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A Valuable Direction: Choosing SEM or system dynamics to research

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Abstract

Structural equation modeling (SEM) and system dynamics (SD) have prevailed considerably in various fields, yet few articles have investigated their major differences. Is there an integration direction that can be applied to both? The current article used SEM and SD to develop one integrated application approach. First, one word-of-mouth SEM model was established as the basis for the subsequent SD model analysis. After verifying the hypotheses in the SEM model, part of the significant empirical evidence was integrated into the subsequent dynamic analysis work in terms of SD.

Keywords: SEM, system dynamics, integrated application

A Valuable Direction: Choosing SEM or system dynamics to research

Structural equation modeling (SEM) and system dynamics (SD) have prevailed greatly in various field research. A search in the Academic Search Premier (ASP)-EBSCOhost of the keywords SEM or SD returns 24,194 and 455,287 studies, respectively; similarly, 7,766 and 3,218 studies, respectively, can be accessed in ABI-INFORM Global-ProQuest. These results certify the importance of these concepts in scientific research. However, few studies have examined the major differences between these two approaches. The current study focuses on several important aspects of this question-namely, research purposes, science bases, variables, models, advantages and disadvantages, and criticisms-in order to compare the two approaches. A preliminary integration application is also explicated for further development.

Uses of SEM and SD

The principal purpose of SEM is confirmative analysis to verify the hypotheses constituting the structural model. However, Popper (1934/1959), the founding father of the logic of social sciences, insists that one can only falsify scientific statements, not verify them. Instead of trying to prove the correctness of a statement using induction (verification), one should try to prove the incorrectness of a statement using the much simpler logic of deduction (falsification). Dijkum (2008) further argued that, in the social sciences, few models other than simple linear models have been used. The analysis of cause-and-effect relations has been simplified to a one-way analysis of linear dependence of the effect on the cause, expressed as a linear correlation. As a result of such simplification, the logic applied to the sciences regressed.

System theory insists that any phenomenon in the world can be viewed as a system. This system has its own identity by being more than just the sum of its parts (Bertalanffy, 1932-1942). SD is suitable for the simulation of long-term and periodical problems of a product’s lifecycle, economic cycles, and various other issues. SD can be applied to data-insufficient research in which statistical analyses are difficult to conduct. Furthermore, SD can base its feedback loop on the causal relationship among variables plus the application of soft variables to implement simulations. SD is appropriate for non-linear and high-order dynamics problems. Common statistical methods are more suitable for linear and normal distribution problems and will face limitations in non-linear and dynamics problems, whereas SD can explore the causal relationships among variables and provide conditional predictions to reference for adept decision making. As SD considers dynamics, feedback, and the time-delay effect (Lane & Schwaninger, 2008), it can provide more comprehensive, long-term, more sophisticated, in-depth solutions for time-related issues.

Scientific Foundations

SEM is based on two major statistical tools: factor analysis and path analysis. Factor analysis is used to deal with latent constructs whereas path analysis is used to explicate the relationship between latent variables (Kaplan, 2000). Historically, Thurstone (1947) used exploratory factor analysis (EFA) to explore the structure relationship between common and measured variables. Anderson and Rubin (1956) subsequently expanded EFA to confirmative factor analysis (CFA) in order to investigate the underlying relationship between measure indicators and latent variables as well as the covariance among latent variables.

Meanwhile, SD is based on cybernetics (Forrester, 1961), common control theory, control theory, decision science, information theory, system theory plus simulation technology, and digital computers and is used to investigate the in-depth feedback loop relationships among stock (level), flow (rate), and auxiliary variables.

Variables

SEM includes two types of variables: latent and manifest. The former cannot be measured or observed directly whereas the latter can be measured or observed. SEM measures latent variables through multi-indictors will be measured and verifies them via reliability and validity. If all variables in a SEM model are observable, the model analysis is called path analysis. Alternatively, if all variables in a SEM model are latent, the model analysis is called typical SEM (Hatcher, 2002). Some variables are observable, but others are unobservable, thereby constituting a mixed model. In the causal structural model of SEM, exogenous becomes cause while endogenous becomes effect, which means the former causes the latter to occur whereas the latter's variance comes from variables outside the SEM model.

In contrast, SD variables can be categorized into three types: level (stock), flow (rate), and auxiliary. The first type, level or stock, represents the status or quantity in the system accumulated over time; visible variables are called stocks (like commodity) whereas invisible ones are called levels (like satisfaction). Research generally focuses on level or stocks variables as building models. The second type, flow (rate), refers to the speed of flow-in or flow-out that will change the system's behavior. The third type, auxiliary, can be the converter among various levels or rates for the reference value (constant, expected water level) in a specific environment, the converter unit of one department (production number/per worker), the imputed test function, or the value represented by a constant or a function.

Advantages and Disadvantages of SEM and SD

The agreed-upon advantages of SEM include multi-group invariance and time series-related research (Collis & Horn, 1991).

The advantage of SD lies in its consideration and following of effects or concepts ignored by SEM-namely, feedback loop (positive or negative), dynamic, time delay, stock (level), and flow (rate). In addition, SD can also validate estimate parameters (calibration) through optimization or select among alternative policies (policy optimization).

Criticisms

Cliff (1983) proposed four concerns for the causal verification intention investigated by SEM researchers. First, the data or evidence obtained by researchers cannot fully verify or deny the appropriateness of a single model because the model is artificial and can be redefined through various methods. This perspective implies that, when data cannot lead to the rejection of one model, it does not represent a model's unique effectiveness. This perspective highlights the indetermination of theory by experience (Garrison, 1986). One important aspect is that confirming one model only indicates that the model provides one acceptable description for a single sample (Biddle & Marlin, 1987). Second, evidence about early or later factors in the sequence does not represent causal relationships. Third, the denomination of latent variables is a subjective process, not an objective fact. The estimation of latent variables leads to a nominalisitic fallacy. Finally, any post hoc explanation encounters honesty and reliability problems; in other words, this perspective denies the appropriateness of some researchers' heavy use of the modification process in order to obtain better fitness of the model.

One Integration Application

After comparing the disadvantages and advantages of SEM and SD, the current research incorporated SEM and SD to illustrate one future development direction. Namely, by incorporating the SEM empirical evidence into the SD model, the firm will be able to benefit from the advantages of both. In this section, one word-of-mouth SEM model based on related hypotheses is established. After conducting strict testing procedures, important and significant evidence will derived and integrated into the subsequent SD model for in-depth dynamic analyses.

Research Purposes of Word-of-Mouth SEM Model

Many industries have devoted their efforts to investigate how to create and increase consumers' brand loyalty, which can benefit a firm by reducing marketing costs associated with attracting new customers (Aaker, 1992; Lin, Li, & Chen, 2008; Reichheld, 1993). Furthermore, loyal consumers not only live up to their loyalty by undertaking repeat purchases on a brand, but also disseminate positive word-of-mouth, thereby encouraging their peers to purchase the same brand (Taylor & Hunter, 2002). Such brand recommendation results in more trials and future brand preferences. However, such research investigating the interactive relationship among behavioral brand loyalty, positive word of mouth (WOM), and purchase intention is lacking, particularly in the Nokia cell phone industry. The associations verified from this study will be integrated into a single system dynamics model to examine their dynamics; related simulations will also be derived.

Research Hypotheses

Behavioral brand loyalty encourages consumers to maintain their repurchase behavior for a long time, frequently repurchasing the brand they prefer over a specified period. Such behavioral brand loyalty is based on past behavior, and it can be assumed that the consumers with behavioral brand loyalty are more likely to repurchase the same brand in the future (Lin et al., 2008). Two critical reasons explain why behavioral brand loyalty has received so much attention from practitioners: Loyal customers can bring great profits for a firm, and they are also less price sensitive than disloyal customers (Reichheld, 1996). Furthermore, identifying behavioral brand loyal consumers may provide marketers with a more effective market segmentation approach and enable them to realize the firm's profit goals by maintaining customers (Doyle, 1998). Purchase intention and WOM are considered the most expected behavioral outcome of brand loyalty (Taylor & Hunter, 2002). Therefore, the current research investigates how behavioral brand loyalty influences purchase intention and WOM.

Behavioral brand loyalty and purchase intention. Purchase intention refers to a consumer's tendency to purchase a product or brand (Hellier, Geursen, Carr, & Rickard, 2003). It implies what consumers are likely to buy and provides an indicator of whether consumers purchase a certain product or a brand over other alternatives (Engel, Blackwell, & Miniard, 1995). Purchase intention is significantly related to consumers' attitudes (Shim & Drake, 1990). Consumers with a favorable attitude are more likely to purchase a product. In addition, demographics as well as social and situational components influence purchase intention. Younger consumers with a higher income have a greater propensity to buy the product and are more easily influenced by the persons important to them (Hellier et al., 2003).

Purchase intention is affected by internal information searches, such as brand familiarity and prior experience (Park & Stoel, 2005). Consumers familiar with a brand have a higher propensity to buy the brand than those not familiar with it. This phenomenon likely stems from risk aversion; thus, previous experience plays an important role in the formation of purchase intention. In addition, both prior experience and attitude will lead to a simultaneous effect on purchase intention. Consumers who have favorable attitudes toward a brand and prior experience with the brand will have greater purchase intention when they respond to intention query (Lin et al., 2008; Yoh, 2001). Based on the evidence mentioned herein, the following hypothesis (H_1) is developed:

H_1: Higher behavioral brand loyalty will result in higher purchase intention.

Behavioral brand loyalty and positive word of mouth. From the input perspective, consumers consider WOM as an information source and have the propensity to trust WOM from their peers instead of the information released by a company (Wirtz & Chew, 2002). Alternatively, from the output perspective, WOM refers to consumers' behavior of telling others about their experience with the brand (Bowman & Narayandas, 2001). Such behavior of disseminating a subjective perception of a brand can serve as an indicator of consumer satisfaction and brand. Furthermore, consumers who share their experience with other individuals are the best advocators of any firm or its products (Gounaris & Stathakopoulos, 2004).

Taylor and Hunter (2002) verified one significant association between positive WOM and behavioral brand loyalty and indicated that loyal consumers are expected to disseminate positive WOM to the people they know. Bloemer and Odekerken-Schroder (2002) concurred that a higher level of brand loyalty leads to a higher level of WOM. Based on such evidence, the following relationship (H_2) is established:

H_2: Higher behavioral brand loyalty will reinforce the effect of positive WOM.

Consumer commitment and positive WOM. *Commitment* is defined as "an enduring desire to maintain a valued relationship" (Moorman, Zathman, & Deshpande, 1992). Based on this definition, consumer commitment in the current study, as it relates to WOM, is defined as an enduring desire to maintain a relationship with Nokia cell phones. Bettencourt (1997) found a positive relationship between consumer commitment to a grocery store and a measure of loyalty that largely represented positive WOM. Based such literature, the following hypothesis is established:

H_3: Higher consumer commitment will increase the effect of positive WOM

Positive WOM and purchase intention. WOM refers to the passing of information about consumer personal experience with a product or service. WOM plays an important role in shaping consumers' behaviors and attitudes, thereby forming loyalty. Some researchers have identified a positive effect of WOM on repurchase intent. Indeed, WOM has been demonstrated to have a positive significant link to repurchase intention (Molinari, Abratt, & Dion, 2008). Hence, the following final hypothesis is established:

H_4: Higher positive WOM will result in increased purchase intention.

Based on the rationale discussed thus far and the resulting hypotheses, a theoretical structural equation model is established (see Figure 1).

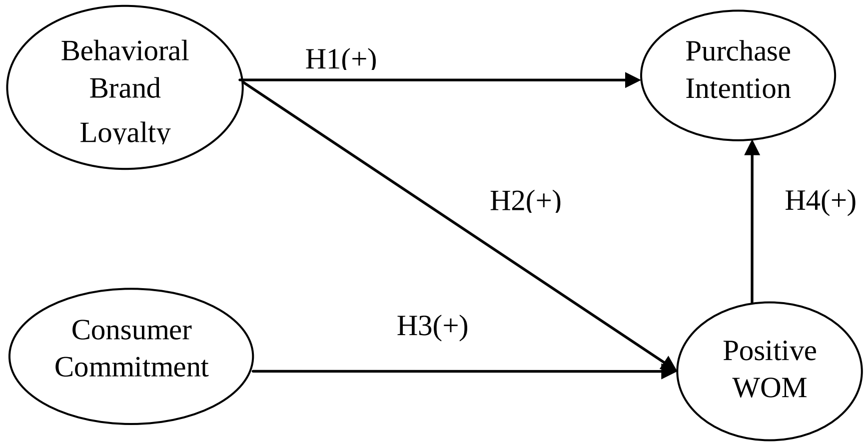

Figure 1. The theoretical model of behavioral brand loyalty, consumer commitment, positive WOM, and purchase intention

Observation Variables and Measurement

Measurement of behavioral brand loyalty. Kenhove, Wulf and Steenhaut (2003) assume that the repurchase probability or relative purchasing frequency for the next purchase is a function of the probability of purchasing the brand on the current occasion. These probabilities of purchase refer to the loyal behavior determined by the probability process based on the time and effect of past purchases. Effective conditional learning provides a fundamental explanation that prior experience with the brand might produce positive reinforcement for future purchase behavior (Iwasaki & Havitz, 2004). The current study adopts the following operational definitions to measure behavioral brand loyalty: I will probably purchase a Nokia cell phone as my next brand (measured on a 5-point scale, where 1 = strongly disagree and 5 = strongly agree). I will only repurchase a Nokia cell phone without any exception (measured on a 5-point scale, where 1 = strongly disagree and 5 = strongly agree) (Cunningham, 1956). Compared to other brands, I have purchased a Nokia cell phone most often (measured on a 5-point scale, where 1 = strongly disagree and 5 = strongly agree) (Jacoby & Chestnut, 1978; Lin et al., 2008).

Measurement of purchase intention. Some researchers focusing on brand level (e.g., Hellier et al., 2003) measure purchase intention with a single item. For instance, participants are asked how likely it would be for them to consider buying a given brand for their next purchase. However, to ensure reliability and validity, the current study will adopt the following multidimensional observation indicators to measure purchase intention: I intend to purchase another Nokia cell phone in the upcoming month (measured on a 5-point scale, where 1 = strongly disagree and 5 = strongly agree). I will purchase a Nokia cell phone in the upcoming month (measured on a 5-point scale, where 1 = definitely will not and 5 = definitely will). I will purchase another Nokia cell phone in the upcoming month (measured on a 5-point scale, where 1 = strongly impossible and 5 = strongly possible) (Lin et al., 2008).

Measurement of positive WOM. WOM can be measured with either a single item or multiple items. Bowman and Narayandas (2001) measured WOM by asking respondents how many people they had told about a given brand. The current study adopts the following three items to measure positive WOM: I will tell more people about Nokia cell phones than other alternatives (Harisson-Walker, 2001). I will say positive things about Nokia cell phones. I will recommend Nokia cell phones to those who seek advice (Zeithaml, Berry, & Parasurman, 1996).

Measurement of consumers' commitment. Four items are used to measure consumers' commitment based on the work of Morgan and Hunt (1994) and Moorman et al. (1992). Participants are asked how much they agree or disagree with several statements (measured on a 5-point scale, where 1 = strongly disagree and 5 = strongly agree): I am committed to my relationship with Nokia cell phones. I really care about my ongoing relationship with Nokia. The relationship that I have with Nokia is something I am very committed to. The relationship that I have with Nokia deserves my maximum effort to maintain it (Brown, Barry, Dacin, & Gunst, 2005).

Empirical Evidence for the SEM Model of WOM

Data collection. In the current study, a questionnaire survey was used with respondents who were selected via convenience random sampling. Two hundred questionnaires were issued to university students to examine their popular use of Nokia cell phones. After deleting 7 incomplete questionnaires, 193 questionnaires were used to perform SEM analysis.

Reliability, validity, and model fitness. Reliability was assessed using Cronbach's α. The evidence shows that the coefficients of the Cronbach's alpha of all constructs exceeded 0.7 (Behavioral Brand Loyalty = 0.84, Consumer Commitment = 0.95, Positive WOM = 0.89, Purchase Intention = 0.91), thereby indicating that the measured variable had an acceptable level of internal consistency reliability. Convergent validity was assessed by verifying the significance of the t values associated with the parameter estimates. The data indicated that all t's were positive and significant ($p < 0.001$), thereby demonstrating acceptable convergent validity. Since the correlation between Consumer Commitment and Positive WOM showed the highest correlation (0.66), it is reasonable to question whether they are measuring two different constructs. Hence, one confidence interval test was used to assess the discriminant validity of Consumer Commitment and Positive WOM. A confidence interval of plus or minus 2 standard errors around the correlation was calculated; the results ranged from 0.486 to 0.842. This confidence Consumer Commitment and WOM interval does not include the value of 1.0, meaning that it is very unlikely that the actual population correlation between Consumer Commitment and Positive WOM is 1.0; thus, discriminant validity is demonstrated.

The hypothesized WOM model was tested with SEM (hereafter, WOM-SEM) using AMOS 19.0. The results indicated that CMIN/DF = 3.0, CFI = 0.94, NFI = 0.91, and RMSEA= 0.103, thereby achieving an acceptable fit level. All hypotheses were significantly supported (see Table 1). The SEM results indicate that the Nokia customers who possessed a higher degree of behavioral brand loyalty would have a higher repurchase intention and tendency to disseminate positive WOM. In addition, when consumers' commitment is higher, they are more likely to disseminate positive WOM. Higher positive WOM from Nokia's customers induces higher purchase intention. The last hypothesis verified by the SEM analysis was integrated into the SD model of WOM (see Figure 2) to conduct further dynamic analyses and simulations.

Table 1. Standardized Estimates of the Hypotheses

Hypotheses	Coefficient (t-value)	Result
H1: Higher behavioral brand loyalty will result in higher purchase intention.	0.392(3.74)***	supported
H2: Higher behavioral brand loyalty will reinforce the effect of positive WOM.	0.470(4.76)***	supported
H3: Higher consumer commitment will increase the effect of positive WOM	0.676(6.57)***	supported
H4: Higher positive WOM will lead to higher purchase intention.	0.265(2.96)**	supported

*** $p < 0.001$, ** $p < 0.01$

System Dynamics Model of WOM

Based on the related rationale of the diffusion process, this model describes a simple diffusion process whereby potential customers of a product are influenced to buy the product through positive WOM from customers who already own the product. The significant empirical evidence (H_4) derived from WOM-SEM was integrated into the WOM-SD. Namely, the WOM effect for purchase intention verified from WOM-SEM was integrated into the WOM-SD to reinforce the validity of the latter. The frequency with which someone who is not a customer of Nokia encounters someone who is a customer was considered. Therefore, the process initially looked at potential customers with anyone, then multiplied the result by the fraction of people who are Nokia customers. The contact between customers and potential customers represents contacts between someone who is a Nokia customer and someone who is not. It is possible that potential customers will—through positive WOM—adopt Nokia and become a customer. The influence of positive WOM is called the fruitfulness from WOM. Furthermore, the WOM effect is assumed to lead to a new customer (Vensim DSS version 5.9c; Ventana System, Inc., 2003). The WOM effect for Nokia resulted in a 0.17 increase in the probability of purchase, while the WOM effect for Sony Ericsson, Motorola, Samsung, Siemens, and others ranged between 0.19 and 0.57 (East, Hammond, & Lomax, 2008). Therefore, the SD model for WOM for Nokia is established (see Figure 2).

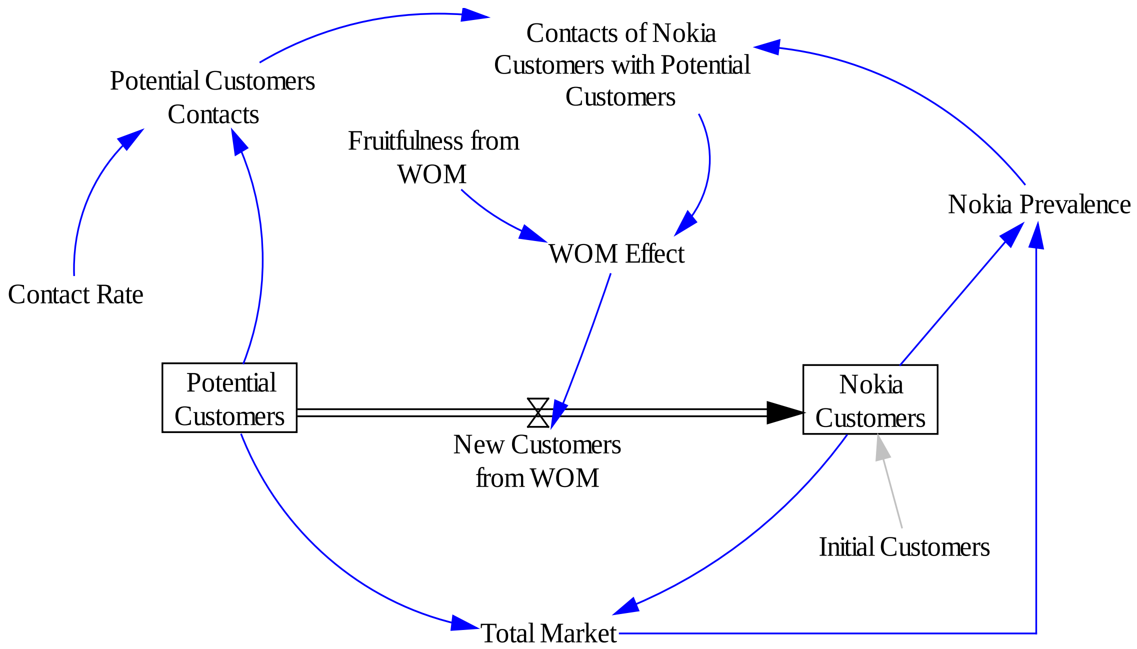

Figure 2. The system dynamics model of WOM for Nokia

Simulation Results and Implications

The model presented herein was naturally validated and tested by analyzing the results of simulations, such as extreme condition tests, behavior reproduction test, and sensitivity analysis (East et al., 2008). The behavior of Nokia customers is sensitive to the fruitfulness from WOM. If the latter takes on the values 0.17, 0.19, 0.21, or 0.25 Figure 3 is obtained; for higher values like 0.25, the number of Nokia customers grows rapidly and saturates early.

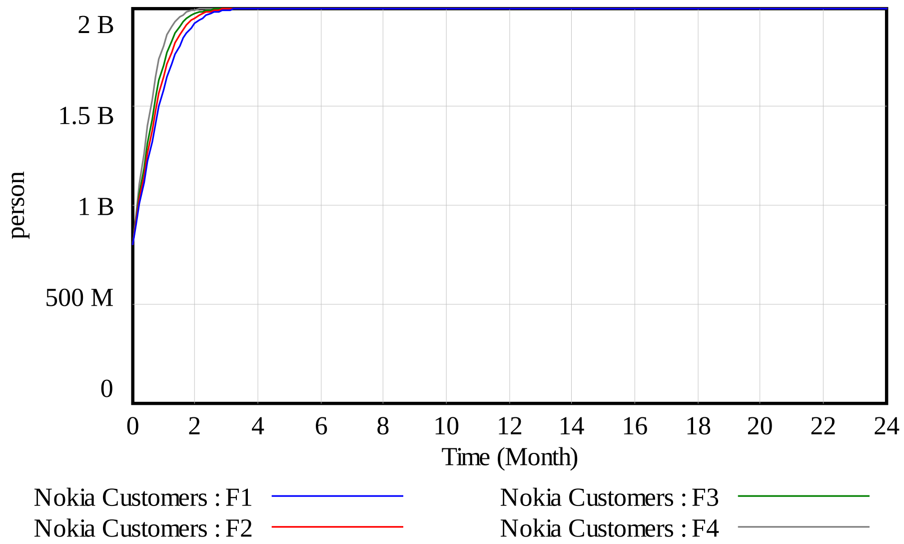

Figure 3. Behaviors of Nokia customers

Next, the Monte Carlo simulation-known as the multivariate sensitivity simulation (MVSS)-was performed. The maximum and minimum values of fruitfulness from WOM were assigned, along with a random distribution to examine the impact on Nokia customers. Figure 4 indicates that the uncertainty of Nokia customers grows over time. At anytime, half of the simulations have generated a value within the 50% region, three quarters within the 75% region, and so on. The outer bound of uncertainty (100%) shows the maximum values of approximately 2 billion persons and the minimum values of 800 million persons. Note the possibility of a growth in Nokia customers.

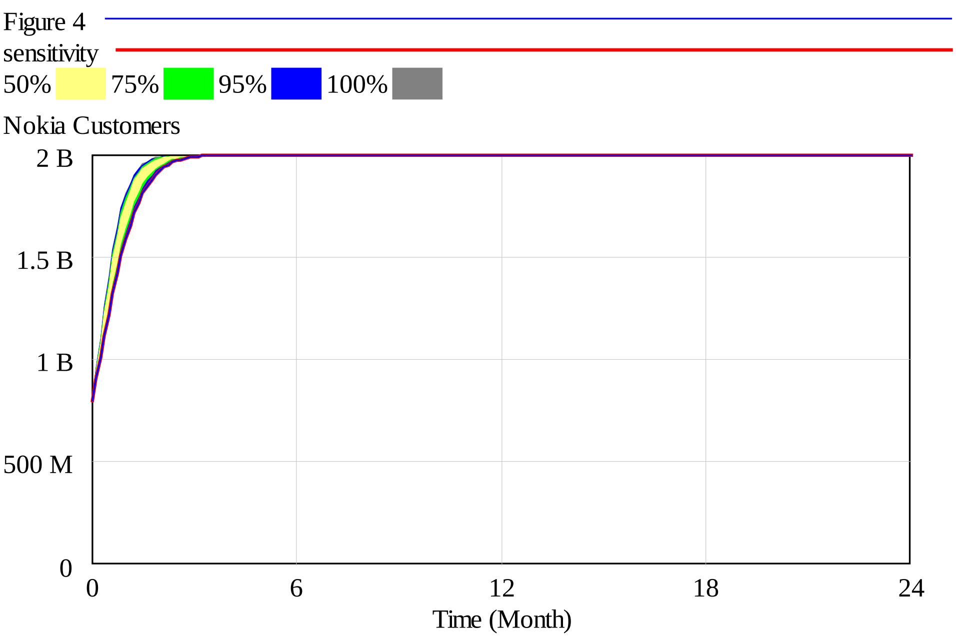

Figure 4. Sensitivity graph of Nokia customers

Conclusion

It is hoped that the information provided herein offers a useful initial insights for business professionals looking for ways to create leverage points to be considered for better practices of the WOM dissemination effect. However, it must be noted that the model needs to be refined and expanded in greater detail by identifying more variables and factors and analyzing their related data in a more rational manner (Yeon, Park, & Kim, 2006).

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一個重要方向：應選擇理論結構方程模式或系統動力學從事研究

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摘 要

結構方程模式（SEM）及系統動力學（SD）已普遍運用於各領域，惟仍缺乏就兩者之主要差異進行研究，並探討兩者間是否存在一整合方向?本研究運用 SEM 及 SD 以發展出一整合運用的方法。首先，本文建立一口碑相傳的 SEM 模式，並以此模式作爲後續 SD 模式分析的基礎。其次，驗證 SEM 模式中所建立之假設，並將所獲得顯著假設之實證證據，融入於後續之 SD 動態分析過程。

關鍵字：SEM、系統動力學、整合運用