



# Knowledge management through technology strategy: implications for competitiveness

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## Abstract

**Purpose** – The purpose of this paper is to conceptualize a learning-based technology strategy along three dimensions: proactive technology posture, process adaptation and experimentation, and collaborative technology sourcing; also to investigate their relationships with plant competitiveness (cost, quality, delivery, flexibility, and innovation).

**Design/methodology/approach** – Hypothesized relationships are tested from three perspectives – direct effects perspective, co-alignment perspective, and mediation perspective – using structural equation modeling with an international dataset.

**Findings** – Results show that although the three dimensions of learning-based technology strategy are not individually related to plant competitiveness (direct effects perspective), their co-alignment strongly impacts plant competitiveness (co-alignment perspective). Furthermore, this co-alignment creates an environment in which employee suggestion and feedback can help make sense of novel situations, leading to superior plant competitiveness (mediation perspective).

**Practical implications** – Many plants develop some aspects of a learning-based technology strategy while paying little or no attention to the rest. As the findings of the present study show, such an approach will contribute very little to achieving competitive advantage in the marketplace. More specifically, it is shown that three dimensions of learning-based technology strategy, when used together, have a significant effect on plant competitiveness. Additionally, it is shown that employee suggestions for improvements drive a learning-based approach to technology strategy. Therefore, managers should adopt a comprehensive approach to technology strategy using all three dimensions and engage their employees in the process of technology development and improvement.

**Originality/value** – The literature has stressed the need for proactive technology posture, process adaptation and experimentation, and collaborative technology sourcing to gain competitive advantage. However, little is known about their mutual interdependence and their combined impact on plant competitiveness. This paper attempts to fill in this gap in the literature.

**Keywords** Plant efficiency; Operations management; Knowledge management; Tacit knowledge; Explicit knowledge; Competitive strategy

**Paper type** Research paper



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## 1. Introduction

Over the years researchers and practitioners have argued that technology can play an important role in gaining competitive advantage. However, despite superior technology, organizations may fail to compete successfully in the marketplace. This is particularly true if organizations take a tactical rather than a strategic view of managing their technology. More importantly, we propose that organizations need to craft their technology strategies that foster continuous learning in order to fully exploit their potential to gain competitive advantage.

Research on organizational learning and knowledge management can be traced back at least 40 years (Cyert and March, 1963). However, only since the early 1990s did researchers begin to explore various aspects of knowledge management in the context of production technology. Much of this stream of literature has been prescriptive or uses case studies based on limited observations (Bohn, 1994; Roth *et al.*, 1994; Leonard-Barton, 1992). More recently, a number of researchers have reported their empirical findings on specific issues related to learning in production environments, such as the relationship between process innovation and learning by doing (Hatch and Mowery, 1998); learning dimensions in total quality management efforts (Mukherjee *et al.*, 1998); management of technological transitions (Iansiti, 2000); knowledge creation through scientific experimentation (Lapr e and van Wassenhove, 2001); the relationship between operating knowledge and productivity improvement (Skilton and Dooley, 2002); and mechanisms of knowledge creation in six sigma projects (Choo *et al.*, 2007).

Much of the existing literature takes an organization's production technologies as given and investigates the factors that affect learning and their resulting impact on achieving organizational goals. The literature has paid very little or no attention to understanding how or why organizations acquired these technologies in the first place. Were the decisions to acquire and adapt production technologies guided by long-term objectives to develop new manufacturing capabilities? Do these organizations collaborate with the technology suppliers to incorporate their process knowledge into the new production technologies? Do these organizations have coherent technology strategies that foster knowledge creation and retention? If so, how do these efforts impact an organization's ability to compete in the marketplace? These important questions need to be answered and we attempt to fill in this gap in the literature. Specifically, we investigate the impact of learning-based technology strategy on competitiveness. We, however, limit our investigation to production technology and our unit of analysis is a manufacturing plant.

In this paper, we first describe learning-based technology strategy and its dimensions. Next, we state hypotheses to be tested and explain the research frameworks. Section 3 provides the research setting and data source. Model estimation and results are presented in Sections 4 and 5. Finally, we interpret and discuss our findings and provide implications for practice.

## 2. Learning-based technology strategy and competitiveness

Zahra *et al.* (1999) found two dominant perspectives in the literature on connections between competitive and technology strategies. The first perspective presents a view of a company's technology choice jointly determined by its competitive strategy and internal capabilities. The second perspective views technology as a subset of resources that a company can use to attain competitive advantage. Zahra *et al.* (1999) argue that

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both perspectives are static, and they present a third perspective which posits that technology and strategy variables influence each other continuously, and hence, both variables should embody an element of prospecting to pave the way for novel development to evolve. That is, one aspect of technology strategy should be to explore and proactively seek manufacturing capabilities in advance of needs and to anticipate the potential of new manufacturing technologies. A company's technology strategy should reflect its proactive technology posture (PTP) which involves constantly exploring for innovation in process technology and commitment to continuously advancing its manufacturing technology (Chang *et al.*, 2005).

Technology strategy, according to Ford (1988), involves long-term plans for acquiring, managing, and exploiting technological knowledge and ability to attain competitive advantage. Exploitation of technology entails continued experimentation with existing process technologies so that further improvements can be made. The knowledge created in the process, in turn, becomes valuable input to developing technology strategy in the future. Upton and Kim (1998) emphasize the need for learning by doing on the shop floor manufacturing technologies in order to achieve continuous process improvement.

As competition has increased, a firm's technology sourcing strategy has become ever more critical to its performance (Hill and Rothaermel, 2003). A plant can source its technology internally or externally. While sourcing all technologies internally increases a firm's risk, including obsolescence (Eisenhardt and Martin, 2000), relying completely on external technology sources can lead to competitive disadvantage due to the inability to foster innovation internally (Teece, 1986). Thus, extreme positions along the internal-external technology sourcing continuum may minimize a plant's potential to be competitive in the marketplace. Rothaermel and Alexandre (2009) define the ambidexterity perspective of technology sourcing as the simultaneous pursuit of exploration and exploitation by combining internal and external sourcing. From the ambidexterity perspective to technology sourcing, Rothaermel and Alexandre (2009) argue that balancing internal and external technology sourcing can have positive implications for performance because this balance allows a firm to leverage its core competency and incorporate innovations from external sources. Collaborative technology sourcing (CTS), when a plant works closely with external technology sources to develop new process technology, provides such a balance. For this reason, developing technology in collaboration has become an important component of technology strategy (Vilkamo and Keil, 2003; Bailey *et al.*, 1998).

Based on the literature above, we define learning-based technology strategy (TECHSTR) as a long-term vision for managing technology that sets a pattern of consistent decision making to foster creation and exploitation of knowledge to attain superior competitiveness. We conceptualize TECHSTR along three dimensions: PTP, process adaptation and experimentation (PAE), and CTS.

The exploration-exploitation framework of organizational learning can help understand the relationship between a firm's technology sourcing and its performance. Levinthal and March (1993, p. 105) define exploration as "the pursuit of new knowledge, of things that might come to be known," and exploitation as "the use and development of things already known." TECHSTR allows for both the exploration and the exploitation of process technology. Absorptive capacity is the ability of a firm to identify and value the potential of new knowledge from external sources and assimilate and integrate the new knowledge into the firm's existing knowledgebase

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(Rothaermel and Alexandre, 2009; Ouyang, 2008). The learning-based technology strategy builds and enhances a plant's absorptive capacity through continual exploration and exploitation of its process technology.

Drawing on literature on product technology, process technology, and technology strategy Gregory *et al.* (1996) present an integrative technology management process framework. The framework consists of five sub-processes: identification, selection, acquisition, exploitation, and protection. Identification includes scanning internal and external knowledge sources to find potential technologies. Selection involves assessing potential technologies against a set of decision criteria to determine if such technologies would effectively contribute to long-term technology management. Acquisition entails making a decision whether to develop the technology in-house and to map out a detailed plan to accomplish it. Exploitation involves exploiting existing product and process technology knowledge to develop competencies for current and future market needs. Protection establishes plans for preventing the competition from gaining access to technological know-how. The three dimensions of TECHSTR we presented directly incorporate the four sub-processes (identification, selection, acquisition, and exploitation) mentioned above and indirectly account for the fifth sub-process (protection) since learning (particularly, tacit knowledge) that occurs due to exploration and exploitation is embedded in the socio-technical system making it inimitable and thus providing protection.

In the following section, we present hypotheses relating the dimensions of learning-based technology strategy to competitiveness. We define competitiveness as the achievement of an organization relative to its competition with respect to common competitive priorities such as cost, quality, delivery, flexibility, and development time.

### 2.1 Proactive technology posture (PTP)

A static strategy is of limited use since any resulting competitive advantage will be short lived, especially for technology strategy. Organizations that select manufacturing technologies by only accounting for current contexts and without much regard to the future needs are destined to be defeated by the competition. Therefore, organizations' technology strategies need to be dynamic as emphasized by Grant *et al.* (1991, p. 52):

[...] the choice of manufacturing technology is not concerned simply with static optimization, it must also be concerned with dynamic optimization: the selection of a time path for manufacturing improvement that sustains competitive advantage [...]

Similarly, Day *et al.* (1997) stressed that "anticipation" of the future is an integral part of an effective strategy.

Taking a knowledge ecology perspective, Bowonder and Miyake (2000, p. 666) underscore that failure to adequately attend to "technology scanning" and "technology foresight" may very quickly lead to the extinction of technological superiority:

Technology scanning concepts deal with the issues relating to the need for monitoring the technology change process and understanding the emerging technology trajectory [...]. The concepts under technology foresight deal with generating a technology vision, creating technology forecasts, evolving new future directions through cognitive processes.

Therefore, an organization's effort to anticipate the potential of new manufacturing technologies and capabilities is expected to help it gain competitive advantage:

*H1.* PTP of a plant is positively related to its competitiveness.

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### 2.2 *Process adaptation and experimentation (PAE)*

Weick (1990) argues, “The point at which technology is introduced is the point at which it is most susceptible to influence.” Typically, a misalignment occurs with the existing technologies and/or work systems when a new process technology is introduced. This apparent disruptive phase provides an opportunity for adaptation, improvement, and learning, which Tyre and Orlikowski (1993) refer to as the “window of opportunity.” Experimentation during and after this adaptation phase not only helps resolve the current misalignment but the accumulated knowledge also provides new insights into how the entire process can be improved. Such experimentation also helps identify requisite organizational and skills changes that need to be made for effective adaptation (Gouvea da Costa and Pinheiro de Lima, 2009).

Chew *et al.* (1991) suggest four methods of learning related to process technology: vicarious learning – learning from other organizations; simulation – building artificial models and experimenting with them; prototyping – building and operating a smaller version of the process technology; and on-line learning – experimenting with the full scale of the process technology when it is in use for production. While each method contributes to process knowledge, they all have advantages and disadvantages. For example, learning from others (vicarious learning) is feasible if others are willing to share the knowledge. Simulation is only useful to the extent that the model represents reality. While on-line learning has the highest fidelity, it is costly.

Many organizations use prototyping to bring a balance between cost and fidelity. However, in the context of semiconductor manufacturing, Hatch and Mowery (1998, p. 1466) found that “Even in the unlikely case that the production environment of the development fab (including production volumes) is identical to that of the manufacturing fab, some knowledge is lost in the transfer of the manufacturing process technology from one group of employees to another.” Thus, despite the cost, online learning is a better environment for the creation and retention of knowledge. This is not surprising since on-line learning reinforces operational learning as well as conceptual learning. Based on experienced events, conceptual learning attempts to make sense of the cause-and-effect relationships, i.e. it attempts to “know-why.” Operational learning, on the other hand, attempts to “know-how” to effectively resolve such issues in the future by systematically experimenting based on conceptual learning (Mukherjee *et al.*, 1998). Thus, for continuous exploitation of knowledge, the role of experimentation with process technology cannot be over emphasized:

H2. Effort in PAE of a plant is positively related to its competitiveness.

### 2.3 *Collaborative technology sourcing (CTS)*

From time to time organizations need to acquire new process technologies. Such initiatives are often driven by competitive pressure or strategic intent and involve major capital outlay. As such, any wrong decisions can have tremendous impact on the organization’s survival. These acquisitions also present opportunities to influence development of the new technologies based on the organization’s accumulated process knowledge. Such a collaborative effort in sourcing technologies can create competitive advantage. For this reason, firms are increasingly managing technology partnerships as an integrated element of their technology strategy (Vilkamo and Keil, 2003).

Using complexity theory, Davenport *et al.* (2003) reconceptualize technology strategy as the sum of a number of dynamic processes, particularly mutual learning

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and co-evolution with collaborative technology partners, which transform a firm from a broad dabbler to a focused technology exploiter. In a project-level study, Iansiti (2000: 170) argues:

Technology selection decisions in projects may be microscopic in nature when compared to setting firm objectives. When their effect is aggregated, however, these decisions can have a critical strategic impact on the performance and cost of future products, the speed and efficiency with which they are developed, and the firm's overall competitiveness.

An organization has a unique window of opportunity during the time technology selection decisions are being made when it can work closely with its technology suppliers to develop process technologies by incorporating its accumulated process knowledge into the design. Such efforts help improve process technologies and are expected to enhance the organization's competitiveness:

*H3.* Effort in CTS of a plant is positively related to its competitiveness.

#### *2.4 Synergy among three dimensions*

The dimensions of learning-based technology strategy are mutually reinforcing. For example, an organization with a PTP is in constant search of next generation process capabilities. PAE allows that organization to continuously learn through experimentation and identify capabilities that will be needed in the future. A broad range of experimentation also helps that organization recognize new technological possibilities (Lant and Mezias, 1992; Daft and Weick, 1984). Finally, CTS allows the organization to work with technology suppliers to incorporate knowledge to achieve process capabilities it identified during experimentation. Working together, these dimensions form a co-alignment or internal consistency that is expected to enhance an organization's competitiveness more than any one of the dimensions alone:

*H4.* Co-alignment of the three dimensions of a learning-based technology strategy is positively related to plant competitiveness.

#### *2.5 Role of employee suggestion and feedback (ESF)*

Companies spend a huge amount of time, money, and effort to analyze and refine technology strategies but they do not pay sufficient attention to harnessing the human resources needed to realize the goals of these strategies (Averett, 2001). This is surprising given that an organization's attempt to create and retain process knowledge cannot be successful without employees' active involvement. The employees' keen observations help identify idiosyncratic behaviors of a production system (Leonard-Barton, 1992). The accumulation of such observations leads to tacit knowledge that is hard to emulate and, hence, can be a source of competitive advantage. To take full advantage of this phenomenon, an organization needs to create an atmosphere in which employees are encouraged to make improvement suggestions. Furthermore, to gain the confidence of the employees, management has to show that it values all suggestions and takes them seriously. This can be accomplished by implementing those suggestions that have potential to improve process technology and explaining why other suggestions are not implemented.

Without proper encouragement or the right environment, employees will avoid making suggestions, resulting in the loss of many potential learning opportunities. Consequently, the organization will fail to exploit employees' tacit knowledge to gain

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competitive advantage. The learning-based technology strategy described above creates an environment in which employees' suggestions can be effectively channeled to identify and accumulate process knowledge. Thus, learning-based technology strategy facilitates the link between employee suggestions and competitiveness:

- H5.* The impact of employee suggestions and feedback on a plant's competitiveness is mediated by the learning-based technology strategy.

### *2.6 The theoretical frameworks*

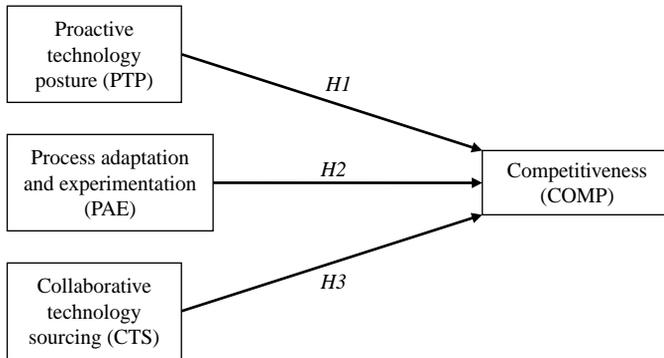
Working together, the three dimensions of learning-based technology strategy foster both tacit and explicit knowledge that is valuable and hard to imitate, which leads to superior organizational competitiveness as predicted by the resource-based view (Barney, 1991). Additionally, from the dynamic capabilities perspective (Teece *et al.*, 1997), learning-based technology strategy and employee involvement (employee suggestions and feedback) enable an organization to integrate, build, and reconfigure socio-technical competencies to address rapidly-changing environments and, thereby, enhance organizational competitiveness (Figure 1).

### **3. Research setting and data source**

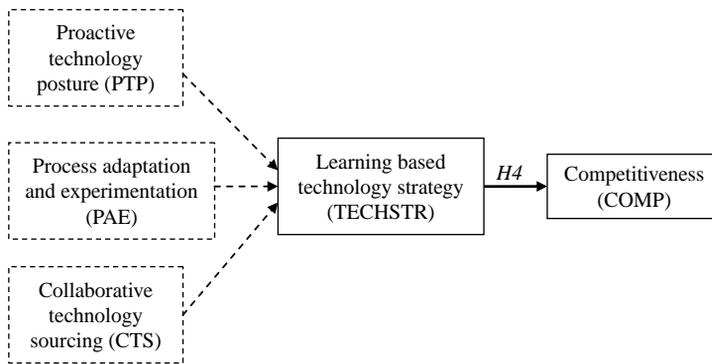
We use data collected as part of the high performance manufacturing (HPM) project being conducted by a team of researchers at several universities in the USA, Europe, and Asia (Schroeder and Flynn, 2001). Face validity of the questionnaires was insured by having three different researchers develop items for the scales. The researchers then reviewed these items for content validity. The questionnaires were pilot tested using industry experts and academics, and some of the items had to be rephrased to make them more representative of the intended constructs. The questionnaires were translated and then back-translated by different individuals to check for accuracy. Any differences identified during this process were resolved before administering the surveys in non-English speaking countries.

The stratified random sampling method was used to select plants from three industries: automobile, electronic, and machinery. Interested plant managers appointed plant research coordinators who communicated with the researchers during the data collection process. These plant research coordinators were managers with at least three years of experience in the plant and were knowledgeable about employees' major responsibilities in the plant. The coordinators were instrumental in identifying the right respondents (managers, engineers, supervisors, and workers) who had pertinent knowledge, experience, and ability to provide accurate and unbiased responses to the questionnaires.

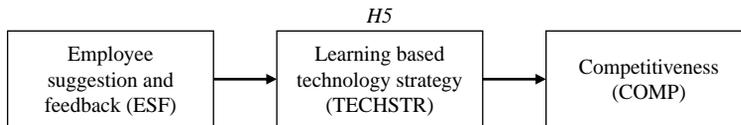
About 60 percent of the manufacturing plants contacted agreed to participate in the study. This high response rate may be attributable to the fact that each plant manager was contacted by telephone by one of the researchers. Moreover, the researcher promised the participating managers a profile report regarding the plant's standing compared to other plants in the industry relative to manufacturing practices used and performance achieved. We use a part of the HPM data from Germany, Italy, Japan, the UK, and the USA for the present study which includes 152 manufacturing plants after eliminating responses with missing data.



(a) Direct effects perspective



(b) Coalignment perspective



(c) Mediation perspective

Figure 1.  
Theoretical frameworks

#### 4. Measurement model

Structural equation modeling was employed to test the hypotheses using analysis of moment structure software. The two-step modeling approach was used where the fit of the structural model is assessed independently of the measurement models (Anderson and Gerbing, 1988; Schumacker and Lomax, 1996). The first step involves estimating and, if necessary, respecifying the measurement model. The second step involves predicting the direct and indirect relations specified among latent variables in the structural model. Thus, the measurement models provide an assessment of convergent and discriminant validity, while the structural model provides an assessment of predictive validity.

Constructs used for this study were measured using five-point scales as shown in Appendix. The measurement properties of each construct were assessed by evaluating unidimensionality, reliability, and convergent and discriminant validity using confirmatory factor analysis (Hair *et al.*, 1998). The metric of each factor was established by fixing the factor loading of one item to 1.0 (Sharma, 1996). In all situations where refinement was indicated, items were deleted one at a time and the fit of the revised model assessed before further action. Theoretical implications were considered before the final decision was made to delete an item. The data were examined for skewness, kurtosis, and normality before conducting confirmatory factor analyses. No serious violations were observed.

A review of the factor loadings, asymptotically standardized residual values, and modification indices suggests a few items should be dropped from the scales. Each of these items was examined to ensure that dropping it did not compromise content validity of the scale. Items were dropped one at a time and the measurement model was respecified. The  $\chi^2$  statistic ( $\chi^2 = 111.18$ ) for the final measurement model (Appendix for dropped items) was non-significant ( $p = 0.11$ ) indicating that the covariance matrix of the proposed model does not differ significantly from the observed covariance matrix. However, researchers tend to use other heuristics given this statistic's sensitivity to sample size.

Historically, Bentler and Bonett's (1980) normed fit index (NFI) has been one of the most frequently reported fit indices. Bentler (1990) has revised the NFI to account for sample size and proposed the comparative fit index (CFI) which, according to Bentler, should be the index of choice. Based on their experiment, Ding *et al.* (1995) concluded that  $\chi^2$  per degree of freedom and non-NFI (NNFI) were independent of sample size and CFI was affected by sample size to a small degree. Because of these considerations, the  $\chi^2$  per degree of freedom, CFI, and NNFI have become primary indices of choice to assess model fit among researchers (Koufteros, 1999). We report these fit indexes along with the root mean square error of approximation (RMSEA) which accounts for model complexity (Browne and Cudeck, 1993).

Based on these indices the final measurement model had acceptable fit ( $\chi^2/df = 1.18$ , CFI = 0.98, NNFI = 0.97, and RMSEA = 0.03). Table I shows the standardized regression weights for the final measurement model. Evidence of convergent validity was seen via the significance of all factor loadings (at  $p < 0.001$  level). Each of the final scales was found to be unidimensional and demonstrated acceptable internal consistency. All scales showed high reliability ( $\alpha \geq 0.7$ ) except for CTS for which  $\alpha$  was 0.62 (Appendix). However, this value of Cronbach's alpha was considered adequate given that CTS is a new scale (Boyer and Pagell, 2000; Flynn *et al.*, 1990). We examine discriminant validity of the constructs next.

Discriminant validity refers to the degree to which a construct differs from other related constructs. The discriminant validity between two scales is supported if the correlation between the scales is significantly less than one. Therefore, the discriminant validity of the scales was established by estimating 12 MLE models (six constrained to correlation of 1, and six unconstrained) and conducting six  $\chi^2$  difference tests. Table II lists the results of these tests. Each of the  $\chi^2$  values associated with the estimates of unconstrained models is lower than the corresponding constrained models, and respective  $\chi^2$  differences are highly significant ( $p \leq 0.001$ ), demonstrating discriminant validity of the scales. Interpretation of the measurement and structural

Indicator		Construct	Standardized regression weight
COST	↑	COMP	0.53
QUAL	↑	COMP	0.61
DELI	↑	COMP	0.65
FLEX	↑	COMP	0.57
INNO	↑	COMP	0.55
PTP1	↑	PTP	0.80
PTP2	↑	PTP	0.78
PTP4	↑	PTP	0.78
PAE1	↑	PAE	0.74
PAE2	↑	PAE	0.57
PAE3	↑	PAE	0.69
CTS1	↑	CTS	0.80
CTS2	↑	CTS	0.57
ESF1	↑	ESF	0.62
ESF2	↑	ESF	0.71
ESF4	↑	ESF	0.94

**Table I.**  
Standardized regression weights for the measurement model

**Note:** All values are significant at:  $p \leq 0.001$

Test	Correlation	<i>t</i> -value	Constrained model $\chi^2$ (df)	Unconstrained model $\chi^2$ (df)	$\chi^2$ difference
<i>PTP with [...]</i>					
PAE	0.78	13.02	24.06 (9)	6.99 (8)	17.07
CTS	0.72	9.15	16.41 (5)	4.37 (4)	12.04
ESF	0.52	7.11	111.41 (9)	6.20 (8)	105.20
<i>PAE with [...]</i>					
CTS	0.68	7.36	14.28 (5)	0.88 (4)	13.40
ESF	0.65	9.16	44.05 (9)	7.43 (8)	36.62
<i>CTS with [...]</i>					
ESF	0.41	4.15	31.11 (5)	3.13 (4)	27.98

**Table II.**  
Results of discrimination validity tests

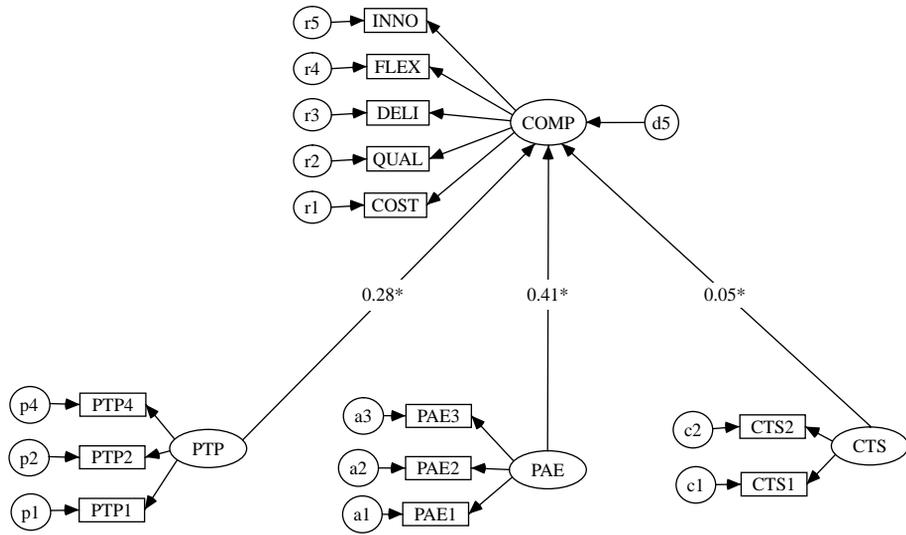
**Note:** All *t*-values and  $\chi^2$  differences are significant at:  $p \leq 0.001$

model results should be undertaken with care because the same observations were used for calibration and validation purposes due to small sample size.

## 5. Analysis and results

### 5.1 Structural model: direct effects perspective

The first three hypotheses (*H1-H3*) propose direct relationships between plant competitiveness and each of the dimensions of learning-based technology strategy: PTP, PAE, and CTS. These three relationships were tested by linking each dimension to plant competitiveness directly through three paths as shown in Figure 2. One of the factor loadings for each factor was set to 1.0 to alleviate scale indeterminacy problems. Although the model showed an acceptable fit ( $\chi^2 = 77.22$ ,  $p = 0.06$ ,  $\chi^2/df = 1.31$ , CFI = 0.97, NNFI = 0.96, and RMSEA = 0.05), none of the relationships hypothesized were statistically significant at 0.05 level (Figure 2). Thus, *H1*, *H2*, and *H3* were not supported by the data.



**Figure 2.**  
Structural model: direct effects system

**Note:** Not significant at: \* $p \leq 0.05$

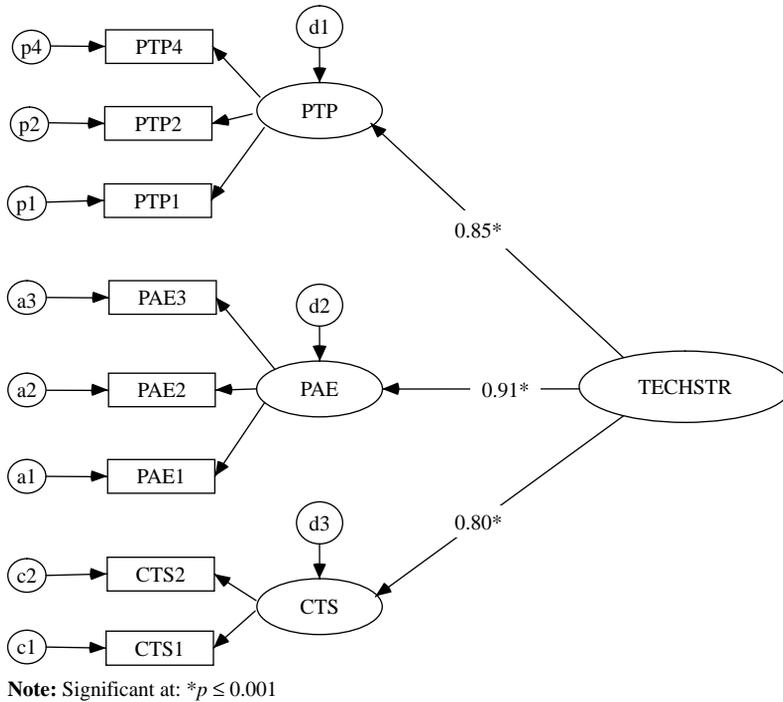
### 5.2 Structural model: co-alignment perspective

The  $H4$  proposes that three dimensions (PTP, PAE, and CTS) of learning-based technology strategy working together foster synergy and, thus, form a co-alignment with a strong positive relationship to plant competitiveness. This co-alignment perspective was examined with a second-order factor model where the first-order factors represent the dimensions to be coaligned. Here, the second-order factor represents an unobservable construct which we refer to as learning-based technology strategy (TECHSTR) as shown in Figure 3. Fit indexes ( $\chi^2 = 18.25, p = 0.37, \chi^2/df = 1.07, CFI = 0.99, NNFI = 0.99,$  and  $RMSEA = 0.02$ ) indicate an acceptable fit of this second-order factor model to the data. The path loadings from learning-based technology strategy to each of the three dimensions were positive and significant ( $p < 0.001$ ). Therefore, the second-order factor analysis indicates that the pattern of covariation among PTP, PAE, and CTS is adequately captured as a separate unobservable construct – TECHSTR.

Figure 4 shows the model used to test  $H4$  where the second-order factor (TECHSTR) is related to plant competitiveness (COMP). The model showed an acceptable fit ( $\chi^2 = 77.49, p = 0.08, \chi^2/df = 1.27, CFI = 0.97, NNFI = 0.97,$  and  $RMSEA = 0.04$ ). The path loadings from TECHSTR to each of the three dimensions were still positive and significant. Importantly, the relationship between learning-based technology strategy (TECHSTR) and plant competitiveness (COMP) was positive and highly significant ( $p < 0.001$ , Figure 4), with TECHSTR accounting for 52 percent of the variation in COMP. Thus, the data provided support for  $H4$ .

### 5.3 Structural model: mediation perspective

$H5$  proposes that learning-based technology strategy (TECHSTR) mediates the relationship between ESF and plant competitiveness (COMP). Figure 5 shows the mediation effect model used to test  $H5$ . The model showed an acceptable fit

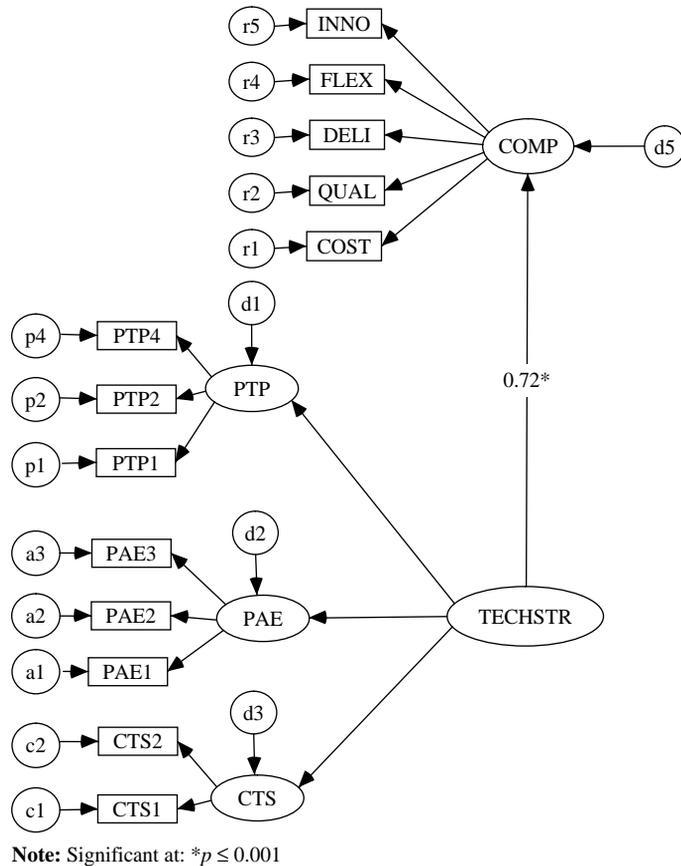


**Figure 3.** Second-order factor analysis for learning-based technology strategy

( $\chi^2 = 115.51$ ,  $p = 0.12$ ,  $\chi^2/df = 1.17$ , CFI = 0.98, NNFI = 0.98, and RMSEA = 0.03). The path loading between ESF and learning-based technology strategy (TECHSTR) was highly significant ( $p < 0.001$ , Figure 5). Similarly, the path loading between learning-based technology strategy (TECHSTR) and plant competitiveness (COMP) was also highly significant, providing support for  $H5$ .

### 6. Discussion

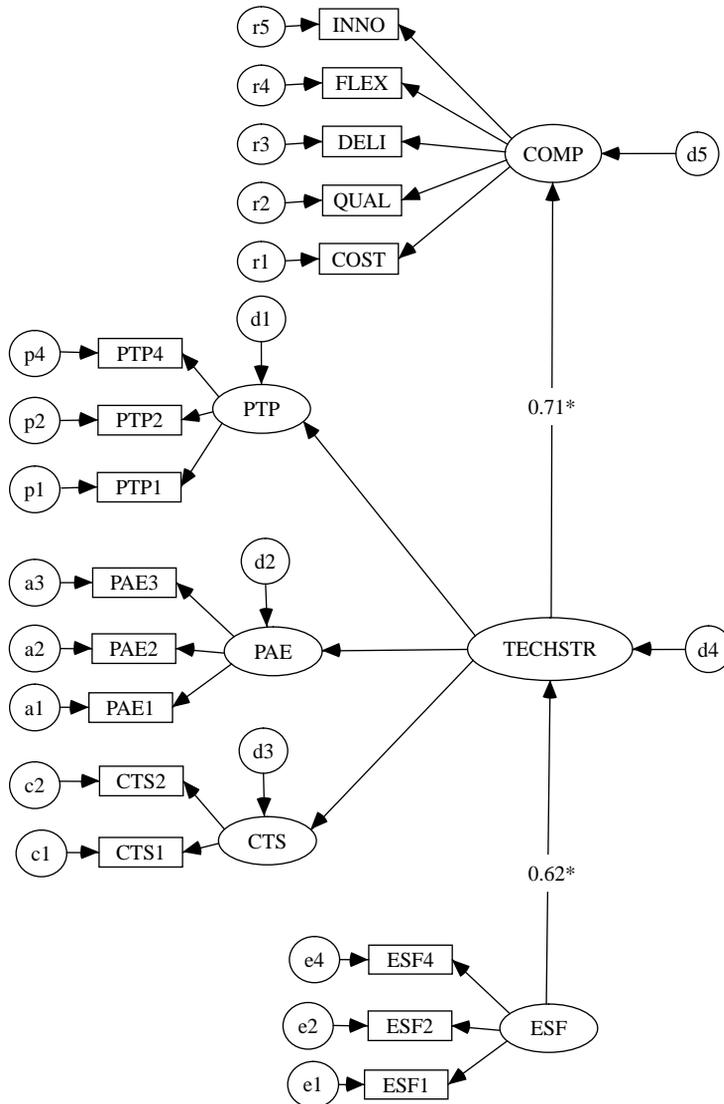
The three hypotheses ( $H1-H3$ ) representing the direct effects perspective were not supported, yet the hypothesis related to co-alignment perspective was supported. In the context of strategic manufacturing planning process and its effectiveness, Papke-Shields *et al.* (2002) found similar results where the direct effects perspective was not supported while the co-alignment perspective was. The findings of our study are consistent with the view expressed by strategy researchers that attention to any one area is insufficient for an effective strategy; consistent attention to all areas is needed (Venkatraman, 1989). More specifically, this finding emphasizes the need for a systems approach to developing learning-based technology strategy. From a socio-technical systems viewpoint, learning-based technology strategy provides a platform on which technology, existing know-how, and work procedures undergo mutual adaptation to achieve a fit between the technical sub-system and the social sub-system. Such a fit yields shared understanding and knowledge that is socially constructed and embedded within the organization. The three dimensions of learning-based technology strategy, when implemented together, foster synergy, leading to superior competitiveness,



**Figure 4.**  
Structural model:  
co-alignment perspective

because other organizations have difficulty emulating such a socio-technical system. Many plants take a piecemeal approach and develop some aspects of learning-based technology strategy while paying little or no attention to the rest. As the findings of the present study show, such an approach will contribute very little to achieving competitive advantage in the marketplace.

Employees are reservoirs of process knowledge; thus, knowledge accumulation cannot happen without their active participation. However, management has to create a proper environment to foster employee involvement and idea exchange. The learning-based technology strategy provides such a conducive environment in which employees can share, suggest, and experiment with their ideas for process improvement which ultimately leads to enhanced plant competitiveness. Thus, support for the mediation perspective (*H5*) highlights the importance of learning-based technology strategy (TECHSTR) in the context of ESF. *H5* also draws from the “sensemaking” perspective and resource-based view. The process of attaching meaning to a stream of experience, information, and insights has been termed “sensemaking” (Weick, 1995). Employees gather knowledge as they interact with each other in a social context (such as a production environment). This knowledge and



Note: Significant at \* $p \leq 0.001$

**Figure 5.**  
Structural model:  
mediated system

understanding impacts employees' behaviors, perceptions, interpretations, and cognitions (Berger and Luckmann, 1966) which helps them make sense of novel situations, generating both tacit and explicit knowledge. This aspect of learning-based technology strategy (TECHSTR) provides knowledge ambiguity, asset specificity, complexity, and inimitability leading to superior competitiveness, as predicted by the resource-based view (Barney, 1991).

## 7. Conclusions

Liu and Barrar (2009) report that consistency between a company's competitive strategy and its manufacturing technology decisions positively impact its performance. Thus, the role of long-term process technology decisions on plant competitiveness cannot be overemphasized. Based on manufacturing plants, our study indicates that the management of technology has significant implications for competitiveness. More specifically, a plant with PTPs is expected to achieve superior competitiveness if it is able to foster an environment in which learning can take place during PAE. The resulting knowledge can then be utilized strategically in technology sourcing decisions. The findings of this study also emphasize the ineffectiveness of a piecemeal approach to technology management. This has an important implication for practice as many organizations pursue only parts of learning-based technology strategy and consequently fail to increase their competitiveness.

Organizational knowledge enhances a firm's ability to cope with environmental changes so it can differentiate itself from competitors and provide competitive advantage in the marketplace (Leonard-Barton, 1992). The resource-based view of the firm posits that resources which are valuable, rare, inimitable, and lack a substitute are expected to generate superior competitiveness (Barney, 1991). The results of our study show that the learning-based technology strategy provides an environment and context in which production technology being used and process knowledge created can be inimitable, yielding superior competitiveness.

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## Appendix

*PTP*  $\alpha = 0.83$

- PTP1 We pursue long-range programs in order to acquire manufacturing capabilities in advance of our needs
- PTP2 We make an effort to anticipate the potential of new manufacturing practices and technologies
- PTP3 Our plant stays on the leading edge of new technology in our industry<sup>a</sup>
- PTP4 We are constantly thinking of the next generation of technology
- PTP5 Manufacturing capabilities in the plant are stagnant<sup>a,b</sup>

*PAE*  $\alpha = 0.70$

- PAE1 We search for continuing learning and improvement after installation of the equipment
- PAE2 Once a new process is working, we leave it well enough alone<sup>b</sup>
- PAE3 We pay particular attention to the necessary organizational and skill changes needed for new processes
- PAE4 We are a leader in the effective use of new process technology<sup>a</sup>
- PAE5 We often fail to achieve the potential of new process technology<sup>a,b</sup>

*CTS*  $\alpha = 0.62$

- CTS1 We work closely with suppliers in developing new process technology
- CTS2 Working with suppliers of equipment is critical to our plant's success
- CTS3 We buy new process equipment off the shelf<sup>b,a</sup>
- CTS4 Even if we do not build proprietary process equipment, we have a strong influence over its design<sup>a</sup>

*ESF*  $\alpha = 0.80$

- ESF1 Management takes all product and process improvement suggestions seriously.
- ESF2 We are encouraged to make suggestions for improving performance at this plant.
- ESF3 Management tells us why our suggestions are implemented or not used.<sup>a</sup>
- ESF4 Many useful suggestions are implemented at this plant.
- ESF5 When I think of ways to improve manufacturing processes at this plant, I make suggestions to management.<sup>a</sup>

*Competitiveness (COMP)*  $\alpha = 0.72$

- COST Unit cost of manufacturing
- QUAL Quality of product conformance
- DELI Delivery performance (on-time delivery)
- FLEX Flexibility to change volume
- INNO Speed of new product introduction

**Notes:** <sup>a</sup>This item was dropped from the scale following refinement;  $\alpha$  = Cronbach's alpha; all scale questions use a five-point Likert response scale where 1 = I strongly disagree and 5 = I strongly agree; please circle the number which indicates your opinion about how your plant compares to its competition in your industry. 5 = superior, 4 = better than average, 3 = average or equal to the competition, 2 = below average, 1 = poor or low end of the industry; <sup>b</sup>this item is reverse coded

Table AI.

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