E-Market Segmentation for Internet-Mediated Fashion Brands: A Conceptual Framework with Mean-Variance Consideration

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Abstract
E-market segmentation takes a crucial role in marketing for fashion brands. Its applications for collaborative functions such as estimating the advertisement budget, retaining customers, carrying out direct tailored marketing, and implementing dynamic pricing are essentially important and critical for their e-business. Unlike the bricks-and-mortar traditional store retailers, fashion brands which operate online can keep track of the details of the online customers easily and precisely. How to make use of these customers details in segmenting the e-market for each particular function becomes an important issue. As a result, we propose and discuss in this paper a conceptual model for carrying out e-market segmentation and we focus on the areas of dynamic pricing and advertisement budget estimation. Through extensive discussions with mean-variance consideration, we believe that the model can be incorporated into other existing market segmentation analyses. Managerial implications are discussed.
Keywords Fashion branding, e-market segmentation, internet marketing, mean-variance

1 Introduction

For fashion brands which operate solely in the traditional bricks-and-mortar retailing mode, keeping track of the buying behaviours and preferences of each specific customer is a difficult, if not impossible, task. Even if the fashion brands can collect some customers' data by observation, the results are relatively sketch [1]. Unlike the bricks-and-mortar stores, fashion brands which have its online channel (we call them EFBs (e-fashion-brands)) can precisely keep track of the online customers' buying behaviours easily. Details such as the surfing habit, buying preference, price sensitivity, loyalty, etc can all be recorded and estimated. Obviously, information of these details can help the EFBs in making good business decisions. One of the most intuitive uses of these observed customers buying data is for marketing purpose (see [2] for the discussion of the issue of marketing on the Internet).

Market segmentation*, as defined in Chaffey [4], is the *"identification of different groups within a target market in order to develop different offerings for*

*See [3] for a recent review and discussion on a framework for market segmentation and its applications.

the groups". It involves identifying segments in the market, grouping customers into segments, and targeting, positioning and developing a differential advantage over competitors [5]. It also represents a rational and precise adjustment of the products and services for customers [6]. A good market segmentation scheme implies a good analysis of the target market and an identification of the true requirements of each specific group of customers [4, 7-9]. In modern business world, market segmentation has been realized as an essential part in nearly all marketing projects [4,10-11].

According to Dibb and Stern [8], the literature of market segmentation mainly goes to two distinct streams. The first stream treats market segmentation as a technique in determining and studying different segments in the market. The second stream views market segmentation as an approach for an efficient allocation of resource to different segments in the market. This paper basically follows the viewpoint of the second stream. In both the academic literature [10-12] and the industrial practice [13], in general, we need two types of information for market segmentation. The first type is called the "classification variables" which include four types of variables: Demographic variables (e.g. age, gender, etc), geographic variables (e.g. city, country, etc), psychographic variables (e.g. risk attitude, lifestyle, etc) and behavioral variables (e.g. brand loyalty, usage level, etc). The second type is the descriptor variables which describe each particular segment and are used to distinguish one segment from another. Many classification variables would function as the descriptor variables, too.

Market segmentation can be a complicated process in business. For example, suppose that after adopting the conventional segmentation steps with the classification according to the geographical and demographic variables, we have obtained a number of different segments. An important question to ask is: "Should we continue to break down the segments into smaller segments?" No matter the answer is "yes" or "no", we need to have a good reason for it. In other words, a good market segmentation scheme requires a good stopping condition. It is true that there are a few rules of thumbs for decision makers to decide the number of segments and when to stop the segmentation process. Some factors [13] that decision makers will bear in mind include:

(1). The size of the segments must be large enough.

(2). The segments must be reachable by the company's marketing strategies (e.g. promotion, pricing, etc).

(3). The segments must be relevant to the company's products and different segments should be clearly and sufficiently different.

These guidelines are important and practical but they do not provide a precise decision model for decision makers for making a wise and optimal decision for a specific collaborative function with market segmentation.

With the advance of science and technology, market segmentation can now be done by a computerized decision support system. Methods which rely on data mining and artificial intelligence [14-15], advanced database system [16], operations research and management science optimization techniques [6,10,17-18] , and others [11-12,14,19-20] have been widely tested and applied. However, none of these methods dominate the literature and each of them has its pros and cons.

As many recent research projects revealed and discussed, market segmentation is very important for Internet-enabled e-commerce [4,16,21-22]. This also gives rise to the term "e-market segmentation" which represents the segmentation of the electronic market. In fact, good e-market segmentation is generally believed to be not only important for maintaining the company's competitive edge, but it is also essential and crucial, for EFBs in the knowledge-based economy. When we look deeper into the potential collaborative applications of the e-market segmentation scheme for EFBs, we can identify several major functionality areas for it. Some of them include the following:

1. *Estimating the advertisement budget for acquiring different groups of customers:* Different customers have different values for the EFBs. Some of them only surfed around and did not buy a single item at all; some made one purchase and then did not come back; some made repeated purchases and showed a strong sense of trust on the EFB (see Moe and Fader [23] and Betts [24] for the identifications of the four types of online shopping visits). Since it can be very expensive to acquire new customers on the Internet [25], the advertising strategies should be more focused. The expenses spent on advertisement for different groups (i.e. segments) of customers should be made different, too. This can be achieved by a good e-market segmentation scheme. On the other hand, the information from the estimation of advertisement budget can be useful for e-market segmentation.

2. *Direct marketing by providing tailor-fit services and products to the interested customers:* Different customers have different preferences and requirements. If an EFB can provide the right product to the right customer at the right price at the right time in the right place, then a transaction results. Even though it is impossible for the EFB to exactly predict all of these aspects, good market segmentation can help to narrow down the error in terms of the direct marketing offers of product type, selling price, etc. It can also help in turning browsers into buyers [23-25] and improve customer relationship management [26].

3. *Dynamic pricing:* Different consumers have different sensitivities towards prices and other attributes for the products [1,27]. Some consumers are highly price-sensitive while some care more about service and reliability. Surveys also show that many customers purchasing online do not shop around and they just buy from the EFB which they first visit. According to a survey as reported in Baker et al. [27], the percentage of consumers who buy online from the first

website they visit ranges from 76% to 89% for various products including CDs, books and electronics. In light of this, EFBs should try to attract the customers at the very beginning by bringing the products in front of the consumers when they are in need (it is mentioned in the last paragraph). At the same time, how to set the selling prices dynamically for different groups of customers so that the profit for the EFB is maximized becomes vitally important. Failing to do so can lead to the collapse of the business (see the example of Sun Country in Dutta et al.[28]). In order to exercise a profit-making dynamic pricing scheme for different groups of customers, we need to segment the market properly.

4. *Retaining customers:* For all kinds of retail businesses, there are always some loyal customers. For every loyal customer, there is a sense of trust between the retailer and herself. However, the importance of customer's loyalty varies among different retailers. For instance, a retail store whose customers are mainly the tourists from overseas countries care relatively less about the loyalty of the customers since it is unlikely for the overseas tourists to come back again in the near future while a cosmetics retailer always wants to maintain a loyal customer base (since the loyal customers are more likely to try some other products and have repeated purchase'). Since most of the customers buying online have to contribute some private data to the EFB (e.g. the credit card number) but they cannot touch the product and cannot visit the store to talk with the sales staff face-to-face, they simply won't make a purchase without trusting the EFB. As a consequence, compared with the bricks-and-mortar stores, the trust and loyalty of customers is especially important for EFBs. Moreover, having the loyal customers can help the EFBs in at least two ways. First, a loyal customer is more likely to repeat her purchase. Second, a loyal customer tends to refer new customers to the EFB she is loyal to. It is why Reichheld and Schefter [1] have proposed that "price does not rule the web; trust does". In order to gain the trust and keep the loyalty of the customers, we have to focus on their needs. Without proper market segmentation, building and keeping the loyalty of the customers becomes more difficult.

From the above description, we can see that a good e-market segmentation scheme is undoubtedly crucial for the success of EFBs and it can be applied to different collaborative functionality areas. However, what is a good e-market segmentation scheme for each particular collaborative function? Obviously, a good e-market segmentation scheme depends on its specific targeted functionality area. For example, a good e-market segmentation scheme for dynamic pricing may not be good for the estimation of advertisement budget. As a result, we propose in this paper a decision model for carrying out e-market segmentation for different specific functionality areas. We focus our attention on two important functionality areas: Advertisement budget estimation, and dynamic pricing.

These are important functions for EFBs and they can be collaborated with the conventional e-market segmentation scheme. Through the incorporation of the performance measure (for the collaborative function) into the e-market segmentation decision model, we can provide more precise e-market segmentation results for the marketing managers to make an optimal decision (with each particular function). The idea behind this proposed decision framework is inspired by the classical Markowitz' mean-variance theory in financial portfolio management [29] with which we quantify and control the uncertainty associated with a decision by the variance of that measure (this point will be discussed in the next section). With the illustrative examples, we demonstrate the applicability of the proposed model.

The organization of the rest of this paper is as follows. We first present the mean-variance decision framework which combines the conventional e-market segmentation and the collaborative function in Section 2. The detailed e-market segmentation schemes for estimation of advertisement budget and dynamic pricing are proposed in Sections 3 and 4. The e-market segmentation schemes for other functionality areas are discussed in Section 5. We conclude with the discussion of managerial insights in Section 6.

2 Mean-Variance Decision Models

Before we present each particular e-market segmentation model for the specific function area, we propose in this section the basic general decision Model. In performing e-market segmentation, as we mentioned earlier, it is usual that the marketing managers would make use of the demographic variables, geographic variables, psychographic variables and behavioral variables. Despite the intuitive physical meanings behind these variables, some of the classifications with these variables may not be very helpful for all specific collaborative functions. For example, when the objective of a particular market segmentation project is to decide the advertisement budget (and hence the advertisement strategy), the profit that can be generated by each customer becomes a key measure. As a result, we should incorporate a measure of the profit generated by the customers in the market segmentation scheme. However, different customers can carry different profit-values to the company, a precision control rule is hence essential for building a good market segmentation decision. In the advertisement budget estimation example we mentioned above, a precision control rule can be imposed on the degree of uncertainty of the profit. Thus, a mean-variance consideration with which the average profit is used as the performance measure variable and the variance of profit is applied as a precision control variable. In this paper, we call the market segmentation scheme which includes the average objective performance measure and the variance of this performance measure for a particular market segmentation project the "*mean-variance performance measure market segmentation scheme* (MVPM)". With MVPM, we can carry out market segmentation following a mean-variance consideration with which the segmentation is performed with a measure by the "mean" and its precision is controlled by the "variance". Since the variance is an absolute measure, we make use of the relative measure of the coefficient of variation, defined as "the standard deviation divided by the mean" as the precision measure.

The general idea behind MVPM is that: The e-market segmentation scheme follows the conventional type of segmentation policy and yields a number of e-market segments. This segmentation process is treated as an initial and basic e-market segmentation. After that, depending on different collaborative functions, the manager of each function would impose an additional measure on each of the segments. Systematic and precise evaluation is carried out and further segmentation or re-segmentation may be required depending on the evaluation results. By doing so, tailor-fit e-market segmentation results are provided to each collaborative function and optimal decision can hence be made.

In the following sections, we outline the use of the concept of MVPM for several important collaborative functionality areas with e-market segmentation.

3 Segmentation for Estimation of Advertisement Budget

The expenses companies spent on online advertisement is expected to increase in the coming years. As reported in Bhatnagar and Papatla [21], Forrester Research has estimated that the spending on online advertisement in the United States will reach US$22 billion by 2004, which is more than 8% of the total spending for advertising in the United States. In fact, acquiring customers on the Internet can be very expensive. As estimated and shown in Hoffman and Novak [25], many EFBs have spent more than US$100 to acquire a new customer and some have even spent US$500! However, the "values" of most new customers, as measured by the expected lifetime spending on the EFB, are less than these advertising expenses. In fact, some consumers shopping around the Internet only surf and buy nothing; some of them may only make one purchase and never come back; some may have repeated purchases and are loyal customers. As we mentioned above, since it is expensive to acquire new customers on the Internet, the advertising strategies should be more focused.

Recalling from the well-agreed Pareto rule (or called the 80-20 rule), *the majority of profit is actually generated by a relatively small amount of customers.* It is thus a wise decision to focus the company's resource on promoting to the customers which can bring higher profits. Furthermore, the expenses spent on advertisement for different groups (i.e. segments) of customers should be made different. This can be achieved by a good e-market segmentation scheme. In the literature, there are a number of methods proposed to help. They include the use of the customer's searching behavior [21] and the use of personalized advertisement [9,14]. In this section, we apply the MVPM to build a decision model for the estimation of the advertisement budget for different market segments.

Under our proposed mean-variance model, MVPM, the EFB should incorporate the performance measure and the precision control measure for "the profit that can be generated by the customer" into the decision model for market segmentation. Thus, when EFBs try to evaluate the "value" of the customers purchasing online, they should investigate the e-market segments with respect to the profit generated by the customers in each of these segments with a precision control. To be specific, we have the following market segmentation decision model:

"The EFB first segments the customers according to the conventional segmentation scheme by, for example, the geographic and demographic variables. Then, the EFB checks (and/or further segments) each group with respect to the average generated profit and the variance of profit from the members of that group. The objective is to ensure that the coefficient of variation of profit, defined as the standard deviation of profit divided by the average profit, for each segment is under the EFB's precision control and the segments size is large enough. After that, the final outcome from each market segment will have an average value for the customers in that segment and this average value can be a good representative measure since its variation is under the EFB's control."

To illustrate the above statement, let us consider a simple example. Suppose that an EFB has classified his customers according to the conventional segmentation scheme with respect to the customers' variables of location, gender, age and education, and under a constraint on the size of each segment. After this segmentation scheme, he has obtained different market segments. When the EFB looks deeply into each obtained market segment, he can identify the profit that has been generated by each customer inside each market segment. He can then obtain the average profit and the variance of profit generated by all the members in each market segment. For a particular segment, if the coefficient of variation of profit is larger than a certain threshold (decided by the EFB), the level of uncertainty of the profit generated by the members inside this market segment is too large. Further market segmentation should be carried out by adding another attribute (e.g. the purchear frequency of the customers). If the coefficient of variation of profit is less than a certain threshold (decided by the EFB), the market segmentation that has been done is good enough and the EFB can stick with it. However, if the coefficient of variation of profit is too large but the market segments size is also relatively small, further market segmentation should not be carried out. In this case, the EFB needs to reconsider carrying out the market segmentation in another way with consideration of other variables at the very beginning. We summarize this approach in the following proposition.

Proposition 1. *The e-market segmentation scheme for estimating the advertisement budget can be stopped when the coefficient of variation of profit generated by the members of that segment is less than a threshold α. If the coefficient of variation of profit is larger than α, then further segmentation or re-segmentation is needed.*

To give a better picture of the proposed decision model in Proposition 1, let us have an illustrative numerical example below.

Example 1. An EFB has performed a market segmentation scheme by using the conventional variables of city, gender and age and identified 18 e-market segments. Suppose that this EFB looks into two distinct segments: Segment 1 and Segment 2, where Segment 1 refers to the group of customers who live in City 1, male, and aged between 22-25, and Segment 2 refers to the group of customers who live in City 2, female, and aged between 18-21. The desirable minimum size of each segment is 500. For Segment 1, there are 1600 customers and for Segment 2, there are 850 customers. The profit generated by each one of the customers can be found from the EFB's database. When the EFB calculates the average profit per head (AP), variance of profit (VP), standard deviation of profit (SDP), and coefficient of variation of profit (CVP) generated by the members of each segment, he has the following results,

Table 1.1 Example 1

	Segment 1	Segment 2
Average Profit (in \$)	50	180
Variance of Profit (in \$^{2})	35^2	80^2
Standard Deviation of Profit (in \$)	35	80
Coefficient of Variation of Profit	0.70	0.44

Obviously, even though the VP of the members in Segment 1 is smaller than the members in Segment 2, the CVP is much larger. In fact, the profit uncertainty for Segment 1 is too large to be ignored. Thus, if the precision threshold of the EFB (α) is 0.5, then the e-market segmentation for Segment 2 is good enough because its CVP is less than 0.5. However, the e-market segmentation for Segment 1 is not good enough because Segment 1's CVP is larger than α. Since the size of this segment is 1600 and the minimum segment size is 500, the EFB can consider carrying out further segmentation on Segment 1 by using another classification variable. After the e-market segmentation scheme with the precision control over the profit generated by the members of each segment, the EFB can make use of the estimated average profit for each segment as an indicator to decide the amount of budget for advertisement on each segment. In this example, the value for each customer in Segment 2 is \$180 and a reasonable budget (say \$100 per head) for advertising towards customers in this market segment can hence be estimated.

As summarized in Proposition 1 and illustrated by Example 1, we can see that a decision model which provided a tailor-made stopping condition for the e-market segmentation process has been proposed. As we mentioned earlier, advertisement for e-commerce can be very expensive. Nowadays, on-site banner, pup-up screen, emailing, affiliate program, TV and radio commercials, etc are all popular means of advertisement. However, obviously, different means of advertisement carry different costs. As a result, it is a wise decision to decide the advertisement budget for each specific group of customers before considering the specific means of advertisement. By having the market segmentation scheme as described in Proposition 1 where the members of each segment are grouped together with the consideration of the average profit generated under precision control, we can identify precisely the "value" of each member of that particular market segment. As a consequence, the EFB can allocate the optimal advertisement resource to focus on the most profitable customers, and decide the most appropriate advertisement scheme for them.

4 Segmentation for Dynamic Pricing

The online consumers have different sensitivities towards price and other non-price factors. Some consumers are highly price-sensitive and they like to use the shop bots for finding the EFBs which offer the lowest prices while some care more about service, reliability and trust. As a result, how to set the right selling prices dynamically for different groups of customers so that the EFB's profit is maximized becomes very important and, in fact, crucial (the failure stories due to the lack of good pricing policy can be found in [28]). One of the effective ways for dynamic pricing is to carry out dynamic price testing. The idea of the dynamic price testing [27,30] is that: From changing the listed price showing on an EFB's website and keeping track of the customers' purchasing rates at that price, the EFB can know the expected profitability of each listed price. For example, when the EFB sets the product's listed price as \$10, it is observed that 2 out of 10 visitors will buy the product; when the EFB changes and tests the price at \$9.5, it is found that 3 out of 10 visitors will buy the product. The purchasing rates are 20% and 30% for \$10 and \$9.5, respectively. The EFB can then decide whether \$9.5 is better than \$10 or not based on the corresponding observed purchasing rates and profit margins. However, in order to exercise an effective dynamic price testing scheme (and hence a good dynamic pricing), the EFB needs to segment the e-market properly. From the sales record of the customers for that product (or a closely related product if the data for that product is not sufficient or available) in the past, the EFB can keep track of the exact purchasing price of each customer. As a result, the EFB can first segment the e-market for that product according to the conventional approach by the customers' age, gender, etc. After that, the EFB can check the average purchasing price and the variation of the purchasing price per each segment following the concept from MVPM. Similar to the proposed method for the segmentation for advertisement budget estimation, we have the following model:

"From the database of the customers, the EFB first segments the customers according to the conventional segmentation scheme by, for example, the geographic and demographic variables. Then, the EFB further segments each group with respect to the average purchasing price and the variance of purchasing price from the customers in that group. The objective is to ensure that the coefficient of variation of the purchasing price, defined as the standard deviation of purchasing price divided by the average purchasing price, for each segment is under the EFB's precision control and the segments size is large enough."

With the above method, the EFB can effectively identify the group of customers with a specific average purchasing price. After that, a tailor-made dynamic price testing scheme can be arranged for that particular market segment. It is thus more effective than performing the dynamic price test blindly. We summarize this proposed method in Proposition 2 below.

Proposition 2. *The e-market segmentation scheme for dynamic price testing (and hence dynamic pricing) can be stopped when the coefficient of variation of the purchasing price of the members in that segment is less than a threshold θ. If the coefficient of variation of profit is larger than θ, then further segmentation or re-segmentation is needed.*

Example 2 below gives an illustrative numerical example for the proposed e-market segmentation model presented in Proposition 2.

Example 2. An EFB has performed conventional market segmentation (by using the variables such as age, city, gender, etc) for the customers of a specific product and has identified 20 e-market segments. Suppose that this EFB looks into two distinct segments: Segment A and Segment B. The desirable minimum size of each segment is 500. For Segment A, there are 1300 customers and for Segment B, there are 1500 customers. When the EFB calculates the average purchasing price, variance of purchasing price, standard deviation of purchasing price, and coefficient of variation of purchasing price generated by the members of each segment, he has an khown in Table 1,

From Table 1, the coefficient of variation of the purchasing price for customers in Segment B is much larger than the customers in Segment A. Suppose that the EFB has set the precision threshold θ(for the coefficient of variation of the pur-

Table 1.2 Example 2

	Segment A	Segment B
Average Purchasing Price (in \$)	100	90
Variance of Purchasing Price (in $\$^2$)	25^2	50^2
Standard Deviation of Purchasing Price (in \$)	25	50
Coefficient of Variation of Purchasing Price	0.25	0.56

chasing price) to be 0.5. By Proposition 2, the e-market segmentation result for Segment A is good enough because the coefficient of variation of the purchasing price is less than θ. Thus, for consumers in Segment A, the EFB can carry out the dynamic price test with a reference price of \$100 and the dynamic testing prices can be set within a reasonable range. On the other hand, the e-market segmentation for Segment B is not good enough because Segment B's coefficient of variation of the purchasing price is larger than θ. Since the size of this segment is 1500 and the minimum segment size is 500, the EFB can consider further segmenting Segment B by using another classification variable.

5 Segmentation for Retaining Customers, Direct Marketing and Others

In Sections 3 and 4, we have discussed the e-market segmentation schemes, following the concept of MVPM, for two important collaborative functions for EFBs. We will discuss more functionality areas where MVPM can be applied for e-market segmentation in this section.

As we mentioned earlier, trust and customers' loyalty are two important issues for EFBs doing business on the Internet. Without proper e-market segmentation, building and keeping the loyalty of the online customers becomes more difficult. As a result, when the EFB performs the e-market segmentation, it is important for him to bear in mind that he has to be able to identify precisely the need of the customers inside that market segment and be focused [1]. This objective follows exactly the MVPM where the need of the customers inside each e-market segment refers to the average measure of that need and the precision for the understanding of this need in the corresponding e-market segment is reflected by the coefficient of variation of that need measure. This is what the MVPM captures. As an example, suppose the EFB would like to retain the customers by providing a membership system. In order to attract the customers, the EFB would like to provide bonus points for the customers who join the membership and make some purchases. Obviously, in order to attract more customers to be members, the amount of the bonus points and the amount of required purchases should be offered differently to customers in different segments. The concept of MVPM can hence be applied for providing a measure for this purpose.

Similarly, for an EFB who wants to provide the right product and service to the right customer for the right price at the right time in the right place with direct marketing strategy [31-32] , the MVPM also works where it provides a mechanism for e-market segmentation which helps to narrow down the error in terms of the product type, selling price, etc. For instance, the EFB can make use of the data on the products bought by the customers in the past to help in segmenting the customers and measuring the customers likelihood of buying the product that will be direct marketed.

6 Conclusion and Managerial Implications

We have proposed in this paper a conceptual decision model, called the *"mean-variance performance measure market segmentation scheme (MVPM)"*, for e-market segmentation for different specific collaborative functions. As we all know, the traditional market segmentation relies on the classification variables like the demographic, geographic, psychographic and behavioral variables. However, in spite of the intuition behind the classification by using these variables, researchers have questioned the reliability of the available market segmentation techniques (e.g. [8]). Furthermore, the classifications with these conventional variables may not be very helpful for a specific collaborative function. As a result, we propose to incorporate the collaborative function's performance measure and its precision into the e-market segmentation scheme for effective decision making by the managers of the corresponding functions.

A mean-variance consideration with which the average or expected performance measure (e.g. the average profit) is used as the performance measure variable and the degree of variation of the performance measure (e.g. the coefficient of variation of profit) is applied as a precision control variable. This market segmentation scheme is thus called the mean-variance performance measure market segmentation scheme (MVPM). With MVPM, EFBs can carry out e-market segmentation for each particular collaborative functionality area following a mean-variance consideration. We have discussed the use of MVPM for EFBs with the estimation of advertisement budget, dynamic pricing, retaining customers and direct marketing.

Since brand managers are involved with the resource allocation and decision making for the EFBs, effective and precise market segmentation schemes can provide them with good assistance in making a sound and optimal decision. Under MVPM, the e-market segmentation decision is under a control on the precision of the specific performance measure. As a consequence, better resource allocation decisions for different collaborative operations can be made by the fashion brand managers optimally and precisely. We can thus view MVPM as an uncertainty control model which targets at reducing and constraining the degree of uncertainty associated with the performance measure. We believe that MVPM is especially important for e-commerce (and mobile commerce) because the e-market is highly volatile with a large amount of uncertainty sources and customers details can easily be recorded and analyzed. Notice that, even though we focus on the use of MVPM for Internet enabled e-market segmentation schemes, the conceptual framework of MVPM can actually be applied to the general market segmentation systems. The model of MVPM can also be implemented into an intelligent computerized decision support system which automatically helps managers in making wise and scientifically sound decisions.

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