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Pacific Asia Conference on Information Systems (PACIS)

Summer 6-27-2016

DEVELOPMENT OF A UNIFIED OPEN E-LOGISTICS STANDARDS DIFFUSION MODEL FOR MANUFACTURING SUPPLY CHAIN INTEGRATIONS

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Abstract

Open E-Logistics Standards (OELS) is important to facilitate the integration of the supply chain. In OELS, the transmission and the manipulation of data are governed by open data and process standards that define their format, structure, and the semantics of data flow between trading partners. Despite the significant investments made by governments and leading firms, there remain concerns about OELS' slow development progress and low adoption rates. The potential failure of OELS represents a significant stumbling block for governments and supply chain practitioners who have envisioned a globalized supply chain network electronically enabled by OELS.

Researchers are also concerned about the inadequate models that are used to explain and understand the adoption of OELS. Although analysing adopter configurations in what is known as configuration analysis has been examined in disciplines related to science and economics, its application in the study of OELS remains sparse. This research aims to integrate multiple theoretical views, and apply configuration analysis with an improved methodological approach in order to examine OELS diffusion decisions and processes. The project will result in a new algorithm integrating structural equation modelling and neural network, and a decision support system which helps firms improve their OELS adoption decision.

Keywords: Open E-Logistics Standards, configuration analysis, OELS, neural network.

1 INTRODUCTION

This research is motivated by the following questions: What determines the diffusion of Open E-Logistic Standards (OELS), and how can OELS be successfully implemented in the manufacturing industry? Despite OELS's promise, it still suffers from low adoption and slow development progress. Academics are concerned that there are inadequate theoretical models and frameworks to understand and manage OELS adoptions. Without a good understanding of successful OELS adoption conditions, it will result in missed business opportunities caused by poor supply chain integration, and leading to inefficient government economic policies.

Over the past decades, researchers have proposed various OELS adoption models which aim to guide firms towards successful OELS development and implementation. However, the key limitation of the traditional models is the focus on explaining OELS adoption from a single adopter's behaviour, or multiple single adopters' behaviour in game theory models. The key missing link in OELS adoption studies is the failure to recognize that adoption and development are influenced by clusters of adopters (known as adopter configurations). An example of such a setup could be a customer with strong bargaining power aligning its vision with its suppliers, and eventually influencing the structure and functionality of OELS. Furthermore, the value of OELS to the firm is highly dependent on other firms using it as well, and therefore network effects and inter-organizational relationships play important roles in understanding OELS adoptions. Methodologically, researchers have continued to build empirical models based on linear approaches, thus neglecting the actual complexities involved in OELS adoptions, resulting in impractical adoption strategies that are formulated based on these models. This pioneering research aims to be the first to develop a OELS diffusion model by incorporating adopter configurations and the supply chain environments which involve network effects and supply chain interorganizational relationships. Previous methodological limitations will also be solved by employing a unique data analysis algorithm combining Structural Equation Modelling (SEM), the Bayesian Markov Chain Monte Carlo (MCMC) algorithm, and neural networks.

2 REVIEW OF PAST STUDIES

2.1 Supply Chain Integration through Open E-Logistic Standards.

OELS are defined as IT standards that facilitate web-based business information sharing in a supply chain (Nurmilaakso, 2013). OELS define the business process, data exchange format, and communication standards, and allow information flow to be automated between organizations (Weitzel, Beimborn, & König, 2006). Unlike traditional standards, OELS are developed by an open community, use open standards, and are built on the Internet for exchanges between supply chain members (Rampersad, Troshani, & Plewa, 2012; Zhu, Kraemer, Gurbaxani, & Xu, 2006). OELS are highly complex in their development, and diffusion processes, as the main stakeholders may include the OELS community, the developers who are also the potential adopters, other adopters who might not be part of the development team, and the clusters of adopters within the industry or the supply chain. As a result, the adoption of OELS will be subjected to various social constructions and network effects (Klein et al., 2012; Lyytinen & Damsgaard, 2010, 2011; Nelson, Shaw, & Qualls, 2005). Despite its practical and theoretical significance, to the best of our knowledge, there has not yet been an empirical examination of a unified OELS adoption model based on our proposed research model.

2.2 Multi-criterion Adoptions Decisions of Open E-Logistic Standards.

Past studies on OELS have always treated multi-criterion adoption decisions as an instance of viral behaviour within the population (Lyytinen & Damsgaard, 2010; Schellhammer, 2011; Venkatesh & Bala, 2012). Thus these studies examined a single firm's decision to adopt OELS based on a "viral" paradigm outlined in models such as Diffusion of Innovation (Rodger, 1995), Theory of Planned

Behaviour, Technology Acceptance Model (Davis, 1989), Unified Theory of Acceptance and Use of Technology model (Venkatesh, Morris, Davis, & Davis, 2003; Venkatesh, Thong, & Xu, 2012). A key weakness of these studies is their emphasis on examining the multi-criterion adoption decision from a single firm's point of view, and in assuming that adopters are independent, and that the decision was voluntarily based on whether to accept or reject the OELS or related technologies (Lyytinen & Damsgaard, 2010, 2011). Figure 1 shows an overview of the adoption perspective in traditional analysis and adopter configurations analysis (Weitzel et al., 2006). The small circles in Figure 1 represent independent, and potential OELS adopters. The white coloured circles represent non-adopters, while the ones in black are adopters. The model in Figure 1 assumes that the adoption (e.g. changing from white to black) is dependent on the properties of the singular adoption unit (Lyytinen & Damsgaard, 2010; Rampersad et al., 2012). The transitions from being a non-adopter to an adopter based on traditional models can be identified by observing the characteristics of the individual adopters, such as their properties (Y.-M. Wang, Wang, & Yang, 2010; Xu, Zhu, & Gibbs, 2004; Zhu, Kraemer, & Xu, 2006), technology attributes (Lin & Lee, 2005; Sharma, Citurs, & Konsynski, 2007), and the environment in which the firm operates (Sodero, Sinha, & Rabinovich, 2013; Tsai, Lee, & Wu, 2010). However, OELS adoption is very complex due to the inter-relationships and network effects that exist. Therefore it is important to extend the traditional adoption criteria with additional considerations.

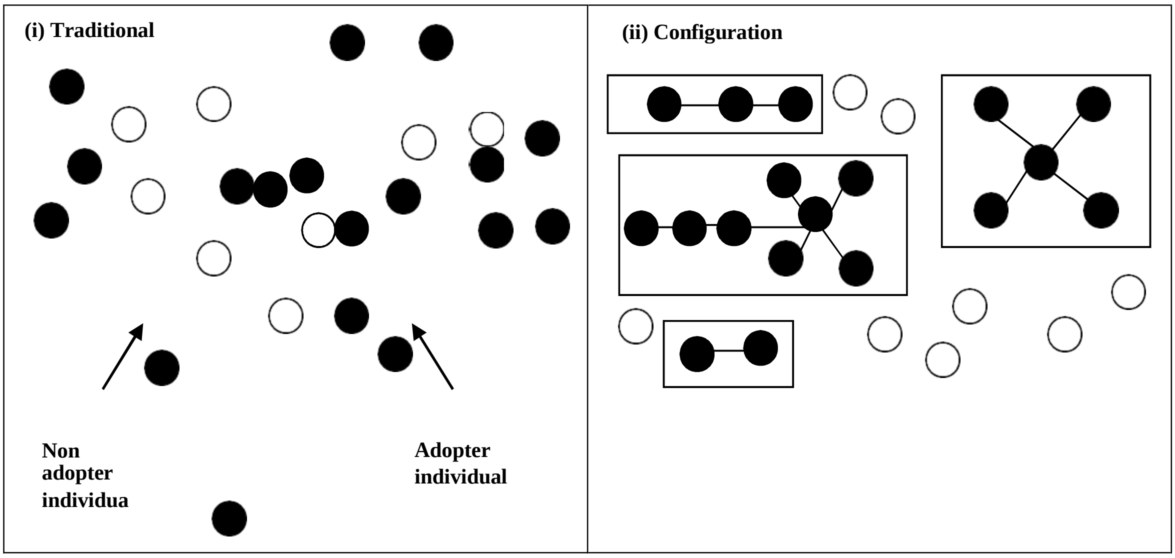

Figure 1. Analysing OELS adoption1

The proposed model will examine the adoption behaviour of clusters of firms based on adopter configurations (See Figure 1(ii)) as opposed to using a single firm (See Figure 1 (i)). As adopter configuration is defined as a set of interrelated adopters of OELS, it can be grouped based on key elements such as organizing vision, key functionality, structure, mode of interaction, and mode of appropriation (See Table 1) (Lyytinen & Damsgaard, 2010). These elements show the complexity involved in implementing and designing OELS since there are various ways of interpreting the functionalities and goals of OELS (Lyytinen & Damsgaard, 2011). In general, based on the elements, the topology of adopter configurations of OELS can be classified into the dyadic, hub and spoke, industry and community topology, as shown in Figure 2. However, each supply chain member might belong to multiple adopter configurations, and implement various OELS in "different pockets" of a firm (Lyytinen & Damsgaard, 2010, 2011). This further highlight the complexity involved in examining OELS diffusion. For example, a firm might implement OELS in a business process, such as order requesting with its supplier to form a dyadic relationship (Figure 2 (a)), and at the same time, its powerful customers might request suppliers to connect it to the customer base similar to the mandatory

[1] *The total number of firms with OELS adoption remains the same in both Figures 2(i) and 2 (ii))*

requirements by Wal-Mart, forming a hub and spoke configuration (Figure 2 (b)). The firm then connects with the industry based on the industry supported standard such as RosettaNet (industry configuration) (e.g. Figure 2 (c)). An important assumption from configurations analysis is that understanding adoption decisions from singular adopters will not be sufficient to understand why adopter configurations are formed, and how they affect the OELS adoption behaviour and the overall OELS diffusion. Thus the key missing link in past OELS research is the failure to understand why certain firms are more prone to adopt OELS, whereas others are not, depending on the types of adopter configurations they are in (Lyytinen & Damsgaard, 2011).

Elements of adopter configurations	**Definitions**
Organizing vision	This is the vision of the OELS in terms of how it can improve the structure and interorganizational processes in the supply chain.
Key Functionality	The functions that the OELS support to integrate the supply chain processes. It defines the type of exchanges, its contents, and formats (e.g. Partner Interface Processes in RosettaNet.
Structure	The structural relationships among the firm in the adopter configurations.
Interaction Mode	The relationships between the supply chain partners implementing OELS (e.g. hierarchical, horizontal relationships).
Appropriation Mode	The intensity, key emphasis, and the level of supply chain process integration.

Table 1. Main Elements of Adopter Configurations

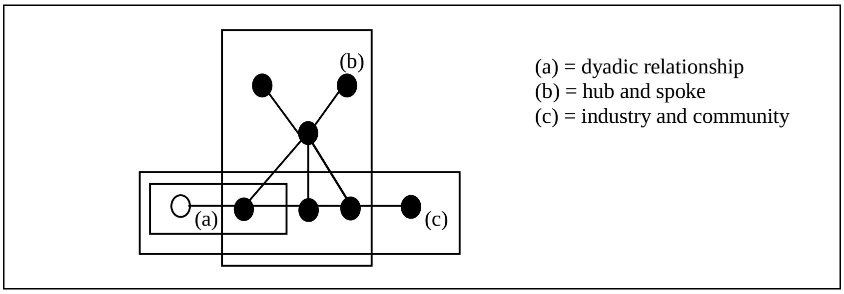

Figure 2. Examples of adopter configurations

Besides adopter configurations, theories derived from the network effect and interorganizational relationships will be examined and incorporated in the proposed research model. Network effect theory states that the benefits that OELS adopters will gain are directly related to the size of the network (Cranmer, Desmarais, & Kirkland, 2012; Shapiro & Varian, 1999; Zhu, Kraemer, Gurbaxani, et al., 2006). OELS require supply chain members to invest in compatible systems, and share information with each other. OELS development also requires joint efforts by the supply chain members, and the benefits from OELS adoptions are dependent on the status of OELS adoptions by other firms as well. Thus the network effects in OELS might be different from the past technologies adoption (e.g. EDI) studies (Maggiolini & Valles, 2012; Marcussen, 1996). Theories related to inter-organizational relationships include Transaction Cost Theory (TCT), Resource Dependence Theory (RDT), and GuanXi. TCT states that the transaction costs involved in managing relationships and interactions with potential suppliers, such as searching, negotiating and monitoring execution of the transactions are significantly economically valuable (Chang & Adviser-Shaw, 2003; Y.-S. Wang, Wu, Lin, Wang, & He, 2012; Williamson, 1994), and this cost can be reduced through OELS adoption (Fink, Edelman, Hatten, & James, 2006; Iskandar, Kurokawa, & LeBlanc, 2001). In RDT, firms depend on others in their environment for resources in order to ensure their on-going viability (Sila, 2013; Singh, Power, & Chuong, 2011). Therefore in an uncertain environment where dependencies increase, firms will form closer relationships in order to improve "information exchanges, commitment, legitimacy, and exchange stability" (Fink et al., 2006). Guanxi is based on "personal relationship networks of informal social bonds in which the individuals will carry out expectations and obligations in order to facilitate the exchanges of favours" (Leung, Lai, Chan, & Wong, 2005). When implementing OELS among Chinese firms, it is possible that firms with better established GuanXi are willing to adopt OELS with their suppliers/customers (Cheng, Yip, & Yeung, 2012). This research would be one of the first known studies to draw theories from TCT, RDT, GuanXi, Network Effects Theory, and adopter configurations to examine OELS diffusion.

2.3 Data Analysis Algorithm Incorporating SEM and Neural Network

A review of the existing literature found that the majority of studies on the examination of OELS and related technologies adoption are empirically examined using linear models. These past models often apply “preferences regression”, whereby they all share the same prior assumptions that the processes for firms’ adoption decisions are linear compensatory (Chiang, Zhang, & Zhou, 2006). These models assume that a shortfall in an adoption factor (e.g. ease of use) can be compensated by improving other factors (e.g. cost) (Chiang et al., 2006). However, not all the processes of evaluation are compensatory. Linear models such as SEM will often oversimplify the complexities when making technology adoption decisions (Venkatesh & Goyal, 2010). In this connection, even if the actual relationship between the adoption decisions and the adoption outcome is curvilinear, linear models would oversimplify the relationship and mask the true relationships among the variables (Venkatesh & Goyal, 2010). There is increasing awareness in the organizational behavior literature regarding the simplicity of linear models. For example, Venkatesh and Goyal (Venkatesh & Goyal, 2010) found significant non-linear relationships between the adoption factors chosen in their study and information systems continuance usage. Another limitation with SEM is that there could eventually be hundreds of meaningful models that can be derived (Hunter & Schmidt, 2004; Raftery, 1993). As mentioned by Raftery (Hunter & Schmidt, 2004), given that some of the arrows or path relationships can be in or out, there is a possibility of having 2^{20} or one million competing models. He argued that it is not appropriate to merely conduct significance tests using P-values, and a better approach would be to determine “which model predicts the data better”. However, to manually compare the possible millions of models would be very challenging given the limited amount of time. Neural networks however, can be integrated with SEM to identify and select the most appropriate research model. However, the challenge is on how to identify the most accurate model as there are numerous models that could fit the criteria, modification indices, and path relationships. Thus a neural network algorithm needs to be designed and trained to identify and select the most accurate SEM model using inputs from various SEM output values.

3 RESEARCH METHODOLOGY

3.1 Investigation of Factors Affecting OELS Diffusion

Before proceeding with analyzing the data, it is important to ensure that the model developed will be able to provide detailed explanations of OELS diffusion.

3.1.1 Identify The Past Technology Adoption Models Applied, Technology Examined, and Result.

Past technology models developed are sometimes examined individually, or integrated with each other, or combined with theories from different disciplines in order to study the relevant technology. Although not all the models have been applied to OELS, some of the models have been studied in technologies that are closely related to OELS, such as EDI and E-Commerce. We will also conduct an initial case study with Klinik Mediviron, a company in the medical industry, in order to confirm the variables as well as in determining additional input variables that we may not have included in our initial conceptual model development.

3.1.2 Conduct meta-analysis to examine past models.

One of the weaknesses in the past research is that the models applied often neglected variables which the authors claimed should be included in future studies. Although it is not possible to include all the possible variables and their interactions, conducting a meta-analysis will provide a subjective evaluation of the literature. The Hunter and Schmidt Method (2004) will be employed to conduct the analysis, and the effect sizes (*r*) of the published models will be used for the meta-analysis. In summary, the approach is to identify a common measure of effect size, for which a weighted average will be the output of a meta-analysis. The weighting will be related to sample sizes within the individual studies. The aim of conducting the meta-analysis is to estimate the true "effect size" instead of a smaller "effect size" derived in a single study (Hunter & Schmidt, 2004). This will allow us to verify the model proposed in this research, and to re-look at any possible variables which might not have been included. This will allow us to create a unified model incorporating all the significant variables.

3.2 Model Development and Design of Data Analysis Algorithm

3.2.1 Adopter configurations development.

The concept of adopter configurations is relatively new (Rampersad et al., 2012). There is no empirical confirmation of adopter configurations in technology adoption studies. In order to develop the adopter configurations to be used in the empirical analysis, the typologies available for OELS implementation will be examined. At this stage, empirical confirmation of the adopter configurations can only be conducted once the data has been collected. However, the identification of attributes are required to classify OELS adoptions. The attributes would include the organization vision, the functionalities, the OELS supply chain processes supported, and the mode of interaction. Klinik Mediviron will participate with us in order to determine the types of configuration and typologies of OELS, and case studies with Klinik Mediviron group will be conducted.

We will describe examples of OELS configurations based on Klinik Mediviron (note: For illustration purpose as well as the constraint of space, we have kept the configurations and scenario simple). The three examples illustrated here are the Dyadic View, the Actor Centric View, and the Ecosystem View. Klinik Mediviron is chosen as our industrial partner as they are planning to implement OELS with their supply chain partners, and they have characteristics that typify the challenges faced by firms which would like to implement OELS. Klinik Mediviron has more than 100 clinics, pharmacies, and consulting firms and these business processes need to be integrated as part of their supply chain management. For example, besides connecting to patients, the company also needs to connect to their suppliers (e.g. medicine, equipment etc.), government, and insurance providers. The first typology of OELS configuration is the dyadic view and this occurs when one of the clinics (note: As an example, we have chosen a clinic from Klinik Mediviron to illustrate this example although they have other businesses) is the focal unit, and it forms dyadic relationships with one of its medical suppliers.

Figure 3 (a) shows a buyer-seller relationship (as shown in the two black dots and inside the box). For example, the Klinik Mediviron clinic purchases medical supplies from its supplier, and this is conducted via an OELS. A challenge with such configuration as stated by Schellhammer (2011), is that the dyadic relationship does not explain why OELS diffuses in the industry in terms of various actors implementing the same technology.

Besides the dyadic relationships, another scenario can occur when the clinic and its supplier maintain relationships with other multiple partners. For example, one of the clinics needs to be linked to the remaining hundreds of clinics, and the supplier needs to link to other customers and government agencies etc. Such a scenario is shown in Figure 3 (b) and is known as the actor centric model. In the actor centric model, there is a larger number of relationships and there is more influence on the diffusion of OELS. Each of these actors will be influenced by different factors in their OELS diffusion decisions, as well as their considerations of other actors.

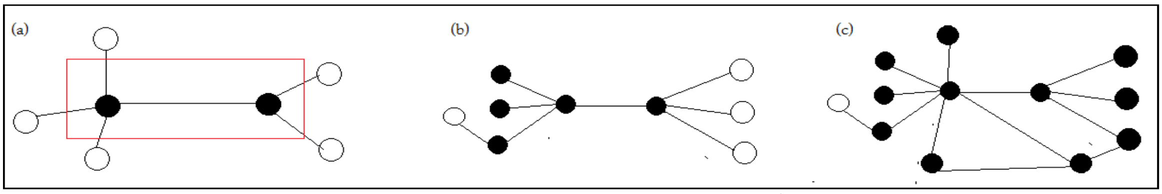

Figure 3. *Possible adopter configurations in industrial partner (Klinik Mediviron)*

Lastly, the example shown will be an OELS ecosystem environment whereby the OELS environment may extend beyond the perspective of the Klinik Mediviron Group of Clinics (i.e. Figure 3 (c)). For example, the medical clinics, pharmacists, wholesalers etc. are all connected to OELS, as required by the government and insurance companies. In such a scenario, the groups of clinics are no longer a single unit of identical actors. They are differentiated into small communities, groups and cooperatives. In this connection, the main task involved at this stage would be to work closely with the Klinik Mediviron Group of Clinics and conduct case studies to identify potential adopter configurations.

3.2.2 Model Confirmation

At this stage, the model will be finalized based on the meta-analysis, case study with Klinik Mediviron Group of Clinics, and the adopter configuration development results. An example of the conceptual model developed is shown in Figure 4 (Subject to change after conducting previous phases). The finalized model will be used for the analysis of data, and simulation studies of the diffusion process in the final phase.

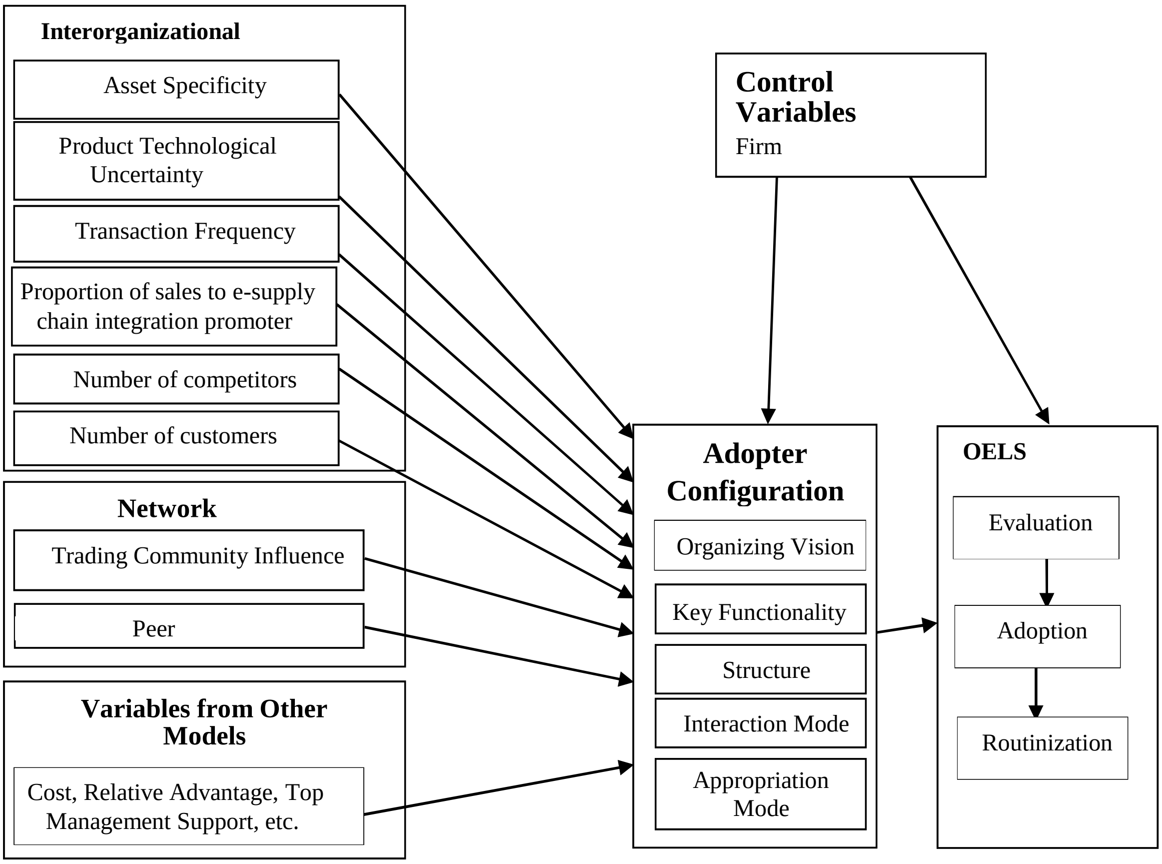

Figure 4. *Proposed Conceptual Model*

3.2.3 Development of Data Analysis Algorithm.

There is a need to develop an appropriate algorithm that can integrate SEM and neural network analysis. SEM allows the analysis of linear relationships between the variables from the analysis of the covariance among the variables. SEM evolves from both factorial analysis and multiple regression. By employing SEM, we will be able to examine simultaneously the multiple sources of influence on the dependent variables. SEM will integrate the errors of measurement into a statistical model; by doing so, the estimation of regression coefficients becomes more precise.

As stated earlier, one limitation with SEM is that there could eventually be hundreds of meaningful models that can be derived (Hunter & Schmidt, 2004; Raftery, 1993). Therefore it is not appropriate to merely conduct significance tests using p-values, and a better approach would be to determine "which model predicts the data better". This is when integrating the neural network to the model becomes necessary and useful. SEM is able to verify whether the causal relationships in the research model are valid by examining the goodness of fit of the model. Neural network on the other hand, will be applied to examine the model fit by comparing the incremental index, absolute index, X^2 value, and the associated degrees of freedom. One of the current challenges with SEM analysis is that there is no established, consistent guideline to help researchers pick and choose an index that provides the best fit evidence for the specific analysis. We will therefore use simulated data to train the neural network to identify the most appropriate groups of fit indices for the research model. The neural network will be trained to identify the combinations of fit indices which will provide the most reliable and accurate model.

Together with the model fit indices, the supported relationships in the SEM will be used as the neural network structure. Based on these values, the neural network will be applied for three purposes. First, it will be used to examine the possible non-linear relationships between the variables in the study. Second, as mentioned by Lyytinen and Damsgaard (2010), there is no single way to identify instances of adopter configurations, and this can only be discovered through detailed analysis of the data. Neural networks are known to be highly accurate in identifying patterns (e.g. adopter configurations), and will be used to examine the adopter configurations. Third, as the SEM will offer multiple models, each with different path relationships, the neural network will be employed to predict which of the SEM models will offer the most accurate understanding of the OELS diffusion.

3.3 Data Collection and Analysis

Data will be collected from manufacturing firms in Hong Kong, China and Malaysia. Firms will be selected from appropriate OELS consortia such as RosettaNet, OASIS, STAR and from directories such as the Business Directory of Hong Kong, the ShangHai stock exchange, the Hong Kong Stock Exchange, and the Kuala Lumpur Stock Exchange.

In order to measure the relationships amongst the constructs, a series of statistical techniques are required. Conceptually, it is important to highlight each procedure. These statistical analyses, in chronological order, are: (a) Cluster analysis; (b) Reliability Testing; (c) Exploratory Factor Analysis (EFA); (d) Confirmatory Factor Analysis (CFA); (e) SEM and MCMC; (f) Neural Network Analysis; and (g) Testing the research model with industrial firms.

Acknowledgement

The work described in this paper was supported by a grant from the Research Grants Council of the Hong Kong Special Administrative Region, China (Project No. PolyU 15201414); a grant from The Natural Science Foundation of China (Grant No. 71471158); and a grant from the Research Committee of The Hong Kong Polytechnic University under student account code RUN2. The authors also would like to thank The Hong Kong Polytechnic University Research Committee for financial and technical support.

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