REVERSE MARKET SEGMENTATION WITH PERSONAS

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Abstract: In this study the user experiences of commercial educational product were gathered in order to build the personas that can be used to revising the market segmentation. Personas are empirically formed archetypical characters representing distinct behavioural clusters, goals and the motivation of end users. Usually personas are used in different production phases as tools that help designers and marketing people in decision making. In this study, the personas were formed by applying k-means cluster analysis into quantified user interviews. According to the results of the study, qualitatively formed personas showed their strengths as decision making tools: They helped publisher to maintain the focus on a learner's needs, wants and requirements during the whole process of development.

1 INTRODUCTION

According to Cooper (1999) personas are empirically formed archetypical characters representing distinct behavioural clusters, goals and the motivation of end users. Usually personas are used in different production phases as tools that help developers, producer and publishers to make reasonable and empirically based design decisions (e.g. Cooper, Reimann & Cronin 2007).

In practice, personas and market segmentation has been seen as complementary methods (e.g. Kujala & Kauppinen 2004; Grudin & Pruitt 2002). Traditional market segmentation can help the designers to build commercially more effective personas for product development.

However, in this study, the real user experiences were used to build the personas that can be used when revising the market segmentation. In other words, the “from segments to personas” -process is reversed to “from experiences to personas to segments”

The reason, why the reversed market segmentation is used relays to the complexity of adaptive/personalized content. The idea of adaptive educational systems is to produce individual and optimized learning experiences (Eklund & Brusilovsky 1999; Brusilovsky 2001) and the high end user models that are relatively complex. In terms of complexity, a definition for a complete adaptive system can be based on the capability of self-organization.

The persona approach provides a sound design framework for complex adaptive learning materials. One of the main benefits of using personas is that it helps to eliminate the problem of the "elastic learner". An elastic learner stretches and adapts during the design process, allowing designers to implement almost anything. However, real learners are not elastic. Thus, the persona method aims to design of learning materials that will stretch and adapt to the learner's needs - not the other way around. Such an approach is the key to effective learning experience.

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2 RESEARCH TASK AND METHODS

2.1 Research Tasks

This study focuses on the 1) evaluation of the product and 2) finding most suitable customers (segments) for Mathematics Navigator. The collected data includes qualitative and quantitative variables. In this study the focus is on qualitative data. Quantitative data, such as test scores and improvement measures in learning results are used to support the decision making.

In this study, user prototypes are formed empirically according to qualitatively measured user experience. The research tasks are:

1. To form personas from the user experiences gathered with interviews.
2. To find most suitable market segment for Mathematics Navigator.
3. To evaluate the usefulness of the persona - method.

The sample (n=74) consists of first year class teacher students at the University of Turku, Department of Teacher Education in Rauma. All of the participants had an upper secondary school degree on mathematics – Basically all of the mathematics related to this study is based on upper secondary school mathematics curriculum.

2.2 Materials

Mathematics Navigator is a product family published by Otava Publishing Company Ltd. Mathematics Navigator is designed to operate as a personal tutor and guide in the studies. It supports the development of a student's mathematical skills and abilities and helps the student in recognizing his/her mathematical strengths and weaknesses.

Mathematics Navigator gathers information on the student's actions while studying. On the basis of these, Mathematics Navigator adjusts the set of exercises and/or content presented to the student in order to optimally support his/her development. Thus, the learning paths are formed individually. Furthermore, the student is able to follow the development of his/her competence profile.

The user interface of Mathematics Navigator consists of a menu-bar and three main areas (Figure 1). At the left side of the interface is the table of contents that have two different views of the content: 1) The traditional book-like table of contents and 2) an exercise adapted table of contents.

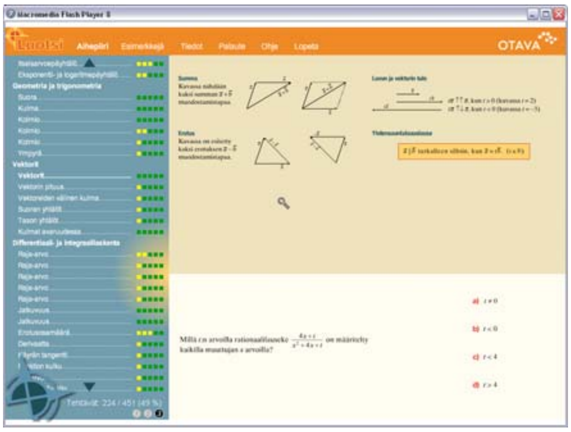

Figure 1: User interface of Mathematics Navigator and the basic mathematics course (in Finnish).

The exercises are presented in the right-bottom corner of the user interface one at a time. The exercises can't be neglected, changed or left behind without giving an answer. The learning profile is always (real-time) adjusted on basis of the answer to the current exercise. The exercises are selected to support the individual user's needs. There are no fixed paths through the topics: the path is based on the student's learning profile and by Mathematics Navigator estimated need for exercises and contents. The guiding factors in the exercise selection are: 1) The course structure (the traditional table of contents). 2) Student’s learning abilities and areas of weaknesses measured and estimated by Mathematics Navigator during the studying process. 3) Critical points, derived from the learning community's actions, derived from generalized success patterns in answering the exercises.

The competence profile values are indicated with colours that vary from red (insufficient skills or not yet estimated skills) to green (good skills). Those skills mastered and measured within a certain theme will be transferred with certain estimates to other themes requiring similar (by proximity or by hierarchy) skills.

2.3 Measures and Analyses

In the beginning of the experimental period, a pre-test, and at the end of it, a post-test, were arranged for measuring the educational effect of the Mathematics Navigator. The tests were based on the Finnish lower secondary school and partly upper secondary school mathematics curricula. After the post-test feedback was gathered through the following two open questions (originally in Finnish):

1. What kind of good or positive experiences did you have during your work with Mathematics Navigator?
2. What kind of development needs or negative experiences did you encounter during your work with Mathematics Navigator?

At first, feedback was analyzed with a quantitative method – a thematic analysis was conducted. The thematic analysis started with forming main themes. The themes were formed as archetypes of enough similar comments. The themes were reviewed by two independent professional learning material producers. One has a background in social sciences and the other has a background in natural sciences. Finally 16 themes were determined. Several themes could occur in one feedback. The number of times a theme was emphasized was not calculated. The theme either exists in the feedback or then there was no such theme in the feedback. The number of different themes in a single feedback varied from zero to eight themes per feedback.

The quantification of the qualitative data was done as a binary data matrix, where each test person was represented by a case (as done traditionally). Each theme was represented by a variable, the value of which is either 1 or 0. The variable got a value of 1 only if the theme that variable described was expressed in the feedback. In the other case, the value of the variable was 0. The quantified data was extended by the results from the pre- and post test.

In this study, k-means clustering was used to build the personas according to the quantified binary data. Thus, k-means clustering was designed to work with continuous variables. It is note worthy that k-means clustering has been successfully used with binary data (e.g. Postaire, Zhang & Lecocq-Botte 1993; Ordonez 2003). The differences between continuous and binary data should be taken into account while analyzing the results. Finch (2005) has shown that there are small differences between different proximity calculation methods with k-means. In this study, k-means cluster analysis was used to maximize the distances between clusters. In this approach, the proximity calculations are not as crucial as compared to cases where we are aiming to form tight clusters and extract all the outliers.

In this paper, the clustering result is discussed along with literature on behavioural theories in order to ensure the validity of clustering. Secondly, we use clustering to characterize the personas, the clustering result is not in and of itself a result alone - it is a starting point for building personas.

3 RESULTS

3.1 Thematic Analysis

The written feedback was classified into thematic categories in three iteration phases (table 1).

Table 1: Theme frequencies and descriptions.

Count	Description
42	Freedom and independence while working and selecting the place and time for working were positive features.
22	Mathematics Navigator penalizes too much when the user does not succeed at exercises.
21	The workload was too great. (without mention of penalties)
18	Mathematics Navigator is good for revising mathematics, but not as the only method.
17	The need for more teaching and tutoring exists.
16	Mathematics Navigator was easy to use.
16	There was a need for theoretical content and more specific examples related to the exercises.
12	Mathematics Navigator could not trigger motivation
12	Correct and complete enough solutions for exercises were needed.
11	There would be a need for more instructions and explanations about how Mathematics Navigator operates.
10	The competence profile and other adaptive features were experienced as positive.
10	Users would prefer to select the exercises according to their own interests
10	User assumes that there are errors or bugs in Mathematics Navigator. [experience is registered, no matter if there really were something wrong]
10	The possibility of guessing the answer was felt to be a negative feature.
8	Mathematics Navigator increases motivation towards studying
8	Workload during the course was not equal for all students.

In the first phase all the different expressions were extracted. In the second phase, the expressions were integrated into 14 themes. In the third iteration phase, the themes were reviewed by two external people (not the authors) who are professional learning material producers. One has a background in social sciences and the other has a background in natural sciences. During this review, two themes were divided into four themes and finally there were 16 themes with relatively unambiguous definitions (table 1).

Most of the feedback expressions contained several themes. The number of different themes in a single feedback varies from zero to eight themes per feedback. The number of times a theme was emphasized was not calculated. The theme either exists in the feedback or then there is no such theme in the feedback.

3.2 Clusters based on Thematic Analysis

Quantifying the qualitative data is described in method -section. The visualization of k-means clustering is shown in figure 2. In the clustering, the distances between clusters were maximized in order to build personas that 1) form a proximate group and 2) are as different as possible to other clusters in order to support further development design.

The clusters are interesting when comparing the learning achievements and skills between the clusters. Generally, the average improvement in test scores was 5 points (median, when N=74), which achieves a statistically significant difference (t=-2,054, df=146, p=0,042). When focusing on learning achievements by clusters, there was only one group with a statistically significant improvement.

Table 2: Learning outcome for each cluster.

Cluster	pre test score (median)	post test score (median)	improvement in scores (median)	number of members
1	31	36	5	18
2	27	29	2	12
3	38	41	3	14
4	34	39	5	18
5	38	48	10*	12

In Table 2 the learning outcome (improvement in test score) and skills (test score) measured in pre- and post-test are shown. According to the results, only members in cluster 5 have had a statistically significant improvement (t=-2,082, df=22, p=0,049) in test scores.

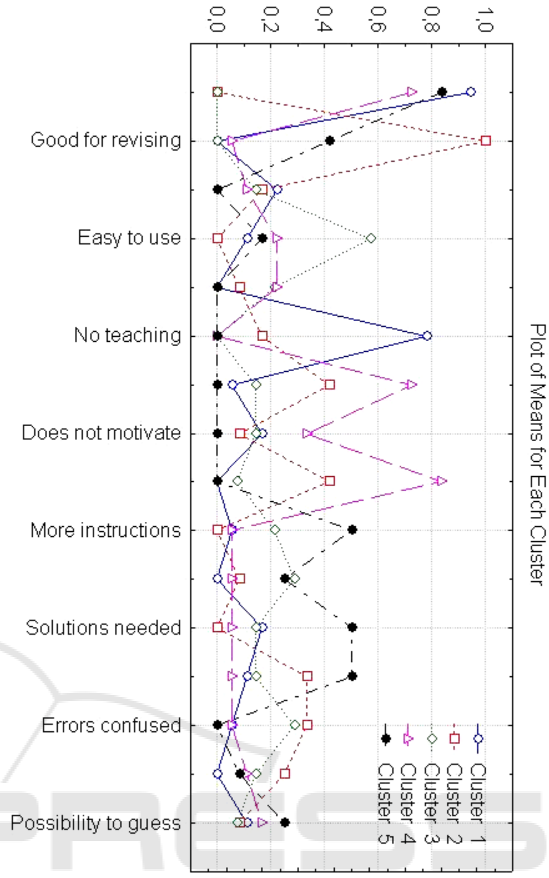

Figure 2: Plot of means for clusters received from quantified feedback data.

Next we build qualitative descriptions of the personas according to the classification of features of the clusters. For this we determine the major feature, which is represented by the theme that is mentioned by more than 60% of the cluster members. A minor feature is represented by the theme that is mentioned by more than 40% of the cluster members, but less than 60% of the cluster members.

According to these limits, we can build the following personas and their descriptions (Table 3). The personas (each cluster) were given a name in order to highlight their definitions as user archetypes. Short descriptions of the personas are following:

Matti (representing cluster 1) values freedom and independence in digital learning systems. However, he still wants clear teaching and tutoring features. Teaching and tutoring make him feel more confident due to his average skills in mathematics.

Kirsi (representing cluster 2) prefers traditional classroom teaching. She thinks that digital learning materials are good for revising, but are not adequate as the only method. She does not like learning systems that penalize too much for mistakes made, but she values positive encouragement. Kirsi does not like to work much for success that usually leaves the learning outcome poor.

Table 3: Personas and their descriptions.

Persona	Gain	Major features	Minor features
1 Matti	Average	Freedom Not enough teaching	
2 Kirsi	No	Good for revising	Too much work Penalizes too much
3 Aapo	No	Easy to use	
4 Eero	Average	Too much work Penalizes too much Freedom	
5 Anna	Good	Freedom	More instructions needed Solutions needed More examples needed

Aapo (representing cluster 3) is relatively good at mathematics. He masters the use of digital products quite well and easily masters the use of new systems. Aapo values challenges that motivate him. Non-challenging tasks do not engage Aapo.

Eero (representing cluster 4) is a student that wants everything to be easy. He values freedom and independence in studying, but does not like to work much for success. Eero does not like learning systems that penalize too much for mistakes made, but values positive encouragement.

Anna (representing cluster 5) values freedom and independence in digital learning systems. She needs a lot of theoretical content and specific examples of exercises. Furthermore, she needs extensive, clear instructions and explanations about how learning systems operate. She also values complete and correct solutions for exercises. Although, Anna's mathematic skills are relatively good, working with good digital learning materials encourages her to reach an even higher skill level.

3.3 Analysis about Personas

The formed personas are classified as primary, secondary and tertiary personas in accordance with their importance to define the potential customers.

Anna (5) is selected as a primary persona because of her good learning outcome and constructive design ideas. Also Matti (1) is classified as a primary persona. Anna and Matti will also be the main sources, when further developing Mathematics Navigator. By accepting all three needs for further development suggested by persona 5, we can also support persona 1's suggestion for more teaching and tutoring: Adding detailed solutions to exercises with more detailed content can be expected to help persona 1 in some way. Because of his lower skills at the beginning, we cannot be sure if this is enough.

Kirsi (2) is selected as a secondary persona: By developing instructions as suggested by Anna, we can also deliver ideas on how Mathematics Navigator can be used during classroom teaching in a pedagogically meaningful way. However, several pedagogical tests without a scientific context have been done in classrooms by teachers. We can produce directions about good practices in classrooms after we have collected feedback from those teachers.

Aapo (3) and Eero (4) are classified as tertiary personas. Aapo has relatively good skills with relation to the objectives of the learning material. We can hope that he learned something that we have not measured. Aapo's positive feedback about Mathematics Navigator allows us to determine that there was nothing critical in Mathematics Navigator.

However, when developing Mathematics Navigator we have to ensure that the user interface remains as easy to use as it is now. Eero has a negative attitude against learning, self-studying in particular. Learning is not always easy. It can certainly be fun, but according to previous studies, a good learning outcome requires work. It would be a crucial mistake to make Mathematics Navigator easier or more abbreviated. Hopefully more informative directions will help this persona to better understand the nature of self-studying and learning.

Kirsi's and Eero's concern about the competence profiling system being too penalizing is valuable from a motivational point of view. In order to engage and motivate users, the profiling system will be fixed. In the future, the exercise selection will be based on a real competence profile, while the visible competence profile will be designed to be more humane: it will not immediately penalize for one mistake.

4 CONCLUSIONS

Personas are powerful design tools if they are used correctly. They help designers, producers and publishers to maintain focus on a learner's needs, wants and requirements during the whole development process. Furthermore, personas enable the whole production team to achieve a shared understanding of the requirements and the context within the learning taking place. Production team can make decisions based on user archetypes rather than basing the decisions on their own intuition or personal likes.

In this study personas were constructed in order to ground publishing decisions of Mathematics Navigator. Qualitative user feedback was analyzed thematically at first. Secondly the users were bound to a certain clusters according to the proximity of their feedback. Finally strict clusters with meaningful common nominators were named as personas. Personas in this study are based on the mathematical modelling of quantified user experiences and therefore they are highly valid archetypes of the tested population. If the archetypes had been formed only according to thematically analyzed feedback, the outcome of the study would have been different.

Furthermore, several decisions about further development have been made according to results of this study: 1) The quality and quantity of feedback from Mathematics Navigator to the learner will be improved. Complete solutions to exercises will be added. Also, tools for accessing completed exercises and solutions will be designed. 2) General instructions will be rewritten in accordance with the feedback. However, this could have been done without the personas -method, but the importance of the task would have not been so clear to the developers. 3) The competence profile that was experienced as being too penalizing will be fixed. Exercise selection will be based on a real competence profile, while the visible competence profile will be designed to be more humane: it will not penalize immediately for one mistake.

During this study a new research challenge emerged: Is it possible to construct artificial test users according to personas? According to this idea artificial users represent archetypes of human users with a certain variance in behaviour. In other words, the artificial users are computational representations of personas: They will be constructed according to the behaviour of real users in digital environments by analyzing the behaviour as quantitative phenomena and designing a representation of a system, corresponding to the behaviour. Such a system can be implemented as a software agent. As a test person, a software agent can communicate with the educational systems by e.g. Web Services interfaces. An interesting question is related to the behaviour of the artificial user: Is its general level comparable to the behaviour of human users?

REFERENCES

Brusilovsky, P. (2001) Adaptive Hypermedia. User Modeling and User-Adapted Interaction. 2001 vol 11, pp. 87-110.

Cooper, A. (1999). The inmates are running the asylum. New York: Macmillan.

Cooper, A., Reimann, R. & Cronin, D. (2007). About Face 3: The Essentials of Interaction Design. Indianapolis, Indiana: Wiley Publishing Inc.

Eklund, J. & Brusilovsky, P. (1999). InterBook: an Adaptive Tutoring System. UniServe Science News; 1999 vol 12.

Finch, H. (2005). Comparison of Distance Measures in Cluster Analysis with Dichotomous Data. Journal of Data Science, vol 3(1), pp. 85-100.

Grudin, J. & Pruitt J. (2002). Personas, participatory design and product development: an infrastructure for engagement. In Proceedings of the 7th biennial particpatory design conference, Malmö, Sweden, June 2002, pp. 144-161.

Kujala, S. & Kauppinen, M. (2004). Identifying and Selecting Users for User-Centered Design. In Proceedings of the third Nordic conference on Human-computer interaction, October 2004. Tampere, Finland, pp. 297-303.

Ordonez, C. (2003) Clustering Binary Data Streams with K-means. In Association for Computing Machinery (ACM) Special Interest Group: Management of Data (SIGMOD) Workshop on Research Issues on Data Mining and Knowledge Discovery (DMKD), pp. 10-17.

Postaire, J.G., Zhang, R.D. & Lecocq-Botte, C. (1993). Cluster Analysis by Binary Morphology. IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 15(2), pp. 170-180.