations can make the most efficient use of the data residing in their enterprise systems. Our results support the notion that operating policies with respect to enterprise information use are important drivers of success in an ERP environment. Thus, while much of the literature focuses on the performance improvements possible from the implementation of specific technologies, this research reinforces the need for the implementation of corresponding infrastructural changes regarding information use in order to realize the full potential of technological adoptions (Bharadwaj, 2000; Rosenzweig and Roth, 2007).

Managers can only absorb a finite amount of information at one time, and management attention is necessarily a limited resource (Bendoly and Swink, 2007). Furthermore, there are technological constraints on how enterprise systems present information. These technical bounds play an important role in how IT influences firm performance, and empirical models can be improved by including these concepts (Bresnahan et al., 2002; Kohli and Devaraj, 2003). DEA explicitly incorporates such technical boundaries and can be a valuable lens for examining issues in the management of technology (c.f. Swink et al., 2006). The strong results from this study linking the efficiency of information use to objective profitability performance demonstrate the efficacy of this approach.

The managerial implications of this study are clear. Software, no matter how sophisticated, cannot be viewed as a “silver bullet” solution. According to Davenport (2008), “Despite the fact that companies often justify IT projects on the basis of better decisions, there is seldom a direct tie between the information a particular system produces and the decisions that are supposed to be based on it.” In line with Davenport (2008), this study indicates that managers would be well-served by examining how such enterprise data is used within their organizations.

Roth and Miller (1992) proposed that operational policies and procedures may have a greater impact on firm performance than technology investments alone, and many other studies have since reiterated the importance of organizational factors in the adoption of complex IT (Boudreau and Robey, 2005; Brynjolfsson et al., 2002; Carr, 2003; Devaraj and Kohli, 2000; Powell and Dent-Micalef, 1997; Sambamurthy et al., 2003). Our findings suggest that manufacturers need to be cognizant of their desired strategic outcomes when reengineering their operational procedures to leverage enterprise technologies. Manufacturers should expect the biggest bang for the buck when they focus their attention on enterprise information that is aligned with their desired strategic outcomes. This pertains not only to the day-to-day transactional use of these systems, but also to the use of the information embedded within and continuously collected by these systems.

So, how might an inefficient manufacturer characterize a relative focus on product leadership enterprise information and strength on customer intimacy strategic performance, for example, go about improving its overall performance? Our study of ERP system adopters implies that to get closer to or to reach the performance frontier, a manufacturer should perhaps de-emphasize the use of product leadership information in lieu of a focus on customer intimacy information.

However, our data suggests that the benefits of enterprise systems also accrue to manufacturers that focus much of their attention on information related to operational excellence. This finding is consistent with Stratman (2007), who found that firms pursuing operational excellence goals were more likely to experience performance benefits from ERP adoption. We speculate that this result is related to the strict transactional discipline imposed by most enterprise systems. Thus, returning to our example above, an alternative approach to getting closer to or reaching the performance frontier is to again de-emphasize the use of product leadership information, but to do so at the expense of focusing on some combination of customer intimacy and operational excellence information, as we show that the use of operational excellence information is a key driver of success in an ERP environment.

5.2. Research limitations and opportunities for future research

Although our results are intriguing, they simply represent a first attempt at studying the interrelationships among efficient information use, information focus, and profitability. Several limitations to our study must be recognized. To begin with, the merger of three separate datasets (data from two time-distinct field studies and public financial records) limited our sample to 63 records, which in turn limited the statistical power of specific forms of analysis. While significant results were demonstrated along anticipated lines, we suggest future researchers validate our findings using a bigger sample, perhaps even a sample that is industry-specific (although industrial sector membership did not seem to be an important factor in our analyses).

Our data also prohibited us from assessing a particular manufacturer’s movement along a performance frontier over time. Likewise, the data limited us from examining specific improvement paths, or “outward shifts” of the frontier (Clark, 1996; Hayes and Pisano, 1996; Lapre and Scudder, 2004; Rosenzweig and Easton, 2008; Schmenner and Swink, 1998). Detailed longitudinal data is needed in this regard. And while our collection of enterprise information use and strategic performance data was separated temporally by 3 years in order to help avoid
issues of reverse-causality, as well as to ameliorate concerns of common source bias, this time lag may have been somewhat excessive. It might be more appropriate to make use of more closely timed input- and output-related data in future work, if the above concerns can still be adequately accounted for.

Future research would benefit from taking this more integrated, time-dependent approach to viewing the operational use of information systems. Such studies could facilitate a richer discussion of how information-use policies may evolve over time, and how more advanced approaches to information access and analysis (e.g., data mining) might be most fully leveraged. For some organizations, it is only through such a rich understanding of the time-based evolution of information-use requirements that complete prescriptions for strategy execution and performance attainment can take place.

Finally, from an analytical perspective, DEA has been applied to a wide range of contexts. Our use of the method is fairly specific to this particular context, but it does provide a convenient and established mechanism for estimating efficient information use. There are a number of alternatives to the CCR approach to data envelopment analysis, and those methods may provide additional insights into efficient information use. Furthermore, there are likely to be other logical mechanisms for estimating “focus” in information use. Because we concentrate on the development and testing of theory, rather than undertaking a comparative study of analytical methods for testing such a theory, our work invites further examination by future researchers.

Acknowledgements

We are grateful to Robin Cooper, John H. Van de Vate, the Supply Chain Council, and APICS for their roles in our data collection. We would also like to acknowledge the valuable suggestions of the Associate Editor and three anonymous reviewers.

Appendix A. Confirmatory factor analysis results for the combined sample (n = 63)

<table>
<thead>
<tr>
<th>Scales and associated items</th>
<th>Average (SD) [Range = 1–7]</th>
<th>Stdzd path loadings</th>
<th>p-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Use of information relevant to operational excellence (x_o)</td>
<td></td>
<td>AV = 0.59</td>
<td></td>
</tr>
<tr>
<td>• Resource status (e.g., scheduled maintenance)</td>
<td>3.70 (1.90)</td>
<td>0.764</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>• Lead time quotations to customers</td>
<td>3.35 (1.44)</td>
<td>0.758</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>• Order handling requirements</td>
<td>3.06 (1.80)</td>
<td>0.831</td>
<td>-</td>
</tr>
<tr>
<td>Use of information relevant to customer intimacy (x_i)</td>
<td>AV = 0.62</td>
<td></td>
<td></td>
</tr>
<tr>
<td>• Customer post-delivery contract items</td>
<td>3.51 (2.12)</td>
<td>0.903</td>
<td>-</td>
</tr>
<tr>
<td>• Customer feedback</td>
<td>3.49 (1.44)</td>
<td>0.835</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>• Sales promotion data</td>
<td>3.23 (1.46)</td>
<td>0.819</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Use of information relevant to product leadership (x_p)</td>
<td>AV = 0.61</td>
<td></td>
<td></td>
</tr>
<tr>
<td>• Product specifications</td>
<td>3.92 (2.21)</td>
<td>0.950</td>
<td>-</td>
</tr>
<tr>
<td>• Product development timelines</td>
<td>3.75 (1.75)</td>
<td>0.751</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>• Notes on design changes</td>
<td>3.48 (1.89)</td>
<td>0.920</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Strategic performance in operational excellence (y_o)</td>
<td>AV = 0.52</td>
<td></td>
<td></td>
</tr>
<tr>
<td>• We pursue process standardization</td>
<td>3.22 (1.12)</td>
<td>0.793</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>• We are known in the marketplace for our conformance quality</td>
<td>3.45 (1.94)</td>
<td>0.825</td>
<td>-</td>
</tr>
<tr>
<td>• We are known for our on-time delivery performance</td>
<td>3.34 (1.02)</td>
<td>0.618</td>
<td>&lt;0.01</td>
</tr>
<tr>
<td>• We are known for our speedy deliveries</td>
<td>3.45 (1.48)</td>
<td>0.697</td>
<td>&lt;0.01</td>
</tr>
<tr>
<td>• We continually pursue price reductions</td>
<td>3.18 (1.28)</td>
<td>0.809</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Strategic performance in customer intimacy (y_i)</td>
<td>AV = 0.51</td>
<td></td>
<td></td>
</tr>
<tr>
<td>• We consistently surpass customer expectations</td>
<td>3.33 (1.86)</td>
<td>0.770</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>• We are more effective at attracting new customers than competitors</td>
<td>3.29 (1.87)</td>
<td>0.786</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>• We encourage our sales force to maintain ties with our customers</td>
<td>4.21 (1.90)</td>
<td>0.720</td>
<td>&lt;0.01</td>
</tr>
<tr>
<td>• Relative to other firms in our industry, we are better able to accommodate customer preferences</td>
<td>3.80 (1.94)</td>
<td>0.794</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>• We make extensive use of customer data when developing marketing plans</td>
<td>3.27 (1.07)</td>
<td>0.917</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>• We provide customers a broad range of offerings to ensure their specific needs are filled</td>
<td>3.87 (1.03)</td>
<td>0.876</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>• Relative to other firms in our industry, the annual number of solutions we propose to existing clients is high</td>
<td>3.62 (1.96)</td>
<td>0.979</td>
<td>-</td>
</tr>
<tr>
<td>• We target niche markets</td>
<td>3.30 (1.19)</td>
<td>0.722</td>
<td>&lt;0.01</td>
</tr>
<tr>
<td>Strategic performance in product leadership (y_p)</td>
<td>AV = 0.48</td>
<td></td>
<td></td>
</tr>
<tr>
<td>• We are known in the marketplace for the performance quality of our products</td>
<td>4.18 (1.83)</td>
<td>0.628</td>
<td>&lt;0.01</td>
</tr>
<tr>
<td>• Our products are known for their features and functions</td>
<td>3.92 (1.96)</td>
<td>0.738</td>
<td>&lt;0.01</td>
</tr>
<tr>
<td>• Our design team keeps up with recent advances in the field</td>
<td>3.70 (1.18)</td>
<td>0.692</td>
<td>&lt;0.01</td>
</tr>
<tr>
<td>• The number of times our patents are cited by external parties is high</td>
<td>2.90 (1.26)</td>
<td>0.830</td>
<td>-</td>
</tr>
<tr>
<td>• We are always the first to deliver a new product/service to market</td>
<td>2.78 (0.97)</td>
<td>0.777</td>
<td>&lt;0.001</td>
</tr>
</tbody>
</table>

a The range for all individual items is 6 (1–7). Values of 1 and 7 were observed for all items.

b A scale is said to display convergent validity if the average variance extracted (AVE) surpasses the approximate threshold value of .50 (Fornell and Larcker, 1981).
Appendix B. A competing moderated multiple regression (MMR) Model

As an additional test of the strength of the DEA-based approach to interaction analysis, we compare our modeling approach to the more commonly applied moderated multiple regression (MMR) analysis approach in terms of explaining profitability (Hypothesis 1 test results). We note that interaction effects are notoriously difficult to detect using techniques like MMR, especially when examining impact with respect to IT-related performance.

To effectively serve as a competing model, however, it is necessary to develop measures for the MMR analysis that roughly correspond to the DEA efficiency estimate described in detail in Section 3.3. That is, for the MMR analysis, we need to construct measures that generally account for the overall level of enterprise information use and strategic performance for each manufacturer. We do so by means of two meta-scales, which we refer to as InformationUse and StrategicPerformance.

InformationUse is simply the average of the three enterprise information use scales \( (x_o, x_c, x_p) \) derived for the DEA analysis. Likewise, StrategicPerformance is the average of the three strategic performance scales \( (y_o, y_c, y_p) \). Finally, the modifying variable is the product of the InformationUse and StrategicPerformance meta-scales \( \text{InformationUse} \times \text{StrategicPerformance} \). Methodologically speaking, the key difference between the two profitability regression models being compared here is this: the MMR results include an interaction term defined as InformationUse \( \times \) StrategicPerformance, while the DEA results include the efficiency term.

Looking first at the MMR results of regressing profitability on the overall level of enterprise information use (Table 5, panel A), it is clear that InformationUse alone is a poor predictor of profitability \( (\beta = .389; \ p = .354) \), which tends to corroborate the findings on the financial impact of enterprise software investments (Hendricks et al., 2007). In fact, neither the level of enterprise information use, the level of strategic performance \( (\beta = .798; \ p = .316) \), nor the interaction of these two variables \( (\beta = .393; \ p = .381) \) is a significant predictor of profitability. Given these results, it is not surprising that the \( R^2 \) associated with the MMR analysis is a mere .113.

In contrast, panel B of Table 5 shows that the DEA-based efficiency value is a strong predictor of profitability \( (\beta = 17.325; \ p \leq .001) \), with the panel B regression showing a significant increase in explained variance (from 11.3% to 28.9%) over the panel A regression when the interaction term is replaced by the DEA efficiency variable. Thus, our DEA modeling approach, which derives efficiency estimates of the relationship between enterprise information use and strategic performance to ultimately explain variance in profitability, is superior to the more traditional MMR modeling approach in the context of this research.

References


