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Social media marketing evaluation using social network comments as an indicator for identifying consumer purchasing decision effectiveness

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Abstract

It is very difficult to measure the effectiveness of social media marketing, and such measurement has not been done in any systematic way. This study shows how to develop a measurement instrument to evaluate consumer comments made on a social media community site to test their influence on consumer purchasing decisions. Comments on a Samsung Mobile Thailand Facebook fan page were categorized and recorded on a daily basis for a period of 5 months. A model was developed and tested using confirmatory factor analysis to determine how comments representing four variables affected purchasing decisions. The study found that the most influential comments focused on the following: usage experience issues, information requests, business practice issues and comments about product launches and developments. These four variables can be indicator variables for consumer purchasing decisions in social media marketing. Marketers can apply these four key indicator variables to evaluate social media marketing.

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Introduction

Word of Mouth Marketing (WOM)

The internet and social media have completely transformed the ways companies communicate with consumers, to the extent that they have become key drivers of new marketing and public relations rules.[1] Over 3 billion people now have internet access globally and are going online to find out about new products and trends, and they turn to online communities, blogs and social network sites to seek and share product reviews with fellow consumers. The Word-of-Mouth Marketing Association (WOMMA) aims to bring the various marketing disciplines involved together, as well as to inform marketers about WOM strategies and to promote their application.

With the advancement of the internet, electronic word-of-mouth (e-WOM) has spread much faster than its more conventional off-line WOM

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Advance of e-WOM

predecessor.[2] Consumers now exchange ideas and opinions about products and services via e-WOM.[3] Various studies have pointed out that WOM leads to potential purchasing intentions.[4–6]

Growth in social media users

Membership of various established social networking websites has grown so quickly that Facebook.com had 1.49 billion monthly active users and 1.31 billion mobile monthly active users as at 30 June 2015.[7] The remarkable growth in social media users has attracted companies to create brand communities in social media, such as Facebook fan pages.[8] In addition, companies see social media as a way to spread WOM.[9] Many studies also point out that consumer behaviour in purchasing decisions is highly prone to community recommendations.[6]

Limited social media measurement

It is difficult to measure the effectiveness of social media marketing, and it has not been done in any systematic way.[8–10] Companies know the number of followers in their brand communities and how interactive the followers are with comments. Only very limited research has explored the performance of social media marketing — Yang *et al.*[11] developed a measurement instrument for measuring blog service innovation in social media services using questionnaires for data collection.

Consumer purchasing decisions

The primary purpose of social media marketing is to motivate consumers to buy products. One possible way to evaluate the effectiveness of social media marketing is the evaluation of consumers' purchasing decisions. Therefore, this study aims to develop indicator variables representing consumer purchasing decisions for social media marketing by focusing on consumer comments made on a Facebook fan page.

Related theory

Online community as an information source

A brand community is defined as any group of people that possess a common interest in a specific brand and create a social universe with its own myths, values, rituals, vocabulary and hierarchy.[12] Muniz and O'Guinn[13] divide the main characteristics of social communities into three core components: the connection that members feel towards one another, shared traditions and a sense of responsibility. In the past, community growth was restricted by geography, while now a brand community is a specific, non-geographically bound community, based on a structured set of social relationships among admirers of a brand.[13] These brand communities will most likely be formed around brands with a strong image and are often open social organizations without membership requirements. The members of the brand community have a feeling of strong connection among the group members. Although members may not know one another, the community members still differentiate themselves from other groups. This means that members feel they are a part of a large virtual community.

Consumer intentions and behaviours

Brand community members provide a form of assistance to address problem solving or offer suggestions on issues based on the knowledge gained from long-term use of the brand. Several studies have shown how brand communities help to influence consumer intentions and behaviours.[14,15] It has been a mission for marketers to create brand communities for some time. This is based on the belief that a close

community of friends and family, or even people with similar interests, tends to value the opinions of other members of that group.

Social network online community

The evolution of brand communities has also moved from off-line to virtual communities on the internet, and studies have shown how companies benefit from virtual communities.[16,17] Casalo *et al.*[18] explored the effects of consumer participation in a virtual brand community on consumer behaviour and found this created trust in the brand, which translated into consumer loyalty. Zhou[19] also found that virtual communities influence consumer participation. Thomas *et al.*[20] examined fashion-related discussions on MySpace.com to identify the four most popular discussion categories (personal style, brands, designers and retailers) to suggest that consumer-driven marketing is growing.

Critical mass and intention to use

Several studies have examined how consumers use and respond to social media marketing. One of these studies (Rauniar *et al.*[21]) explored voluntary usage behaviour on social networking websites and found that the perceived usefulness and trustworthiness of a social networking website were the main factors that affected user decisions. Another study (Lee *et al.*[22]) examined the use of social media in the meeting planner's activities and its impact. The research found that perceived critical mass directly affects the intention to use social media, and also indirectly affects attitudes and intentions to use social media through the perceived ease of use and perceived usefulness of social media. Pietro *et al.*[23] found that the perceived enjoyment of online social networks has the most effect on attitudes towards the use of social media when choosing tourist destinations.

Significant information source

From the social information processing theory perspective, social networks are a significant information source and people get hints for behaviour and action from it.[24,25] Social networks have direct effects on the spread of e-WOM, which in turn influence purchasing intentions.[4] Jalilvand and Samiei[5] state that e-WOM not only affects purchasing intentions, but also has an impact on brand image. The motivations of brand-consumer interactions in social networks are a source of entertainment, brand engagement, timeliness of information and service responses, product information, and incentives and promotions.[26] The consumers' engagements in online social network communities have a positive impact on consumers' brand awareness, WOM activities and purchasing intentions.[27]

Facebook

Facebook is the most popular online social network community.[28] Facebook fan pages are also becoming an important part of marketing communication strategies that use social media to create brand awareness to increase sales.[8] The willingness of consumers to use Facebook fan pages is the key factor that explains the increased loyalty to fan pages.[29]

Brand experience

Effective use of social media as a communication channel towards consumers can enhance awareness of a brand, which in turn can affect the purchasing decision process. For example, consumers use online social networks to help them make purchasing decisions.[28] Another example is the case of an academic library that integrated social media advertising in its marketing strategies to promote the library and found this approach to be more effective than the traditional strategies.[30] The brand experience is

the key in addressing the interests of users on social networks. Brand experience affects consumer satisfaction and loyalty through brand personality associations.[31] Various companies are developing marketing strategies for internet brand communities, such as Coca-Cola.[17]

Andreassen and Streukens

Andreassen and Streukens[3] studied e-WOM by analysing the content of online consumer discussions from a product perspective. They identified four core discussion content categories in the online forums: business practice issues (BPI), usage experience issues (UEI), information requests (IR) and comments about product launches and developments (PLD). The effectiveness of WOM in consumer purchasing decisions can be the primary determining factor of all purchasing decisions.[32]

Hierarchy of effects theory

Various hierarchy of effects (HOE) models have been developed over a century by researchers and practitioners. The original HOE model was built by Elias St. Elmo Lewis, an American advertising and sales pioneer, in 1898. These models have the same basic idea in explaining a series of steps in the consumer's psychological experience, from initial exposure to products or advertisements to the purchase decision.[27] The number of consumers moving from one step to the next is decreased, which is the reason this model is known as a 'hierarchy'. Practitioners used HOE models as a guideline to develop their marketing communication strategy.[33] The most-often recognized HOE model was developed by Robert Lavidge and Gary Steiner [27] (see Figure 1). The Lavidge-Steiner HOE model was made up of six sequential steps that show advertisement influence on consumer decisions starting with initial exposure to a product or advertisement through to purchase decision. The steps are awareness, knowledge, liking, preference, conviction and purchase.

Awareness, attitude and decision

At the beginning of the HOE model, advertisements or WOM can create awareness through product information. In today's world, technology has changed people's lives by providing many channels to communicate with others. Companies may integrate social network online communities into their marketing communication and advertising strategy. These provide opportunities for companies to give information about a

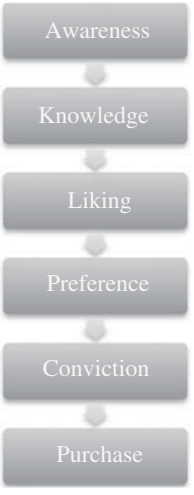

Figure 1: Lavidge and Steiner hierarchy of needs model

product to consumers that enables them to build their knowledge. Then consumers develop favourable attitudes towards a product. After that, consumers may create a product preference based on their favorable attitude towards the product. Subsequently, consumers develop a conviction that it is worth purchasing an advertised product, and finally consumers buy the advertised product. The understanding of a sequential hierarchy of effects in advertising can help marketers to predict consumer behaviour, plan marketing strategy and develop conceptual tasks for a company.[33]

Confirmatory factor analysis

CFA is a type of structural equation modelling (SEM). It is a measurement model that studies the relationship between indicator variables and their underlying latent variables. A latent variable in SEM is a hypothesized and unobserved concept that cannot be measured directly, but can be quantified by indicator variables. A latent variable can be measured indirectly by examining the consistency among multiple indicator variables.[34] This gives SEM the power to be a tool to measure theoretical concepts that are developed by prior experience or other research findings. A model is a representation of a theory, which is developed by prior experience or other research findings.[34]

Fit index of the model

CFA can be used as an independent analysis or a prerequisite analysis of the SEM process.[35] It enables researchers to prove that there is a relationship between indicator variables and their underlying latent variables. The CFA process starts with defining the number of latent variables and their indictor variables in the measurement model, which represents the theoretical model hypothesised by researchers. The model is then tested statistically. The fit index of CFA statistics is used to access how well indicator variables represent their associated latent variables that are not measured directly. If the fit index of the hypothesised model meets the requirements, the theoretical model hypothesised by researchers is accepted. This means that the proposed measurement theory is confirmed.

Research model and hypothesis

Consumer product comments

According to HOE theory, consumers receive and use information to make purchasing decisions.[27] The primary purpose of social media marketing is to motivate consumers to buy products. One possible way to evaluate the effectiveness of social media marketing is to evaluate consumer purchasing decisions. Therefore, the proposed model was designed to develop indicator variables for consumer purchasing decisions in social media marketing by using consumer product comments on social network platforms. The CFA was used as a tool to test and confirm that the proposed theory could use the four core groups of product-related comments (BPI, UEI, IR, PLD) made in online forums as indicator variables representing purchasing decisions. These comments influenced consumers when they made purchasing decisions.[27] Such variables can therefore be performance indicators of social media marketing.

Performance indicator of social media marketing

The proposed model was based on a study by Bughin *et al.*,[32] which states that the power of WOM is the primary factor behind all purchasing decisions. In addition, the model applies research from Andreassen and Streukens[3] who used four core categories to measure the significance of

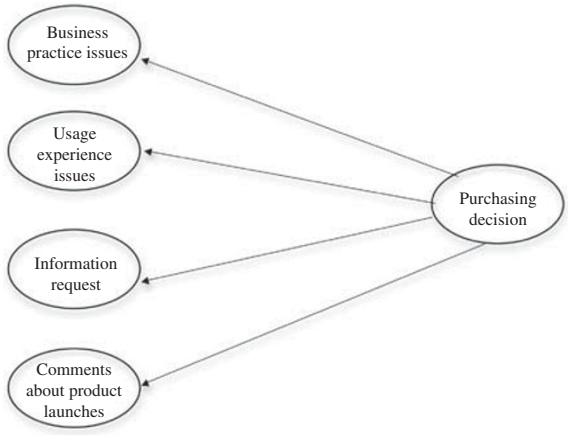

Figure 2: The research model

message content in on-line discussion forums. CFA was applied as the statistical tool to prove that a relationship existed between the four core discussion groups and purchasing decisions. The theory and the CFA were applied to build the proposed research model as shown in Figure 2. PD in this study refer to the purchasing decisions of the people who followed Samsung Mobile Thailand's Facebook fan page. The followers were either already product users or were target consumers for Samsung products. Both groups sought advice about how to use a product, requested information for new Samsung products, shared product performance reviews about Samsung products, or wanted to know when Samsung planned to launch new products or update versions of current products. The study hypothesises that the BPI, the UEI, the IR and the comments about PLD can be used as the indicator variables for the latent variable of consumer purchasing decisions in social media marketing.

Business practice issues

Consumer attention to conventional media has been declining and moving drastically towards online channels.[4] Online social networks play an important role in social media marketing and provide many opportunities for companies, such as allowing them to observe and get close to their consumers, to collect information, and to participate in discussions through their online brand communities.[36] Since it costs so little for consumers to participate in online social networks, companies can have easy and instant access to consumers, and they have the ability to communicate with them as often as desired. Consumers can also give the companies feedback about their business practices through comments about the quality of customer services and sales representatives. Companies have the ability to provide a quick response and can implement fast improvements in their business practices.[8] Sharing opinions about business practices on social networks motivates consumers to participate in the development of a company's business activities. When consumers feel they are part of the company, they are more likely to continue to use and buy its products.

Usage experience issues

Consumers can exchange ideas and opinions about products and services via e-WOM.[3] Consumers can now use online social networks to

consider a variety of product and service information sources, such as consumer reviews and comments about their experiences, before they make purchasing decisions. This allows them more power and control in the consumption experience.[4] For example, a consumer who would like to purchase a digital camera but does not know which model to buy goes to an online community to get product reviews and usage experiences from other consumers. This information search process allows the consumer to gradually refine his requirements to determine which model of a particular brand he will ultimately buy.[37]

Information requests

On-line communities in social networks may serve as information sources for consumers to make purchasing decisions.[28] Consumers may post questions in online forums for specific products, such as asking how easy a new product version is to use or to request specific details about the products they intend to buy. Companies can use social networks as a channel to communicate with their customers by sharing the requested information. The interactions that occur in such channels have positive effects on purchasing decisions.[27]

Comments about product launches

Many companies use online social networks as a communication channel to entice their customers to follow their pages for product updates. When they launch new products, they use the product's official social network page to make announcements and to advertise both marketing activities and special offer events.[26] Interactions between consumers and the company about the product launch raise consumer awareness of the product and later have the potential to positively influence purchasing decisions.

Research methodology

Facebook fan page

Most social media marketing is conducted on social network websites. Facebook is one example of a social network site that has a vast audience with the potential to generate sample data. Facebook fan pages have high traffic that produces many messages, rich data and a high degree of member interaction. This meets the requirements for using the forum-based data collection method recommended by Kozinets.[38] Therefore, this study aimed to collect data from a Facebook fan page.

Samsung Mobile Thailand

Various researchers have noted that WOM is a good marketing tool for technology-related products that have complex features and functions. Products with high value and complexity tend to be those that consumers are most likely to seek expert advice about or on which they generate user opinions. The brand selected for this study had to have a large enough number of members on its Facebook fan page to generate enough comments and regular interactive discussions. The fan page had to meet the information adoption criteria suggested by Cheung *et al.*,[2] who found that the information's relevance, timeliness, accuracy, comprehensiveness and source credibility were the keys to determining customer perceptions of information quality, which was, in turn, used to predict potential buying behaviour. This study chose Samsung Mobile Thailand as the brand that met the above criteria, since it was also one of the top three mobile phone

Table 1: Latent variable and its associated indicator variables (UEI)

Usage experience issues latent variable (UEI)	Characteristics of comments (Observed variable)
Quality of product (UEI1)	Discussions about quality of the product
	Comparing quality/other models against competitors
	Discussion on standard related to the product
Price (UEI2)	Price related comments (expensive, cheap, fair)
	Price comparison discussions
Experience related to features (UEI3)	Usability experiences of product features
	Ergonomically related product issues
Emotional experience (UEI4)	The emotional response to usability
	The performance frustration in using the product
	Other emotional issues regarding the product
Experience with product category (UEI5)	Comments on usability of other competing products
	Recommendations for other Samsung models

Table 2: Latent variable and its associated indicator variables (BPI)

Business practice issues latent variable (BPI)	Characteristics of comments (Observed variable)
Quality of customer service (BPI1)	Stating directly how customer contact centre responds to an enquiry
	How long customers had to wait on the call/wait to get answer from social network
	The way customer representatives speak, give recommendations about where to buy product or repair product
	Follow-up on product repair
Quality of dealers (BPI2)	Dealer facility-related comments
	Are the dealers professional or not?
	Do the dealers have long waiting times for the product?
Availability of dealers (BPI3)	Are there enough dealers?
	Dealer location-related comments
Business practice (BPI4)	Financial performance of the company
	Markets and trends of the industry
	The company direction, leadership and employees

market leaders in Thailand. Then we needed to define the types of comments that would be the data set for the study.

Identifying specific comments for data set

The types of comments made on Samsung Mobile Thailand's Facebook fan page were categorized into latent variables and the associated indicator variables, which were defined so that coding could be done and data could be interpreted for analysis, as shown in Tables 1 to 4. Discussion topics were coded according to the following categories: BPI, UEI, IR and comments about PLD. These four latent constructs and their associated indicator variables were derived from Andreassen and Streukens[3] and are described below.

Business practice issues

The first latent construct, BPI, had four associated indicators: the quality of customer service; the quality of dealers; the availability of dealers; and business practice concerns. BPI were defined as how companies conducted business in order to have an impact on customers, such as how customer service representatives responded to customer calls. The availability of dealers that could act as channels for customer interaction points was another example of a business practice issue.

Table 3: Latent variable and its associated indicator variables (IR)

Information request latent variable (IR)	Characteristics of comments (Observed variable)
How to use a product (IR1)	Asking for advice on product usability
	Seeking advice on features
	Asking advice from product users
Technical questions (IR2)	Seeking advice about product specifications
	Seeking technical clarification
	Asking questions about standard of the product
Request for additional information (IR3)	Asking for general information about the company
	Requests for product information
	Requests for user feedback about product usage experience

Table 4: Latent variable and its associated indicator variables (PLD)

Comments about product launch latent variable (PLD)	Characteristics of comments (Observed variable)
New introduction (PLD1)	Company product introduction
	Discussions about product PR and marketing-related issues
	Comments about competitor responses to the new introduction
Expectations regarding new introduction (PLD2)	How consumers react to the new product introduction before the product launch
	What are the expectations of the new product before the release?
Comments and desires regarding new introduction (PLD3)	What do consumers want to see in the new product after the launch?
	After seeing or using the product, what does the consumer desire from the product experience?
	Comparison against former models

These business practices offered customers a positive experience when expectations were met.

Usage experience issues

The second latent construct, UEI, had five indicators: the quality of the product; price; experience related to features; emotional experience; and experience with the product category.

Information request

The third latent construct, IR, had three indicators: how to use a product; technical questions; and requests for information. Consumers usually search for product information before making a purchasing decision. Their reasons could include a need to determine product usability and product features. The usefulness of the information they find can lead to both positive and negative experiences.

Product launches and developments

Finally, the fourth latent construct, comments about PLD, had four indicators: new product introductions; expectations regarding product launches; comments regarding new product introductions; and consumer desire regarding the newly introduced products. When companies launch a product they often have a channel through which to inform consumers about how to use various communication sources. These teasers are public relations tools that create consumer expectations of the product. These new product launches have an

Table 5: Sample comments with valence and coding

Comment	Valence	Indicator variable
I brought my Galaxy S3 to a Samsung shop to change the phone case. The staff were very nice.	Positive comment	Quality of customer services (BPI1)
How can I copy my Samsung phone data to my computer?	Neutral comment	Technical question (IR2) How to use a product (IR1)
Can Samsung Galaxy Tab 2 load an.apk file?	Neutral comment	Technical question (IR2)
I bought a Galaxy S3 last week. Now I have a problem with my S3 battery. It won't charge at all. I cannot believe it. I have to wait for a month to repair my Galaxy S3. I had no doubts about their quality from comments I read on the social network. It was a big mistake to buy it.	Negative comment	Quality of product (UEI1)

impact on consumer expectations as well as on the emotional experience, which can vary from product to product.

Data collection

Comments and responses

Researchers collected comments from the official Samsung Mobile Thailand Facebook fan page over a period of 4 months (December 2011–March 2012). We collected comments that remained posted for at least 7 days as this gave people enough time to see, discuss and give feedback on a topic. Comments were collected on a daily basis and responses to the prime comments were also collected. The quantity of comments was collected as well as the content of the comments in order to determine the valence. Positive, negative and neutral contents were coded according to an approach used by Liu[39] and by Godes and Mayzlin.[40]

Coding comments

Two people coded independently for valence and indicator variables for each comment. Table 5 shows the comment characteristics with the corresponding valence and indicator variable. When coding was finished, the results were compared with the comment coding data. If the comment data was coded in the same way by each person, those comments were coded into the system for CFA analysis. However, if one person's coding was different for the comment data, a third person was consulted to decide what should be the assigned value.

Comment type and number

After coding the comments, we summarized the number of comments by the daily observed variable and comment type into each indicator (BPI1, BPI2, …, PLD2, PLD3) as shown in Table 6. The data set contains the number of comments by indicator variable and by comment type that were made each day. The second row in Table 6 represents the number of positive comments on day 142 by variable, that is there were no positive comments for BPI1, BPI2, BPI3 and BPI4, only one positive comment for UEI1, and so on. The third row in Table 6 represents the number of neutral comments on day 142 for each variable, that is there were 22 neutral comments for BPI1, no neutral comments for BPI2, 37 neutral comments for BPI3, and so on. The fourth row in Table 3 represents the number of negative comments on day 142 for each variable, that is there was one

Table 6: Sample data used in SEM, AMOS programme

Row	Day	Comment Type	BPI1	BPI2	BPI3	BPI4	UEI1	UEI2	UEI3
1.....	Day 1	Positive							
367	Day 142	Positive	0	0	0	0	1	0	0
368	Day 142	Neutral	22	0	37	33	67	8	51
369	Day 142	Negative	1	6	0	9	10	1	6
370	Day 143	Positive	1	2	0	0	1	0	0
371	Day 143	Neutral	18	0	24	37	93	11	50
372	Day 143	Negative	1	2	1	8	11	1	4
373	Day 144	Positive	0	0	0	0	0	0	0
374	Day 144	Neutral	22	1	30	26	57	7	38
375	Day 144	Negative	3	0	0	5	9	0	8
...443	Day 153	Negative							

Row	Day	Comment Type	UEI4	UEI5	IR1	IR2	IR3	PLD1	PLD2	PLD3
1.....	Day 1	Positive								
367	Day 142	Positive	1	0	0	0	0	3	0	0
368	Day 142	Neutral	5	1	25	62	19	70	0	6
369	Day 142	Negative	7	3	0	0	0	0	0	1
370	Day 143	Positive	2	0	0	0	0	26	0	0
371	Day 143	Neutral	6	5	16	66	31	139	4	12
372	Day 143	Negative	9	2	0	0	0	4	0	0
373	Day 144	Positive	1	2	0	0	0	4	0	0
374	Day 144	Neutral	4	5	22	61	15	93	0	4
375	Day 144	Negative	8	1	0	0	0	0	0	0
...443	Day 153	Negative								

negative comment for BPI1, six negative comments for BPI2, no negative comments for BPI3, and so on. This data collection structure is the format that is used in the AMOS program for CFA analysis.

Data coding process

During the preliminary analysis, we found that the data distribution was not normal, and thus we needed to collect one more month of data in order to meet the SEM assumptions. A total of 459 cases or rows (30,375 comments) were loaded into the AMOS program for CFA analysis. After the outlier checking process of the data set in SEM, we took out the outlier of 3.5 per cent and the usable data that was left consisted of 443 cases (24,795 comments). These were the comments used in the research that were captured from the official Samsung Mobile Thailand Facebook fan page over a five-month period. Table 7 displays the summarized data used in SEM.

Observed variables

The data used in the study was in the SPSS format. The data file had 15 observed variables and 443 cases that were plugged into the research model. These 15 observed variables were BPI1, BPI2, BPI3, BPI4, UEI1, UEI2, UEI3, UEI4, UEI5, IR1, IR2, IR3, PLD1, PLD2 and PLD3. A row contains the number count for the comments for each observed variable. Each observed variable had 443 rows that were plugged into the research model; for example, BPI1 had 443 rows of input, BPI2 also had 443 rows of input, and all the rest, up to PLD3, had 443 rows of input into the SPSS program as shown in Table 6.

Detection of multivariate outliers

The squared Mahalanobis distance (D^2) was used to detect the multivariate outliers in SEM. This statistic measures the distance in standard deviation units between a set of scores for one case and the

Table 7: Summary of comments data

Collection period	Number of comments
Month 1	3,113
Month 2	3,369
Month 3	4,808
Month 4	4,349
Month 5	9,156
Total	**24,795**

Table 8: Observations furthest from the centroid (Mahalanobis distance)

Observation number	Mahalanobis *d*-squared	*P*1	*P*2
371	120.418	0.000	0.000
453	116.585	0.000	0.000
…			
24	28.427	0.012	0.000
409	28.126	0.014	0.000
207	26.583	0.022	0.000
455	26.412	0.023	0.000
329	25.925	0.026	0.000
362	25.830	0.027	0.000
335	25.640	0.029	0.000
20	24.424	0.041	0.000
365	24.330	0.042	0.000
447	23.477	0.053	0.000
65	23.409	0.054	0.000
242	23.084	0.059	0.000
…			

sample means for all variables. We took out the case with a D^2 value that was so different from all the other D^2 values in the data set. The multivariate outlier analysis displays the observation furthest from the Mahalanobis distance associated with the *P*1 and *P*2 values, as shown in Table 8. The *P*1 shows the probability that any arbitrary observation should have a larger distance from the centroid while *P*2 shows the probability of the largest distance from the centroid.[41] The research uses 0.05 as the *P*1 value criteria in the selection of the outlier cut-off point, as recommended by Gaskin.[42] The recorded data with a *P*1 value of less than 0.05 were for candidates for outliers, which were then removed from the data set.

Data analysis and results

Structural equation modelling

A second-order factor model is a structural equation modelling technique that is used to test the research model, since purchasing decisions cannot be measured directly. Therefore, a first-order factor is used as the measurable representative of a purchasing decision. The second-order factor (purchasing decision) is measured by the four first-order factors (usage experience issues, information request, comments about product launches and developments, and business practice issues), in the same way that the first-order factor is measured by observed variables.

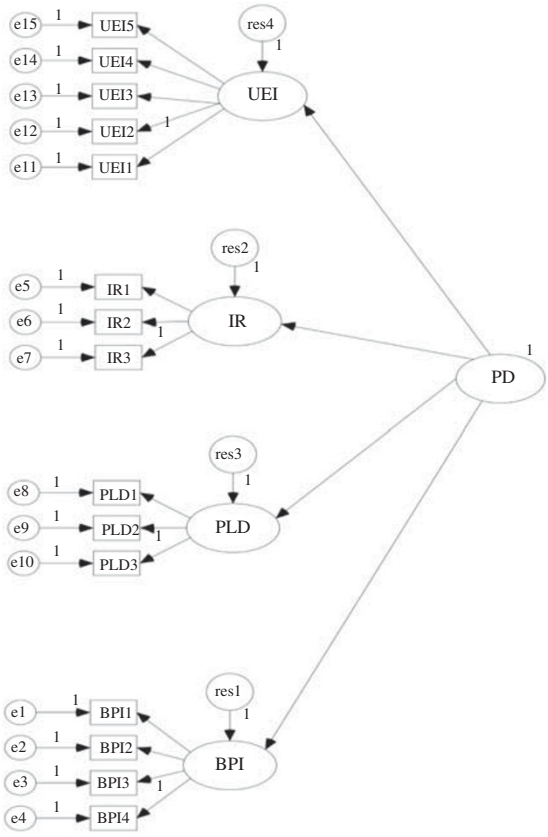

Figure 3: The hypothesized second-order model of factorial structure

Second-order purchasing decision factor

The second-order purchasing decision factor was hypothesised to account for, or explain, all variance and co-variance related to the first-order factors. A PD did not have its own set of measured indicators because it was linked indirectly to those measuring the first-order factors. There were 15 observed variables, as indicated by the 15 rectangles (UEI1–UEI5, IR1–IR3, PLD1–PLD3, BPI1–BPI4). Any error of measurement associated with each observed variable was represented by e1–e15 while any residual error term associated with each of the lower level factors was indicated by res1–res4. Figure 3 shows the hypothesised second-order model of factorial structure for this study.

Degrees of freedom

The hypothesized model was recursive and over-identified with 86 (120–34) degrees of freedom. Moreover, the higher-order portion of the model was over-identified with 2 (10–8) degrees of freedom. Since the sample data was not normally distributed (C.R. value>5.00), the analysis was based on an asymptotically distribution-free method, which was appropriate in this case.

Model evaluation

During the examination of the confirmatory factor analytic model, the hypothesized model was re-specified. Two observed variables in UEI (UEI1, UEI3) were highly correlated with a coefficient of 0.9. Therefore, we combined the two observed variables UEI1 and UEI3 into one. The final model of the factorial structure for this study is shown in Figure 4.

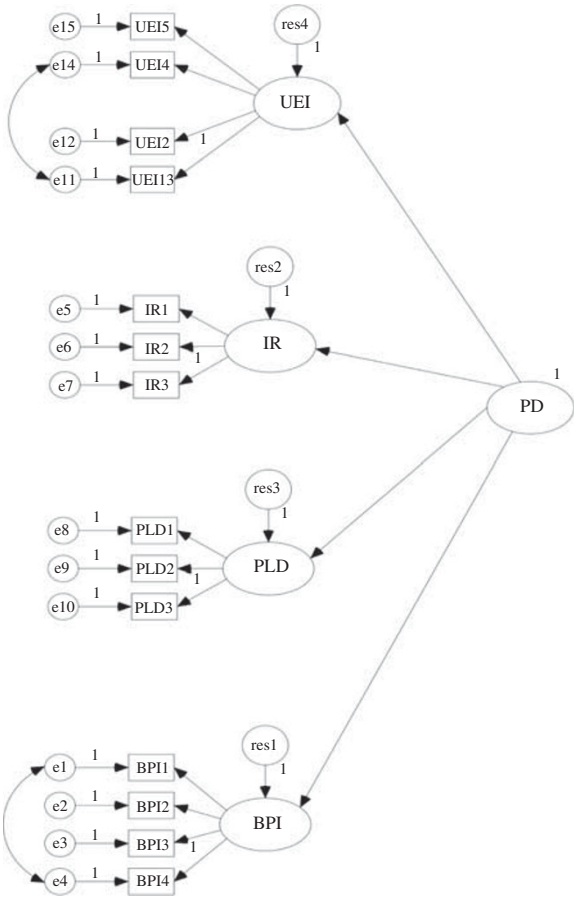

Figure 4: The final model of the factorial structure

The χ^2 value for the model was 163.97 with 71 degrees of freedom and a probability level of 0.00. Table 6 shows a fit index for the hypothesized model. (Table 9)

Fit indices

The final model adequately represents the sample data because Hoelter's 0.05 and 0.01 values were 248 and 274, respectively, which exceeded 200, Hoelter's benchmark.[43] The relative χ^2 or χ^2/df value was 2.3, which is in the acceptable range for a relative χ^2, since it is less than 3.[44] The PCFI value was 0.65, which is greater than 0.5.[45] The CFI value was 0.84, which is adequate, but marginal. A CFI value between 0.80 and 0.89 is considered an adequate but marginal fit according to CFI evaluation guidelines. The RMSEA value of the hypothesized model was 0.05, which is considered a good fit.[45] These fit indices met the recommended levels of the evaluation guidelines, and hence we can conclude that the hypothesised model fits the represented data. The average variance extracted (AVE) is the average amount of variation of the purchasing decision latent variable that explains the associated indicators UEI, IR, PLD and BPI. The AVE had a value of 0.90, while the construct reliability (CR) had a value of 0.97. The minimum acceptance levels for AVE and CR are 0.5 and 0.7, respectively.[34] Therefore, both the AVE and CR values in the hypothesized model met the requirements.

Table 9: Fit index between evaluation guidelines and hypothesized model

Fit index	Evaluation guidelines	Hypothesized model
Hoelter's 0.5 and 0.1	>43	248, 274
Relative χ^2	<44	2.3
PCFI	>45	0.65
CFI	Good fit>45	
	Adequate but marginal = 0.80 to 0.89	0.84
	Poor fit = 0.60 to 0.79	
	Very poor<0.60	
RMSEA	Good fit <45	0.05
	Moderate fit = 0.08 to 1.0	
	Poor fit>1.0	
AVE	>34	0.90
CR	>34	0.97

Table 10: Factor loadings of PD construct

	Factor loading
UEI←PD	0.995
IR←PD	0.996
PLD←PD	0.808
BPI←PD	0.990

Statistical analysis for the proposed model

Table 10 shows the standardized regression weights or factor loadings for the second-order factor model. All of the factor loadings in the research model were found to be statistically significant. The factor loadings that represented the correlations between UEI versus PD, IR versus PD, PLD versus PD and BPI versus PD values were 0.995, 0.996, 0.808 and 0.990 respectively. The four first-order factors in the research model were identified as UEI, IR, comments on PLD and BPI, all of which had a high positive correlation with purchasing decisions. Therefore, based on the evaluation model above, it can be concluded that these four variables can be indicator variables for consumer purchasing decisions in social media marketing. The hypothesis of the study is true.

Discussion and conclusion

Proxy for social media marketing effectiveness

The research objective was to prove that product-related discussions on social network websites can be used as a proxy to evaluate the effectiveness of social media marketing. The research model was developed using the online comment categorization introduced by Andreassen and Streukens,[3] which identified four core comment category groups in on-line forums. Bughin *et al.*[32] found that WOM was the primary factor behind 20–50 per cent of all purchasing decisions. The primary goal of social marketing is to influence consumers to buy products. The research results showed that the fit index of the hypothesised model met the requirements of evaluation guidelines, and thus we can conclude that WOM communication in online discussion forums could be

categorized into four key groups that can be used as the indicator variables of consumer purchasing decisions in social media marketing on social network platforms. The research findings underpin HOE theory, in which messages that consumers receive from interactions with members of an online brand community influence purchasing decisions.

Influence of discussions

The research demonstrated how WOM communication in online discussion forums could be categorized into four key groups to evaluate consumer purchasing decisions. The four core features of on-line product discussions that indicated a strong positive correlation with PD were identified as BPI; UEI; IR; and comments about PLD. The UEI and IR had the strongest impact on PD, while discussions about BPI ranked second in importance and PLD comments ranked third. The more that discussions focused on these four factors (BPI, UEI, IR and PLD), the more likely it would be that they would influence purchase decisions and confirm the effectiveness of the social media marketing programme.

Making good purchasing decisions

Usage experience issues had a very strong correlation with PD. Online social network fan pages not only allow users to build relationships with other users, they also allow users to share experiences about a company's products and services.[29] Consumers go to social network sites to read comments about product and service user experiences.[28] They seek out opinions and advice from other consumers who have used a specific product. Online social networks offer consumers easy access to UEI information,[22] which can increase consumer confidence in making good purchasing decisions.

Ease of contact

Information requests and business practice issues also had strong positive correlations with PD. It is easy for consumers to contact companies via online social network fan pages regarding product questions they may have or to ask companies for additional information.[29] Consumers hope to receive a quick response and accurate information from companies, especially regarding technical questions.[8] Companies use them as a cost-effective means of communicating with consumers to spread viral messages. Online social media can help companies to be pro-active in their consumer communications and interactions. Social media platforms are not only for promoting and selling products. They also give consumers the ability to participate in the product development process and help companies respond to customer service issues and customer feedback in a proactive manner.[26] These social media interactions have a positive effect on purchase decisions and allow companies to learn about consumer attitudes towards their products.[27]

Instant consumer feedback

Samsung Mobile Thailand, for example, uses its Facebook fan page to communicate with its customers since it is a cost-effective way to receive quick feedback about its products and services. This instant access to consumer feedback gives Samsung an opportunity to quickly improve its products and services to meet or exceed consumer expectations. Samsung can use social media to create a brand community and attract future consumers by motivating them to participate in social media activities. Effectively integrating social media in marketing strategies can have positive economic effects on companies.

Viral messages

This study found that comments about Samsung product launches were also indicators of consumer purchasing decisions. Fan pages provide a platform to introduce new products. Companies use this channel to inform their consumers about new product information, such as point of sale, price and technical characteristics.[8] It is undeniable that social media has become very popular among consumers. It is also the best platform to spread viral messages among social media users. Consumers have the opportunity to become familiar with products by discussing them with other users. This can create brand awareness that, in turn, can have a positive effect on purchase decisions.

Chief Customer Officer

To boost sales, companies should focus on answering consumer enquiries because consumer feedback can be used to improve product and service quality, develop more user-friendly devices, and ensure that staff conduct business in a polite and sincere manner. When Samsung consumers receive terrible service from a shop, they can immediately inform Samsung Mobile Thailand about the experience on the official Facebook fan page. This allows the company to respond quickly enough to restore consumer confidence by fixing a problem. When customers are happy with the products and services they receive, they will share their positive experiences on-line with other people through e-WOM. This form of customer engagement has become so important to many companies that they appoint a senior executive to be in charge of this: the Chief Customer Officer. Social networks are an important tool that a company should use to retain its customers and to motivate satisfied customers to share their positive experiences in order to attract new customers. In addition, companies need to be aware of the power that unhappy customers can exert through social networks if customer engagement is not managed properly. When consumers are upset, their negative messages on social networks have the power to hurt a company's reputation.

Limitations and implications

Limitations of the study

At the time we collected data from Samsung Mobile Thailand's Facebook fan page, most fan pages only generated enough comments to evaluate purchasing decisions for a brand, as opposed to a specific product made by a brand. Therefore, we were not able to conduct an analysis for a specific Samsung product or device. Although the hypothesized model fitted the represented data, it was not a perfect fit — the CFI value was 0.84, not 0.90.

Implications for research

From a theoretical perspective, it is difficult to measure the effectiveness of social media marketing, and the measurements have not been done in any systematic way.[8–10] Only very limited research has explored the performance of social media marketing.[11] Companies only know the number of followers in their brand communities and how interactive the followers are by their comments. Social media activities influence a series of steps described in the HOE model.[27] The HOE described consumers' mental processes from the initial exposure to a product or advertisement to the final purchase decision. The findings from this study provide indicator variables for consumer purchasing decisions

on social media marketing. These indicator variables can be performance indicators of social media marketing.

WOM and purchasing decisions

From a managerial perspective, marketers can evaluate consumer comments published on social network websites for specific products, such as Facebook fan pages, in order to gain a better understanding of consumer behaviour. The research demonstrates that there is a strong positive correlation between WOM effectiveness and purchasing decision that is driven by social media marketing to influence consumer purchase decisions. This study has shown that one way to evaluate social media marketing performance is to identify the various factors that influence consumer purchasing decisions. Although, as mentioned above, one limitation of the study is that it focused only on mobile devices, our model could also be applied to other product segments. Advances in mobile broadband Internet technology have made it possible for consumers to enjoy significant access to the growth in social networks via their mobile devices. Another interesting study should be done on mobile social media marketing.

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