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Abstract

News consumption is evolving from offline newspapers to online news. Nevertheless, no profitable business model exists for online news, and publishers are still reporting drops in revenue. Personalized news aggregators (PNAs), which rely on new information and communication technologies, provide a new way to aggregate content that might provide the basis for a revenue model in order to design a business model. Nonetheless, there is very little research about user willingness to pay (WTP) for a PNA service, in part because WTP strongly depends on the ideal configuration of a PNA. Based on an adaptive conjoint analysis (ACA) with 146 participants, this study explores the importance of different attributes in a user's estimation of total utility and a user's WTP for changing attribute levels. We show that price, contract duration, and revenue model are the most important attributes. €2.50 per month would be acceptable in combination with an advertising-based revenue model. Changing the contract duration from 12 months to one month shows the highest WTP. However, even if the importance of personalization functionalities is high, there is limited WTP for it.

Keywords: Personalized news aggregator, PNA, business model, willingness to pay

1   Introduction

For some time, publishing houses have provided news with the main business model of selling the newspaper as well as selling advertising in the paper. Owing to digitization, the amount of online news and the possibility to consume it complimentary have increased. Publishers therefore have two primary problems: On the one hand, newspaper sales are decreasing, resulting in a strong revenue decline. On the other hand, people still believe that online content in any form should be free, and consumers generally show low willingness to pay (WTP) for online content (Dou, 2004). Scholars argue that this low profitability results from the absence of an appropriate business

model (e.g. Cawley, 2008; Chyi, 2005). Publishers thus need to find new business models in order to monetize news and to counteract strong revenue declines. According to Veit et al. (2014), this type of question is a crucial and persistent issue in information systems (IS) research.

Traditionally, newspaper articles have been selected and bundled manually (e.g. by journalists). With the advent of new information and communication technologies, the bundling process has been changed dramatically, and automatic content aggregation has become possible. A prominent example is Google News, which automatically aggregates content from different sources. However, this research area has seen much attention from different scholars (e.g. Schroeder & Kralemann, 2005). In the meantime, technologies have evolved, and automated content aggregation and personalization according to a user's preferences has become possible. This is already being used in new service types: personalized news aggregators (PNAs), which provide content in an optically unified interface, automatically adjusted and personalized to a user's personal preferences, as well as mostly optimized for mobile devices. Flipboard is a well-known approach of this type of service.

There is a correlation between online news, personalization, and new business models (Saeaeksjaervi, Wagner, & Santonen, 2003). However, PNAs and the impact of this new form of content aggregation has not yet been explored, and should be scientifically researched. Information about the configuration of a profitable revenue model is at the center of attention as it is a primary part of business models. Since WTP strongly depends on the configuration of this new service type, it is necessary to obtain more information about the ideal configuration of a PNA from a user's perspective. Based on this information, it is possible to deduce information about how to increase a user's WTP. To address this research gap, we examine the importance of different attributes and PNAs' preferred attribute levels from the perspective of users. We also show the WTP for changing attributes levels.

This paper is structured as follows: In Section 2, we present related literature. In Section 3, we present the research framework, including our deducing of the research attributes. In Section 4, we continue with the research methodology and analysis for the adaptive conjoint analysis (ACA) and the WTP. Section 5 contains our empirical results. In Section 6, we discuss our results, highlight implications, and present study limitations.

2 Related Literature

2.1 Social Recommender Systems and News Aggregators

In the first years recommender systems were used only to provide well-structured information in searching, sorting, or filtering content. The Tapestry system of Goldberg et al. (1992) was one of the first recommender systems. With the development of the internet and the increasing availability of content, recommender systems were first used in e-commerce. As the technologies were developed, classic recommender systems can now also be used for digital products (e.g. music or news). Thus, the most widely used systems are content-based filtering, collaborative filtering, and hybrid filtering (Adomavicius & Tuzhilin, 2005).

With the rise of user-generated content and Web 2.0, the amount of available content has drastically increased, leading to the intensification of information overload. Also,

social networks have become well known, and personal information about users and the relationships between them have become available (Carmagnola, Vernero, & Grillo, 2009). By using interpersonal information about a user and their friends, social recommender systems can recommend content accordingly. These systems might have the potential to improve the selection and weighting of content, and can increase the overall recommendation accuracy (Arazy, Kumar, & Shapira, 2010). As a result, IT-enabled personalization mechanisms such as recommender systems have been integrated into aggregation applications. Madnick and Siegel (2001), as one of the first, predicted increasing usage of aggregation applications, owing to a faster bundling of content and a minimization of costs. Webster et al. (2006) analyzed news aggregators to provide a filtering mechanism in order to reduce the information overload of RSS feeds. Isbell (2010) classified existing news aggregators in four categories (feed aggregators, specialty aggregators, user-curated aggregators, and blog aggregators). Nanas, Vavalis, and Houstis (2010) as well as Paliouras et al. (2008) were among the first to concentrate on news aggregation applications, showing higher interest from potential users. Nanas et al. (2010) developed a news aggregator concept that analyzes usage behavior and provides content accordingly. The mechanism presented by Paliouras et al. (2008) aggregates content automatically, sorting it into different categories and presenting it in an adaptively personalized interface.

2.2   Business Models for Online News

Digitization is the primary reason why publishers have begun to move from printing newspapers to online news. Publishers are experimenting with business models, especially with new revenue models for online news. According to Chyi (2005), the most popular revenue models are the subscription model, the advertising model, the transactional model, and the bundled model. While research shows that the advertising model has become the primary revenue source for online news, it is not a guarantee for a sustainable revenue stream (Chyi, 2005; Herbert & Thurman, 2007). Therefore, in the future, new revenue models such as *freemium* might have the potential for a new strategy (Wagner, Benlian, & Hess, 2013).

Research has been done on WTP for online news (Chyi, 2005; Dou, 2004) as well as for digital content such as music (Breidert & Hahsler, 2007; Regner & Barria, 2009) or video on demand (Mann et al., 2008). Using quantitative surveys, Dou (2004) as well as Chyi (2005) confirmed the general belief that online content should be accessible for free. They state that if a website is going to charge for its content and services, users will immediately switch to free alternatives. Wang et al. (2005) showed different results and stated that additional functionalities such as a higher service quality do influence the WTP for a subscription-based online news service. Frijters and Velamuri (2010) also confirm these results and acknowledge that users show a greater WTP for content with a specific purpose. One example is specific business news offered by the *Wall Street Journal*. Gentzkow (2006) measured the WTP to access washingtonpost.com and found that the average person would pay $0.30 per day.

Chellappa and Shivendu (2010) analyzed different personalization strategies and their monetization possibilities. In these authors' view, companies should collect information about their customers to enhance the personalization of their content. Li and Unger (2012) suggest that news websites can charge for personalization efforts, especially if the providers show added value in comparison to competitors. To determine the price

sensitivity of highly personalized newspapers, Schoder et al. (2006) performed a conjoint analysis, and found that some users are willing to pay for a personalized newspaper – for instance, well-educated people. Saeaeksjaervi et al. (2003) also analyzed business models for personalized online newspapers and showed that content personalization could provide additional earnings.

3   Research Framework: Attributes of User Value

To provide a research framework, we explore attributes that affect the user value of PNAs. User value is thus our dependent variable, as has been the case in similar cases (e.g. Zeithaml, 1982).

The derivation of different attributes is based on several steps that seem appropriate (e.g. Papies, Eggers, & Wlömert, 2010). First, we conducted a content analysis of current PNAs. Second, we conducted a literature analysis to derive existing attributes for our case. Previous research about the customer value of digital goods included the price, revenue model, platform support, and offline access (Breidert & Hahsler, 2007; Doerr et al., 2010; Papies et al., 2010). Price, personalization, content integration, and social networks have also been used in previous studies to determine the behavioral intention to use a PNA (Oechslein & Hess, 2013). Third, a qualitative study confirmed these attributes and explored further attributes. This was conducted in mid-2012 with more than 30 semi-structured interviews with technology experts and bloggers. Nine attributes were identified for the research framework: *revenue model*, *price*, *contract duration*, *classic personalization*, *social personalization*, *content integration*, *social networks*, *platform support,* and *offline access*.

The *revenue model* (free with advertising vs. charged without advertising) was integrated, since some online services use only an advertising-based model (Papies et al., 2010). *Price* (€0, €0.50, €2, €7, €10) describes the monetary cost for a monthly usage of a PNA that includes all functionalities. We need to include this attribute in our research model, since it is necessary for the calculations of the WTP. €0 is necessary for the possibility of a free revenue model. A price range of €0.50 to €7 was adopted from a study that investigated overall WTP for news aggregation applications (Oechslein & Hess, 2013). Since our reference product is available for €10 per month, we integrated this price. We followed Doerr et al. (2010) concerning *contract duration* (1, 6, or 12 months), describing the minimum time before the user can terminate the contract. *Classic personalization* (explicit vs. implicit personalization) is the functionality of a PNA to provide personalized and adjusted content for a user. It can be either implicit by automatically analyzing a user's clicking and reading behavior, or explicit by the user stating his or her interests directly (e.g. Gauch et al., 2007). *Social personalization* (by social networks, by profile information, by reading behavior in social networks, or by none) is also a primary functionality of PNAs (Oechslein, Fleischmann, & Hess, 2014). Social personalization is the integration of interpersonal data in a PNA to provide personalized content, by means of recommendations by information from a user's social network (e.g. Facebook) as well as information from a user's profile. A user's reading behavior in a social network can also be used. However, it is also possible that there is no social personalization functionality. *Content integration* (yes vs. no) is the possibility of integrating individual content from other sources, such as a certain blog or website. *Social networks* (yes vs. no) allow one to simultaneously integrate social networks (e.g. a Twitter news stream) in a PNA and share content in a social network. *Platform*

support (browser vs. app) describes the way to use a PNA (in a browser or as an app for a tablet or smartphone). Finally, *offline access* (yes vs. no) is the possibility of using a PNA without an active internet connection.

WTP is modeled as a direct correlated construct with the user value. We discuss the measurement of WTP from utility data later (see Figure 1).
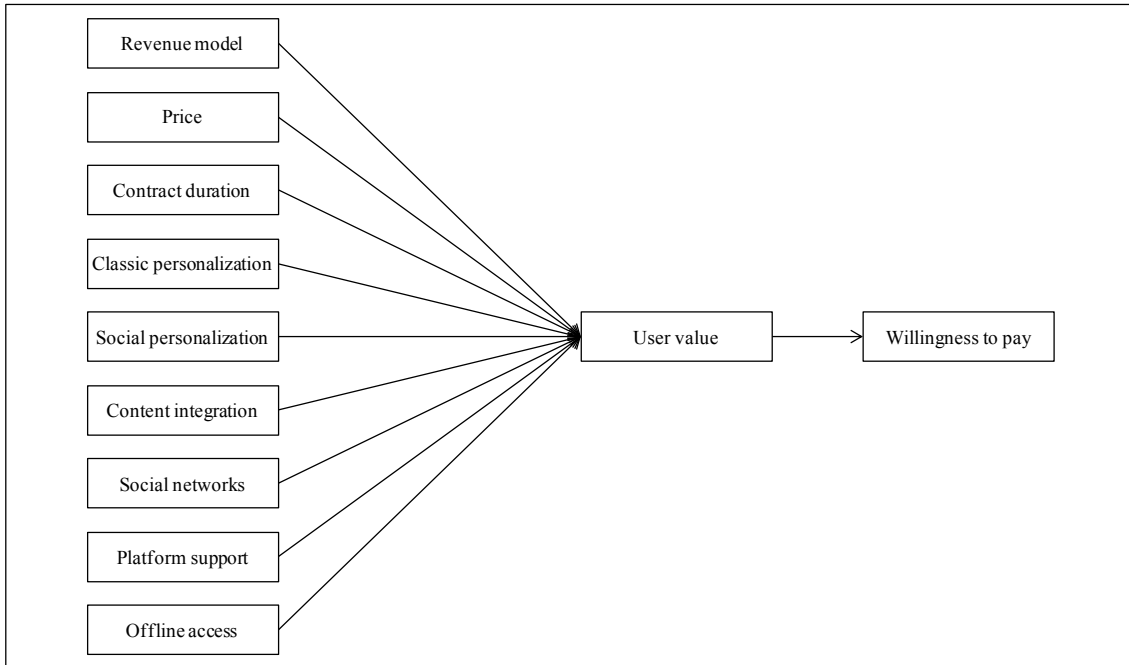

Figure 1: Research framework: Attributes that determine the user value

Based on our research framework, we formulated three research questions. This study's overall aim and goal is to analyze the revenue model as part of a future business model of PNAs. To determine a proper WTP for PNA, we must address PNA attributes, their importance, and preferences for them. Adding a single component can determine the future success of PNAs (also referred to as PNA service).

Research question 1 addresses the relative importance of each attribute in a user's estimation of total utility.

RQ1: How important is each attribute in a user's estimation of total utility of a PNA service?

Research question 2 addresses the specification of each attribute. It is possible to analyze the preferred specification of the attributes from a user's perspective and its influence on the buying decision.

RQ2: Which attribute levels are preferred and how do they influence the buying decision?

Research question 3 concerns the WTP for each attribute. Since it is possible to calculate a user's WTP for each PNA attribute, we can calculate the WTP with changing attribute levels by means of a sensitivity analysis.

RQ3: How much would a user's WTP for a PNA service rise or fall with changing attribute levels?

4 Research Methodology and Analysis

4.1 The Method of Adaptive Conjoint Analysis

Conjoint analysis is a method to analyze the user value of multi-attribute objectives. Therefore, a user's preferred combination of these objectives can be evaluated by offering alternative product configurations (Green & Srinivasan, 1990). Here, ACA was used, being validated by several scholars (e.g. Breidert & Hahsler, 2007). The questions will be adjusted to the users while the questionnaire is being answered, to find out each attribute's maximum. Furthermore, the questionnaire's length will be reduced without losing expressiveness, which also significantly reduces complexity as well as dropouts (Johnson, 1987).

The ACA is based on four general assumptions (Johnson, 1987). First, it is stated that products are a bundle of different attributes. In this case, a PNA consists of a certain bundle of attributes that increase user value and in turn increase a user's WTP for the service. These attributes have a number of specified levels (also referred to as specification). An individual's total utility for a PNA is equal to the sum of the utilities he or she receives from each attribute having a specification. This can be expressed formally as:

$$(1)\ u_{it} = u_i(a_1) + u_i(a_2) + u_i(a_3) + u_i(a_4) + u_i(a_5) + u_i(a_6) + u_i(a_7) + u_i(a_8) + u_i(a_9)$$

u_{it} is the totally utility for an individual i for the product configuration t. These attributes are compensatory, and we therefore follow a simple addition approach. The total utility is a function of $u_i(k_t)$ with the individual i's part-worth utility for each specification of the attribute k in the product configuration t. In our case, we use the attributes with its specifications as follows: a_1 *revenue model* (free with advertising vs. charged without advertising), a_2 *price* (€0, €0.50, €2, €7, €10), a_3 *contract duration* (1, 6, or 12 months), a_4 *classic personalization* (explicit vs. implicit personalization), a_5 *social personalization* (by social networks, by profile information, by reading behavior in social networks, or by none), a_6 *content integration* (yes vs. no), a_7 *social networks* (yes vs. no), a_8 *platform support* (browser vs. app) and a_9 *offline access* (yes vs. no).

Second, we assume that each attribute level has a certain value for the participant that in turn describes his or her preference for a product. These individual preferences are described by the part-worth utilities. Third, we assume that a product's total utility is the sum of the part-worth utilities of the attributes. It is now possible to predict the preferred product. Fourth, the third assumption can also be applied the other way round. Instead of adding the part-worth utilities, it is possible to deduce underlying utility values from a complete product concept (Johnson, 1987).

The conduct of an ACA is divided in four steps. First, in the *preferences for levels* module, the preferences of the participants for each attribute will be prompted (see Figure 2).

Please evaluate how important is contract duration for you?		
	Not important at all Very important		
1-month contract duration	○ ○ ○ ○ ○ ○ ○		
6-month contract duration	○ ○ ○ ○ ○ ○ ○		
12-month contract duration	○ ○ ○ ○ ○ ○ ○		

Figure 2: Example: Preferences for levels

Second, the attribute importance module compares the relative importance of each attribute with the highest and the lowest rating (see Figure 3). Both modules were measured on 7-point Likert scales (where 1 = the lowest score and 7 = the highest score).

All others being equal, how important would the following difference be for you?	
Browser use **vs.** **app use**	Not important at all Very important ○ ○ ○ ○ ○ ○ ○

Figure 3: Example: Attribute importance

Third, the paired-comparison trade-off questions follow. In this module (using a semantic differential), two different product configurations are compared prompting the conjoint trade-offs. Also, only two to three different attributes will be considered in this module (see Figure 4).

Which of these PNA services would you prefer?		
6-month contract duration **No social network integration** **Browser use**	Not important at all Very important ○ ○ ○ ○ ○ ○ ○	**1-month contract duration** **Social network integration** **App use**

Figure 4: Example: Paired-comparison trade-off

The ACA's fourth module consolidates all previous steps. The calibrating concept shows the participant a product configuration with five different attributes, in order to evaluate his usage probability (see Figure 5). Here, the participant must indicate a value between 0 and 100, where a higher value refers to a higher probability of using the service.

If the following PNA service were offered to you, how likely would you be to use it? *Please estimate in values between 0 (would definitely not use it) and 100 (would definitely use it)*	
Browser use **Offline access** **Social network integration** **1-month contract duration** **Charged without advertising**	**%**

Figure 5: Example: Calibrating concept

4.2 Measuring Willingness to Pay from Conjoint Data

We follow the approach by Kohli and Mahajan (1991), to derive a user's WTP for the attributes. This procedure has been validated before (e.g. Mann et al., 2008; Strube, Pohl, & Buxmann, 2008). This approach compares a certain product configuration's total utility to a reference product's total utility. The user will choose the proposed new

product configuration when its total utility (u_{it}) is higher than or equal to the total utility of the reference product (u_{iRP}). This can be stated as follows:

(2) $u_{it} \geq u_{iRP}$

The WTP equals the price when the product configuration's total utility is not lower than reference product's total utility. We use a status quo product as reference product. We use the PNA Niiu, which has been around Germany since the beginning of 2013. It has a charged without advertising revenue model, charges €10 per month, and has a 1-month minimum contract duration. The technology is based on explicit recommendation and uses no social personalization. It is possible to integrate content information and social network information. It uses an app and provides offline accessibility. To calculate the WTP, we state:

(3) $u_{it|-p} + u_i(p_t) \geq u_{iRP|-p} + u_i(p_{RP})$

$u_{it|-p}$ is the individuals i total utility of the product t without the price and $u_i(p_t)$ is the individual i's part-worth utility of the price of product t. $u_{iRP|-p}$ is the individual's total utility of the reference product RP without the price. $u_i(p_{RP})$ is the part-worth utility of the price of the reference product RP. In this case, the new product configuration's utility must be higher than or equal to that of the reference product (Strube et al., 2008).

By using conjoint analysis, we can only include a limited number of attributes for the price: €0, €0.50, €2, €7, and €10. However, by means of a linear interpolation, we can also calculate the utility values $u_i(p)$ for other prices. This can be stated in the following formula:

(4) $u_i(p) = u_i(p_1) + \dfrac{(p - p_1)\left(u_i(p_2) - u_i(p_1)\right)}{(p_2 - p_1)}$

To estimate the individual's WTP for different product configurations, we use two price points' p_1 and p_2. For instance, if we want to calculate the utility value for the price of €4, we use p_1 with €2 and p_2 with €7. To calculate the WTP, we started with a price $p = 0$ for each product and raised it in steps of €0.25 until the equation (3) is no longer valid (Strube et al., 2008). Following Kohli and Mahajan (1991), we assume that the price point prior to the violation of equation (3) equals the user's WTP for product t.

4.3 Data Collection

The data for this empirical study was developed with the software Sawtooth Version 8 and collected in July 2013, using a standardized online survey. Data collection and analysis was part of the thesis of Verena Lindinger (B.Sc.), supervised by the Institute for Information Systems and New Media at the Ludwig-Maximilians-Universität, Munich. A pretest was conducted. All participants were invited via an invitation link per email to 4,224 students. We followed the regular approach of asking a student sample in this early research (e.g. Chyi, 2005; Fuchs & Sarstedt, 2010).

The questionnaire had seven parts. First, we showed a short video explaining the core functionalities of a generic PNA. Second, we explained all attributes and presented the status quo product used as the reference product in the derivation of the WTP from data. All ACA modules followed. Finally, we considered questions about media usage behavior and general demographic questions. Items were adopted from Teo, Limb, and

Lai (1999). The analysis of the exported data was done with the software Sawtooth Version 8 (Hierarchical-Bayes model).

5 Results

5.1 Sample Description

We collected 149 valid datasets. The average participant age was 25 years, the youngest being 18 and the oldest 63; 66 participants were male and 83 were female. At least 97% had a high school degree or equivalent. More than 40% are online for more than three hours per day. Most use the internet as primary information source and to consume news. Approximately 79% of the participants own a smartphone. The most popular PNA is Flipboard, known to more than 45% of the participants.

5.2 Part-Worth Utilities of the Attribute Levels

To describe a user's preference structure, we first address the relative importance of the attributes and then the part-worth utilities for the different attribute levels. It must be noted that relative importance is determined by the ratio between the utility of one attribute in comparison to the utility of all attributes. Table 1 provides an overview of the results.

Revenue model (11%)	Utility mean	Std. dev.	Price (25%)	Utility mean	Std. dev.
			€0.00	106.41	47.45
Free with advertising	17.23	53.50	€0.50	61.75	31.40
			€2.00	8.59	17.73
Charged without advertising	-17.23	53.50	€7.00	-61.32	28.13
			€10.00	-115.38	43.57

Contract duration (13%)	Utility mean	Std. dev.	Social personalization (10%)	Utility mean	Std. dev.
1-month	50.99	36.84	None	13.58	57.97
6-month	2.67	14.17	Reading behavior in social network	0.01	36.22
12-month	-53.65	29.01	Profile information	-2.53	25.38
			Social network	-11.07	22.19

Classic personalization (8%)	Utility mean	Std. dev.	Content integration (8%)	Utility mean	Std. dev.
Explicit	17.30	37.74	Yes	33.46	26.50
Implicit	-17.30	37.74	No	-33.46	26.50

Social networks (7%)		Utility mean	Std. dev.	Platform support (8%)		Utility mean	Std. dev.
Yes		16.19	32.09	Browser		-21.22	33.48
No		-16.19	32.09	App		21.22	33.48
Offline access (10%)		Utility mean	Std. dev.				
Yes		42.30	24.63				
No		-42.30	24.63				

Table 1: Importance of the attributes and part-worth utilities of the attribute levels

To answer RQ1, the importance weights are calculated by the mean of all individual importance weights. The price (25%) of a PNA service shows the highest relative importance, followed by contract duration (13%), revenue model (11%), social personalization (10%), and offline access (10%). The least important attributes were classic personalization (8%), content integration (8%), platform support (8%), and social networks (7%).

By analyzing the part-worth utilities, we can answer RQ2 and can get an idea of what is important for a user. We can also provide a preferred product configuration. Nevertheless, when we consider the part-worth utilities, we bear in mind that this is interval-scaled data and not ratio-scaled data. By using zero-centered utility values, all preference utility values add up to 0. By transforming the data and shifting the utilities by a constant, so that the worst attribute level is equal to 0, no information will be changed (Orme, 2010). However, it is possible that differences of part-worth utilities of one attribute can be compared to other attributes' utilities. The results for price are ranked as expected, and are distributed equally. Also, there is a strong preference for shorter contract durations, since there is a higher utility for a 6-month or even a 1-month duration. Concerning social personalization, the user prefers either no social personalization or profile-based personalization. Furthermore, offline access increases the utility value the most, as well as a possible content integration and app-based platform support. In comparison, it seems that other functionalities – for instance, the existence of social network integration – shows the least utility.

5.3   Willingness to Pay for Changing Attributes Levels

To calculate the WTP for changing attribute levels, we followed the approach of Kohli and Mahajan (1991) and compared the prices with the reference product – Niiu. To answer RQ3, we performed a calculation for every single case and only changed one attribute at a time. Thus, we could determine the WTP for the individual attributes, as summarized in Table 2.

Attribute	Changing attribute level	WTP for changing the attribute level
Contract duration	12-month to 1-month	Δ €6.50 per month
Contract duration	6-month to 1-month	Δ €2.75 per month
Classic personalization	Implicit to explicit	Δ €2.00 per month

Social personalization	Reading to none	Δ €0.75 per month
Social personalization	Profile information to none	Δ €1.00 per month
Social personalization	Social network to none	Δ €1.25 per month
Content integration	No to yes	Δ €4.00 per month
Social network	No to yes	Δ €1.75 per month
Platform support	Browser to app	Δ €2.25 per month
Offline access	No to yes	Δ €5.25 per month

Table 2: Willingness to pay for changing attribute levels per € and per month

The results show that users are willing to pay an additional amount if the product configuration is changed at attribute level. The highest WTP is for shorter contract duration. For instance, users were willing to pay €6.50 more per month for a 1-month contract duration in comparison to a 12-month one. However, there is less than half the WTP for the change from a 6-month contract to 1-month one. Our results also show that offline access (€5.25), content integration (€4.00), and usage with an app (€2.25) increase the price most. Users were willing to pay €2.00 per month to use explicit personalization rather implicit functionality. The social personalization results show that the provider should even lower the price if it adds social personalization into a PNA. Also, additional functionality for adding social networking information shows one of the lowest WTPs – at €1.75.

6   Conclusion, Implications, and Limitations

This study's primary goal was to investigate the configuration of a revenue model for PNA's, as a new form of content aggregation. In particular, since the WTP depends on a PNA service's configuration, we wanted to shed light on the importance of usage attributes from a user's perspective. By using an ACA with 149 participants, we could analyze the importance of different attributes and part-worth utilities of their attribute levels. Also, by using the method of Kohli and Mahajan (1991), we could calculate the WTP for different product attributes.

First, our study results show that the attributes price, contract duration, and revenue model are the most important ones (49% in total), relating to the configuration of the underlying business model. Personalization is also an important attribute for PNAs. Social personalization shows little more importance than classic personalization, followed by the attributes of content integration and social network integration. The PNA's platform support and the integration of social networks show the least importance from a user's perspective.

Second, concerning the attributes' part-worth utilities, it seems logical that lower pricing increases the user's total utility. For instance, a decrease of the contract duration by 6 months shows about the same increase of utility if the price is lowered by €3. Also, the provider could keep the price the same and could lower the contract duration, and this would have the same utility for a user. Offline access functionality shows especially high user values. This addresses the fact that people still worry about poor or inconsistent internet access. While classic personalization as an attribute still has a lower value, explicit functionalities show a higher value than implicit ones. This result is in line with social personalization results, since using social networking information or reading behavior show very low values.

Third, WTP results are in line with the tendencies of the utility values. Attributes with the highest difference in the part-worth utilities show the highest WTP. These are – for instance – a change in the contract duration from 12 months to one month and to the availability of offline access. Users were willing to pay approximately €6.50 more per month if they can choose a 1-month contract duration. Also, for offline access, users were willing to pay €5.25 more per month. In contrast, different forms of social personalization do not increase WTP at all. Additionally, the revenue model results must be interpreted differently. It is not possible that users were willing to pay €2 per month to have a free revenue model. It is rather useful to interpret these results to show the overall importance of a free version for a user.

Concerning our results, a clear and consistent PNA configuration can be identified. Price is the most important attribute, according to this attribute's importance and the high difference in the results of the part-worth utilities for higher pricing. Contract duration also shows very high importance, as well as the highest WTP for a shorter contract commitment. While offline accessibility is less important, it is an important attribute, owing to a very high WTP. Revenue model is also an important attribute. Finally, while content integration has a lower attribute importance, there is a very high WTP for it. The main functionality of a PNA with different personalization types provides mixed results. Social personalization is somewhat more important than classic personalization. However, results show the highest WTP for classic personalization. Finally, the platform support and the integration of social networks in PNAs are not important; these attributes show both low importance and low WTP. To sum up, the following attribute combination shows the ideal PNA configuration: 1-month contract duration, explicit personalization, and no social personalization. The possibilities of adding content sources, social networks, usage as an app, and offline accessibility should be present. The revenue model should be free with advertising. However, we propose a price of €2.50 per month, based on the WTP results. Advertising in addition to a low pricing model could provide the basis for a profitable business model.

This study has some limitations. First, our sample consists mostly of people between 20 and 30 years old and might not be representative for future PNA users. Nevertheless, our study participants are highly internet literate, and therefore tend to use PNAs more easily. However, this sample might provide a lower WTP and might bias our results. Future studies should use a representative sample and should repeat our study in order to interpret the results for the entire PNA market. Second, we only considered a limited amount of attributes, owing to limitations of the ACA method. Future studies should also explore other attributes in order to help provide a more complete picture of a PNA configuration and utility values. Third, in the future, the development of mobile technologies should be considered in the exploration of PNAs. Also, the (dis)continuance of PNAs should be explored.

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