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Market Segmentation of Facebook Users

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Abstract

In this paper, I develop afresh a comprehensive approach to market segmentation of Facebook users. The approach considers the implications of Facebook's business model built around its multi-sided platform (MSP). In the first part of the study, I present a series of five propositions that inform the formulation of segmentation and targeting strategies for Facebook and more generally MSPs. These are based on a review and synthesis of extant literature on multi-sided markets and classification of Facebook and social media users. The second part of the study uses empirical survey data from 261 Facebook users to (a) evaluate some of these propositions, and (b) develop a segmentation scheme that may guide the development of marketing strategy for social networking sites (SNS) like Facebook.

The empirical analysis makes use of cross-tabs, classification and regression trees, linear discriminant analysis, cluster analysis, and artificial neural networks (ANN). The basis variables of importance to Facebook for market segmentation are frequency of use and level of engagement. Important descriptors that help determine segment membership are: marital status, blogging habits, use of Facebook mobile, general interest in online social networking (OSN), and use of competing OSNs such as LinkedIn and Google +. I conclude with a discussion on future research priorities in strategizing for social networking sites.

Introduction

In recent years, several research studies (Brandtzaeg and Heim 2011; Bernoff 2010; Lorenzo-Romero and Alarcon-Del-Amo 2012; Lee, Jarvinen and Sutherland 2011; Foster, West and Francescucci 2011) have tried to classify users of social media including those of social networking sites (SNSs) such as Facebook. These studies offer classifications or typologies of users rather than comprehensive market segmentation*, the objective of this paper. Also, current research ignores the fact that Facebook's business model, based on its multi-sided platform, generates revenue from affiliate marketers and developers of apps/games. Facebook doesn't get any money from users though they make it possible from the marketers and developers. A market segmentation strategy for Facebook cannot be optimal at the platform level unless the interests of marketers and developers are factored in. I address these gaps in this research to arrive at a more comprehensive market segmentation strategy for Facebook.

*Segmentation (Smith 1956) is based upon developments in the demand side of the market and represents a rational and *more precise adjustment of product and marketing effort* to consumer or user requirements. In the language of the economist, segmentation is disaggregative in its effects and tends to bring out recognition of several demand schedules where only one was recognized before (italics added).

Meaningful classification of users of social media or those of SNS is a moving target because social technologies and their usage are evolving at a rapid pace. In view of this fact, I try to distinguish between variables that are likely to endure as determinants of segment structure and those that are likely to change with passage of time. For example, age may cease to associate with low rate of adoption and use of Facebook in future because the share of people who had late exposure to SNS or Facebook is decreasing with time. Similar is the case with subjective norms (Ajzen 1991) and normative beliefs that are changing over time. With continual innovations on functionality and accelerating positive network externality, users are doing an increasing share of instant messaging, chatting and emailing on Facebook in recent years even in a developing country like India (TCS Study 2013). SNS is becoming a multiplex of wide ranging activities with recent additions like social shopping, social care and social search. Perhaps, the biggest of transformations of the social technologies landscape is about to begin with ubiquitous smart phones and wearable computers that not only keep people online anytime anywhere but also provide bountiful apps that seamlessly integrate with social technologies. In this paper, with an extensive empirical analysis of segment structures, I identify and evaluate basis and descriptor variables for market segmentation that are relatively time invariant in usefulness. They are also consistent with the marketing objectives of affiliate marketers and developers, the sources of revenue for the Facebook Company. The approach I propose can be extended to accommodate variations in business model as well.

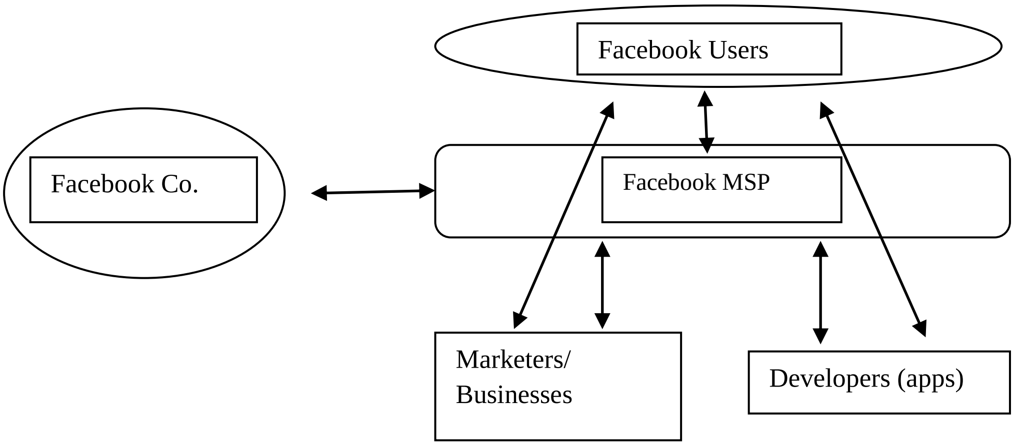
Considerable research has accumulated on two-sided or multi-sided platform strategy in recent years, but most of it deals with pricing strategy and in my observation, there is none that deals with market segmentation strategy. Similarly, there are several studies on classification/profiling/segmentation of Facebook users. But none goes beyond profiling or clustering users into different groups. These studies fall short of structuring segments in terms of basis and descriptor variables with predictive relations. They also ignore the implications of the MSP based business model of Facebook for market segmentation. A market segmentation strategy for a SNS like Facebook is not straight forward like it is for a conventional service provider because of interdependencies and disparities in the interests of different parties and network effects.

Facebook's Business Model

As shown in figure 1 in next page, there are four parties to the use of the multi-sided platform (MSP) provided by Facebook – the Facebook Company, users, affiliate marketers* (of their own products/brands) and affiliate developers (of apps/games). In the current business model, Facebook makes money by enabling direct interactions on the MSP (Hagiu and Wright 2011; Enders et al 2008)) between marketers and users and developers and users. Marketers and developers do get some of the utilities and services for free but pay for others. Users get free

* Though I often use the term affiliate marketer or just marketer, it may be more appropriate to call them businesses because they are increasingly doing activities such as social care, crowd-sourcing and so on that go beyond marketing/advertising. I also use ‘user’ for ‘personal users’ as opposed to business users.

access to the platform for online social networking (OSN) which is their primary motive for using Facebook. While Facebook offers its facilities to users free of cost today, this need not necessarily continue in the same form in future. It is possible that, like LinkedIn, it may adopt a freemium model offering some premium features for a price.



Facebook’s MSP and Business Model
Figure 1

Facebook users may choose to interact with affiliate marketers by responding to advertisements on their own Facebook pages or by connecting to a marketer’s business page on Facebook by ‘liking’ the brand or the marketer. The latter mode is often used by marketers to drive engagement* (Doorn et al 2010) in addition to more targeted advertisements for sales. Facebook earns fees for advertising and also fees for facilitating posts from marketers to users who have ‘liked’ them. Targeted advertising is the predominant source of Facebook’s revenue and profits. Advertisers may reach users based on the information shared by users such as age, gender, location, education, work history or specific interests. Developers of apps/games reach out to users mainly through the App Centre on user’s Facebook page and also through advertisements on the user’s page. Facebook makes money from developers mainly through its share of 30% of value transacted between developers and users. Most of the money from developers is based on purchase of virtual goods and services that accompany the use of apps/games.

As a MSP, Facebook has two types of network effects (Eisenmann, Parker and Van Alstyne 2006). Same-side (also called direct) and cross-side (indirect) effects each of which can be positive or negative. Both positive and negative may coexist too. A same-side effect, in which increasing the number of users on one side of the network makes it either more or less

* I measure engagement (p 15) as behavioural as well as attitudinal manifestations beyond the act of purchase.

valuable to users on the same side; and a cross-side effect, in which increasing the number of users on one side of the network makes it either more or less valuable to the users on the other side. Cross-side network effects are typically positive, but they can be negative. An increase in ads on Facebook pages may repel users. Same-side network effects are positive for SNS users but usually negative for marketers and developers if competitors are added. It is positive when marketers of complementary offerings are added. There are positive cross-side network effects between users and marketers, and users and developers. Increase in number of users benefits and attracts more marketers as well as developers. Increase in developers has positive effect on users. The effect may be negative when addition of marketers results in more advertisements. There can be situations when some users benefit from adding a marketer whereas other users find it intrusive. However, when marketers use Facebook as a store front or as a channel of customer care, the cross-side effect on users are clearly positive.

Objectives

The key research question I try to answer in the first part of this paper is; how market segmentation for a multi-sided platform (MSP) provider like Facebook is different from that in the conventional single sided case? Based on my review of research literature spanning strategies for multi-sided markets, classification of social media and Facebook users and market segmentation, I put forth a series of five propositions that may inform development of segmentation strategy for a MSP like Facebook. In the second part, I make an empirical investigation into the segment structures existing in this market. I answer the question of how best can we segment the market of Facebook users in terms of basis variables (Lilien and Rangaswamy 2004) that can be accessed via descriptors they are associated with. I select basis variables that can be consistent across the interests of the three business users (or user groups) of the MSP – the Facebook Company, affiliate marketers and affiliate developers. I also evaluate predictive validity of the proposed segmentation model using the basis and descriptor/access variables.

The Facebook Company may segment the users of its social networking site (SNS) or platform for more effective marketing (Smith 1965; Fank, Massy and Wind 1972). The marketing objectives may be to drive penetration, raise share of time spent on SNS, increase rate of use, intensify engagement, decrease price sensitivity, enhance brand equity, and improve revenue or profitability and so on. Strategies may be tailored for each target segment to optimize at the aggregate level. The company's business model today makes it primarily depend on advertising revenue from product marketers. 85% is ad revenue from marketers and 15% is fees that are mainly from developers. To raise the advertising revenue, Facebook needs to grow the number of active users, their rate of use and if possible their inclination to respond to the advertisements. Advertisers may also be concerned about the relative level of engagement of users with the SNS medium and related opportunity costs. A higher level of engagement of the user with the SNS may raise the chances of response and engagement with marketers in many cases. But it may not make a difference or even lower the chances when the marketer's stimulus is viewed as a distraction. We examine such issues in the section on propositions.

There are obvious constraints in developing an optimal segmentation scheme in the absence of specific information on marketing objectives and other elements of marketing strategy. An optimal segmentation and targeting scheme for a new product launch is likely to be different from that for a new positioning strategy for the same product. So, what is optimal is elusive in the absence of definite information about the context in which such a scheme would be implemented. Marketing strategy is essentially about S-T-P (Segmentation-Targeting-Positioning), 4 P's and branding. In the present context, we have the additional consideration of synergizing marketing strategy, including segmentation and targeting, across the three interfaces – Facebook Company – user, marketer – user and developers –user. A further complication is that marketers are a diverse group with activities that are increasingly non-standardized. The extent to which Facebook can accommodate the interests of this diverse group in its segmentation and targeting strategy is limited. Though there is less diversity in the activities and interests of developers, here again, addressing such interests collectively may not benefit the atypical developer adequately.

Market segmentation is only one element albeit a fundamental one in the strategy document. In the absence of information on the context of objectives and rest of the strategies for Facebook, we may develop only a general guideline with standard assumptions about the context. The empirical analysis may inform rather than prescribe.

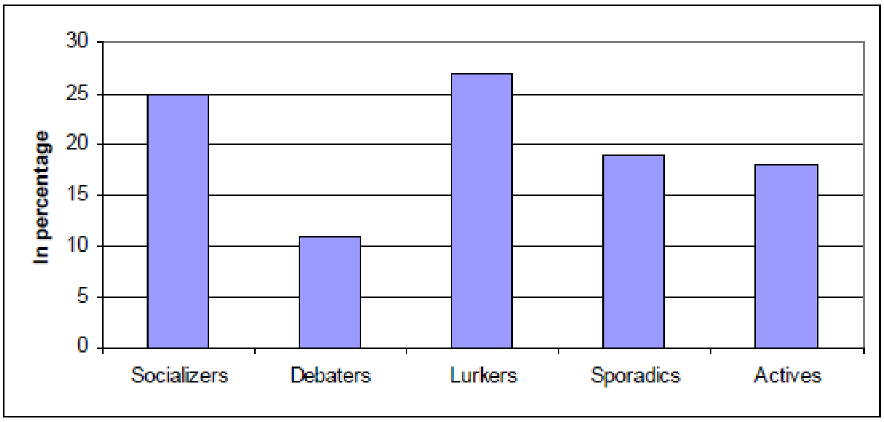
Literature Review

Social networking sites (SNS) may be defined (Boyd and Ellison 2007) as web-based services that allow individuals to (1) construct a public or semi-public profile within a bounded system, (2) articulate a list of other users with whom they share a connection, and (3) view and traverse their list of connections and those made by others within the system. Users come to the Facebook platform primarily for information, social connection and entertainment (Heinonen 2011) and their primary activities on the platform are consumption of content, participation and production of content.

SNS like Facebook constitute a growing segment in the social media space. Below, I review five research studies that classify or segment Facebook/SNS/Social Media users. A common pattern is evident in all these studies. The segments differ on frequency/duration of use and also on types/range of use. A clear pattern is creative use versus responsive or assenting use, social influence versus social surveillance. Demographic variables such as marital status and age and in some cases education level may help access the segments of interest in these studies. However, these studies do not go beyond the task of grouping users on a range of variables.

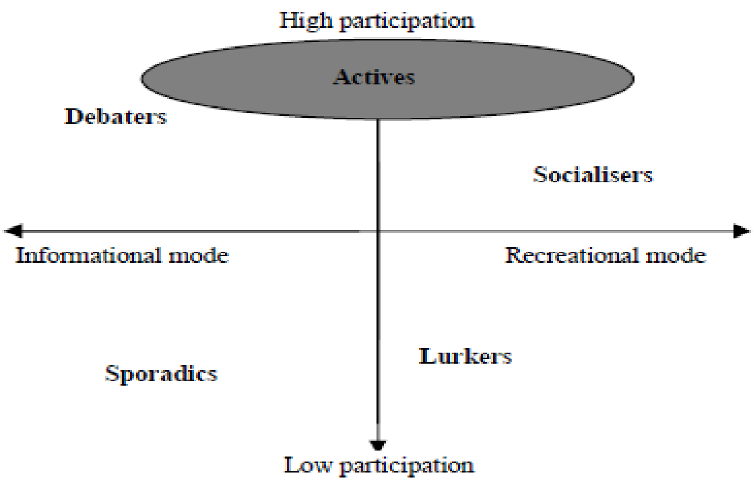
A very elaborate classification study (Brandtzaeg and Heim 2010) of SNS users is based on an analysis of the survey data from 5,233 respondents in Norway in four major SNSs - Facebook, Orkut, LinkedIn, and MySpace. The study found five distinct user types:

1 sporadic 2 lurker 3 socialiser 4 debater and 5 active



Typology of SNS users *Source: Brandtzaeg and Heim 2010*

Figure 2A



Typology of SNS users
Figure 2B

This typology is based on quantitative and qualitative aspects of SNS use. The sporadic constituting 19% are occasional users with little initiative. They respond but hardly upload any content. Key benefit they seek is information from time to time. Circle of contacts on SNS is very limited. Surprisingly, they are spread evenly across age groups and genders. Lurkers making up 27% are also passive users and contribute little UGC (user generated content), but they may additionally use SNS for recreation and *time pass*. Their presence cuts across the 4 SNS studied. A lurker is more likely to be a female (58%) than a male (42%).

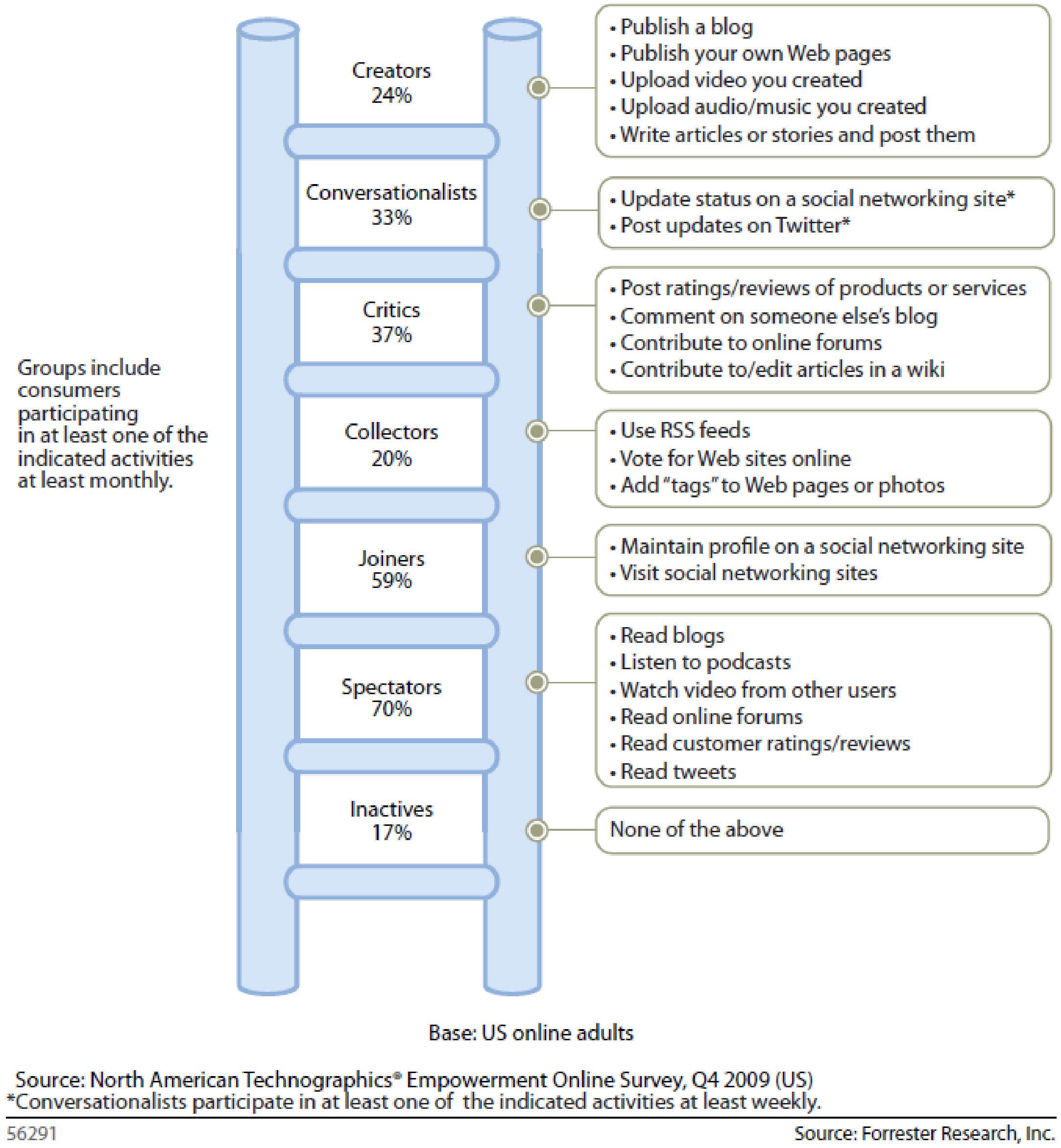
Socialisers at 25% incidence are unlike the sporadic or the lurker. The socialiser has distinctly higher level of participation; follows up and comments on pictures of friends, even seeks out new friends on SNS and tends to be young in age group. SNS interests her much more than it does to the sporadic and the lurker. However the occurrence of socialisers differs a lot across the different SNS studied. Debaters at 11% have a participation level that matches that of socialisers, but the activities are qualitatively different. With university education and older age, they tend to be more intellectual in their choice of activities. They read, write and discuss more on the internet but are unlikely to post videos. Actives at 18% have the widest range of activities such as community events and publishing music or videos. Unlike debaters, they have a balance of informational versus recreational mode in their activities.

A more recent segmentation study (Lorenzo-Romero and Alarcón-del-Amo 2012) makes use of latent class segmentation technique to arrive at 3 segments – introvert users (41%), versatile users (47%) and expert users (12%). Introverts are mostly women who are more than 51 years in age, use at most once a week for less than 1 hr, have less than 50 contacts. They hardly make new friends online. Versatile users use SNS several times a week for a total of 1-5 hrs and are predominantly females in the 25-32 age group. They have wide ranging activities on SNS, but do not make friends online. Keeping in touch and entertainment are dominant motives. Expert users (only 12%) are mostly females less than 25 years in age. They use it more than once in a day. They have the widest range of activities on SNS including informing others about brands or products they use. Dominant motives are making new friends, experiencing the novelty of SNS, and pursuit of professional interests.

Social Technographics (see Figure 3 in next page) by Forrester Research (Bernoff 2010) profiles* social media users as shown. Although a trade publication, it is authoritative because of its large sample of 10,112 consumers among other things. In Forrester's ladder of social media sophistication, regular SNS users form a group called conversationalists just below the group called creators in the top rung. It is interesting for the context of our research that several social media activities cut across different types of platforms – SNS, blogs/micro blogs, wikis, ratings and review sites, media/file sharing sites, social gaming sites, social commerce sites and discussion forums.

The savviest users of social media at the top rung create content – textual, pictorial, audio, and video content and upload or publish it on the web. These 24% of creators distinguish themselves from the spectators who consume content – read, listen or watch content but do not create/upload/publish it. The Facebook user has similar choice of activities within Facebook. She can take on roles similar to that of a creator or critic or spectator or joiner or inactive. So, we can classify Facebook users in terms of their initiative and creativity, their consumption of content or entertainment and their level of activity. In a similar vein, Foster et al. (Foster et al. 2011) find 3 dominant online social behavior - creator, socializer and information seeker. The position of SNS users on Forrester's ladder implies that regular SNS users who update status at least once a month belong in the top two rungs. They are among the savviest users of social media.

* Groups are allowed to overlap on some of the important aspects.



Social Technographics (2010): Grouping Consumers by How They Participate

Figure 3

Lee et al. (2011) present a segmentation scheme that takes into account the interests of marketers in the form of 3 measures – opinion leadership, deal proneness and market mavenism. They find clusters that primarily differ on gratifications/motivations - social interaction, entertainment, self-expression and information seeking gratifications. A large segment of 32% is labelled *middle of the road* because members are average on all four motivations as well as minutes on internet and Facebook. It has a high 86% (sample average is 66%) of members who have become fans of one or more companies on Facebook pages. This segment, also has an above average rate of use for apps/games and average score on opinion leadership and market mavenism. (In the author's opinion, a better indicator of responsiveness to marketing stimuli would consider a higher threshold than a single 'like' for a company.)

The second cluster, *social interactors* (15%) has higher social interaction and entertainment motivations and lower information seeking and self-presentation motives. They have fewer but deeper friends than average on Facebook. They are low on use of apps/games, coupons/promotions on Facebook and market mavenism. The third cluster, the second largest group, labelled *maximizers* (26%) scores highest in all four gratifications sought. They tend to maximize use of Facebook features. They are higher in frequency as well as duration of use. A maximize is likely to be a fan of a company and send out mass messages.

The fourth cluster, *information seekers* (20%) value information seeking more than the other three gratifications. They have significantly more friends (average 1243) than the other clusters. Almost all (98%) are fans or members of a group on Facebook. The fifth cluster, labelled *laggards* (7%), is similar to the *middle of the road* cluster in the pattern of gratifications sought. It simply lags behind the other clusters in Facebook gratifications. It has the least frequent users of Facebook with few friends each. These users are more self-serving than other groups in that they are more likely to use Facebook to sell something.

Propositions for Segmentation of Users for the MSP

Based on the preceding review of published research on social media segmentation and multi-sided markets (Haigu and Wright 2010; Rysman 2009; Eisenmann et al. 2006; Rochet and Tirole 2006; and Evans 2005) along with findings of a pilot study of 50 Facebook users, I offer five propositions that may inform the market segmentation and targeting strategies for a SNS like Facebook or more generally for MSPs like Facebook. These propositions may be viewed as imperatives of an effective market segmentation strategy for the platform provider. I try to evaluate these propositions to some extent using the findings of the subsequent empirical study on market segmentation of Facebook users.

Proposition 1

Market segmentation of Facebook users for the Facebook Company, to be optimal, has to be guided by the company's business model based on the architecture of the multi-sided platform (MSP). It has to take into account the business interests of affiliate marketers and developers while giving primacy to interests of the Facebook Company.

Users of Facebook with personal profiles/accounts constitute the biggest asset for the company. The company's profit potential is a function of their number, rate and range of activities and level of engagement with the OSN platform. So a primary business objective of the company is to grow the user base, its usage and engagement with the Facebook Company. An effective segmentation strategy needs to help drive use and engagement in the face of competing OSNs. However, the company derives returns from this asset (user base) through affiliate marketers and developers. This is somewhat like some real estate brokers who take a commission only from the seller and not from the buyer. A key role for Facebook is that of a matchmaker. Growing segments of users whose interests match with that of the marketers and developers on the MSP would serve Facebook's business and marketing objectives better than growing users whose interests are not aligned with that of the marketers and developers. Viewing from the other standpoint, the imperative is to affiliate with marketers and developers whose interests are aligned with that of the segments of users Facebook is able to cultivate. For example, as Facebook's appeal to teens is on the wane (Shontell 2013) in recent times, marketers whose primary target segment is teens may shy away from Facebook if they think the trend is irreversible. Similarly, matching interests of career/job seekers with that of recruiters is better on the MSP of LinkedIn than on that of Facebook.

In the current business model, Facebook users get to use the Facebook internet platform for free though it is possible for the company to adopt a freemium model. Such a model may offer a version with superior features for a price premium or provide an ad-free version of the SNS for a price to users who are averse to advertisements and would pay for a respite. But, such a business model may make the SNS less attractive to advertisers and reduce their ad spend on Facebook. Some of them may withdraw facilities like social care as well and look for alternate platforms. It raises questions about whether the net effect on profits would be positive. It is unclear what would be the same-side and cross-side network effects. The MSP may become less attractive to affiliate marketers because they are denied access to what may be a very lucrative segment of Facebook users. Because marketers who persist with remaining users have a smaller and more price sensitive user base to address, they may not be able to make better offers and drive better engagement on Facebook. This may lead to same-side negative network effects among marketers. It may also limit the adoption and usage of Facebook by users in the long term because marketers/businesses have less to offer them on Facebook. Given the fact that SNS is a highly competitive market space, competing sites may offer those very opportunities to advertisers that Facebook denies them.

A very promising component of revenue from affiliate marketers is for the services of Facebook Company to affiliate marketers for facilitating marketing communications in the form of posts to fans (those Facebook users who *like* brands/marketers and so connect with the business pages of the brands/marketers for communications) and friends of fans. A new trend in service industries like banks is driving fan base and customer engagement through social customer care. Advertising is much more effective when it is directed at fans and friends of fans. Such communications may span a range of activities beyond advertising; promotional content, special offers, market research interactions, crowd-sourcing activities, customer service and so on.

A common thread that runs through most though not all of these activities is the drive for customer engagement (Barwise 2010) that is beyond the act of purchase. Leading marketers, Barwise points out, have created lively exchanges with and among customers on sites such as

OPEN Forum (American Express), Beinggirl.com (Procter & Gamble), myPlanNet (Cisco), and Fiesta Movement (Ford), tapping into participants' expertise and creativity for product development. This is apart from the fact that social media can also boost brand awareness, trial, and ultimately sales, especially when a campaign goes viral.

More important for most companies, however, is that through social media they can gain rich, unmediated customer insights, faster than ever before. Social media such as Facebook can help unlock tremendous value and productivity for businesses (Chui et al 2012) through the engaging interactions made possible by the new range of social technologies. Given the huge potential of marketer – user interactions on Facebook, affiliate marketers have the overarching role in generating revenue and profits for Facebook. Market segmentation strategy for Facebook has to be evaluated in terms of what would be its impact on marketer-user interactions and resulting cash flows. Interestingly, if marketplace or customer insight is a dominant motive of affiliate marketers or businesses like Virgin Atlantic (Barwise 2010) in their social media activity on Facebook, they may benefit from interacting with nonusers and infrequent or competitive users on social media.

The 30% share of revenue Facebook currently gets from developers of apps/games is mostly generated from the sale of virtual goods associated with apps/games. Facebook does offer a range of games that is exclusive to Facebook and traction is building up for Facebook apps/games as evident from the rising share of this revenue stream from developers over the years. The social networking context enhances the use of apps/games. Users can easily choose to play multiplayer games on Facebook with the help of information on what games their friends are playing. Still, apps/games offer benefits that are distinct from the main fare of OSN on Facebook and this warrants additional considerations for market segmentation. The segment of users that generates profits may differ from the segment that generates profits from marketers and also from the segment that engages with the Facebook OSN.

Proposition 2

Extent of use and engagement are key basis variables on which we may effectively segment Facebook users. These basis variables, in general, are useful and important for market segmentation of users not only for the Facebook Company but also for its affiliate marketers and developers.

What this simply means is that rate of use and levels of engagement are not only effective basis for behavioural segmentation of users by the Facebook Company but also for a marketer/business affiliate like ICICI Bank, a leading business user of Facebook in segmenting its customers. Such a segmentation scheme may help move the bank's customers from infrequent user of social app of the bank to frequent user and finally to engaged user. In fact driving engagement is high on the bank's agenda in its official social strategy. There is merit in maintaining consistency on basis variables like this because there is more commonality than difference in the context. A customer of ICICI Bank who uses Facebook occasionally would be difficult to engage with on the SNS platform. A frequent user is more amenable and likely to engage with and an engaged user even more so.

A marketer/business which mainly advertises on Facebook for sales, however, may need to use basis variables such as click through rate of user for category advertisements and related purchase rate and value. The marketer-user interface is more complex than what it is in the preceding example because of the variety of ways in which the interaction may take place between a marketer and user. Nevertheless, we may choose to segment users into infrequent, frequent and engaged users to our advantage. We are aware from published data that only a small fraction of Facebook users use or respond to marketing communications from affiliate marketers either in the form of advertisements or posts from their business pages. Even among fans or those who have liked brands/marketers on the web and so are connected to their business pages on Facebook, less than .05% respond to posts from the brands/marketers. Here we can employ measures such as number of responses to marketing stimuli or communication in a day/week/month as a measure of frequency of use and extent of behaviour such as displaying, sharing, tagging, spreading or participating in brand activity as a measure of engagement. This way of segmenting users with respect to Facebook, marketers and developers is particularly meaningful because, to a considerable extent such grouping may hold good across categories.

Developers of apps/games may also use the infrequent – frequent – engaged paradigm of segmentation. For them, engaged may include those who generate positive word of mouth or recommendations on top of frequent use. To incorporate the profit potential angle better, purchase of virtual goods may be factored in as a necessary condition for engagement.

There are three cross-side interactions; Facebook – user, marketer – user; and developer – user. The second and third interactions generate revenue and the first makes it all possible though it doesn’t directly generate revenue in the current business model. For each of these interaction type, we may classify users to be in 3 possible states – infrequent user, frequent user (who is low on engagement), and engaged user (frequent user who is high on engagement).

In the Facebook-user interaction, we may notice a progression from infrequent to frequent to engaged state. Behaviourally, this makes sense as a system of segmentation. Facebook drives numbers (penetration and even better adoption numbers) and then usage rate (frequency and also duration) and finally engagement (behavioural and attitudinal). Here, we must note that even a low frequency of 2/3 times a month for 5 – 10 minutes is of value to Facebook. Weak ties (Granovetter 1973) are of value to people. The frequent or everyday users value Facebook more because they can interact with these less frequent or infrequent users through Facebook. The very presence of the infrequent adds value. Without them, frequents shall be lower in number and may be less frequent in usage than they are now. A finer point is infrequent versus irregular or occasional users. Those who find time to use Facebook once every week (albeit for only 15 minutes) are regular though the periodicity is low. They are likely to be of greater value to Facebook than those whose average is 1.5/2 visits (of similar duration) a week but irregular (5 times in some weeks and 0 times in other). The former can be more predictably reached for communication/interaction through Facebook than the latter.

Proposition 3

(3a) The interests of Facebook Company, marketers and developers may converge for some while it may diverge for other segments. Tradeoffs are called for where they diverge.
(3b) Positive (negative) cross-side network effects can facilitate convergence (divergence).
(3c) There are synergistic interactions that facilitate convergence.
(3d) Multi-homing facilitates divergence.
(3e) The greater the convergence (bilateral or trilateral) the higher is the profits.

Developers may care about externality such as which users spend on apps/games and not how many users of the SNS are there or even who are the engaged users of the SNS. Marketers are concerned about whether a user is ready to connect, respond or engage with them. (The click through rate or CTR is around .05 % according to 2011 Webtrends report, but these are opt-in prospects unlike in conventional media.) Some users may have negative externality towards advertisements while others may view it positively. This may be a key basis for segmentation for marketers. The platform provider or intermediary Facebook is of course concerned about driving adoption, use and engagement to build a user base that can be used as an asset.

The benefits or value propositions of the Facebook OSN platform, marketers and offerings of developers are distinct from each other though they share the social context of Facebook. A social shopper looking for deals or offer on Facebook has an interest that may be relatively independent of his or her interest in apps/games or in the OSN fare of Facebook. On the other hand, using/playing apps/games may be enhanced and made more interesting because of the social context afforded by the OSN. One can identify and choose playmates from among friends for playing games on Facebook. One can find fellow hobbyists who may help choose apps that relate to the hobby. These are instances where there is synergy between different cross-side interactions. Like in a mall, customers frequent some shops more than others; Facebook users may frequent some options more than others. Like in a mall however Facebook can benefit more if users frequent a wider range of offerings on the platform across OSN, marketers and developers.

Convergence and Divergence of Interests

Segment	combination	Facebook Co	Marketers	Developers	size	Remarks	Imp
1	F1 M1 D1	#	#	#	8	sparse	
2	F1 M1 D2	#	#	√	6	sparse	
3	F1 M2 D1	#	√	#	7	sparse	
4	F1 M2 D2	#	√	√	5	sparse	
5	F2 M1 D1	√	#	#	4	potential	*
6	F2 M1 D2	√	#	√	3	niche	*
7	F2 M2 D1	√	√	#	2	lucrative	*
8	F2 M2 D2	√	√	√	1	cream	*
	Possible segments of interest	5, 6, 7 & 8	3, 4, 7 & 8	2, 4, 6 & 8			

F, M and D followed by 1 are infrequent in use or response to marketers or using apps/games.

Table 1

We may develop a theoretical market segmentation scheme (Table 1) based on convergence and divergence of interests of the 3 business users or parties as follows. For a simple exposition in the table below, we divide users into two groups for each party - √ (2) for frequent and # (1) for infrequent. Here, SNS user is divided into F1 and F2. For marketers, users are divided into M1 and M2 and for developers D1 and D2. We may say 2 is the more responsive or frequent in use segment and 1 the less so. This can be easily extended to the 3 groups case with frequent subdivided into engaged (frequent and engaged) and frequent (with low engagement).

The profitable segments according to Facebook's current business model may very well be 8, 7 and 6 (in that order) which frequently respond to marketers' communications (ads or posts). Or use apps/games frequently. It is interesting to note that segment 5 that consists of frequent users of Facebook contributes little to Facebook's revenue because they are infrequent in their response to marketers' communications or apps/games on offer. A fraction of such frequent users of Facebook who are engaged with Facebook however may be receptive to a freemium model as discussed elsewhere in this paper. Even if they cannot be monetized directly, they do contribute towards same-side network effects. Besides, the social media space is evolving at a fast pace. Therefore, usage and engagement behaviour are in a state of flux and more often than not on the ascendancy.

The differences among the segments can be partly explained by network effects – same side and cross side network effects. Segment 8 is likely to be benefitting from cross-side network effects. A strong user base with varied interests and higher on the social media ladder (Bernoff 2010) can raise frequency of interaction with all 3 parties. Segment 1, 2, 3 and 4 are likely to be sparse in users. It is implausible that that users visit Facebook for marketing communications and/or apps/games alone and not for the main fare of OSN. These segments may be rather uninhabited.

Multihoming may facilitate divergence because, it provides more competing options. So because a Facebook user multihomes, she picks what is best for her at Facebook and goes for G + or LinkedIn for a feature/affordance that is best there. Let's say, she may choose to use OSN at Facebook and apps/games at G +.In the absence of multi-homing, perhaps, engagement with Facebook's SNS would automatically pave the way for using apps/games on Facebook unless G + has a big edge in apps/games and she gets to know that. For the Facebook Company as well as the marketers, developers and users it would be very useful to understand the factors, controllable and uncontrollable, that drive convergence and divergence. If they can orchestrate convergence as a team, the system as a whole optimizes.

Proposition 4

If a Facebook user is more engaged with Facebook compared to any other media (SNS or otherwise) through which a marketer or brand can reach him or her, then it may be better for the marketer or brand to engage with him or her on Facebook than on any other media provided cost or other strategic considerations do not outweigh the benefits.

Corollary

(a) The engaged segment of Facebook users is the prime target for marketers.
(b) Ceteris paribus, an engaged user has higher customer lifetime value (CLV) to a marketer compared to the non-engaged.

The engaged segment shows engagement attitude and behaviour (Van Doorn 2010) beyond the act of using Facebook for OSN. In addition to being frequent users, they have greater attachment and readiness to involve themselves in activities related to Facebook. They have stronger commitment or continuance intention. Often, this is backed up by a clear preference over competing offerings. They may have positive emotions such as love towards Facebook. They are less price sensitive with Facebook. If they enjoy being on Facebook more than in other media, then Facebook is the best place to try to engage them with conversations about the marketing content or propositions and start driving engagement for the brand or company. For example, if a customer uses Facebook as well as LinkedIn for equal length of time a day, the marketer may choose one SNS over another on the basis of extent of engagement and fit of the SNS with the product. As Barwise (Barwise 2010) points out Facebook may not be the best place to drive purchase, but provided you already have customers who have experienced your products, Facebook may be among the best places to drive engagement. Proposition 4 posits that this is more so when the customer is engaged with Facebook as a SNS.

On the other hand, irregular users of the SNS may be difficult to engage with on Facebook though such users may be good customers of the concerned marketer already. For a SNS user to be an appropriate target for marketing, regular (does not mean frequent; two days a week is regular but not frequent) use is a necessary condition for effective reach and the fact that the user is a prospective or existing customer of the marketer's offerings may be the sufficient condition. The preferred medium may facilitate higher level of engagement though there may be exceptions to this general rule. We may also note that increasingly the media space is getting integrated by social and related technologies with people reading news on online apps and viewing TV programs in social context. With social technologies enmeshing and even integrating mainstream media such as TV programs, print and electronic, social may be the key to more effective engagement in any medium. This is primarily because of the interactive features of social media and its superior connectivity. People can like, comment on, curate, tag, share and spread the content they consume in different media during the day. They can do so with content elsewhere through Facebook.

Trade literature on Facebook and social media marketing already talk about 'value of a fan.' In general, it is plausible that value of a user to a marketer, among other things, is a function of the rate of use of Facebook's SNS and level of engagement with it. There is likely to be interaction effects – higher the use and engagement with SNS, greater the response to marketing stimuli and engagement with marketers on Facebook platform.

Proposition 5

These are propositions that may help identify characteristics of user segments that interest marketers (Lee et al 2011) and developers on Facebook. Some of them delineate key interdependencies.

(5a) Users who do little multihoming (say less than 20% share of total time spent on SNS is on platforms other than Facebook) would tend to use apps/games on Facebook more often than those who do more muti-homing.

(5b) those who rate and review products online such as at amazon.com would tend to 'like' and engage with brands/marketers on Facebook more than those who do not.

(5c) Connecting with marketers is independent of using apps/games

(5d) Value of purchase in response to advertisements on Facebook is independent of purchases from developers of apps/games.

Consumer behaviour literature in marketing (Lilien, Kotler and Moorthy 2004) observes that a large share of consumer choices is made using satisficing rather than optimizing heuristic. Time and monetary cost of search for alternatives and processing of information to evaluate fresh alternatives may inhibit and restrict the consideration set as well as choice set. Search and cost is lower for those who multi-home (also use other platforms or media that provide similar range of SNS plus market offerings plus apps/games). Like people have a limitation in the number of malls they would visit for shopping every month, they may limit themselves to only few platforms where they get substitutes or alternatives to what they get on the Facebook platform. Because multihoming increases readily available alternatives and lowers search costs, it may lead to lower convergence - one may use the Facebook SNS more but use apps/games mostly on Google + and engage with marketers/brands usually on Twitter.

As observed in Forrester's ladder of profiles for social media users, there are strong interdependencies in behaviour across social platforms. Findings of our pilot study for the empirical research also shows association between reading and commenting on blogs and SNS use. It is plausible that those who rate and review products online are more frequent online buyers and so may tend to engage with marketers more on Facebook.

Apps/games tend to be very different in functionality and benefit from responding to a marketer's ads or engaging with brands on Facebook (barring a few overlaps). There may be a segment of young who are not involved in household purchases but have the pastime of playing games for hours on Facebook every day.

It may be possible to identify some of the key factors that give rise to positive (negative) cross-side externalities and so cause convergence (divergence). Secondary trade/industry literature on Facebook and social media may yield hypotheses and insights of value in this direction.

Market Segmentation: Empirical Study

In this section, I present the findings of an empirical study to develop a market segmentation strategy for Facebook. This is based on around 261 (50 pilot and 211 in final round) responses from current and past students of Indian Institute of Management Bangalore, a premier business school in India. (Link for IIM B Facebook Study* Questionnaire: https://qtrial.qualtrics.com/SE/?SID=SV_ahlxGCTWQEyk4mN). The study gathers information on user characteristics, use and engagement. Variables of interest for the market segmentation study may be outlined as follows.

User Characteristics

Demographic Profile:

gender, age, marital status, stay alone or with family, mother's employment status, price of your mobile, proximity (% Facebook friends who stay within 5 km of your place of stay), program/category

Behavioural Profile:

active OSN accounts (Twitter, Google +, LinkedIn and Facebook), recency of activity on leading (4) OSNs, level of social media category activity such as blogging/skyping, devices for accessing Facebook, online hrs, years with Facebook, range of people in Facebook network, share of OSN for time pass, flow

Attitudinal Profile:

perceived benefits (14) such as association with social influence or satisfying social curiosity, subjective norms such as whether Facebook perceived as more for teenagers than adults, perceived behavioural control such as whether use of Facebook is effortful, values, personality, stated share of time, competitive share, share of *time pass* activities, priority, concerns (negatives such as privacy and security)

Other correlates of Facebook use:

network externality (n_ext, #close friends in facebook network), psychographic correlates such as preference for outdoor versus indoor leisure activity, physical versus mental activity, whether they experience flow while working online.

Use

recency of using OSN accounts, functional measures (type and rate) for like, comment, status update, follow, album and apps/games; # mobile visits in last 24 hrs, # login/ visits a day, minutes a day, average minutes a visit # Facebook Friends, # Facebook groups, # close friends who are on Facebook, self rating as a user of Facebook: extent, range of features and proficiency, years with Facebook, % opp sex on Facebook , % within 5 km of place of stay

*This survey was carried out as part of a multi-purpose research by the author along with Praveen S. and Tushar Tanwar in May 2013 at IIM Bangalore. The sample size of 261 excludes 17 respondents who reported not having active Facebook accounts.

Engagement

habituation or daily routine, continuance intention, feeling of being out of touch without access, anxiousness without , love, need to deactivate, worry (negatives) brand equity/price sensitivity

I have used a repertoire of analytical techniques to design and evaluate a range of segmentation schemes. I have used simple tools like cross tabs and classification trees and also more involved techniques like discriminant analysis, logistic regression, cluster analysis (K means and Two step), and artificial neural networks (ANN). These investigations help identify the underlying segment structures that leaves little room for doubt on what should be the basis for effective segmentation and what descriptors or independent variables may help access the resulting segments. Some of these techniques help predict the basis or dependent variables on the basis of data on a few independent variables or descriptors. Interestingly, there is a lot in common in the outcomes from the different analyses in terms of segment structures. We present segmentation scheme I below based on cross tabs to begin with because in a simple way it captures the essential structure comprehensively.

Segmentation Scheme I: Cross Tabs and Two Step Cluster

Segmentation Scheme I

Segment	X: Engaged User	Y: Frequent User	Z: Infrequent Users
Basis	frequent use & high engagement	frequent use & low engagement	infrequent use
Basis Variables	(f_24* = 1 & ps_1a = 1)	(f_24 = 1 & ps_1a = 0)	(f_24 = 0 & ps_1a = 0/ 1)
Size (%) (N=211)	29.4 (62)	49.3 (104)	21.3 (45)

Table 2A

*f_24 is whether used F (F stands for Facebook) site for at least 5 minutes in last 24 hrs – 0 for No & 1 for Yes; ps_1a is whether likely to continue using F if a monthly rent of $1 is charged from tomorrow (0/1 scale)
Cross Tab: f_24~ps_1a : Chisq = 9.349, df = 1, p-value = 0.002231

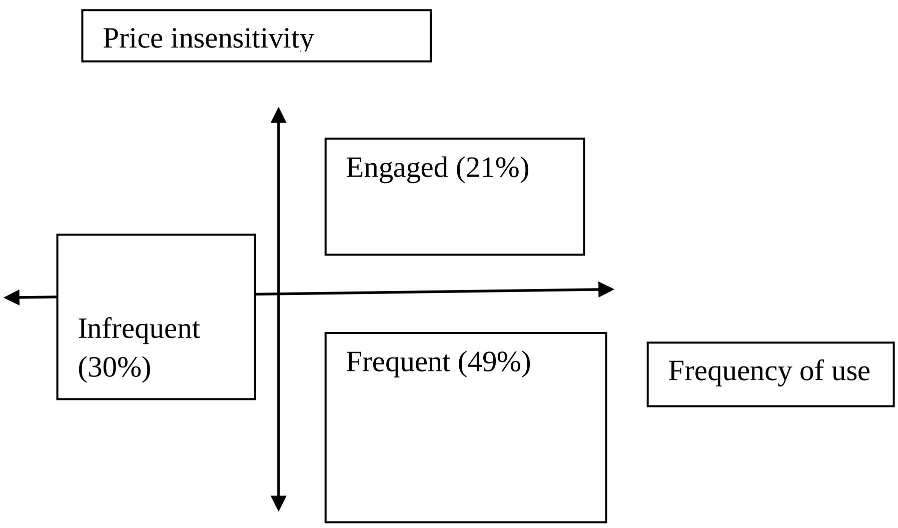


Figure 4A

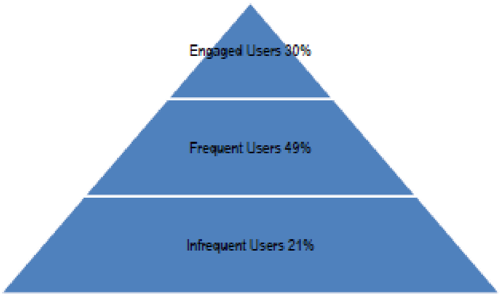


Figure 4B

As shown in Table 3A and Figure 4A, frequency of use and engagement can segment the users into 3 groups – infrequent, frequent and engaged. Here, the engaged group is different from the frequent group in terms of its low price sensitivity or relative insensitivity to price rise. Segment Y Frequent denotes frequent in use but price sensitive (or not engaged) in the figure above. Here frequency is measured in a categorical scale by whether respondent accessed Facebook at least once for more than 5 minutes in last 24 hrs. This measure was verified to be more objective and reliable than other measures on the basis of triangulation. Engagement is measured in terms of whether the respondent is likely to continue using Facebook if a monthly rent of $1 is charged from tomorrow. This is also a 0/1 scale. The triangle in Figure 4B showing the % distribution of users in segments signifies a hierarchy (or progression) in terms user's intensity and engagement with Facebook. The sample used for the above computations excludes people who do not have an active Facebook account. I show the segment structures as delineated by a wide range of segment descriptors below in two tables. (Whether the descriptor significantly contributes to heterogeneity across the 3 segments is shown in terms of superscripts a, b, c or *.)

Metric Scaled Descriptors:

	Descriptors for Segment	Engaged Users	Frequent Users	Infrequent Users
	Metric (mean) measures	$X^{\#}$	Y	Z
1	curious	3.61^{a}	3.51^{a}	2.82^{c}
2	interesting	2.87^{a}	2.69^{a}	2.24^{c}
3	time pass	3.96^{a}	3.94^{a}	3.44^{c}
4	in touch	3.21^{a}	2.77^{b}	2.09^{c}
5	love	3.61^{a}	3.04^{b}	2.53^{c}
6	daily routine	3.76^{a}	3.54^{a}	2.04^{c}
7	continue	3.97^{a}	3.67^{a}	3.09^{c}
8	anxious	2.58^{a}	2.3^{a}	1.56^{c}
9	useful for career/business	3.02^{a}	2.86^{a}	2.42^{c}
10	open online	3.18^{a}	2.8^{ac}	2.58^{c}
11	more for teens than for adults	2.58^{a}	3.05^{bc}	3.33^{c}
12	trivial or frivolous	2.95^{a}	3.28^{ac}	3.53^{c}
13	priority_o	3.11^{a}	2.95^{a}	2.33^{c}
14	priority_f	2.84^{a}	2.65^{a}	1.80^{c}
15	tp_general	19.07^{a}	26.47^{b}	22.24^{ab}
16	SNS share of time pass (%)	20.25^{a}	16.48^{ac}	10.14^{c}

17	share of time of F (%)	68.69^{a}	64.97^{a}	37.87^{c}
18	share of time of L (%)	18.63^{a}	20.0^{a}	34.02^{c}
19	F mobile visits (last 24 hrs)	4.03^{a}	3.54^{a}	$.60^{b}$
20	# F groups	9.35^{a}	7.81^{a}	3.31^{b}
21	# F friends	555^{a}	491^{a}	244^{b}
22	F minutes a day (average)	56.97^{a}	43.94^{b}	15.71^{c}
23	like	3.95^{a}	3.67^{a}	1.53^{c}
24	status update	2.27^{a}	1.71^{b}	1.02^{c}
25	comment	3.55^{a}	2.88^{b}	1.33^{c}
26	follow	2.94^{a}	2.38^{a}	1.00^{b}
27	album	2.21^{a}	1.63^{b}	1.11^{b}
28	chat	3.03^{a}	2.25^{b}	$.82^{c}$
29	apps/games	1.02^{a}	$.84^{ac}$	$.44^{c}$
30	use rate (self rate)	5.16^{a}	5.0^{a}	2.13^{c}
31	use range (self rate)	4.0^{a}	3.63^{a}	1.8^{c}
32	use proficiency (self rate)	5.85^{a}	5.19^{a}	3.69^{c}
33	authentic	2.56^{a}	2.29^{ac}	1.93^{c}
34	t_mins (%)	7^{a}	8^{a}	16^{c}
35	g_mins (%)	5^{a}	6^{a}	13^{c}

[#] If two segments share a superscript a/b/c, difference is not statistically significant ($\alpha = .05$). Else, the difference is significant. In 33 and 34 above, segments X and Y are not different, but Y and Z are not different in 33 and different in 34.

Table 3B

Non-metric Scaled Segment Descriptors

	Categorical (%)	X	Y	Z
1	d_m** (use f mobile)	77.4	63.5	46.7
2	blog_c** (comment on blogs)	21.0	30.8	4.4
3	l_24**(used LinkedIn in 24hrs)	45.2	32.7	13.3
4	m_games** (plays games on mobile)	66.1	51.0	35.6
5	e-chat***	88.7	81.7	46.7
6	father on F^{ns}	25.8	19.2	11.1
7	mother on F^{ns}	21.0	10.6	15.6
8	spouse on F^{ns}	37.1	44.2	55.6
9	partner on F* (overall 20.4%)	27.4	22.1	6.7
10	pro_acq^{ns}	80.6	75.0	66.7
11	female^{ns} (overall 21.3%)	12.9	22.1	31.1
12	marital*** (overall 51.2%)	41.9	46.2	75.6
13	stay alone*	51.6	53.8	31.1
14	age (>35)**	14.5	17.3	40.0

χ^2 significant at * $\alpha = .05$ ** $\alpha = .01$ *** $\alpha = .001$ ^{ns} not significant

Table 3C

The segments or clusters are described in detail in Table 3D below.

Segment Description

Segment X **Engaged User (30%)**	Segment Y **Frequent User (49%)**	Segment Z **Infrequent User (21%)**
<u>Profile</u> Engaged users (X) average 57 minutes a day on Facebook. These are frequent users who are higher (refer preceding table) than segment Y and Z on engagement variables such as (a) love Facebook (b) intend to continue using it for a long time (c) use it as a daily routine (d) feel out of touch in a while without Facebook, and (e) Facebook use is not a low priority activity. Importantly, segment X is relatively price insensitive unlike Y and Z who are likely to discontinue using it tomorrow if a rent of $1 per month is charged per account.	Frequent users, averaging 44 minutes a day on F, are comparable to segment X on rate, range, proficiency and priority of Facebook use, but their use differs qualitatively as well as in total duration. They are as responsive as engaged users on Facebook on activities such as *like* and playing games but significantly less frequent on a range of initiatives such as status updates, use of album, comment and chat. They score lower than the engaged users on most engagement variables (see under X on the left). It is likely that Facebook is not integral to their basic social activities such as keeping in touch with friends, relations and acquaintances.	With an average of 16 minutes of use a day, Facebook is not a daily habit for segment Z. They are lower on frequency of use and engagement. They have less than half as many friends and groups on Facebook compared to segment X and Y. For them social media and OSNs have lower priority in a day's activity. Only a few of them access Facebook on the mobile. A higher proportion of segment Z are married, stay with family and are older; factors that probably lower the use of OSNs and Facebook . Some of them may be infrequent or lower in duration of use because they use G + or LinkedIn or Twitter longer than X and Y (see preceding table). Subjective norms may be a strong reason for infrequent use. In Z, a higher proportion thinks it is trivial and more appropriate for teenagers. A high 60% of Z is uncomfortable exposing thoughts online.
<u>Frequency of use</u> Frequent use is a necessary but not sufficient condition to be an engaged user. 37% of frequent users constitute the engaged users of segment X.	63% of frequent users constitute segment Y; these frequent users are low in engagement. They are price sensitive compared to X. Perceived value may be lower.	Around 58% of infrequent users used it at least for 5 minutes in last 1 week and 24% have done so between a week to a month.
<u>Engagement</u> For 29%, OSN is low priority, for 45% F is low priority, for 69% daily routine, 81% have continuance intention, 21% become anxious without it, 53% feel out of touch if they miss out on F for a while; and reportedly, 56% love Facebook.	For 42%, OSN is low priority, for 50% F is low priority, for 63% daily routine, 66% continuance intention, 16% anxious without it, 29% feel out of touch in a while without it, and 28% love Facebook. None are willing to pay $1 a	For 69% OSN is low priority, for 84% F low priority activity, for 7% daily routine, 42% intend to continue for long, 2% anxious without it, 13% feel out of touch in a while without it, and only 7% say they love Facebook.

All willing to pay $1 a month.	month for using Facebook.	
<u>Demographics</u> 42% are married (sample % is 51) young (85% are 35 or less) 52% stay alone (away from family)	46% are married young (83% are 35 or less) 54% stay alone	76% are married old (60% are 35 or less) 34% stay alone
<u>Subjective Norms/Beliefs</u> 21% think F is more for teens, 31% find it trivial, for 48% it is more stylized self-presentation than authentic socializing, and 31% not comfortable exposing thoughts online	34% think it is more for teens 41% find it trivial 66% find it less authentic 49% uncomfortable opening up online	47% think it is more for teens 49% think it is trivial/frivolous 80% more stylized self-present, 60% not comfortable exposing thoughts online
<u>Behavioural</u> 8 out of 10 use F mobile interest in social media and SNS is higher for segment X 89% chat on internet 21% read and comment on blogs 66% play games on mobile 45% used LinkedIn in 24 hrs Facebook gets 69% of time for SNS (F,L, G+ & T) 39% find it useful for career/business Features or affordances of Facebook that the engaged segment use more often than the frequent segment are: status update, comment, album and chat. On use of apps/games, X and Y are comparable. (see metric descriptors table 3B for more details)	6 out of 10 use F mobile larger share of SNS in time pass for X and Y than Z 82% e-chat 31% read and comment on blogs 51% play games on mobile 33% used LinkedIn in 24 hrs Facebook gets 65% of SNS time 24% find it so for career/business Rate, range and proficiency of use is remarkably higher for the engaged and frequent segments compared to the infrequent – it's more than twice (refer table 3B).	5 out of 10 use f mobile priority of OSN and Facebook falls from segment X to Y to Z 47% e-chat 4% comments on blogs. 36% play games on mobile 13% used LinkedIn in 24 hrs Facebook gets 38% of SNS time, LinkedIn, Google + and Twitter get more time in this segment 16% find it so for career/business Frequency of use is significantly lower for almost all types of features or affordances.

Table 3D

In this model of segmentation, we are taking into account only people with active Facebook accounts. While these segments suggest a hierarchical progression in the pyramid (Figure 4B) , such progression may be true only for some of the users. Many users may choose not to go all the way up like in the case of the brand equity (Keller 1993) model. This may be because of level of interest in the SNS subcategory or preference for competing SNS or subjective norms (Ajzen 1991) that limit use and attachment. Being married or staying with family may lower the need for socialising on SNS because of factors such as proximity, intimacy and privacy.

From the point of view of Facebook Company, marketers and developers, the objective is to move users up this pyramid – higher the number of engaged users, the better. There are however qualifications. We see that the segment of engaged users has more varied usage and uses apps/games significantly more than the infrequent user segment but not necessarily more than the frequent user segment. It is possible that some specific apps/games have more takers among frequent users than among engaged users. These are people who may visit Facebook more for using some apps/games than for the main fare. Similarly, a greater share of engaged users than frequent users may be averse to advertisements and marketing communications from marketers on Facebook. So some marketers may find the segment of frequent users more engaging than the segment of *engaged users of Facebook*. The current study however cannot validate these propositions adequately.

Interestingly, a Two Step clustering procedure in SPSS that used 4 significant basis variables (the SPSS term is input features); in touch (feel out of touch in a while without Facebook) and adult (not more for teeanagers than for adults) apart from f_24 and ps_1a, yielded the same segmentation scheme as the preceding segmentation scheme I. The silhouette measure of cohesion and separation below shows that the market segmentation solution is good enough in terms of validity and reliability.

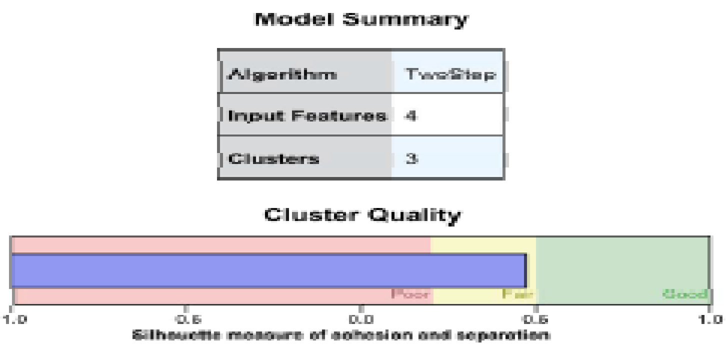


Table 4A

Cluster	2	3	1
Label	Frequent	Engaged	Infrequent
Description	Similar to Frequent in Scheme I	Similar to Engaged in Scheme I	Similar to Infrequent in Scheme I
Size	49.3% (104)	29.4% (62)	21.3% (45)
Features	f_24 1 (100.0%)	f_24 1 (100.0%)	f_24 0 (100.0%)
	ps_1 binary 0 (100.0%)	ps_1 binary 1 (100.0%)	ps_1 binary 0 (73.3%)
	in touch 2.77	in touch 3.21	in touch 2.09
	adult 2.95	adult 3.42	adult 2.67
Evaluation Fields	d_m 1 (63.5%)	d_m 1 (77.4%)	d_m 0 (53.3%)
	blog_c 0 (69.2%)	blog_c 0 (79.0%)	blog_c 0 (95.6%)
	marital 1 (53.8%)	marital 1 (58.1%)	marital 2 (75.6%)
	age 30.60	age 29.94	age 35.11
	m_price 16.17	m_price 18.17	m_price 17.11
	status_update 1.71	status_update 2.27	status_update 1.02

Table 4B

Segmentation Scheme II: Two Step Cluster

We add one more basis variable status update rate to scheme I for a 4 cluster solution.

Model Summary

Algorithm	TwoStep
Input Features	3
Clusters	4

Cluster Quality

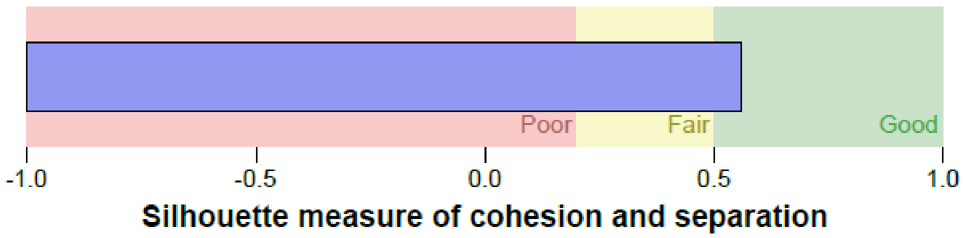


Table 5A (above) and Table 5B (below)

Clusters

Feature Importance
1.0 0.9 0.8 0.7 0.6

Cluster	1	2	3	4
Label	Frequent	Infrequent	High Initiative	Engaged
Description	Similar to the frequent in scheme I but lower in s_up rate	Similar to the infrequent in scheme I	This new group is qualitatively different in use	Similar to the engaged in scheme I but lower in s_up rate
Size	40.8% (86)	21.3% (45)	20.9% (44)	17.1% (36)
Features	f_24 1 (100.0%)	f_24 0 (100.0%)	f_24 1 (100.0%)	f_24 1 (100.0%)
	ps_1 1.50	ps_1 1.80	ps_1 2.80	ps_1 3.40
	status_update 1.15	status_update 1.02	status_update 4.09	status_update 1.11

Segmentation Scheme III: K Means Cluster

We use the K Means clustering algorithm in SPSS to arrive at a 4 cluster solution as follows. This scheme has a similar pattern as segmentation scheme I above. Here, we have taken Likert scaled variable daily routine instead of the binary variable f_24 (whether used in last 24 hrs) and price sensitivity on 4 point bipolar scale. This restructuring reveals a segment of attached users who may not use every day yet are relatively price insensitive. This may be due to more attitudinal loyalty than behavioural.

Final Cluster Centers (Scheme II)

	Cluster			
	1	2	3	4
intouch	2	4	2	3
ps_1	3.0	3.2	1.3	1.6
daily routine	2	4	2	4
sensible	3	3	2	3

Tables 6A

Segment*	%	Description of profile
1 Light but loyal user	19	Not a daily routine for most, yet attachment is high, tends to use Facebook less for keeping in touch with friends than those in cluster 2 and 4. Unlike cluster 2, does not find Facebook a trivial or frivolous activity. Likely to pay $1 a month to use a Facebook account.
2 Engaged user	21	Daily routine and high engagement, habituated to Facebook use for keeping in touch with friends, finds Facebook activities meaningful and serious rather than trivial or frivolous. More likely than the other 3 groups to pay a price for using the Facebook account.
3 Infrequent user	22	Not a daily activity and low in engagement, doesn't feel out of touch when s\he misses out on Facebook for a while; Facebook is a trivial activity. Unlikely to pay even $1 a month towards using a Facebook account.
4 Frequent user	38	It's a daily routine, but engagement is low, Facebook is useful for keeping in touch but extent of habituation is limited, finds it sensible to use Facebook. Unlikely to pay even 1$ a month for use.

**Method of Extraction: K Means Clusters*

Table 6B

ANOVA

	Cluster		Error		F	Sig.
	Mean Square	df	Mean Square	df		
in touch	35.791	3	.714	207	50.123	.000
ps_1	47.792	3	.385	207	124.222	.000
daily routine	63.301	3	.430	207	147.170	.000
sensible	8.941	3	.741	207	12.070	.000

Table 6C

Segment Structure Analysis I: Decision Trees

Here I present some analysis of segment structures using classification trees. There two trees for f_24, the binary variable for frequent use and two more for the binary (transformed) price sensitivity variable. Evidently, it is easier accessing (or predicting) those who are frequent than those who are price insensitive. These trees help identify the influential descriptors for the given bases.

The following classification tree (Figure 5A) shows how the characteristics of users are structured and how frequency of use is influenced. We can see that the incidence of 79% of frequent users rises to 91% if we take the subgroup that tends to feel out of touch if they cannot use Facebook for a while. This may be endogenous due to reverse causality to an extent. Habituation drives frequency of use and vice versa.

If we consider only the unmarried the % rises from 91 to 95. If we consider among them only those who comment on blogs, the share of frequent users shoots up to 100%! The other variable that influences higher frequency of Facebook use is use of Facebook on mobile (d_m).

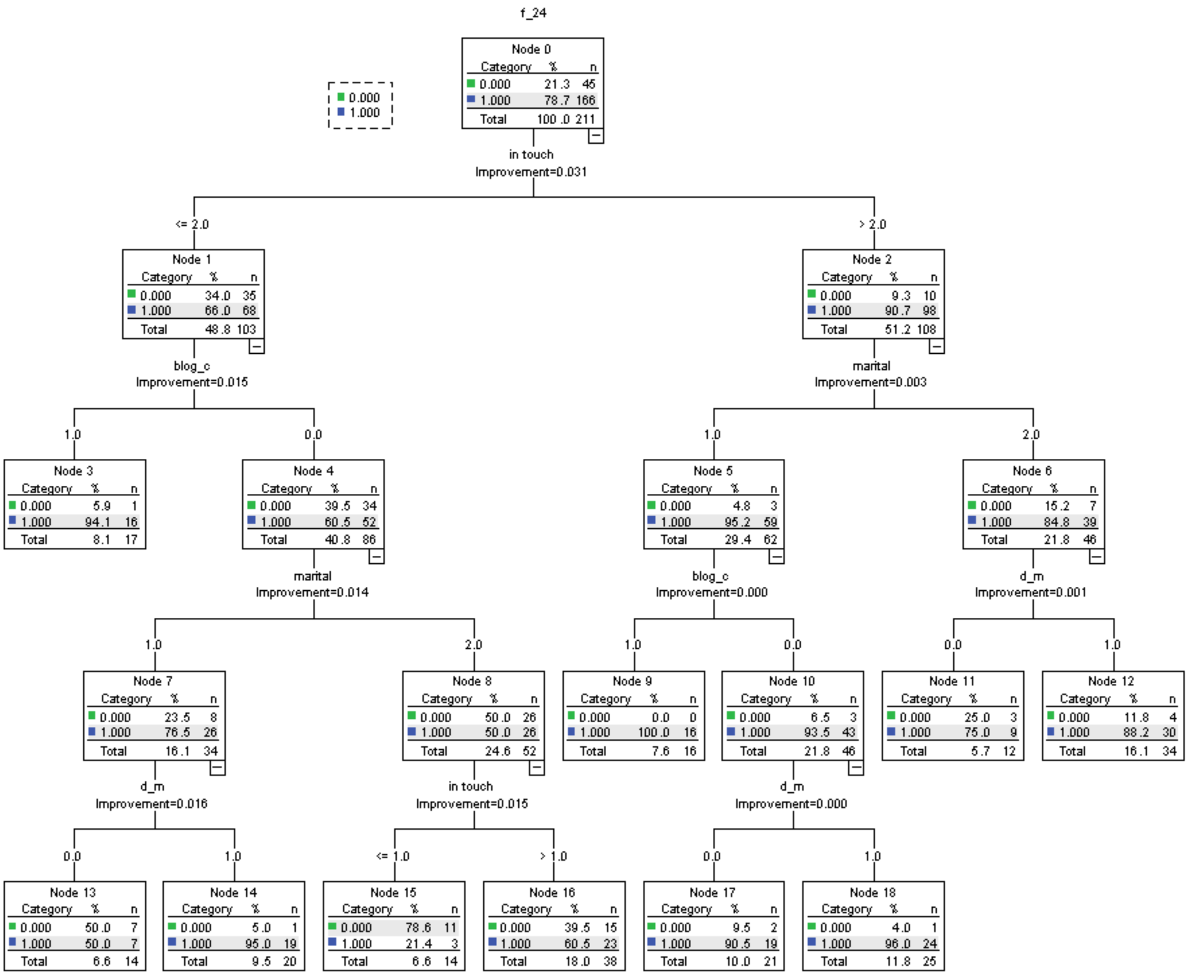


Figure 5A

Another variable of interest that influences frequency of use is extent of multi-homing – use of LinkedIn in this case. We can see in the tree in Figure 5B that while those who are habituated to be in touch with friends on Facebook and are married constitute 85% of the sample, all frequent users of LinkedIn (used at least once in last 24 hrs) out of this 85% are frequent users of Facebook also. The accuracy of prediction is 97% for frequent users of Facebook for this tree and the aggregate accuracy is 82.5% (a gain of 3.5%) as shown in the classification table.

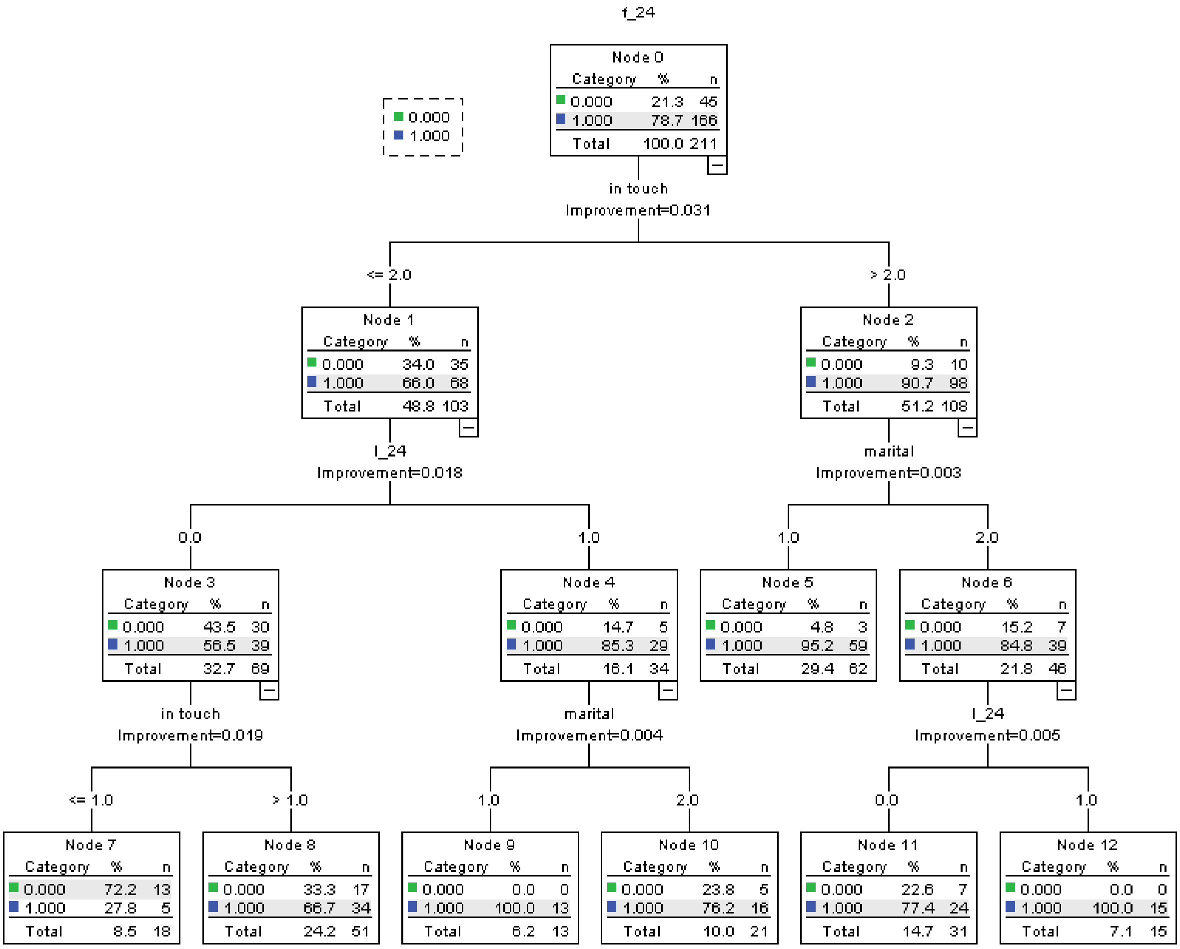


Figure 5B

Classification

Observed	Predicted 0	Predicted 1	Predicted Percent Correct
0	13	32	28.9%
1	5	161	97.0%
Overall Percentage	8.5%	91.5%	82.5%

Table 7A

The tree for binary price sensitivity variable ps_1a is lower on overall predictive accuracy as seen from the classification table 7B below.

Classification (ps_1a)

Observed	Predicted		
	0	1	Percent Correct
0	130	7	94.9%
1	60	14	18.9%
Overall Percentage	90.0%	10.0%	68.2%

Table 7B

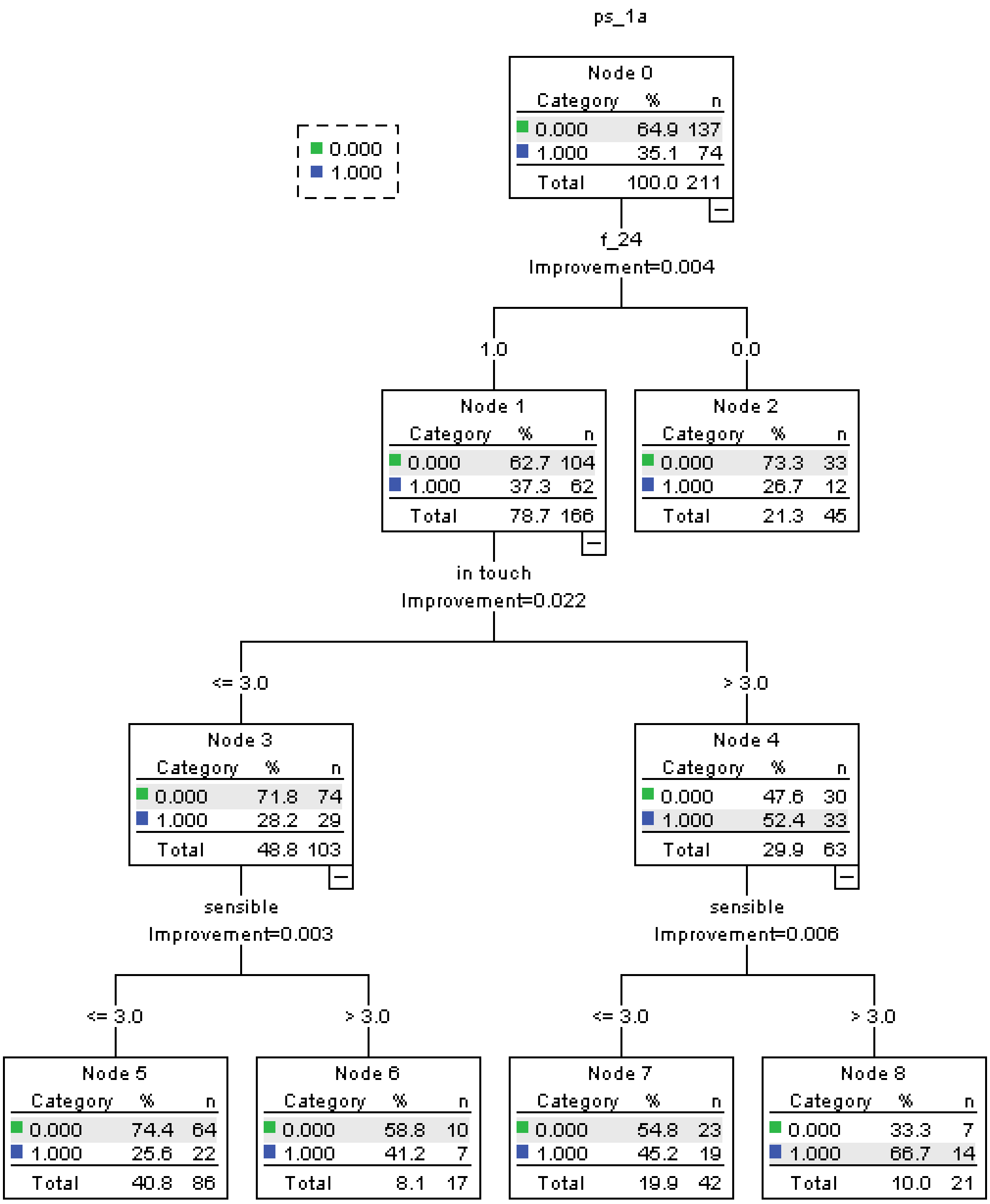


Figure 5C

Habit of keeping in touch and whether the user finds Facebook activities frivolous or sensible can considerably lower price sensitivity (Figure 5C). Though these two variables can accurately identify or access the predict price sensitives 95% of the time, they are poor in predicting the price insensitive. It implies that other conditions may need to be satisfied for a user to become price insensitive. Below are some others.

Classification (ps_1a)

Observed	Predicted 0	Predicted 1	Percent Correct
0	107	30	78.1%
1	37	37	50.0%
Overall Percentage	68.2%	31.8%	68.2%

Table 7C

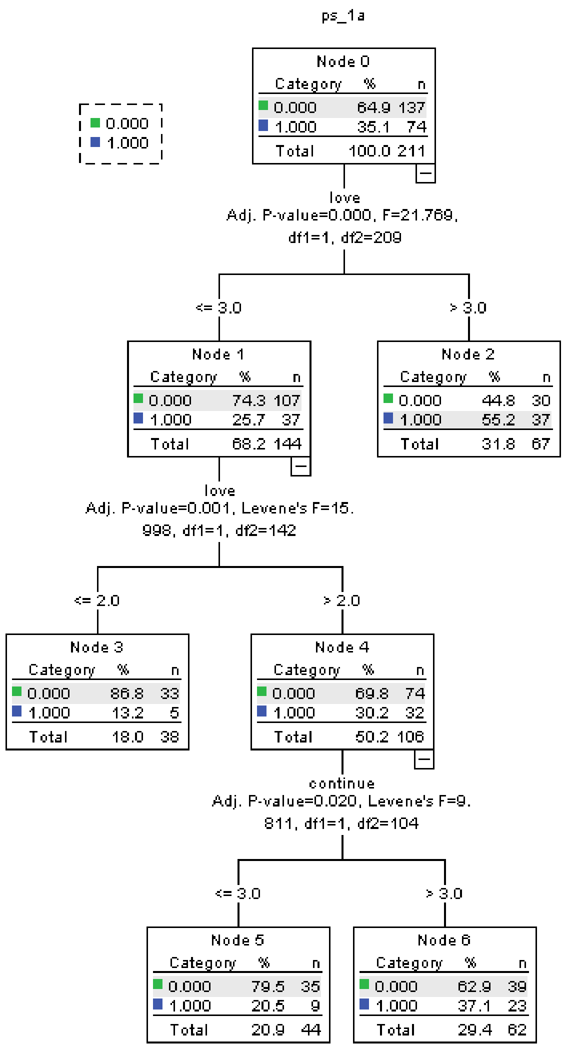


Figure 5D

Segment Structure Analysis II: ANN

Using Artificial Neural Network (ANN), I found that a few specific variables can help predict dependent variable frequent users (f_24 = 1) with an accuracy as high as 95% as shown below in Table 5A. The variables are shown in table 5B below. The overall accuracy of 86% in training as well as testing is also gain over the sample incidence of 79%. It is evident that multi-homing and alternate means or ways of keeping in touch strongly influences frequency of use.

A finer point is if you have used LinkedIn in last 24 hours, you are significantly more likely than others to have used Facebook also during the same time period. But, in the same case, you are significantly more likely to be price sensitive as well.

Classification

Sample	Observed	Predicted 0	Predicted 1	Predicted Percent Correct
Training	0	15	16	48.4%
	1	5	117	95.9%
	Overall Percent	13.1%	86.9%	86.3%
Testing	0	8	6	57.1%
	1	2	42	95.5%
	Overall Percent	17.2%	82.8%	86.2%

Table 8A

Independent Variable Importance (normalized)

	Importance	Normalized Importance
marital	.090	43.9%
adult	.168	82.3%
in touch	.174	85.3%
priority_o*	.204	100.0%
g_mins	.165	80.8%
l_mins	.199	97.2%

Table 8B

*reference for the importance index

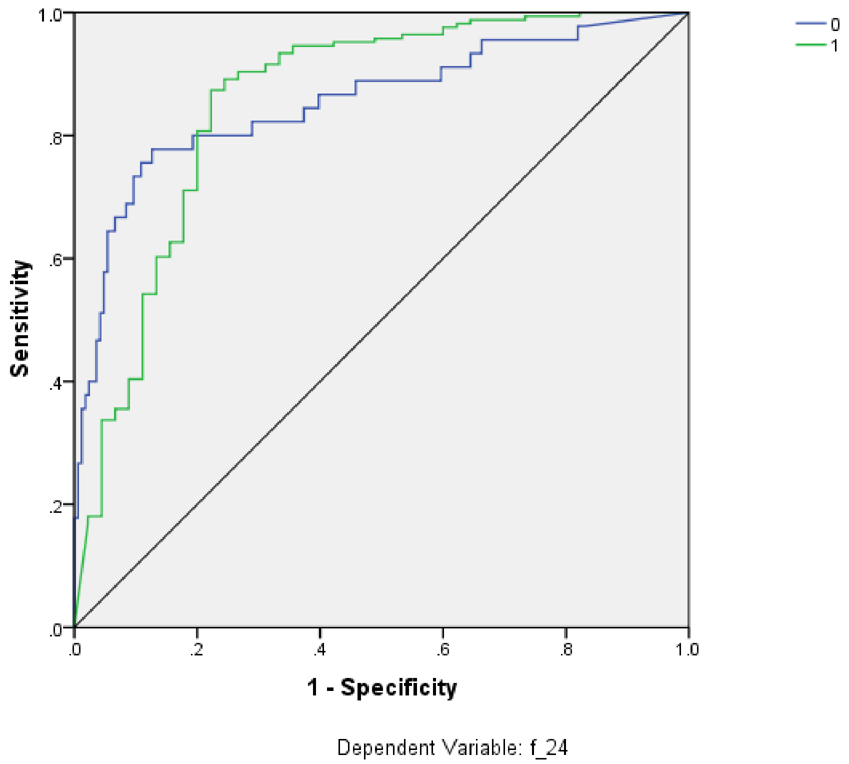


Figure 6A

Predicting price sensitivity with ANN is easier when we use adequate number of descriptors. We can get 84% accuracy in identifying the price sensitive as seen in the classification tree below. The area under the curve is .724. So there is a gain of 22.4% compared to a random process of prediction.

Classification

Sample	Observed	Predicted 0	Predicted 1	Predicted Percent Correct
Training	0	83	10	89.2%
	1	24	15	38.5%
	Overall Percent	81.1%	18.9%	74.2%
Testing	0	17	2	89.5%
	1	14	5	26.3%
	Overall Percent	81.6%	18.4%	57.9%
Holdout	0	21	4	84.0%
	1	12	4	25.0%
	Overall Percent	80.5%	19.5%	61.0%

Table 8D

Area Under the Curve

		Area
ps_1 binary	0	.724
	1	.724

Table 8E

Network Information

Input Layer	Factors	1	marital
		2	blog_c
		3	f_24
	Covariates	1	influential
		2	adult
		3	in touch
		4	sensible
		5	l_mins
		6	g_mins
		7	priority_o
		Number of Units	13
		Rescaling Method for Covariates	Adjusted normalized
Hidden Layer		Number of Units	6[a]
		Activation Function	Softmax
Output Layer	Dependent Variables	1	ps_1 binary
	Number of Units		2
	Activation Function		Identity
	Error Function		Sum of Squares

Table 8F

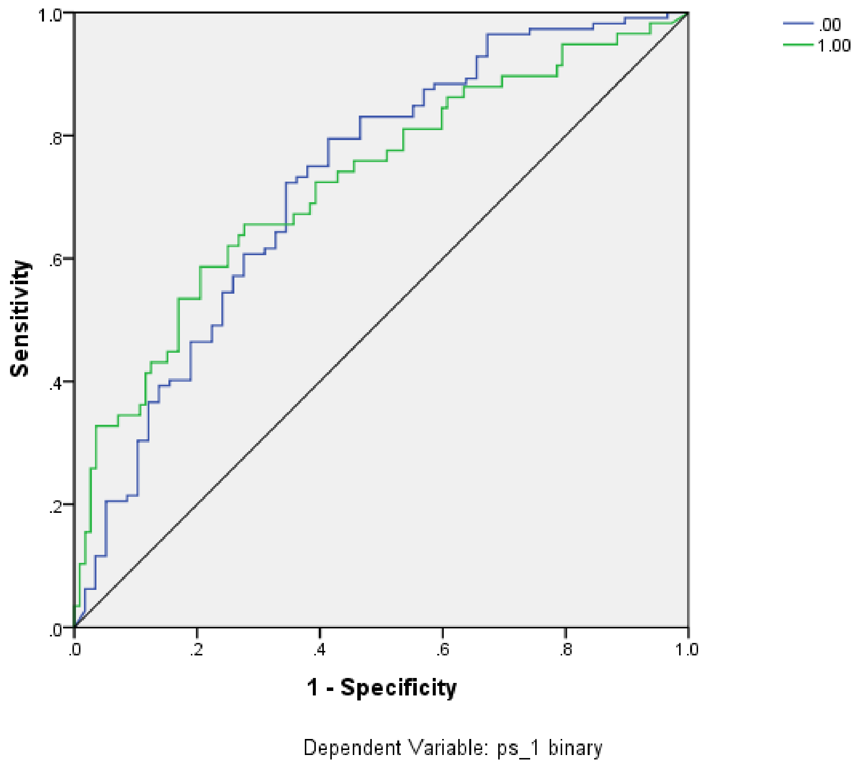


Figure 6B

Independent Variable Importance

	Importance	Normalized Importance
marital	.082	60.6%
blog_c	.082	60.9%
f_24	.074	54.9%
influential	.070	51.7%
adult	.119	88.2%
in touch	.121	90.1%
sensible	.120	89.2%
l_mins	.099	73.2%
g_mins	.099	73.6%
priority_o	.135	100.0%

Table 8 G

Segment Structure Analysis III: LDA

Discriminant analysis based on the key basis variable f_24 for segmentation shows 95.5% accuracy for the validation sample. This is a large gain in predictive accuracy given the fact that the incidence of f_24 = 1 is only 79%. Accuracy of predicting infrequent user is compromised however in this scheme.

Classification Results

			f_24	Predicted Group Membership 0	1	Total
Cases Selected	Original	Count	0	17	14	31
			1	8	114	122
		%	0	54.8	45.2	100.0
			1	6.6	93.4	100.0
Cases Not Selected	Original	Count	0	5	9	14
			1	2	42	44
		%	0	35.7	64.3	100.0
			1	4.5	95.5	100.0

Table 9A

Test Results

Box's M		1.165
F	Approx.	1.152
	df1	1
	df2	22071.984
	Sig.	.283

Table 9B

Classification Function Coefficients

	f_24 0	1
influential	2.283	2.427
in touch	1.893	2.317
l_mins	.108	.075
g_mins	.215	.160
blog_c	-2.125	-.515
marital	8.228	7.602
sensible	2.520	2.716
priority_o	1.448	1.816
adult	2.611	3.078
(Constant)	-24.332	-25.063

Table 9C

Log Determinants

f_24	Rank	Log Determinant
0	1	-.266
1	1	.056
(identity matrix)	1	.000

Table 9D

The preceding analysis shows that a 3 or 4 cluster solution with f_24 (frequency of use) and ps_1a (price sensitivity) as the key basis variables is appropriate in the given circumstances. These basis or dependent variables may be predicted or accessed well by the demonstrated set of descriptor variables. The list of descriptors to predict ps_1a however is rather long. This analysis however provides a segmentation solution that doesn't make sure that the interests of affiliate marketers and developers are addressed adequately. Data on connecting and engaging with marketers is not collected in this survey. Use of apps/games is surprisingly low in frequency. The pilot round revealed that very few in this sample buy apps/games related virtual offerings. Evidence to evaluate some of the propositions for segmenting at MSP level (rather than based on the Face book Company - user interaction) is available to a limited extent in the data set and I shall discuss it in the next section.

Discussions

In this section, I shall discuss in the light of the preceding empirical analysis, some of the propositions put forth earlier. Subsequently, I would try to relate the various strands of understandings gained in the study so far in an overall perspective. The guiding theme is how market segmentation and targeting can be optimized at an aggregate level in the case of a MSP like Facebook. How best the convergent and divergent interests of the four players on the platform can be configured in a way that helps achieve the optimum at an aggregate level.

Propositions

Some aspects of the five propositions I put forth earlier can be examined in the light of the findings of the preceding empirical analysis. The empirical evidence strongly supports segmentation scheme that was proposed a priori (this was based on a pilot study of 50 respondents) in proposition 2 (p 11). For the SNS, infrequent, frequent and engaged are groups that meet the requirement (Lilien et al. 2004; Frank et al. 1972) of appropriate segments as follows.

- There is significant heterogeneity in extent and types of needs (see table 3B and 3C) across the segments.
- Though users are heterogeneous across groups, they do cluster into homogeneous groups.
- These segments respond differently to the firm's promotional activities or marketing communications.
- Prima facie there is no reason to think that addressing segment specific needs would not be cost effective.
- Using descriptor or access variables, it is possible to predict segment membership with reasonable accuracy

In segmentation scheme II (p 25), one sees that among frequent users; when price sensitivity goes down from 1.5 to 2.8 to 3.4 (across clusters 1-3-4), the rate of status update moves from 1.15 to a high of 4.09 to a low of 1.11. (see figure 7 below)

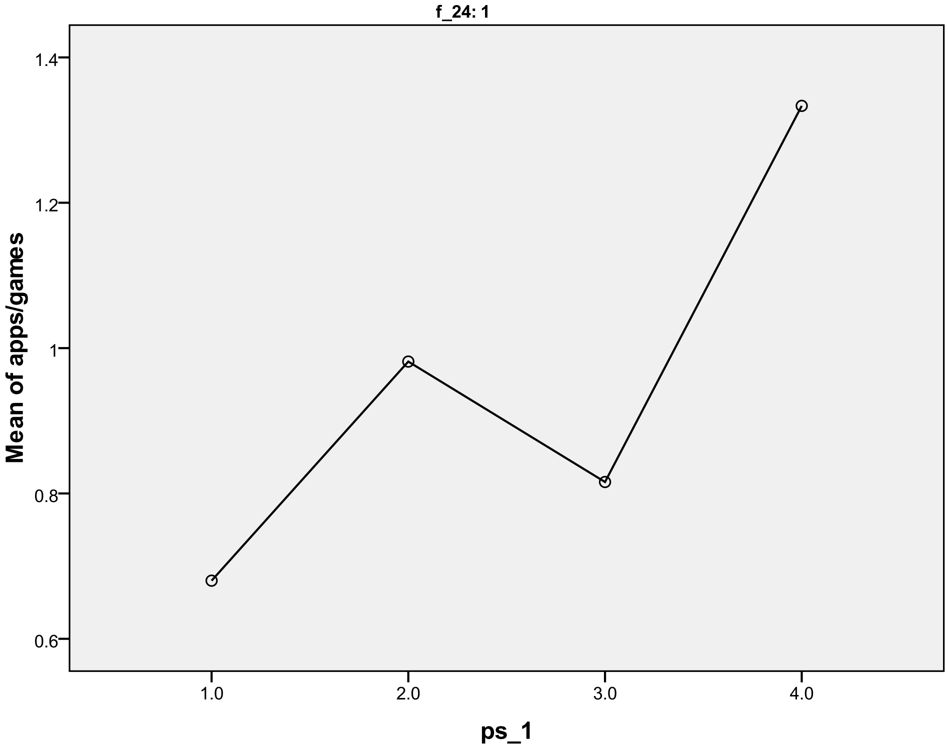


Figure 7

Such nonlinear pattern implies that for a sizeable segment like the engaged in scheme II, some type of activities will not go up with rise in frequency of use or falling price sensitivity (price sensitivity is a proxy measure for engagement as supported by the findings of this study). Therefore, if Facebook, the platform provider drives use and engagement, it doesn't necessarily raise the use and engagement in relation to all types of activities. It may even fall like it does in this case. This is evidence that substantiates proposition 1.

By implication, it is possible that response to marketers and use of apps/games may fall for some segments while use and engagement with Facebook SNS rises. The chart above shows just that. Even if price sensitivity falls from 2 to 3 (from *likely to discontinue if charged $1 a month for Facebook use* to *likely to continue in the same case*), use of apps/games falls from 1 to 0.8. This observation lends support to proposition 1 which may be restated to say that interests of marketers and developers are not addressed adequately and automatically if the interest of Facebook in the Facebook-user interaction alone is taken care of. Ensuring that users use and engage in the best possible way with the platform doesn't necessarily ensure that the users do so with marketers and developers. Sometimes, it may have a negative fallout. There are various same-side/cross-side and positive/negative externality or network effects at work.

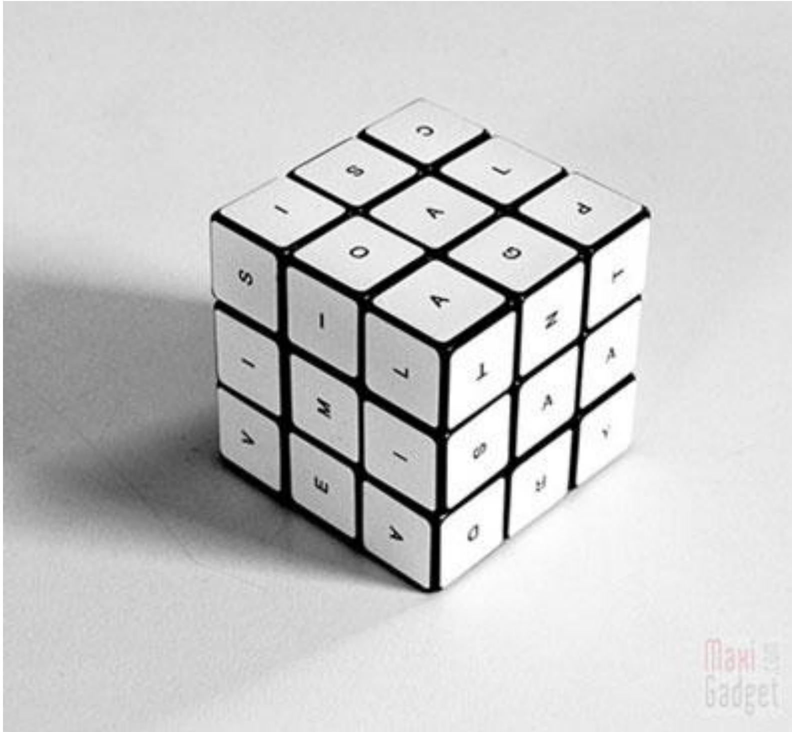
For the Facebook – user interaction, the effectiveness of segmenting users into 3 groups according to proposition 2 was seen earlier with the analysis of survey data (Table 3B). The table and segment structure analyses show that such behavioural segmentation may be more useful from a marketing point of view than segmenting on the basis of variables such as benefits or demographics or psychographics. In the same analysis, we also observe that a similar pattern of classification may hold good for the developer – user interaction through apps/games. Rate of using apps/games are 1.02[a], .84[ac] and .44[c] – engaged and infrequent users significantly differ on frequency of using apps/games. The difference in frequency of use of apps/games between the frequent and engaged users of Facebook however is not statistically significant. This implies that engaged users of Facebook may not be any more lucrative as a segment for developers than frequent users if we assume that profits generated by users of apps/games is proportional to frequency of using apps/games. Adhering to proposition 2 may not always be useful as it may be redundant in some cases because of inadequate heterogeneity across segments. Proposition 2 may be viewed as a general principle that may not be efficient in some situations. Such situations however may be difficult to tell a priori.

Proposition 3d on multi-homing can also be evaluated here to an extent. We see from the tree diagram for f_24 in figure X that variable l_24 (whether used LinkedIn in last 24hrs, a measure of multihoming) makes a substantial difference – a jump from 85% to 100% to f_24, whether used Facebook in last 24 hrs. Very likely, there are complementarities or positive association. In the event of such positive association, multi-homing is likely to lead to convergence rather than divergence. Multi-homing is unlikely to lead to divergence if the user views the concerned offerings as complements.

Comprehensive Market Segmentation

Next, we consider the comprehensive approach to market segmentation of Facebook users. Conventional wisdom says that we should go for not more than 8 segments. But Facebook has more than a billion users. One need not persist with the norm. Theoretically, we can extend Table 1 (p 13) to make room for 3 groups each for Facebook Company, marketers as a group and developers as a group. A priori, the segments may be infrequent, frequent and engaged. In case of developer, ‘engaged’ may include purchase and attitudes/behaviours in relation to apps/games/developers beyond purchase. We may introduce a customer value index based on the average purchase or lower quartile of purchase as an alternative or in addition to engagement. In case of the Facebook Company, the response variables are use and engagement or change in response with stimulus such as change in price. Similarly, for marketers also, we can find 3 groups. Depending on how many independent segments we divide the user base into for each party; we may have 3^3 to 4^3 or 27 to 64 theoretical combinatorial groups/segments instead of the 8 (2^2) groups we got in Table 1 .

On the lines of Table 1, if we divide users into 3 groups (see Figure 8) each (F1, F2 & F3 for SNS users, M1, M2 & M3 for marketers and D1, D2 & D3 for Developers), we would have a range of 27 theoretical groups – a Rubik’s cube (let’s call it F Cube for our purpose here) of segments. Imagine a vertex of this F cube sitting on (x,y,z) axes at (0,0,0). If F1, F2 and F3 are on X axis, M1, M2 and M3 on Y and D1, D2 and D3 on Z and each small cube out of the



F Cube Segmentation Solution

Figure 8

27 has sides representing F, M and D, we have a 3 D scheme that is an extension of the scheme in Table 1. The No. 1 segment is F3 M3 D3 (the cube in the corner opposite to the reference (0,0,0) instead of F2 M2 D2 in Table 1. Out of 27 cubes, 9 cubes have F1 or infrequent users of the SNS only. These are very likely to be sparse in population of users and unlikely to have many M2/M3 or D2/D3. These 9 can be combined to form 1 segment of infrequent users of the MSP. Out of the remaining 18 cubes, only 12 cubes (those with M2 or M3) have high use (or response) or engagement with marketers/businesses. 6 of these with M3 form the lucrative marketing segments. Similarly 6 with D3 form the lucrative apps/games segments. 6 with M2 and 6 with D2 form the frequent segments for marketers/businesses and developers respectively.

Then the task is to identify those small cubes (sparse ones with F1 are already clubbed together) that can be clubbed together because of adequate homogeneity or low share of members. Such consolidation may be informed by empirical analysis for better results. For an internet player like Facebook, it may not be difficult to identify adequate sample of users in each of the 27 (or even 64) groups and experiment with them using marketing stimuli under field conditions to find out their response level to current stimulus and sensitivity to changes in stimulus. Group descriptor data (demographic, behavioural and psychographic and so on) may be gathered to augment information on segment structure and access to basis variables. Such a procedure can be expected to yield a segmentation solution or scheme that is close to optimum. A comprehensive approach to market segmentation for Facebook must consider all same side and cross-side network effects and the key interactions the user has with the three key players – Facebook Company and its affiliate marketers and developers.

As discussed earlier in the section on propositions, a key understanding, theoretical as well as empirical, that is of value in order to develop an effective segmentation strategy for a MSP like Facebook is the factors that lead to convergence and divergence of response at user level for the 3 different business players – Facebook Company, marketers and developers. Such factors can be wide ranging and theoretical as well as contextual. Future research may identify the key factors that would influence segmentation strategy and their extent of influence on outcomes of strategy.

References

Ajzen, I. (1991). The theory of planned behavior. *Organizational behavior and human decision processes*, *50*(2), 179-211.

Barwise, P., & Meehan, S. (2010). The one thing you must get right when building a brand. *Harvard Business Review*, *88*(12), 80-84.

Bernoff, Josh (2010). Introducing The New Social Technographics, Forrester Research

Brandtzaeg, P. B., & Heim, J. (2011) A typology of social networking sites users. *International Journal of Web Based Communities*, *7*(1), 28-51.

Chui, Michael, *et al*. "The Social Economy: Unlocking Value and Productivity Through Social Technologies." *McKinsey Global Institute*, July 22, 2012.

Eisenmann, T., Parker, G., & Van Alstyne, M. W. (2006). Strategies for two-sided markets. *Harvard business review*, *84*(10), 92.

Ellison, N. B. (2007). Social network sites: Definition, history, and scholarship.*Journal of Computer‐Mediated Communication*, *13*(1), 210-230.

Enders, A., Hungenberg, H., Denker, H. P., & Mauch, S. (2008). The long tail of social networking: Revenue models of social networking sites. *European Management Journal*, *26*(3), 199-211.

Evans, David S., and Schmalensee, Richard (2005). The industrial organization of markets with two-sided platforms, NBER Working Paper

Foster, M., West, B., & Francescucci, A. (2011). Exploring social media user segmentation and online brand profiles. *Journal of Brand Management*, *19*(1), 4-17.

Granovetter, M. S. (1973). The strength of weak ties. *American journal of sociology*, 1360-1380.

Hagiu, A., & Wright, J. (2011). *Multi-sided platforms*. Working Paper, Harvard Business School.

Heinonen, K. (2011). Consumer activity in social media: Managerial approaches to consumers' social media behavior. *Journal of Consumer Behaviour*, *10*(6), 356-364.

Keller, K. L. (1993). Conceptualizing, measuring, and managing customer-based brand equity. *The Journal of Marketing*, 1-22.

Lee, C., Jarvinen, V., & Sutherland, J. (2011). Profiling social network site users: Who is the most responsive to marketing attempts? In *conference of the American Academy of Advertising* (p. 59).

Lilien, G. L., Kotler, P., & Moorthy, K. S. (1992). *Marketing models* (pp. 385-397). Englewood Cliffs: Prentice-Hall.

Lilien, G. L., & Rangaswamy, A. (2004). *Marketing engineering: computer-assisted marketing analysis and planning*. DecisionPro.

Lorenzo-Romero, C., & Alarcón-del-Amo, M. D. C. (2012). Segmentation of users of social networking websites. *Social Behavior and Personality: an international journal*, *40*(3), 401-414.

Frank, R. E., Massy, W. F., & Wind, Y. (1972). *Market segmentation*. Englewood Cliffs, NJ: Prentice-Hall.

Rochet, J. C., & Tirole, J. (2006). Two-sided markets: a progress report. *The RAND Journal of Economics*, *37*(3), 645-667.

Rysman, M. (2009) “The Economics of Two-Sided Markets,” *Journal of Economic Perspectives*, 23(3): 125-143.

Shontell, Alyson (2013). http://www.businessinsider.com/its-official-teens-are-bored-of-facebook-2013-3

Smith, W. R. (1956). Product differentiation and market segmentation as alternative marketing strategies. *The Journal of Marketing*, *21*(1), 3-8.

Van Doorn, J., Lemon, K. N., Mittal, V., Nass, S., Pick, D., Pirner, P., & Verhoef, P. C. (2010). Customer engagement behavior: theoretical foundations and research directions. *Journal of Service Research*, *13*(3), 253-266.