Paper

Segmentation of the games market using multivariate analysis

Received (in revised form): 12th June, 2004

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Abstract This paper presents the results of an investigation into customer segmentation in the computer and video games market. A survey of gamers was conducted in order to measure gaming-related behaviour. Statistical techniques, including factor and cluster analyses, were applied with the aim of deriving a reliable gamer segmentation. The results from factor analysis reveal three main components of gamer behaviour: general gaming knowledge and attitudes, playing habits and buying habits. Cluster analysis clearly identifies a two-group solution, namely that of hardcore and casual gamers between which significant differences exist, while differences are far less significant with respect to the standard age-range comparison used extensively by those involved in developing and marketing games. The suggestion is that games developers should seriously consider an attitude/experience segmentation based on the two main categories of gamer: hardcore and casual.

INTRODUCTION

As is well known, the process of customer segmentation varies depending on the market in question, extending from straightforward categorisations of demographic factors such as age, income and social grade, to the incorporation of elaborate techniques involving complex economic theories. Statistical procedures applied to survey results can range from comparatively simple frequency analysis to advanced multivariate analysis. No doubt partly for these reasons, and despite its ubiquitous use, the application of customer segmentation is not without pitfalls: indeed, some believe that it is only very rarely used effectively.[1–4] Gibson[5] and Barron and Hollingshead[6] outline some common problems associated with inappropriate segmentation techniques, including generally poor management of the process and the difficulty of a practical application of results to a market. The problems also seem to be related to difficulties with respect to the effects of

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customer segmentation on corporate decision making, and to rigid and reluctant company policies.[7] Given all this, it is clear that any attempt at segmentation requires careful consideration of the techniques to be used, of the interpretation of the results and of the manner in which they might be integrated into existing company procedures.

The computer and video games industry has developed into a hugely successful international market since its beginnings in the early 1970s. While estimates vary as to its size, valuations given by sources such as ELSPA[8] or Market Research[9] suggest that it was worth around US$17bn in 2002, and it is certainly continuing to rise. In Europe, the annual growth rate of consumer spending on games software is second only to DVD, and considerably ahead of other media such as cinema and music.[10] Despite its size and penetration into popular culture, however, very little has been done in terms of understanding in detail the requirements and expectations of those who buy and play games, other than by applying the conventional divisions of gender and age,[11–16] and there is evidence to suggest that such simplified distinctions may not be adequate.

The games industry has a history of fickleness and volatility. Since the 1970s, there have been two industry crashes (1977 and 1983) due to software glut and the market's apparent inability to deliver what customers wanted.[17–19] Today, criticisms of the industry's approach to satisfying customer expectations are voiced by both gamers and industry professionals.[20] Typically, such criticisms emanate from those who are most in tune with the latest developments, and who have a good understanding of the medium and how the industry operates. The views of experienced gamers can be observed in online discussion forums dedicated to games, and they tend to emphasise the amount of mediocre software available, the design of which is often poorly tailored to the expectations of the various sections of the market. While some criticisms may be at least partly unjustified, there is not often smoke without fire, and there can be little doubt about the computer-games industry's lack of specific strategies for addressing the needs and expectations of the various gamers populating the games market. This paper proposes the use of a method of gamer segmentation which takes into account the variables most pertinent to the problem in order to derive a practical classification of gamers. Various techniques are considered, comparisons are drawn between gamers from different categories as a result of a survey the authors conducted and suggestions are made as to how these can be incorporated into existing corporate decision-making procedures to allow the results to be used in practice.

METHODOLOGY

The first and most important decision in constructing the survey was to determine whether or not demographic distinctions would be sufficient for an accurate segmentation of the computer and video games market. While some segmentation studies have found significant differences using gender and age classifications in terms of sociological and psychological issues, Forsyth *et al.*,[21] Tonks and Farr,[22] Barron and Hollingshead[23] and Soper[24] all point out numerous inadequacies of the demographic approach, and it seemed to the authors that demographic comparisons might indeed not be sufficient for eliciting the most pertinent differences between gamers. Suggestions have been made of value- or needs-based

Table 1: Fifteen variables for gamer segmentation

Variable
1. Modify or extend games in a creative way
2. Willingness to pay
3. Hunger for gaming-related information
4. Gaming-technology knowledge
5. Knowledge of the industry
6. Age first started playing games relative to the age of the industry
7. Play over long sessions frequently
8. Prefer depth and complexity in games
9. Discussion of games in forums/with friends
10. Engaged in competition with CPU/other human players
11. Tolerance of frustrating/difficult games
12. Play games for exhilaration of defeating the game
13. Degree to which purchasing decision is based on the genre/type of game
14. Have a wide selection of old and new hardware/software
15. Need to differentiate from the mainstream — eg importing, early adoption

segmentation procedures which take into account a more detailed evaluation of customers' attitudes and habits towards a particular product or service.[25] The types of gamer recognised by those in the games industry are commonly referred to as 'hardcore' or 'casual', rarely as 'young' or 'old', 'affluent' or 'poor'. The authors needed some method of measuring as precisely as possible the variables contributing to a hardcore/casual classification. They consequently decided to use the 15 variables of gamer classification as proposed in Ip[26] and Jacobs and Ip[27] which would allow a suitably accurate segmentation of the market with respect to gaming behaviour and attitudes. Demographic information in terms of gender and age would also be used for comparative purposes. As well as helping to promote a more detailed segmentation, the results would also provide the opportunity to test the 15 gamer-classification variables for their accuracy as a tool for measuring the different types of gamer behaviour and attitudes which might exist.

Participants for the survey were sourced from university, schools and dedicated gaming forums. A short questionnaire was devised to elicit gamers' attitudes towards each of the 15 variables shown in Table 1 (for a detailed discussion of these variables, see Ip[28]). An e-mail message was sent to university students and gamers from gaming forums, and personal requests were made at local schools for participants who had some level of knowledge of and interest in computer and video games. Those who agreed to take part were asked to provide a score for each of the 15 variables using a seven-point Likert scale (a description of each variable was provided either in person, or if not possible, via e-mail). A standardised score (S) for all 15 variables was then calculated for each gamer. The questionnaire was piloted using a small group of university students. Suggestions were taken into account, and the questionnaire was refined before implementation.

The next decision concerned how the results of the survey could be used to determine an effective and reliable classification. As mentioned above, numerous statistical procedures involving multivariate analysis (factor and cluster analysis),[29] and methods derived from economic theory are available.[30] In addition, Neal and Wurst[31] highlight various emerging techniques such as multidimensional segmentation,

segmentation using neural networks, and fuzzy and overlapping segmentation. Statistical techniques involving multivariate analysis are, however, the most frequently used (see for example, among the plethora of studies, those by Bauer and Fischer,[32] Bierma-Zeinstra *et al.*,[33] Bau *et al.*,[34] Kuo *et al.*,[35] Ulleberg[36] and Gaudreau and Blondin[37]). One of the reasons for which this might be the case is that cluster analysis (hierarchical and K-means) enables the likely number of groups to be determined, from where further group intervals can be derived, while other techniques, such as those involving neural networks, are more complex and require greater computing power while not necessarily producing more accurate results.[38] Consequently, it was decided first to consider how the data could be refined by using simpler multidimensional segmentation; factor analysis would then be used in order to elicit the type of the information represented in the data (various types of gamer behaviour), from where cluster analysis could be applied to determine group assignments.

ANALYSIS OF THE DATA

At the analysis stage, (by chance, precisely) 100 valid responses for the 15 variables were recorded, of which 45 were from those under 20 years of age (young in gaming terms), and 55 from those aged 20 or more (relatively mature for gaming). Only 10 were female: despite some evidence indicating that female gamers are on the increase,[39] there still appears to be a significant majority of male to female gamers (and this particular result seems to suggest that males show a greater interest and regularity for the activity, or at least are able to answer questions about the games industry with a more reliable and consistent degree of knowledge). The analyses were conducted using SPSS (Statistical Package for the Social Sciences), and, as will be seen, the statistical techniques applied in the following sections for factor and cluster analyses have been those suggested in Pallant,[40] Norusis,[41] and Everitt;[42] readers who are considering applying such procedures but who are unfamiliar with them may wish to consult these sources and associated texts for detailed explanations.

Neal and Wurst[43] insist that segmentation techniques should take into account the multidimensional nature of information about consumers (such as needs/benefits and desires), and factor analysis was therefore conducted to see if there was sufficient evidence to show multidimensionality. First, Cronbach's Alpha was obtained as a measure of the scale's reliability, revealing an acceptable level of 0.79 (thus exceeding the recommended value of 0.7).[44] Inspection of the correlation matrix revealed many coefficients of 0.3 and above. The Kaiser–Meyer–Oklin value was 0.80, exceeding the recommended value of 0.6.[45] Bartlett's Test of Sphericity also reached statistical significance at the 99 per cent level. These results thus indicated that factor analysis was suitable for the data, and a scree plot revealed a clear break after the first component, and a gradual levelling after component 3. An inspection of the component matrix also showed fewer factor loadings beyond the third component. Next, a Varimax rotation (the most commonly used method for rotation)[46] was performed, revealing that a single-component solution explained approximately 32 per cent of the variance, while a two-component solution explained 41 per cent, and a three-component solution 50 per cent. These results, together with the scree plot, confirmed that the original scale consisting of 15 variables could be usefully represented using a three-component solution, hence confirming multidimensionality within the data (a detailed consideration of these aspects of the data is beyond the scope of this paper, but a thorough investigation into them can be found in Ip[47]). From Table 1 it can be seen that the three distinct dimensions/components as indicated by the results from factor analysis represent general gaming attitudes and knowledge (variables 1 to 6); playing habits and preferences (variables 7 to 12); and buying habits (variables 13 to 15). The following application of segmentation techniques using factor and cluster analysis demonstrate how this information has been taken into account.

The variables from each of the three subscales (gamer attitudes, playing habits and buying habits) were standardised to giving a score out of 100, and could thus be subjected to cluster analyses to determine the number of possible groups. One of the main disadvantages during the application of cluster analysis is the broad range of techniques available.[48] For hierarchical analysis, there is a choice of methods for combining clusters (such as between-groups linkage, within-groups linkage, nearest neighbour and Ward's method), and a wide choice of distance measures (such as Euclidean distance, squared Euclidean distance and Pearson correlation). Depending on the methods used, slightly different results will be obtained. Furthermore, the choice of techniques is often an arbitrary decision.[49] Based on the suggestions presented in previous studies,[50–53] Ward's method was selected, and the commonly used squared Euclidean distance.

Results from the dendogram and agglomeration schedule indicated two possible groups for the data. K-means analysis was then used in order to determine the threshold between these two groups so as to allow for an accurate group assignment of gamers based on their standardised score (S — see above). K-Means analysis in SPSS presents the results in the form of cluster centres. For a two-group solution, final cluster centres of 0.53 and 0.72 were produced. In order to derive the appropriate threshold, the mid-point between two centres was calculated, from where the interval between groups could be determined. Consequently, group threshold for standardised scores (S) was 0.625. Thus, gamers with a score of less than 0.625 were assigned to Group 1 (casual gamers: $N = 43$), and those with a score of more than or equal to 0.625 Group 2 (hardcore gamers: $N = 57$). On brief examination, the two groups were a possible reflection of 'hardcore' and 'casual' gamers as mentioned above and not 'young' and 'old', since a mixture of ages could be observed for gamers within these groups.

Group validation was performed using a variety of methods suggested by Everitt[54] which can be found in Ip.[55] The results indicate that the groups can be considered consistent and reliable. In addition, validation procedures involving t-tests were conducted. Independent samples t-tests revealed statistically significant differences between the 13 out of the 15 variable scores, as well as overall scores (S), for Groups 1 and 2. Tables 2 to 4 provide descriptive summaries of the final set of 12 variables in their three respective subscales (gaming attitude and knowledge, playing habits and buying habits).

Given the establishment of the fact that the 15 variables measure three separate components of gamer behaviour, a more detailed examination was made for each individual subscale. Cronbach alpha for the six variables in the gaming attitude and knowledge subscale was high (0.86), indicating that these items are reliable predictors. Reliability scores were

Table 2: Summary statistics for gaming attitudes and knowledge

Variables for attitude and knowledge	Mean	Standard deviation	Correlation with total score	Correlation with subscale total score
Knowledge of the industry	4.54	1.59	0.77*	0.87*
Gaming technology knowledge	4.81	1.40	0.74*	0.82*
Willingness to pay	4.99	1.54	0.62*	0.76*
Hunger for gaming-related information	5.21	1.73	0.80*	0.82*
Age first started playing games	5.40	1.36	0.60*	0.67*
Modify or extend games in a creative way	1.94	1.32	0.52*	0.62*
Cronbach alpha			0.85	

*Correlations are significant at the 0.01 level

Table 3: Summary statistics for playing habits

Variables for playing habits	Mean	Standard deviation	Correlation with total score	Correlation with subscale total score
Play over long sessions frequently	4.21	1.49	0.44*	0.66*
Play games for exhilaration of defeating the game	5.25	1.24	0.53*	0.64*
Discussion of games in forums/with friends	4.71	1.82	0.69*	0.63*
Tolerance of frustrating/difficult games	4.13	1.46	0.35*	0.50*
Engaged in competition with CPU/other human players	4.95	1.60	0.13	0.37*
Prefer depth and complexity in games	5.09	1.30	0.28*	0.33*
Cronbach alpha			0.46	

*Correlations are significant at the 0.01 level

Table 4: Summary statistics for buying habits

Variables for buying habits	Mean	Standard deviation	Correlation with total score	Correlation with subscale total score
Have a wide selection of old and new hardware/software	4.33	1.54	0.51*	0.66*
Need to differentiate from the mainstream — eg importing, early adoption	2.91	2.01	0.60*	0.75*
Degree to which purchasing decision is based on the genre/type of game	4.65	1.75	0.05	0.54*
Cronbach alpha			0.31	

*Correlations are significant at the 0.01 level

lower for the latter two subscales — playing and buying habits (Cronbach alphas of 0.46 and 0.31 respectively). The particularly low score for buying habits is likely to be due to the fact that the scale currently contains only three items. A more detailed examination of reliability was, however, obtained via a consideration of item correlations within each scale. First, the data had to be made relevant to the components they had been shown to measure. To do this, a new total score was calculated for each gamer in each subscale (for example, in the first subscale, scores of 2, 3, 4, 5, 6 and 7 gave a total score of 27/42 = 64 per cent), and its correlation with each variable was examined — the data are shown in Tables 2 to 4. This gives an indication as to the degree of consistency and reliability of each item within its own subscale. The results reveal strong correlations between the items and their respective subscale total scores. An examination of the item-to-item correlations also shows strong correlations between items in the same subscale. This information suggests that the 15 items are reliable within their respective subscales, as well as a collective entity when used as a single scale.

Table 2 shows that the items 'knowledge of the industry', and 'hunger for gaming related information' are strong indicators of dedicated gamers — such gamers are more likely to have a high level of relevant knowledge, and a strong desire for information about games (means of 4.54 and 5.21, and subscale correlations of 0.87 and 0.82 respectively). For playing habits, the best indicators appear to be 'play games for exhilaration of defeating the game' and 'discussion of games in forums/with friends', with comparatively higher means and correlations than other variables within the subscale (Table 3). For buying habits, it appears that the variable 'need to differentiate from the mainstream' is a useful indicator of gamer behaviour despite a relatively low mean (2.91), since it has stronger correlations with the overall scores as compared to 'have a wide selection of old and new hardware/software'.

An interesting piece of information emerges from these data for the two variables 'modify or extend games in a creative way' (variable 1), and 'need to differentiate from the mainstream' (variable 15) (Table 4). These are characterised by low means (1.94 and 2.91 respectively), relatively high correlations with overall and subscale total scores (0.52 and 0.62, and 0.60 and 0.75 respectively), and strong factor loadings (0.61 and 0.57). It became clear that only gamers on the 'hardcore' extremity of the scale (the highly-dedicated gamers) would show any significant signs of engaging in such behaviour, thus leading to higher scores. For variable 1, the majority of respondents (54 out of 100 gamers) scored the minimum of 1 (those who never engage in such behaviour), while only 14 scored 4 (the median) or higher; a similar result was found for variable 15: 44 and 21 respondents respectively. Additional comments by those who scored highly on these two variables demonstrated a considerable depth of gaming knowledge and industry awareness. Therefore, a likely explanation is that these two variables are hardcore-gamer oriented, in other words that a person who scores relatively highly for either of these variables is also likely to be a hardcore gamer and to demonstrate significant depth of knowledge with regard to the medium. Future work with respect to a development of the subscales should take these items into account (these issues are discussed below).

Graphical summaries of the differences for mean variable scores between the two groups are shown in Figures 1, 3 and 5. In general, gamers in Group 1 have lower scores than those in Group 2. This result was expected, since hardcore gamers are clearly more likely to be knowledgeable and to exhibit positive attitudes towards the medium. A more detailed observation revealed that the most significant difference could be observed for the first six variables (general gaming attitudes and knowledge — Figure 1). Pertinent differences could also be seen for the other two subscales (playing habits and buying habits — Figures 3 and 5 respectively). The results indicated that the variables with the largest differences between groups in each of the three separate subscales were 3 (hunger for gaming-related

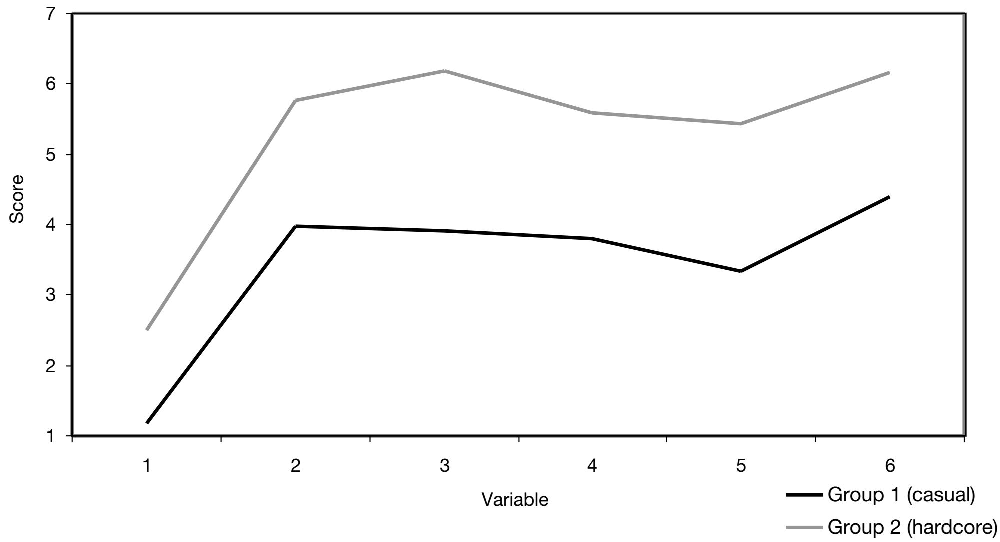

Figure 1 Summary of mean scores for general gaming attitudes and knowledge between hardcore and casual gamers

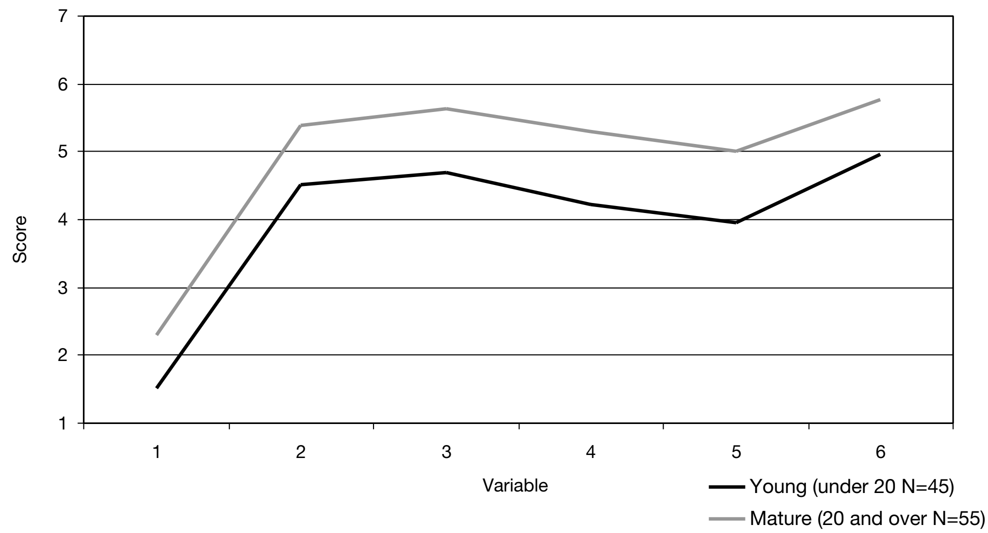

Figure 2 Summary of mean scores for general gaming attitudes and knowledge between young and mature gamers

information), 9 (discussion of games in forums/with friends) and 13 (degree to which purchasing decision is based on the genre/type of game).

Next, an age comparison between young (under 20 years of age) and mature gamers (20 and over) was made. The results are shown in Figures 2, 4 and 6. Apart from some noticeable difference for the first six variables for general gaming attitudes and knowledge (a not unexpected result if one accepts that mature gamers will possess greater knowledge of the medium), variables in the other two subscales (pertaining to playing and buying habits) showed few differences. As can be seen in a general comparison between Figures 1 and 2, 3

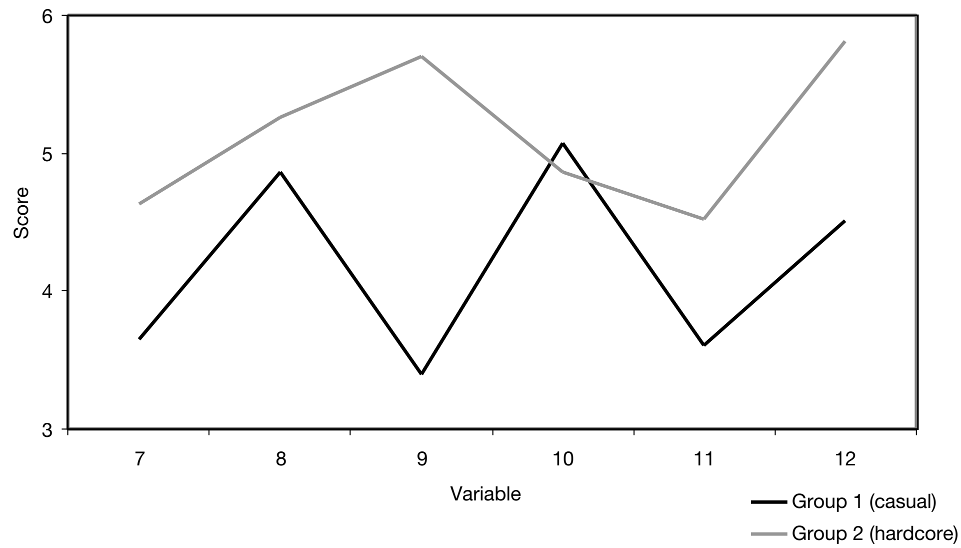

Figure 3 Summary of mean scores for playing habits between hardcore and casual gamers

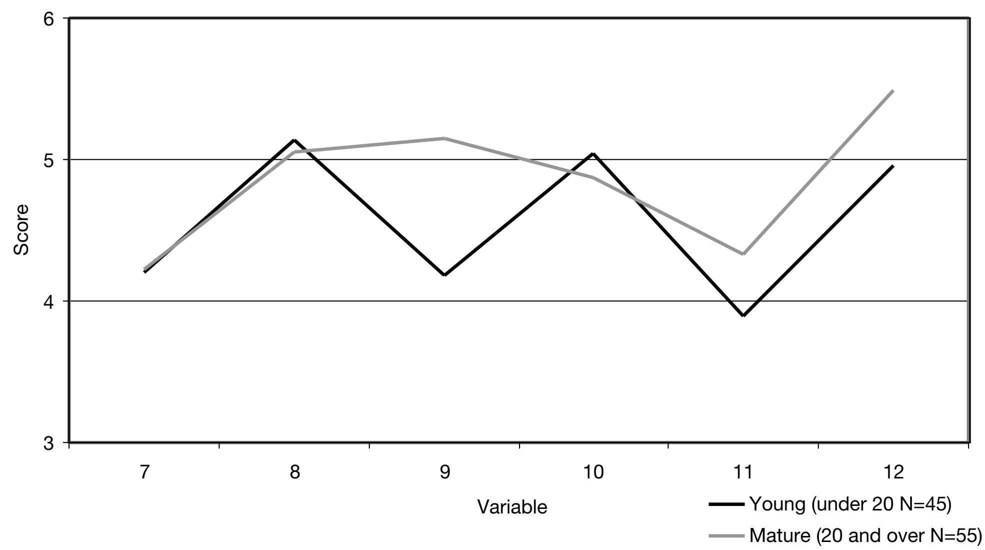

Figure 4 Summary of mean scores for playing habits between young and mature gamers

and 4, and 5 and 6, greater differences can be observed between casual and hardcore than young and mature gamers. These results confirm that age comparisons are not sufficient to expose pertinent differences between gamers, and it is therefore clear that age comparison should, at least, be viewed with a measure of circumspection by those seeking a detailed breakdown of gamer attitudes, knowledge and habits. In effect, the results show that hardcore and casual gamers can be found in both age groups: a young hardcore gamer may be just as knowledgeable and gaming-dedicated as one who is much older and vice versa. The implication of this for those in the games industry is, of course, that given the traditional method of age segmentation, there is cause for

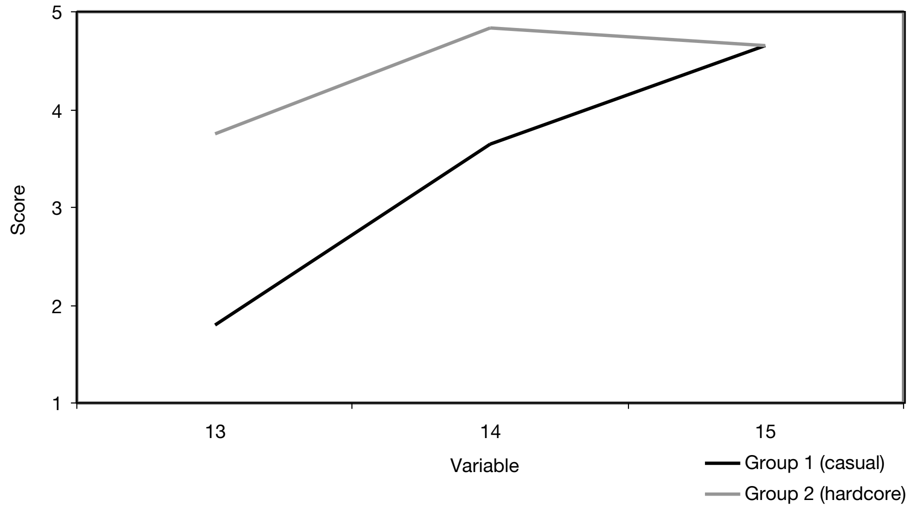

Figure 5 Summary of mean scores for buying habits between hardcore and casual gamers

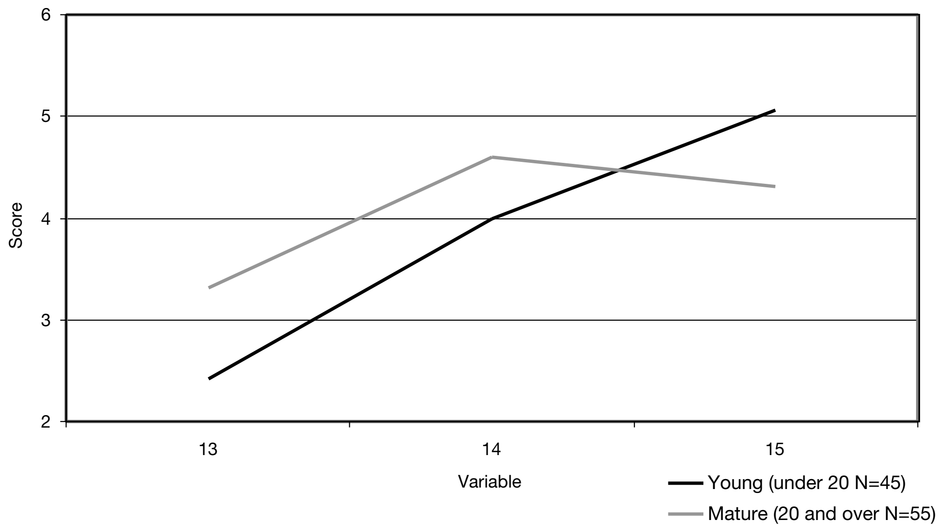

Figure 6 Summary of mean scores for buying habits between young and mature gamers

concern regarding the development and implementation of specific market strategies which may not accurately reflect the demands of the market.

DISCUSSIONS AND FUTURE RESEARCH

Numerous issues are raised by the results of the research undertaken for this paper. A new method of gamer classification has been developed using 15 variables and the results of factor analysis reveal three key dimensions of gamer behaviour: general gaming attitudes and knowledge, playing habits and buying habits. These variables and behaviour dimensions represent a comprehensive list of attributes associated with the distinction between the types of gamer recognised by those in the industry, which up to now has received little attention, and the development of suitable techniques through which they can be classified and used in practice. A Cronbach alpha test revealed a high level of reliability for the first subscale. Correlation analysis and descriptive statistics also indicated a significant degree of reliability for the latter two subscales. Using cluster analysis, a method of accurate segmentation based on gamer information has been obtained, and can be used by games developers and publishers better to understand their customers. In addition, a summary of the 15 variables also yields information as to the aspects which differ most significantly between such gamers, and how they are likely to react to certain types of product which may be developed in the future.

There are, however, certain limitations of the results presented here, the most significant being potential criticism surrounding cluster analysis itself. Clearly, the basis on which results from the analysis are derived are entirely dependent on the factors which are used (in this case the 15 variables described). Should these factors be in any way inaccurate or incomplete, validity may be jeopardised. Yet it is clear from the results that even though the 15 variables may not be foolproof, there is significant evidence to indicate that the conventional and most commonly used division by age does not adequately address the variability within the video games market. More research therefore needs to be conducted to refine the variables used so as to increase the level of accuracy and reliability, including possibly expanding the number of elements measured within the scale. While some suggestions have been made here based on quantitative results, a qualitative approach aimed at those central to the industry seems appropriate in order to discover and affirm salient factors surrounding playing and buying habits. Future surveys can be conducted and quantitative data obtained further to enhance understanding of gamers and their attitudes in order to provide more detailed information on general games-related issues, specific playing habits and buying habits.

Nevertheless, in practice the results here can already be used in a variety of ways, ranging from relatively straightforward gamer classification for determining the appropriate marketing technique (for example, a company may be developing a game in a particular genre, and hence should take into account variable 13 — purchasing decision — in order to develop appropriate marketing), to more complex strategies in product development planning. In particular, the results can be easily combined with existing procedures such as quality function deployment which seeks to obtain information from knowledgeable consumers to enhance the product/service-development process (see Jacobs and Ip[56] for a discussion of this technique applied to the games industry), and analytic hierarchy process — procedures commonly used in industry and studied in academia. In Ip's study,[57] an application of how gamer segmentation, and indeed, segmentation of consumers from any given industry, can be linked directly to existing company procedures is provided. Given the problems regarding the application of segmentation techniques in practical company strategy, it would seem logical that instead of being used as an individual procedure, it should be combined with other management techniques in order to extract maximum effect for the companies involved.

The use of an attitude/experience segmentation of the games market proposed in this paper offers an alternative method for companies in the games industry to understand their audience. In the computer and video games market, where outputs are judged entirely by consumers, a new strategy which recognises that gamers are becoming increasingly knowledgeable about and sensitive towards the quality of new products would appear to be potentially fruitful, and perhaps essential. The market is dominated by a handful of key players who set the standard for the entire industry, and is saturated with poor and mediocre software. The current climate is that of a one-way relationship in which consumers have no choice other than to soak up what the industry offers, but this situation may soon have to change if the risk of a crash reminiscent of those of 1977 and 1983, however remote such a risk may seem in a burgeoning market, is to be avoided. There is an opportunity for companies to develop products catering for factors which are clearly important for experienced and knowledgeable gamers, people who already represent a valuable commodity and who are likely to increase significantly in number.

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