ABSTRACT
News consumption has been evolving from offline newspapers to online news. However, while offline newspapers sales are decreasing, online news business models have never been entrenched. Meanwhile, the new technology of social recommender systems enable automated news aggregation. Personalized news aggregators (PNAs) rely on this technology, and provide personalized news in visually appealing ways that might deliver the potential for a new business model. However, there is no research on PNA configuration or users’ willingness to pay (WTP).

An empirical investigation with 116 participants examined usage features influencing PNA users’ adoption and their WTP for a paid-based service. First, we showed that perceived usefulness, usage comfort, awareness, and (social) personalization significantly influence intention to use a PNA. Users are also considering price. Second, we found an optimal price point of 1.88€ and a price range up to 6.83€ for monthly use.

Keywords
Personalized news aggregator, business model, social recommender system.

INTRODUCTION
Traditionally, news has been provided by newspapers, and the business model of selling newspapers or advertisements has been around for some time. Nevertheless, due to digitalization, newspapers’ sales figures have dropped and the traditional business model might no longer fit anymore. The transformation of an offline to an online business model did work, but in the long run the consumer has many other options through which to consume news complementary. Besides, consumers’ WTP for online content is low (Dou, 2004). To date, publishers still have problems to find an appropriate digitalization strategy in order to monetize news and content and to counteract the decline in revenue.

Online news has an important advantage for consumers: it is possible to adjust news according to preferences. In the literature, it turned out that there is a correlation between online news, personalization, and new potential business revenue strategies (Saeaeksjaervi, Wagner and Santonen, 2003). Meanwhile, the new technology of social recommender systems have improved content personalization and adaptation to a user’s preferences. Content bundling can be transformed from manual bundling to an automated aggregation. This technology is being used in new types of services: personalized news aggregators (PNAs). The service is mostly optimized for mobile devices (e.g. tablet computers) and presents a personalized selection of news and other content sources in an optically unified interface. A first approach to implementing this service is Flipboard.

There is little research about PNAs in the information systems (IS) literature available (e.g., Nanas, Vavalis and Houstis, 2010), and none on PNA configuration in a media context. A service such as PNA might enable the establishment a new digital business model for news. This new content distribution form has not yet been explored and requires, besides the investigation of the underlying technology, a scientific research of economic effects. To design a profitable business model and digitalization strategy for publishers, it is necessary to know which features are in fact needed for the service and to know what the user is willing to pay for it. To provide a first insight, this study examines the importance of different features in order to influence users’ intention to use a PNA. We also examine WTP for this service, to show if there is a general opportunity for a paid-based business model. We address the following research questions:

RQ1: Which features are relevant from a user perspective and how do they influence the intention to use a PNA?
RQ2: What is user WTP for PNA service?
The structure of the paper is as follows: First, we present a review of technologies and business models. We then present the development of our research model, the hypotheses, and the methodological approach to measure the features and the WTP. Next, empirical results are shown. Finally, we discuss findings, highlight implications, and present some study limitations.

RELATED LITERATURE

Social Recommender Systems and Personalized News Aggregators

Personalization mechanisms such as recommender systems have been in existence since the introduction of the first system – “Tapestry” – by Goldberg, Nichols, Oki, and Terry (1992). These technologies assist the user by supplying well-structured information in searching, sorting, and filtering the massive amount of information available online. Initially used in e-commerce (e.g. product recommendations by amazon.com), recommender systems can now also be used for digital products, such as news or music. Different technologies have been developed; the traditional and most widely used ones are content-based filtering, collaborative filtering, and hybrid filtering (Adomavicius and Tuzhilin, 2005).

With the rise of Web 2.0, social networks have spread and (inter)personal information has become available, for instance via Facebook (Carmagnola, Vernero and Grillo, 2009). Based on information about a user or users’ social networking friends, social recommender systems can recommend content (Ricci, Rokach, Shapira and Kantor, 2011). As various scholars note, social recommender systems devise a new way to improve both the selection and the weighting of recommendations, thereby increasing recommender systems’ accuracy and enable a new consumption of content (e.g., Arazy, Kumar and Shapira, 2010). These systems enable the automated selection, bundling, and combination of content from different sources, adapted to an individual consumer’s preferences.

Initially, IT-enabled personalization mechanisms such as recommender system technologies were integrated into aggregation systems. Based on recommender systems, they provided a first solution to the simple task of bundling content. Aggregation systems add value by analyzing and adjusting information from different sources according to a specific objective (Zhui, Siegel and Madnick, 2001). Based on the new technology of social recommender systems, PNAs are the new generation of aggregation systems. Paliouras, Mouzakidis, Moustakas, and Skourlas (2008) explain a mechanism that aggregated content, sorting them into categories and presenting an adaptively personalized interface. Nanas et al. (2010) illustrated, by means of a self-developed PNA, how content-based filtering can be useful for selecting relevant information.

Business Model for News

Traditionally, news was bundled in a paper-based newspaper and has been sold at low prices to individuals or corporate subscribers. Advertising has been sold in order to cover the costs and generate revenue. This established approach became known as the “newspaper revenue model” (Teece, 2010). Owing to digitalization, publishers began to move from print newspapers to an online form; however this has created monetization problems (Saeaeksjaervi et al., 2003). As noted, WTP for online content is low, and it is unclear whether advertising can entirely compensate for the loss in direct revenue.

According to Chyi (2005), publishers have been experimenting with different business models for online news: the subscription model, the advertising model, the transactional model, and the bundled model. For example, Wang, Ye, Zhang, and Nguyen (2005) showed that several factors (e.g. added-value or service quality) influence the willingness to access subscription based news. Additionally, “freemium” – as a new revenue model – has the potential to monetize news, since a free version as well as a paid-based premium version (e.g. without advertisement) are provided (Wagner, Benlian and Hess, 2013). Moreover, research is starting addressing digital media innovations in order to find a solution for news delivery in the future (e.g., Gershon, 2013).

RESEARCH MODEL AND HYPOTHESIS DEVELOPMENT

First, we address the development of a research model in order to answer RQ1. To do so, we want to examine user attitudes to adopting a PNA and how this is influenced by different features. The research model of Dibbern, Heinzl, and Schaub (2007), which analyzes determinants that affect mobile banking services acceptance, seems to be appropriate for this study. The research model is based on the Technology Acceptance Model (TAM) and the Theory of Reasoned Action (TRA) (Davis, 1989; Fishbein and Ajzen, 1975). The purpose of technology acceptance models is to provide a theoretical framework to analyze a technology’s adoption. It argues that an individual’s behavioral intention to perform a certain action is the result of his or her attitude towards this behavior, which leads to a specific use behavior. This procedure has been validated (e.g., Davis, 1989; Doerr, Benlian, Vetter and Hess, 2010).
In this case and according to literature, we examine whether the user attitude (AT) to use a PNA influences the behavioral intention (BI) to use a PNA. It is therefore hypothesized that:

H1: User AT will have a positive influence on the BI to use a PNA.

In a second step, we identified features of a PNA that influence user attitude, and to integrate these into the research framework. We will draw on hypotheses for each feature to analyze its influence on AT. To support the development of the framework a qualitative study was conducted first, with the aim to confirm literature-based features and to discover exploratory new features in the context of PNAs. The study was conducted in mid-2012, including 34 interviews with technology experts, such as employees, bloggers, or journalists. The following features are the result: perceived usefulness (PU), considering pricing (CP), usage comfort (UC), personalization (PE), ease of use (EU), system quality (SQ), platform support (PS), source integration (SI), multimedia content (MC), trusted sources (TS), awareness (AW), social interaction (SO), and social personalization (SP). Following Dibbern et al. (2007), we clustered these features according to three different perspectives: consumer, technology, and network.

In Hypothesis 2, the consumer perspective will be consolidated. PU thereby refers to user beliefs that task performance is efficient, and CP can be described by the underlying payment model and the relevance of occurring usage costs. UC refers to simple and intuitive handling, while PE covers content personalization according to user interests. Hence, the following hypotheses are formulated:

H2a: PU will have a positive influence on user AT to use a PNA.
H2b: CP will have a positive influence on user AT to use a PNA.
H2c: UC will have a positive influence on user AT to use a PNA.
H2d: PE will have a positive influence on user AT to use a PNA.

Hypothesis 3 describes features from a technology perspective. EU refers to the user beliefs that the use of the technology is possible without much effort. SQ is explained by the reliability and presence of the presented information, while PS describes the different types of devices that support PNA. SI can be explained by the ability to involve various and different sources. MC represents the degree of combination of text, image, audio, or video file formats. Thus the following hypotheses are formulated:

H3a: EU will have a positive influence on user AT to use a PNA.
H3b: SQ will have a positive influence on user AT to use a PNA.
H3c: PS will have a positive influence on user AT to use a PNA.
H3d: SI will have a positive influence on user AT to use a PNA.
H3e: MC will have a positive influence on user AT to use a PNA.

Finally, Hypothesis 4 describes a network perspective. TS refers to a source’s credibility and origin. AW relates to the extent of brand popularity and recognition of the PNA. SO includes all forms of exchange, such as commenting or recommending, between users. SP integrates the interests of users’ friends as a basis for better recommendations and selection. This can be summarized in the following hypotheses:

H4a: TS will have a positive influence on user AT to use a PNA.
H4b: AW will have a positive influence on user AT to use a PNA.
H4c: SO will have a positive influence on user AT to use a PNA.
H4d: SP will have a positive influence on user AT to use a PNA.
To answer RQ2 and to achieve a first impression of price sensitivity, we investigated user WTP for a PNA service. To measure the WTP, different methods were applied in research, for example the conjoint analysis method and the Becker-DeGroot-Marschack method (Miller, Hofstetter, Krohmer and Zhang, 2011). In this study, the price sensitivity meter (PSM) of Van Westendorp (1976) seems appropriate, as it is highly suitable for the price estimation of innovative services. For example, it has been validated for the pricing of music-as-a-service (MaaS) (Doerr et al., 2010).

RESEARCH METHODOLOGY

Measures

For part one of the study, to operationalize the research framework, validated constructs were used in the questionnaire. Constructs were measured and rated on 7-point Likert scales, where 1 refers the lowest score and 7 the highest score. The items for BI were adopted from Venkatesh, Morris, Davis, and Davis (2003), while items for AT were measured by a semantic differential by Graf (2007). Items for the features were adapted and worded according to the scale by Sujan and Bettman (1989).

To measure the WTP for part two of the study, four items of the PSM scale were used, to calculate the marginal cheapness (MGP), the marginal expensiveness (MEP), the optimal price point (OPP), and the indifference price (IDP). In the study, we pretended to use a monthly charge for the use of a PNA. Nevertheless, the PSM only measures the price consciousness, but not the intention to buy or pay for the service (Van Westendorp, 1976).

Data Collection

The data for this study was collected using a quantitative standardized online survey. At the start of the survey, we showed a short video explaining the PNA’s functionality, to ensure that all participants had the same knowledge base. A pretest was conducted. The survey was developed with the software Unipark by Globalpark, and data was collected in January 2013. Participants were invited with an invitation link sent via email to 5,030 students of a German university, via Facebook, and
via personal contacts. We collected 498 datasets, but we could only consider datasets from participants who had already been using a PNA. Thus, our final sample comprised 116 valid datasets. We followed the usual approach of asking students in this development stage and in similar use cases (i.e., recommender systems or MaaS) (e.g., Benlian, Titah and Hess, 2010; Chyi, 2005; Wagner et al., 2013). The participants’ age ranged between 18 and 54 years, whereas 85% were between 18 and 29 years old. 54% of the participants were male and 46% were female. The sample comprised 75% students, 20% employees and 5% self-employed. Most of the participants (62%) rarely use a PNA, but 19% already use it weekly, 13% daily, and 6% use a PNA several times a day.

RESULTS

For the first part of the study, structural equation modeling was used to test the hypotheses. Therefore, the software SmartPLS 2.0 M3, using the partial-least-squares (PLS) algorithm, was used for all analysis (Ringle, Wende and Will, 2005). The algorithm has the advantage of modeling latent constructs and predictive models, and is usable with small sample sizes (Chin, 1998). Furthermore, PLS analysis is highly appropriate for our explorative study (Hair, Ringle and Sarstedt, 2011). In this case, the software was used to calculate path coefficients and to determine the paths’ significance in the model (using bootstrapping).

To analyze the quality of the model and provide a valid model, all values have to be above literature-based thresholds. All items except SQ and PS have Cronbach’s α values above .06, which is acceptable in this early research stage (Henseler, Ringle and Sinkovics, 2009). For SQ and PS, one indicator each was rejected. A new calculation of the model now showed values above the threshold. Composite reliability shows values above .70 in all cases (Chin, 1998). Furthermore, the average variance extracted (AVE) showed values above the threshold of .50 (Chin, 1998). Discriminant validity was analyzed by comparing the latent construct correlation and the square root of the specific AVE. For each construct, the AVE’s value was higher that the square root (Fornell and Larcker, 1981). Therefore, all constructs satisfied the reliability and validity criteria.

<table>
<thead>
<tr>
<th>Perspective</th>
<th>Construct</th>
<th>Composite reliability</th>
<th>AVE</th>
<th>Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>Consumer</td>
<td>BI</td>
<td>.966</td>
<td>.904</td>
<td>5.155</td>
</tr>
<tr>
<td></td>
<td>AT</td>
<td>.897</td>
<td>.634</td>
<td>5.389</td>
</tr>
<tr>
<td></td>
<td>PU</td>
<td>.852</td>
<td>.659</td>
<td>6.276</td>
</tr>
<tr>
<td></td>
<td>CP</td>
<td>.730</td>
<td>.503</td>
<td>6.412</td>
</tr>
<tr>
<td></td>
<td>UC</td>
<td>.908</td>
<td>.767</td>
<td>6.014</td>
</tr>
<tr>
<td></td>
<td>PE</td>
<td>.889</td>
<td>.729</td>
<td>6.182</td>
</tr>
<tr>
<td>Technology</td>
<td>EU</td>
<td>.912</td>
<td>.777</td>
<td>6.129</td>
</tr>
<tr>
<td></td>
<td>SQ</td>
<td>.863</td>
<td>.760</td>
<td>6.458</td>
</tr>
<tr>
<td></td>
<td>PS</td>
<td>.853</td>
<td>.746</td>
<td>6.097</td>
</tr>
<tr>
<td></td>
<td>SI</td>
<td>.920</td>
<td>.793</td>
<td>6.294</td>
</tr>
<tr>
<td></td>
<td>MC</td>
<td>.927</td>
<td>.810</td>
<td>4.849</td>
</tr>
<tr>
<td>Network</td>
<td>TS</td>
<td>.870</td>
<td>.696</td>
<td>5.677</td>
</tr>
<tr>
<td></td>
<td>AW</td>
<td>.969</td>
<td>.912</td>
<td>3.383</td>
</tr>
<tr>
<td></td>
<td>SO</td>
<td>.920</td>
<td>.793</td>
<td>4.157</td>
</tr>
<tr>
<td></td>
<td>SP</td>
<td>.953</td>
<td>.872</td>
<td>4.231</td>
</tr>
</tbody>
</table>

Table 1. Composite reliabilities, AVEs, and descriptive statistics

To analyze the structural model, we used Ball’s Q² as the indicator for predictive relevance, as well as Cohen’s effect sizes β and t-values to investigate the paths’ significance. Using the jackknifing procedure, Q² > 0 presents a predictive relevance of the model, whereas Q² ≤ 0 suggests a lack of relevance. All constructs have a positive Q², indicating that we have predictive relevance (Fornell and Larcker, 1981; Sarstedt and Wilczynski, 2009). In a second step, we analyzed β to determine each path’s effect size. A value of .02 indicated a small, a value of .15 a medium, and a value of .35 a large effect size (Cohen, 1988). All of our significant results showed at least a small effect size. Overall, our model and features can explain one-third of the variance in user attitude to use a PNA (R² = .299). Furthermore, AT shows an R² of .400 to explain the variance in BI. In total, 7 of our hypotheses can be supported. First, as expected, AT shows a positive influence on the BI to use a PNA, supporting H1 (β = .632, p < .05). We found support for hypotheses H2a, H2b, H2c, and H2d, whereas PU, CP, UC, and PE positively influence AT (β = .230, p < .05 / β = .188, p < .05 / β = .238, p < .05 / β = .192, p < .05). On the one hand, the only significant relationship for the hypothesis 3 is SQ of a PNA (β = .233, p < .05). But, a negative relationship leads one to reject hypothesis H3b. On the other hand, H3a, H3c, H3d, and H3e also cannot be supported (β = -.079, p > .05 / β = -.063, p > .05 / β = .081, p > .05 / β = .009, p > .05). Therefore, EU, PS, SI, and MC do not lead to a higher AT. AW and SP positively influence AT (β = .208, p < .10 / β = .393, p < .01). Therefore, hypotheses H4b and H4d can be supported. Finally,
TS and SO are significant but show negative relationships ($\beta = -.286, p < .01 / \beta = -.394, p < .01$). Hence, hypotheses H4a and H4c must be rejected.

<table>
<thead>
<tr>
<th>Perspective</th>
<th>Hypothesis</th>
<th>t-value</th>
<th>$\beta$-value</th>
<th>Effect size</th>
<th>Result</th>
</tr>
</thead>
<tbody>
<tr>
<td>Consumer</td>
<td>H1$^+$</td>
<td>9.181</td>
<td>.632</td>
<td>-</td>
<td>Supported</td>
</tr>
<tr>
<td></td>
<td>H2a$^+$</td>
<td>2.040</td>
<td>.230</td>
<td>.067</td>
<td>Supported</td>
</tr>
<tr>
<td></td>
<td>H2b$^+$</td>
<td>2.085</td>
<td>.188</td>
<td>.039</td>
<td>Supported</td>
</tr>
<tr>
<td></td>
<td>H2c$^+$</td>
<td>2.346</td>
<td>.238</td>
<td>.046</td>
<td>Supported</td>
</tr>
<tr>
<td></td>
<td>H2d$^+$</td>
<td>1.968</td>
<td>.192</td>
<td>.039</td>
<td>Supported</td>
</tr>
<tr>
<td>Technology</td>
<td>H3a$^+$</td>
<td>.783</td>
<td>-.079</td>
<td>-.016</td>
<td>Not supported</td>
</tr>
<tr>
<td></td>
<td>H3b$^+$</td>
<td>2.057</td>
<td>-.233</td>
<td>.039</td>
<td>Not supported</td>
</tr>
<tr>
<td></td>
<td>H3c$^+$</td>
<td>.936</td>
<td>-.063</td>
<td>.004</td>
<td>Not supported</td>
</tr>
<tr>
<td></td>
<td>H3d$^+$</td>
<td>.867</td>
<td>.081</td>
<td>.006</td>
<td>Not supported</td>
</tr>
<tr>
<td></td>
<td>H3e$^+$</td>
<td>.102</td>
<td>.009</td>
<td>.010</td>
<td>Not supported</td>
</tr>
<tr>
<td>Network</td>
<td>H4a$^+$</td>
<td>3.084</td>
<td>-.286</td>
<td>.098</td>
<td>Not supported</td>
</tr>
<tr>
<td></td>
<td>H4b$^+$</td>
<td>1.809</td>
<td>.208</td>
<td>.034</td>
<td>Supported</td>
</tr>
<tr>
<td></td>
<td>H4c$^+$</td>
<td>2.958</td>
<td>-.394</td>
<td>.083</td>
<td>Not supported</td>
</tr>
<tr>
<td></td>
<td>H4d$^+$</td>
<td>2.666</td>
<td>.393</td>
<td>.066</td>
<td>Supported</td>
</tr>
</tbody>
</table>

Table 2. Results of the structural equation model and hypothesis validation

To evaluate the WTP for part two of our research, we aggregated all data and calculated four price points, following Van Westendorp (1976). Price indications to the participants are scaled in 0.50€ intervals steps, ranging from 0€ to 20€. Results are shown in a diagram presenting four graphs, with price on the X-axis and the cumulative percentage of the participants on the Y-axis. MGP is calculated by the intersection point of not cheap and too cheap, because users considering the service as too cheap would exceed users determining the service as not cheap. Using two mathematical functions, MGP has been calculated as 0.42€. Obtaining a pricing range for the PNA use, MEP can be calculated by the intersection of too expensive and not expensive, and shows a price of 6.83€. Again, if the price would be higher, the amount of users considering the service as too expensive would exceed the users considering it as not expensive. OPP is calculated by the intersection of too cheap and too expensive, and results in 1.88€ for PNA use. IDP is calculated by the intersection of cheap and expensive, resulting in a higher price than the OPP. Here, IDP is 2.83€, showing that 25% of the users consider it too cheap and 25% consider it too expensive. However, 50% of the users consider it an acceptable price. In this case, there is a high difference between the IDP and the OPP of 0.95€ (2.83€ - 1.88€), indicating that users consider a PNA service to cost more than they are willing to pay for it.

Figure 2. WTP: Price range and optimal price point
CONCLUSION, IMPLICATIONS, AND LIMITATIONS

This study primarily sought to investigate the question whether a PNA service might contain the potential to establish a new business model for news in the digital environment. First, we investigated usage features, influencing the adoption of the service; second, we considered user WTP for the use of this service.

First, the results of our survey showed that the PNA’s perceived usefulness, usage comfort, and awareness of a PNA raise users’ intention to use the service. Considering pricing, the survey shows that the user will have a look at the service’s costs before starting to use it. Last, the personalization of content and the possibility of social personalization are important features for a PNA to have and positively influence intention to use. Contrary to our expectations, system quality, trusted sources, and social interaction lead to lower intention to use a PNA. It shows that users do not want most current affairs all the time and not according to the most trusted sources; what users want is the most suitable news according to his or her preferences. Finally, platform support seems not to be an indicating feature, and neither does integrating different types of sources, video, and music content. Ease of use also seems not to be a feature. Second, the exploration of the WTP and an OPP of 1.88€ shows that users are willing to pay for the use of the service. The pricing of a monthly service is acceptable for the user, even if news is available complimentary. Furthermore, the price range goes up to 7€ as a monthly fee, which might be the basis for a sustainable business model. This study therefore contributes to current research by applying the research framework and the PSM scale to a new research field and by extending the framework with different features.

Concerning the study results, PNAs provide the requirements to establish a new business model for news. A PNA’s configuration should focus on the core functionality so as to simplify users’ consumption of news. Design, surface appearance, and content appearance are important. Our results show that customization is a key feature of a PNA and might lead to higher WTP. Personalization allows for customizing according to user preferences, as stated during usage, but social personalization allows higher recommender accuracy and improves automatic aggregation of content. Since this is one of the main improvements of PNAs, it promises a solid base for PNA development. PNAs can be applied in the environment of one publishing house, to aggregate content from different media formats personalized for each user. It is not necessary to try to sell one newspaper or magazine as a whole. The selection of interesting articles for a user can achieve higher revenues. Selling articles selected by the underlying technology could easily be implemented by a PNA.

The study provides a first insight in a potential future business model. However, our study also has some limitations. First, the sample consists mostly of students and is therefore not representative for PNAs users. Results for the WTP might be biased using this sample, as students provide a lower purchase power. Future studies should make use of a representative sample, in order to transfer the results of the study to a wider population. Second, it should be explored how the development of mobile Internet and mobile technologies affect PNAs in future. The continuance and discontinuance of PNAs is also an interesting research area. Hence, this study is only a snapshot in time and it should be replicated in the future. Third, the research model was tested in only one special application context (i.e. PNAs). The model should be tested with other digital
services or products. Also, other (moderating) variables should be explored in future studies to help draw a more complete picture of the investigated relationships and the affected user intention. However, we could explain 30% of the attitude.

Fourth, predictions about the WTP are affected by other influencing factors that are not addressed in this study. WTP should be examined in future, for example, to investigate price sensitivity for different features of a PNA.

REFERENCES


