International Journal of Business, Human and Social Sciences
ISSN: 2517-9411
Vol:4, No:11, 2010

A Framework to Support the Design of Mobile Applications

E. Platzer

***Abstract*—**This paper introduces a framework that aims to support the design and development of mobile services. The traditional innovation process and its supporting instruments in form of creativity tools, acceptance research and user-generated content analysis are screened for potentials for improvement. The result is a reshaped innovation process where acceptance research and user-generated content analysis are fully integrated within a creativity tool. Advantages of this method are the enhancement of design relevant information for developers and designers and the possibility to forecast market success.

***Keywords*—**design support, innovation support, technology acceptance, user-generated content analysis.

I. Introduction

DURING the past decades people's communication and information behavior changed dramatically as new interactive media became mass phenomena. Internet provides any information somebody could need and mobile phones enable communication anywhere and anytime. By the end of 2008 more than 4 billion people owned a mobile phone which is more than 60 % of world population. Convergence of these two media in form of so called smart phones opens up a whole new marked for various kinds of mobile services which already account for a huge part of the revenues in the mobile business. Predictions concerning their market success are crucial to design and development of such services as they often require high investments in infrastructure. Unfortunately traditional methods of technology acceptance research do not apply for interactive media as two striking examples will illustrate.

Short message service (SMS) was initially not developed for the C2C market and in 1995 owners of GSM-enabled mobile phones sent on average 0.4 text messages per month. In 2009 the average US teenager sent about 1500 text messages per month. It actually became a "killer application" though its success was not forecasted.

The case of mobile TV is different. A study released in 2007 [26] predicted a market volume of more than 655 million Euro for 2012 in Germany. In reality mobile TV failed to become a real success all over Europe [21]. Obviously a new way of supporting design and development and predicting market success is needed.

Traditionally innovation support tools and methods are used from the beginning of the design and development process to gather and evaluate ideas for an innovative service. Acceptance research is conducted at the earliest when a prototype has been built. User-generated content is analyzed only after market launch in order to find out what people liked about the product or what they did not like. Therefore it only supports incremental innovations of the existing service according to the user comments. This procedure does not come up with the very fast development within the market, is very costly and predictions of market success are nearly impossible. Moreover the full potential of the three included parts which are innovation support, acceptance research and user-generated content analysis is not tapped.

This new framework ought to solve problems of development dynamics in mobile business, enhance design relevance of acceptance research and enable radical innovations as well as incremental ones. Moreover it should be possible to do this computer-aided in real-time. Therefore it is planned to integrate acceptance research as well as analysis of user-generated content in the very first stage of idea generation of the service innovation process.

The central research question is therefore: What are requirements for a software solution that is able to detect acceptance factors at an early stage by analyzing user-generated content? Several further research questions arise within this context: Is it possible to find design relevant acceptance factors by analyzing user-generated content? Are these factors more design relevant than those from conventional acceptance research? Is it possible to predict acceptance of mobile services by analyzing user-generated content? Are these predictions relevant for business?

The paper is composed as follows. The theoretical base is elaborated in the first part. It consists of three main parts which are innovation support tools and methods, user acceptance measurement and user-generated content analysis. This chapter also includes brief descriptions of the state-of-the-art methods and techniques in these areas. The second part deals in detail with the proposed framework that ought to support design and development of mobile services. This chapter is structured by addressing the main problems of traditional methods. Finally an outlook of planned future research activities in this context and some concluding remarks are provided.

E. Platzer is with evolaris next level research gmbh, Graz, Austria and the Institute for Information Science and Information Systems, Karl Franzens University, Graz, Austria (phone: +43 (0) 316/380-6451; fax: +43 (0) 316/380-9575; e-mail: elisabeth.platzer@uni-graz.at)

II. Theoretical Background

A. Innovation Support Tools and Methods

Usually a difference is made between product and process innovation as well as between incremental and radical innovation. In the context of this paper the second differentiation is more important than the first one as the goal is to support radical innovations. Unlike incremental innovations that try to improve existing products or services radical innovations are completely new products or services [10].

The traditional innovation process which is depicted in Fig. 1 starts with idea generation which is followed by concept development. Then a prototype is designed and the product is tested "in the market". This step is followed by market launch.

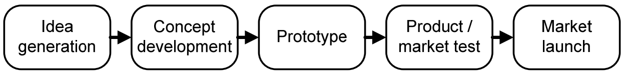

Fig. 1 Five steps of the traditional innovation process

Creativity techniques and tools are often implemented in the first phase of idea generation. These tools include intuitive and discursive methods that act as heuristics more than algorithms. A very popular intuitive method is brainstorming. Morphological analysis is a well-known discursive tool.

Web 2.0 principles offer possibilities to include users in the innovation process. Innovation networks, open innovation initiatives, perpetual beta toolkits are gaining importance especially in the context of software development [16]. Another method of user inclusion is the lead user concept where so called lead users are identified which is a tricky task and then involved in form of innovation workshops [13]. Again web technologies allow easier collaboration of companies and users as they provide interactive communication [2]. All these concepts have in common that the involved users are completely aware of being part of the innovation process. Attempts to include user-generated content analysis into the innovation process like feature based opinion mining aim to achieve incremental innovations. Some approaches also address user acceptance within the innovation process like the Dynamic Approach for Re-evaluating Technologies and Compass-Model [1].

B. Measuring User Acceptance

User acceptance research tries to find out why people adopt and use a certain technology. There exist different types of models that are commonly used for explanation of acceptance.

Technology Acceptance Model (TAM): Davis developed TAM [5] based on two earlier theories that deal with people's behavior which are Theory of Reasoned Action and Theory of Planned Behavior [8]. According to TAM perceived ease of use and perceived usefulness will affect the user's attitude and lead to the behavioral intention of usage. TAM is the most popular and well tested model that has often been extended and there exist numerous derivates of it.

Task Technology Fit Model (TTFM): Main assumption of TTFM [11] is that the systems' abilities to help the user with his task have to fit the user's task. Consistency of these two constructs has been tested in voluntary and mandatory settings especially in organizational contexts.

Dynamic Models: Time is the dynamic component of dynamic models. Most often different levels of acceptance are observed regarding to several phases or periods. A popular example for a dynamic model is the Dynamic Phase Model [15] but also Innovation Diffusion Theory [Rogers] can be regarded as a dynamic model of technology acceptance though diffusion and acceptance can not be set equal in general.

Compound models: Sometimes two or more models are merged in order to get a new model or parts of existing models are combined. An example is the Unified Theory of Acceptance and Use of Technology (UTAUT) [28]. Among the eight models cumulated in UTAUT is TAM as well as the Theory of Planned Behavior.

Flow-models: Flow experience is an important concept of technology acceptance research. It is defined as the result of a joyful activity [4]. In the Four Channel Flow-Model [14] flow is achieved by matching abilities and challenges. The user's perception of this match is indispensable for the state of flow.

C. User-generated Content Analysis

User-generated content analysis aims to extract information and furthermore observe structures within content that is provided by users. There exist various sources of user-generated content in the web like blogs, postings in social media or on platforms and newsgroups, customer reviews and test reports etc. Most of them are highly unstructured text documents in natural language this is why immediate mining of the text is impossible. There is need to somehow extract information out of the text, put it in a data base and then mine it for patterns and structures [19]. Partially-filled data bases allow integration of both processes like proposed in Extraction-Mining Random Fields [18]. The authors suggest a combined procedure of information extraction and data mining based on statistical machine learning and probabilistic models where results from both processes are input of the other one performing a "closed loop".

One way of discriminating approaches to the task of content analysis is linguistic-semantic versus positivist-statistic [17]. A purely linguistic method would try to really understand the meaning of each text document whereas a statistical respectively positivist approach would be based on frequencies of tokens only but not regarding their meaning at all. Adding semantic information to text documents is done in two fundamentally different ways. The first approach requires semantically enriched reference structures that are carefully designed in advanced to be able to handle data structure. The other approach is based on reconstruction of semantics by doing analysis. This reconstruction approach allows automated processes whereas the design of semantic reference structures needs human intellectual abilities [9].

A very fundamental differentiation of methods is supervised versus unsupervised learning. In the case of unsupervised learning the data is screened for similarities and then clustered in order to give a summary-like overview of important topics. If the topics or categories of interest are already known supervised learning is the appropriate approach. Supervised learning techniques require intellectual categorization of input-output combinations so called labeling in the information extraction process. A special form is semi-supervised learning where not all of the documents need to be labeled by hand but the machine is trained by labeling a training set by hand and automating the rest which reduces the time effort needed [19]. Training methods for classification of text documents can be either discriminative, generative or hybrid [6]. Popular generative approaches are naïve Bayes or Expectation-Maximation techniques. Transductive support vector machines, co-training, logistic regression or nearest-neighbor method are commonly used for discriminative classifiers [20]. Generative training is preferable if the amount of training data is low because it will provide better accuracy than discriminative training. Hybrid approaches can combine advantages of both methods and therefore outperform them [6].

Conditional Random Fields is a widely used method that is non-generative and enables inclusion of dependent features of text like capitalization, neighboring words etc that can aid classification. The conditional distribution with an associated graphical structure is called a conditional random field [27]. Hidden Markov Model is also a graphical approach but unlike Conditional Random Fields it is a directed model for sequential data [23].

Tools for classification of text documents are either binary or m-ary ($m > 2$). Binary classifiers decide whether a document belongs to a category independent from their decision on other categories whereas m-ary classifiers produce ranked lists of categories for each document including confidence scores for each candidate and then threshold on the ranks of possible categories [29].

Generalized expectation is a set of criteria that can be applied to models like Conditional Random Fields and will use prior information concerning input factors to learn from them. This method is called active learning as the most indicative labelings are used to improve further classification [7].

III. Framework Proposal

A. Capturing the Potentials for Improvement of the Traditional Process

The very first step towards a new framework has to be a thorough analysis of the existing process. The traditional process and the supporting tools are depicted in Fig. 2.

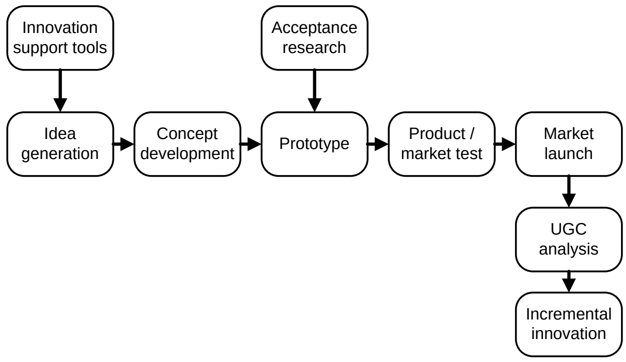

Fig. 2 Traditional links of innovation support tools, acceptance research and UGC analysis to the innovation process

Usually the idea generation and idea selection is supported by creativity techniques. These methods do not take into account factors of user acceptance except for some dynamic models. These dynamic models do so because they include the whole innovation process. This is why once again actual acceptance research takes place at the earliest when a prototype has been built. In this case a group of users is equipped with the new product respectively service and is therefore able to test it. Acceptance data is subsequently gathered by questioning. Questionnaires are mostly composed of standardized items. As said before this is the form of acceptance research that provides result most early. More often than that acceptance research is conducted for existing products or services that are already in use. Again the most common data gathering method is using standardized questionnaires. This is a very time consuming procedure as the whole process of questionnaire design, user sampling, questioning and data evaluation must be gone through. As the mobile service market is a highly dynamic market with short product and service lifecycles this fact exposes the first potential for improvement in the traditional process: Acceptance research must take place in the very first phase of idea generation and leave the common path of questionnaire-based surveys to come up with dynamics of the market.

The questionnaire-based data gathering also brings up another problem. Acceptance factors that are tested are often very fuzzy constructs that are not intersubjectively comprehensible. For example “ease of use” does not mean the same thing to person A and person B. They are also highly aggregated in order to receive research models that allow structural equation modeling. These facts uncover a second challenge within the traditional framework: Common acceptance factors lack relevance for design and development of new mobile services as shown in prior research [22].

User-generated content analysis is usually done for products and services that are already launched. Methods like feature based opinion mining try to find out which parts or characteristics of a product or service users liked or did not like. This information can then be used for incremental innovations of the existing product or service. Here is another potential for improvement: Support must be provided for radical innovations as well as for incremental innovations.

In order to sum up the potentials they are listed below:

- coming up with the dynamics of development
- enhancing design relevance
- enabling radical innovations

B. Reshaping the process within a new framework

The next step is the design of the new framework on the basis of the potentials captured beforehand. Fig. 3 shows the inclusion of acceptance research and user-generated content analysis within the idea generation phase.

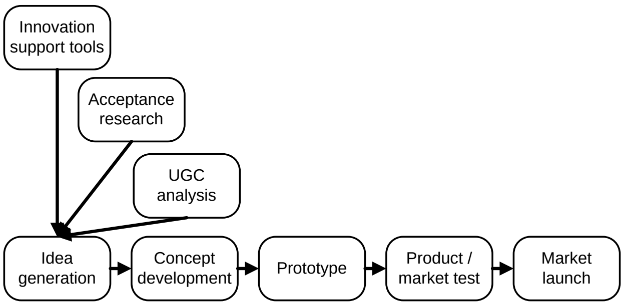

Fig. 3 Suggested inclusion of innovation support tools, acceptance research and UGC analysis within the innovation process

Inclusion of acceptance research in the idea generation step is possible if some pre-conditions are considered. Acceptance factors are people's motives that cause the behavioral intention of adoption and further usage of the product or service. These motives can be seen as requirements or needs. In this case as there are no empirical values from real usage as the product or service is only about to be developed it is reasonable to take a look at currently successful services and products and find out which motives they address. A very useful model of motivation is Reiss-model [24]. It includes 16 basic desires of human beings that are listed in table 1 and aims to cover all areas of motives. These basic desires represent a given canonical list that does not need changes or enlargement just because technological development goes on. The proportions of importance of motives might change as well as the ways to address them but not the motives themselves.

User behavior can be measured by download numbers instead of questioning behavioral intentions by using standardized items. The behavioral intention usually subsumes planned usage, willingness to pay and intentions to recommend the product or service. This additional information can be found in customer reviews where people who already use the product or service recommend it to others and also tell them why. This user-generated content is provided voluntarily and is not manipulated by survey problems like answer bias or else. Moreover the user is not fully aware of being integrated in the innovation process which might also cause bias.

TABLE I
16 BASIC DESIRES

Motive name	Motive	Intrinsic feeling
Power	Desire to influence (including leadership; related to mastery)	Efficacy
Curiosity	Desire for knowledge	Wonder
Independence	Desire to be autonomous	Freedom
Status	Desire for social standing (including desire for attention)	Self-importance
Social Contact	Desire for peer companionship (desire to play)	Fun
Vengeance	Desire to get even (Including desire to compete, to win)	Vindication
Honor	Desire to obey a traditional moral code	Loyalty
Idealism	Desire to improve society (including altruism, justice)	Compassion
Physical exercise	Desire to exercise muscles	Vitality
Romance	Desire for sex (including courting)	Lust
Family	Desire to raise own children	Love
Order	Desire to organize (including desire for ritual)	Stability
Eating	Desire to eat	Satiation (avoidance of hunger)
Acceptance	Desire for approval	Self-confidence
Tranquility	Desire to avoid anxiety, fear	Safe, relaxed
Saving	Desire to collect, value of frugality	Ownership

It is useful to reduce the enormous amount of user-generated content that is available in the web in order to get more focused information. First of all only content that was provided by people who use the product or service should be taken into consideration. They report their motives from experience and not only from imagination. Moreover it is necessary to be able to assign each piece of content to a certain product or service in order to receive information about the market success of it expressed by download numbers.

It would be possible to use unsupervised clustering methods that provide a list of salient topics in the numerous text documents. This approach would not lead to a learning system that matches customer reviews as text documents with motives that are acceptance factors. Therefore it would not enable an always improving forecasting tool and neither assure design relevance of the information provided. Supervised learning could provide most accurate data but the huge number of customer reviews that were to classify manually impedes this solution. User motives can also be extracted automatically from the user-generated content by using semi-supervised machine learning techniques that are described above.

The first step is the manual annotation of trainings data using the 16 basic desires as classes. The machine learning tool will then automatically annotate further data using heuristics that predict annotation. Accuracy of the machine-based annotation can be evaluated by means of precision measures. As a first result proportions of important motives are provided.

The next thing to do is find out which products or services did address the motives best. This is done by simply comparing the reviews assigned to the product or service regarding their annotations. Then best practice examples can be extracted.

Finally prognosis can be obtained by comparing motives assigned to the product or service in question with the general proportions of motives and best practice examples.

C. Coming up with Dynamics of Development

The automated analysis of the user-generated content allows real-time observance of proportional changes of motive importance as well as of services that address these motives best. Moreover it enables immediate usage of this information for the design and development process avoiding time consuming intermediate steps. The results are on hand when needed and the continuous analysis avoids obsoleteness.

D. Enhancing Design Relevance

The idea generation is supported by acceptance factors that are not fuzzy concepts. Instead of high aggregation levels very basic information concerning motives is provided. This information is enriched by best practice examples that allow creative realization of design that addresses users' motives. Designers and developers can trace back motives to design of successful services and if needed full user statements. This possibility solves the problem of intersubjective comprehension.

E. Enabling Radical Innovations

Radical innovations are enabled as the information is at hand at the beginning of the innovation process before investment has been made. Secondly it is about providing an environment for creative design which allows radical innovations as well as incremental innovations for existing products after market launch. The results of the analysis and the best practice examples can be regarded as a focused creativity tool that already considers user acceptance while generating ideas for innovative products and services.

IV. Outlook

A. Technological implementation

The framework that is presented in this paper has not been implemented technologically yet but it is planned to do so soon. Apple's AppStore will be the data source for the first experiment as it is suitable for several reasons. First of all it offers customer reviews in a structured form for its apps. The number of reviews is sufficiently high as there are many users. Finally it provides only reviews written by people that have downloaded the app.

Information extraction will be computed using an existing semi-supervised learning tool that enables automated annotation and classification of the customer reviews. The tool that will be used is called GATE [3]. It is an architecture that enables various tasks of language processing including tools for information extraction, classification, visualization and evaluation of precision.

The customer reviews will be supplied to GATE and then a training set will be annotated manually. This is to say motives are assigned to the single reviews. Moreover download numbers and app names will be matched with the text. After this training it will be necessary to evaluate the precision of the machine-based annotation. Therefore the machine learning tool will annotate parts of training data based on the information from the rest of the manually annotated training data. Then the results of the manual and the machine annotation process will be compared. In case the result of this precision test is not satisfying the training set will be enlarged otherwise the machine-based annotation and classification of the rest of the data can be computed.

The expected results will show which motives are currently most important acceptance factors. Moreover it will be possible to find out which apps addressed these factors best. On the other hand it will also be possible to predict download numbers of a rather new app by feeding the machine with some already existing customer reviews concerning this app and let it forecast the annotation and classification as well as download number itself. These data is then compared to current motive importance and together with the download prediction provides important information for further development.

B. Test and evaluation

Evaluation will take place regarding the main goals that were to achieve.

The first evaluation criterion will be design relevance. According to design science principles [12] a system should be evaluated regarding its ability to solve the problem it ought to. Therefore expert interviews or an expert discussion will be the most reasonable methods to choose. These experts will be five to 15 software developers and service designers as they are the main addressees of design relevant acceptance information. They will be asked whether they find the information they get design relevant or not which is the simplest way of testing the extent to which the target has been reached. Moreover there should be a comparison to acceptance factors in traditional research.

The second criterion for evaluation will be precision of forecast. Two ways of evaluation are imaginable. One is to design apps based on the information the system provides and then observe there market success in form of download numbers. Shortcoming of this method is that it suppresses the influence of creativity. The information that is provided does not automatically lead to a successful service as creativity is still an important part of the process. It will be more useful to analyze the user-generated content related to new apps and try to forecast the success of these particular apps at an early stage. Comparison of forecast and realized download numbers will show forecast precision.

V. Conclusion

This framework does not aim to create an autonomous robot that automatically designs successful mobile services but to provide an environment that is able to support developers and designers during the creative process of creating mobile services. They shall receive design relevant information in order to enhance the probability of designing well-accepted mobile services as the user-generated content is pre-processed and interpreted for them. It is about support of creativity not replacement.

Moreover the forecasting possibility is an opportunity to predict market success at an early stage and therefore avoid high cost and effort of further development as well as of time consuming and expensive market surveys.

References

[1] M. Amberg, M. Hirschmeier, J. Wehrmann, "The compass acceptance model for the analysis and evaluation of mobile services", *International Journal of Mobile Communications* 2(3), pp. 248-259, 2004.

[2] V. Bilgram, A. Brem, K.-I. Voigt, "User-Centric Innovations in New Product Development; Systematic Identification of Lead User Harnessing Interactive and Collaborative Online-Tools", *International Journal of Innovation Management*, 12 (3), pp. 419-458, 2008.

[3] H. Cunningham, D. Maynard, K. Bontcheva, V. Tablan, "GATE: A Framework and Graphical Development Environment for Robust NLP Tools and Applications", *Proceedings of the 40th Anniversary Meeting of the Association for Computational Linguistics (ACL'02)*, Philadelphia, July 2002.

[4] M. Csikszentmihalyi, *Das Flow-Erlebnis: Jenseits von Angst und Langeweile im Tun aufgehen.* (The Flow-Experience: Being carried away with action beyond fear and boredom.), Stuttgart, Klett-Cotta, 1987.

[5] F. Davis, *A Technology Acceptance Model for Empirically Testing New End-User Information systems*, Massachusetts Institute of Technology, Sloan School of Management Thesis, 1985.

[6] G. Druck, C. Pal, X. Zhu, A. McCallum, "Semi-Supervised Classification with Hybrid Generative/Discriminative Methods", *Proceedings of the Conference on Knowledge Discovery and Data Mining*, August 12-15 2007, San Jose, USA, 2007.

[7] G. Druck, B. Settles, A. McCallum, "Active Learning by Labeling Features", *Proceedings of the Empirical Methods in Natural Language Processing*, August 6-7 2009, Singapore, 2009.

[8] M. Fishbein, I. Ajzen, *Belief, Attitude, Intention and Behavior: An introduction to Theory and Research*, Reading, Addison-Wesely, 1975.

[9] U. Frank, "Interview mit Rudi Studer zum Thema "Semantische Technologien" (Interview with Rudi Studer concerning the topic of "semantic technologies")", *Wirtschaftsinformatik* 52(1), pp. 49-52, 2010.

[10] O. Gassmann, M. Zeschky, "Radikale Innovation ist nicht planbar wie ein Produktionsprozess (Radical innovation is not as planable as a production process)", *Innovation Management* 3, pp. 8-10, 2007.

[11] D. L. Goodhue, R. L. Thompson, "Task-Technology fit and individual performance", *MIS Quarterly* 19, pp. 213-236, 1995.

[12] A. R. Hevner, S. T. March, J. Park, "Design Science in Information Systems Research", *MIS Quarterly* 28, pp. 75-105, 2004.

[13] E. v. Hippel, "Lead Users. A Source of novel product concepts", *Management Science* 32, pp. 791-805, 1986.

[14] D. L. Hoffman, T. P. Novak, "Marketing in hypermedia computer-mediated environments: conceptual foundations", *Journal of Marketing* 60(3), pp. 50-68, 1996.

[15] T. Kollmann, *Akzeptanz individueller Nutzungsgüter und –systeme. Konsequenzen für die Einführung von Telekommunikations- und Multimediasystemen* (Acceptance of individual goods and systems. Consequences for the introduction of telecommunication and multimedia systems), Wiesbaden, Gabler, 1998.

[16] J. Kranz, C. Janello, A. Picot, "Die Rolle von Web 2.0-Prinzipien im Innovationsprozess (The role of web 2.0 principles within the innovation process)", *Information Management und Consulting* 24, pp. 39-47, 2009.

[17] M. C. Lacity, M. A. Janson, "Understanding Qualitative Data: A Framework of Text Analysis Methods", *Journal of Management Information Systems* 11(2), pp. 137-155, 1994.

[18] A. McCallum, D. Jensen, "A Note on the Unification of Information Extraction and Data Mining using Conditional-Probability, Relational Models", *IJCAI'03 Workshop on Learning Statistical Models from Relational Data*, August 9-15, Acapulco, Mexico, 2003.

[19] A. McCullam, "Information Extraction: Distilling Structured Data from Unstructured Text", *ACM Queue* 3 (9), 2005.

[20] K. Nigam, A. McCallum, T. M. Mitchell, "Semi-Supervised Text Classification Using EM", in: O. Chapelle, A. Zien, B. Schalkopf, Eds., *Semi-Supervised Learning*, Boston: MIT Press, 2006.

[21] O. Petrovic, C. Kittl, E. Maxl, *Werbefinanzierung und Mobile TV – Internationales Benchmarking von Mobile TV-Werbeformen* (Advertisment-based finance and mobile TV – International benchmarking of mobile TV advertising forms), Schriftenreihe der Rundfunk und Telekom Regulierungs-GmbH, 2009.

[22] E. Platzer, "A critical review of user acceptance research in the area of mobile services", *Libri: international journal of libraries and information services* 59 (4), pp. 213-227, 2009.

[23] L. R. Rabiner, "A Tutorial on Hidden Markov Models and Selected Applications in Speech Recognition", *Proceedings of the IEEE* 77 (2), pp. 257–286, 1989.

[24] S. Reiss, "Multifaceted Nature of Intrinsic Motivation: The Theory of 16 Basic Desires," *Review of General Psychology* 8(3), pp. 179-193, 2004.

[25] E. M. Rogers, *Diffusion of innovations*, 5. ed., New York, Free Press, 2003.

[26] M. Schmid, „*Mobile TV 2012. Marktpotenziale für rundfunkbasiertes Mobile TV in Deutschland* (Mobile TV 2010. Market potentials of broadcasting-based mobile TV in Germany)", Goldmedia, 2007.

[27] C. Sutton, A. McCallum, "An Introduction to Conditional Random Fields for Relational Learning", in: L. Getoor, B. Taskar, Eds., *Introduction to Statistical Relational Learning*, Boston, MIT Press, 2006.

[28] V. Venkatesh, "User Acceptance of Information Technology: Toward a Unified View", *MIS Quarterly* 27, pp. 425-478, 2003.

[29] Y. Yang, "An Evaluation of Statistical Approaches to Text Categorization", *Journal of Information Retrieval* 1 (1/2), pp. 67-88, 1999.