The Effects of Sustainable Innovation in Management Strategies on E-Purchase Intention: An Empirical Study using SEM Statistical Analyses

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ABSTRACT

This paper was intended to determine what factors affect online shoppers’ purchase intention in the e-business environment and to verify how organizations’ internal and external dynamics may underlie the success of e-commerce companies. A set of quantitative surveys and in-depth interviews with the senior managers working with e-commerce companies, a conceptual model and a number of hypotheses were proposed. Both were instrumental to a comparative analysis between two typical e-commerce companies, Alibaba and Amazon. The factor analysis and structural equation modeling (SEM) were adopted for statistical and empirical analyses. The results showed positive correlations among the identified factors indicating a great influence of innovative performance in different areas of management strategies on e-purchase intention; they also demonstrated the great impact from the awareness of sustainability development in e-commerce companies. These results may provide some insight on how e-business companies can improve their performance and win in fierce competition.

Keywords: E-commerce, sustainable innovations, sustainability, management strategies, e-purchase intention, EFA, SEM, path analysis.

1. INTRODUCTION

The terms of e-business and e-commerce are quite common nowadays and are sometimes used interchangeably. But the two terms are different in ways that matter to companies[1][2][3]. Here, the letter e stands for “electronic networks” and describes the application of electronic network technologies e.g., Internet and electronic data interchange (EDI) to improve and change business processes[4][5][6].

E-commerce covers outward-facing processes that touch customers, suppliers and external partners. It includes sales, marketing, order taking, delivery, customer service, purchasing of raw materials and supplies for production and procurement of indirect operating-expense items such as office supplies[7][8][9]. It involves new business models and the potential to gain new revenue or lose some existing revenue to new competitors[10][11]. Ambitious as it is, it is relatively easy to implement because it involves only three types of integration: a vertical integration of front-end web site applications to existing transaction systems, a cross-business integration of a company with web sites of customers, suppliers or intermediaries such as web-based marketplaces, and an integration of technologies with modestly redesigned processes for order handling, purchasing or customer service[12][13][14][15].

While e-business includes e-commerce, it also covers internal processes such as production, inventory management, product development, risk management, finance, knowledge management and human resources [16][17][18]. E-business strategies are more complex, more focused on internal processes and are aimed at improvements in efficiency, productivity and cost savings [19][20][21][22]. So, e-business enables an enterprise to reach the global customers. In an attempt to extend their sales platforms to a futuristic dimension, business houses have incorporated software that can run on platforms offered by the World Wide Web [23][24][25][26][27]. Fig.1 explains e-business service platforms.
Economists have theorized that e-commerce will lead to intensified price competition, as it increases consumers’ ability to gather information about products and prices[28][29][30][31][32]. Research by four economists at the University of Chicago has found the growth of online shopping also affecting the industry’s structure in two areas that have seen significant growth in e-commerce: e-bookshops and travel agencies[33][34][35][36]. Generally, larger firms are able to use economies of scale and offer lower prices. The lone exception to this pattern has been the very smallest category of booksellers, shops with 1-4 employees, which appear to have withstood the trend.

Individuals or businesses involved in e-commerce, whether buyers or sellers, rely on Internet-based technologies to accomplish their transactions[37][38][39][40]. E-commerce is recognized for its ability to allow businesses to communicate and to form transactions anytime and anywhere. Whether an individual is in U.S. or overseas, business can be conducted through the internet. The power of e-commerce has caused geophysical barriers to disappear, making all consumers and businesses on earth potential customers and suppliers[41][42][43][44]. eBay is a good example of e-commerce by which individuals and businesses are able to post and sell their items around the globe[45][46][47][48].

Online selling activities have been very experimental to date, without a sufficient amount of data generated to provide conclusive results[49][50][51][52]. However, important issues have emerged that can be identified for the purpose of promoting future discussion and analyses. These issues vary according to the organization in question, the type of products it sells online, online selling patterns, online customer base, approach to online selling and resource expansions[53][54][55][56].

The objective of the present study is to investigate the factors that influence consumers’ purchase intentions during their individual purchases online, to conduct an empirical investigation for a comprehensive understanding of the effects of factors influencing their purchase behavior, to make available managerial implications for the online retailing industry, and contribute to innovative product research. Via the investigation mentioned above, a great influence of innovativeness and segmentation strategies on consumers’ purchase intention was revealed. These findings may provide some insights on how to improve companies’ performances.

2. Methods

According to the literature review and quality interviews, it was assumed that there were also some relationships among the variables of the conceptual model, as shown in Fig.2 above. This model was later adjusted based on the interviewees’ input.
An SEM with latent variables is composed of up to three sets of simultaneous equations, estimated concurrently: a measurement model (or sub-model) for the endogenous (dependent) variables, a measurement sub-model for the exogenous (independent) variables, and a structural sub-model, all of which are estimated simultaneously [57]. This full model is seldom applied in practice. Generally, one or both of the measurement models are dropped. SEM with a measurement model and a structural model is known as SEM with latent variables [58][59]. Alternatively, one can have structural model without any measurement models, SEM with observed variables, or a measurement model alone (confirmatory factor analysis). In general, an SEM can have any number of endogenous and exogenous variables.

An SEM structural model is used to capture the causal influences (regression effects) of the exogenous variables on the endogenous variables and the causal influences of endogenous variables upon one another [60][61]. The structural model also allows specification of error-term covariance. If the SEM also has a measurement model for the endogenous variables, the structural model will involve latent endogenous variables rather than observed endogenous variables. Similarly, the SEM can have a measurement model and latent variables for exogenous variables. Simultaneous equations (typically estimated with instrumental variables methods) and path analysis are special cases of SEM with observed endogenous variables and multiple observed exogenous variables. An SEM measurement model is used to specify latent (unobserved) variables as linear functions (weighted averages) of other variables in the system [62]. When these other variables are observed, they take on the role of indicators of the latent constructs. In this way, SEM measurement models are similar to factor analysis, with one basic difference, though. In an exploratory factor analysis, such as principal components analysis, all elements of the matrix defining the latent variables (factors) in terms of linear combinations of the observed variables take on non-zero values [63].

SEM provides a test of the hypotheses more stringent than multiple regression analysis or path analysis as it enables the researcher to take account of complete information in a theoretical model and to search for appropriate models by the criteria provided by the goodness of fit in AMOS. The items for each dimension are averaged to create single indicators for each latent variable, considering the large number of parameters being estimated. Studies have shown that a corrected single-indicator model produces parameter estimates that are virtually identical to those produced by a pure latent-variable analysis [64].

These values (factor loadings) generally measure the correlations between the factors and the observed variables, and rotations are routinely performed to aid in interpreting the factors by maximizing the number of loadings with high and low absolute values. In SEM, the modeler decides in advance which of the parameters defining the factors are restricted to being zero constant. Also, in SEM one can specify non-zero covariance among the unexplained portions of both the observed and latent variables [65][66]. Specification of each parameter allows the modeler to conduct a rigorous series of hypothesis testing regarding the factor structure. Since there can be a large number of possible combinations in a measurement model with more than just a few variables, exploratory factor analysis is sometimes used to guide construction of an SEM measurement model [67].

An important distinction in SEM is one between direct effects and total effects. Direct effects are the links between a productive variable and the variable that is the target of the effect. Each direct effect corresponds to an arrow in a path.
(flow) diagram [68]. An SEM is specified by defining with direct effects are present and which are absent. With most modern SEM software, this can be done graphically by manipulating path diagrams. These direct effects embody the causal modeling aspect of SEM. Total effects are defined to be the sum of direct and indirect effects, where the latter represent the sum of all of the effects along the paths between the two variables that involve intervening variables[69]. The total effects of the exogenous variables on the endogenous variables are sometimes knows as the coefficients of the reduced form equations.

The general SEM system is estimated by covariance (structure) analysis, whereby model parameters are determined such that the variances and covariance of the variables implied by model system are as close as possible to the observed variances and covariance of the sample. In other words, the estimated parameters are those that make the variance-covariance matrix predictable by the models as similar as possible to the observed variance-covariance matrix while respecting the constraints of the model[70][71]. Covariance analysis appears at first to be quite different from least-square-regression methods, but it can be viewed as an extension of least squares into the realm of latent variables, error-term covariance, and non-recursive models (i.e. models with feedback loops). In some simple cases, a covariance analysis is identical to least squares [72][73].

3. DATA ANALYSIS AND RESULTS

As mentioned in Section2, SEM provides a more stringent test of hypotheses than multiple regression analysis or path analysis because it enables the researcher to take account of complete information in a theoretical model and to search for appropriate models with the criteria provided by the goodness of fit in AMOS [74]. Because of the large number of parameters being estimated in the present study, the items for each dimension were averaged to create single indicators for each latent variable. Studies have shown that a corrected single-indicator model produces parameter estimates that are virtually identical to those produced by a pure latent-variable analysis[75].

A. Introduction

This chapter presents survey responses and exhibits an exploratory factor analysis (EFA), conducted to verify the construct validly of the measuring scales, along with structural equation modeling (SEM). These statistical methods were used to analyze the survey data and to test the hypotheses. SEM was used to verify both the overall model and the detailed ones on, respectively, attitudes, perceived risks, and perceived ease of use, perceived value, relative advantages, loyal brand strategies, innovation, sustainability, and efficiency in technologies.

B. Data Collection and Participants' Responses

Data were collected from Alibaba’s and Amazon’s online shoppers, vendors and owners from different industries. After that, a large-scale questionnaire was used to secure more information from the CEOs, top managers, HR officers and others. Because a comprehensive questionnaire such as this one would have required much time to answer, most of the respondents were approached through acquaintances.

Although the sample was selected on a convenience basis, there were several benefits from this sampling technique. First, the rate of response was greater than that of a typical mail survey. Second, about two-thirds of the sample was not anonymous, and the dataset was controlled. The lack of anonymity was conducive to the quality of data while ensuring that the appropriate individuals in the industry would complete the survey. Third, to keep the present study manageable, the samples had to be restricted to manufacturing companies only.

Furthermore, through Survey Company questionnaires were sent to the online shoppers, of whom 100 were online shop owners while another 100 were online customers. According to SurveyMonkey.com, drop-off surveys’ return rate with 40 questions is 8%-10%. Thus, 1,250 surveys were sent to randomly selected individuals. About 100-125 questionnaires were expected to be collected from online store owners and shoppers.

Also conducted were face-to-face interviews with online shoppers who had experiences with both Alibaba and Amazon. On hundred questionnaires are expected to be collected from these respondents.

Altogether, 223 online shoppers, owners, vendors, and managers at e-commerce companies were to be involved into this survey.

C. Proposed Models and Hypothesis Testing

In order to test these hypotheses, nine models were created and integrated in the present study. The overall model in Fig. 3 explains the paths and the relationships among the dimensions. The detailed models in this Fig.3 show the impact of the observed variance.
The overall model was developed to test the proposed hypotheses. Fig. 4 is a graphic representation of the results of the overall model. Maximum likelihood was used to estimate the parameters of this structural model.

The statistics in Fig. 4 not only suggest that the hypothesized model considerably explained the causal relationships between the endogenous and the exogenous variables but also indicate that the constructs did have a good predictive validity. Moreover, the estimates of the path coefficients are positive and significant (See Fig. 4).

Observed variables: Sus 1 (Sustainability), Sus 2 (Awareness), Sus 3 (Development), Sus 4 (Consistency), Sus 5 (Business model), Sus 6 (Other models), Ino 1 (Adopter), Ino 2 (Personal innovativeness), Ino 3 (Ease of use), Ino 4 (Compatibility).

Latent variables: Sustainability and innovation

Statistical methods: SEM

On the following pages, a number of sub-topics (viz. offending estimates, construct reliability and average variance extracted, and goodness of fit) will be discussed[76],[77].

Offending estimates: In Table 1, the standard error in Model 1 ranges from .040 to .075, and there are no negative standard errors in this model.
Figure 4. An Overall Model.

Table 1: Model-1 Variances

<table>
<thead>
<tr>
<th></th>
<th>Estimate</th>
<th>S.E.</th>
<th>C.R.</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td>e2</td>
<td>.512</td>
<td>.052</td>
<td>8.002</td>
<td>***</td>
</tr>
<tr>
<td>e3</td>
<td>.479</td>
<td>.060</td>
<td>8.047</td>
<td>***</td>
</tr>
<tr>
<td>e4</td>
<td>.384</td>
<td>.042</td>
<td>9.068</td>
<td>***</td>
</tr>
<tr>
<td>e5</td>
<td>.448</td>
<td>.051</td>
<td>8.761</td>
<td>***</td>
</tr>
<tr>
<td>e6</td>
<td>.410</td>
<td>.046</td>
<td>8.880</td>
<td>***</td>
</tr>
<tr>
<td>e7</td>
<td>.577</td>
<td>.064</td>
<td>9.027</td>
<td>***</td>
</tr>
<tr>
<td>e8</td>
<td>.263</td>
<td>.075</td>
<td>3.506</td>
<td>***</td>
</tr>
</tbody>
</table>

Note: Estimate = Unstandardized coefficients; SE = Standard errors; C.R. = Critical ratio; p = Significance: * p < .05, **p < .01, ***p < .001
Also, as shown in Table 2, the standardized regression weight ranges from .538 to .843, with all of these weights being below 1.0. Thus, it is clear that the offending estimates did not occur in Model 1. Hence, the results on offending estimates are acceptable for Model 1.

Construct reliability and average variance extracted: According to Claes and Larcker, a model is acceptable when its construct reliability is greater than .7, and the average variance extracted (AVE) needs to be greater than .5 to be acceptable[78][79]. In the present study, the construct reliability for innovation was calculated at the suggested low limit of .70, with this formula:

\[
\rho_{c1} = \frac{\left(\sum \lambda_1^2\right)^{\frac{1}{2}}}{\left[\left(\sum \lambda_1^2\right)^{\frac{1}{2}} + \sum \theta_1\right]}
\]  

(1)

\(\rho_{c1}\) is the innovation factor. Let \(\lambda_1\) be the standardized loadings (or the standardized coefficients) for the innovation factor. Let \(\theta_1\) be the error variance for the innovation factor [80]. Based on the data in Table 4-5, the construct reliability of this innovation factor is:

\[
\rho_{c2} = \frac{\left(\sum \lambda_2^2\right)^{\frac{1}{2}}}{\left[\left(\sum \lambda_2^2\right)^{\frac{1}{2}} + \sum \theta_2\right]}
\]  

(2)

The average variance extracted from sustainability in Model 1 was calculated at the suggested low limit of .50, with this formula:

\[
\rho_{v2} = \frac{\left(\sum \lambda_2^2\right)}{\left[\sum \lambda_2^2 + \sum \theta_2\right]}
\]

\(\rho_{v2}\) is the average variance extracted from sustainability in Model 1[81],[82]. Based on the data in Table 3, the average variance extracted from sustainability in Model 1 is .691.

<table>
<thead>
<tr>
<th>Table 2: Model-1 Standardized Regression Weights</th>
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<tbody>
<tr>
<td>Sus 1</td>
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<tr>
<td>Sus 2</td>
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<td>Sus 4</td>
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<td>Sus 3</td>
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<td>Sus 2</td>
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</tbody>
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Note: Estimate = Standardized coefficients
Table 3: Model-1 Factor Loadings, Construct Reliability and Ave

<table>
<thead>
<tr>
<th></th>
<th>Factor loadings</th>
<th>Squared multiple correlations</th>
<th>Error variance</th>
<th>Construct reliability</th>
<th>Average variance extracted</th>
</tr>
</thead>
<tbody>
<tr>
<td>Infor 1</td>
<td>.662</td>
<td>.417</td>
<td>.42</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Infor 2</td>
<td>.579</td>
<td>.456</td>
<td>.51</td>
<td></td>
<td></td>
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<tr>
<td>Infor 3</td>
<td>.672</td>
<td>.452</td>
<td>.37</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Infor 4</td>
<td>.524</td>
<td>.345</td>
<td>.41</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sus 1</td>
<td>.650</td>
<td>.710</td>
<td>.26</td>
<td>.7937</td>
<td>.4924</td>
</tr>
<tr>
<td>Sus 2</td>
<td>.720</td>
<td>.348</td>
<td>.58</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sus 3</td>
<td>.457</td>
<td>.364</td>
<td>.41</td>
<td></td>
<td></td>
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<tr>
<td>Sus 4</td>
<td>.530</td>
<td>.397</td>
<td>.45</td>
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</table>

In summary, the construct reliability was considered satisfactory as both .7937 and .8070 were much higher than the suggested values (.70, respectively). The average variance extracted in Model 1 (.5169) was considered acceptable as it was higher than the suggested values (.50). The value of .4924 was also acceptable as it is close to the suggested values of .50.

The inner quality of Model 1 was, then, acceptable and fit for further analyses (see Table 4).

Table 4: Model-1 Regression Weights

<table>
<thead>
<tr>
<th></th>
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<th>Estimate</th>
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<tbody>
<tr>
<td>Sus 1</td>
<td>---</td>
<td>Infor 1</td>
</tr>
<tr>
<td>Sus 2</td>
<td>---</td>
<td>Infor 2</td>
</tr>
<tr>
<td>Sus 3</td>
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<td>Infor 3</td>
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<tr>
<td>Sus 4</td>
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<td>Sus 2</td>
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<td>Infor 2</td>
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<tr>
<td>Sus 3</td>
<td>---</td>
<td>Infor 1</td>
</tr>
<tr>
<td>Sus 4</td>
<td>---</td>
<td>Infor 2</td>
</tr>
<tr>
<td>Sus 3</td>
<td>---</td>
<td>Infor 1</td>
</tr>
<tr>
<td>Sus 2</td>
<td>---</td>
<td>Infor 2</td>
</tr>
</tbody>
</table>

Note: Estimate = Unstandardized coefficients; SE = Standard errors; C.R. = Critical ratio; p = Significance: * p < .05, **p < .01, ***p < .001.

Table 4 presents a positive and significant (p < .001) relationship between sustainability and innovation. In addition, the four observed variables (sustainability, awareness, development, consistency) had significant and positive effects on innovation. Further, all four observed variables (sustainability, awareness, development, consistency) were positively related to firm’s innovation. As shown in Fig. 3, the four variables (sustainability, awareness, development, Consistency) positively affected firm’s innovation, so Hypothesis 2 was supported. These results show that sustainability was positively related to firms’ innovation[83],[84].

4. DISCUSSION

Finally, conclude your paper at the end of the paper. Discuss all the results you have obtained in concise or detail whatever you want as to show originality and exactness of your manuscript[85].

In Table 4, the standardized regression weight is .50 between quality of innovation and sustainability[86],[87]. The fact that the standardized regression weight is significantly high between these two factors suggests that quality of innovation could help enhance firms’ sustainable development[88],[89]. The detailed standardized regression weights for quality of innovation and sustainability will be displayed in the following paragraph.
Figure 5. Model-1 Path Diagram.

The standardized regression weight of Sus1 (Sustainability), Sus 2 (Awareness), Sus 3 (Consistency), and Sus 4 (Development) are .681, .538, .675, and .588, respectively. Thus, Sus 4 (development) is the most influential variable on innovation.

5. CONCLUSION

The objective of the present study was to investigate the identified how factors of innovativeness (adopted innovativeness, personal innovativeness in IT, usefulness, ease of use, compatibility), management strategies (macroeconomics, attitude and usage, micro-culture, geo-demographics), novel in products (communicability, complexity, divisibility, relative advantages, perceived risks), novel business model, reference value (brand credibility, brand prestige, perceived risks, perceived value of money) will contribute to e-purchase intention[90][91][92]. Path analyses were conducted to show the impact of different factors[93].

A total of 223 questionnaires were collected and subject to analyses. The survey instrument was a self-administered questionnaire, which sought information about the use of mobile banking as well as the demographic data[94][95]. Data bearing on the research questions were analyzed with EFA and SEM. Results of these statistical analyses were presented in Table 4.
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