How to design personalization in a context of customer retention: Who personalizes what and to what extent?

Kwiseok Kwon a, Cookhwan Kim b,∗

a Interdisciplinary Graduate Program of Technology and Management, Seoul National University, 1, Kwanak Street, Kwanak-Gu, Seoul 151-742, Republic of Korea
b Department of Industrial Engineering, Seoul National University, 1, Kwanak Street, Kwanak-Gu, Seoul 151-742, Republic of Korea

1. Introduction

Since competition is keen among products and services, companies have been adopting differentiation strategies to attract and retain customers (Ho 2006, Tam and Ho 2006). A common differentiation strategy is to personalize products or services to better meet each customer’s needs (Tam and Ho 2006). Personalization has drawn increasing research attention from both academia and industry (Fan and Poole 2006). Personalization has been studied for its interdisciplinary characteristics in various academic fields, such as economics, management, marketing, information systems (IS), and computer science. In industry, a lot of personalization systems, such as the recommender systems of Amazon.com or the customization tools of Yahoo.com (MyYahoo), have been implemented in practice. This wide range of research has made it possible to develop a variety of personalization strategies that are different in their elements, such as the subject (who does the personalization) and the object (what is personalized) of personalization. These are the dimensions of personalization in this research.

There is little consensus on how best to design the personalization with their dimensions (Fan and Poole 2006). Studies in marketing have investigated the effect of personalization without considering variation in personalization strategies. Computer studies have investigated the effects of various personalization strategies using accuracy-based metrics, such as rating the differences between actual and predicted values. Because accuracy-based metrics are unable to capture the more complex and subtle aspects of personalization, attempts have been made to develop the more general aspects of personalization effectiveness by advocating comprehensive personalization metrics. These include customer lifetime value, loyalty value, purchasing and consumption experience, and return on customer (Peppers and Rogers 2004, Adomavicius and Tuzhilin 2005). Little is known about the effectiveness of personalization dimensions with regard to the more complex and subtle aspects of personalization though. There have been no empirical studies that compare and contrast various personalization strategies that are different in their dimensions based on comprehensive personalization metrics. Considering the fundamental objective of personalization—to increase customer retention rates by providing superior customer value—personalization strategies and technologies should be compared in the context of customer retention rather than in an accuracy-based context.

The purpose of this research is to answer the question of how best to design personalization strategies in order to increase customer satisfaction and customer loyalty, and thus, to provide a practical guideline for the development of personalization strategies to service providers. This study will investigate the impact of personalization dimensions that constitute personalization by investigating the effects of different personalization strategies. To...
do this, the dimensions of personalization should be identified in advance. Since the dimensions of personalization vary depending on the scope and concept of personalization, it is necessary to define the concept of personalization and its related terms prior to identifying the dimensions.

The paper consists of the following sections. Section 1 is an introduction. Section 2 reviews the related literature and provides a definition and the dimensions of personalization. Section 3 develops hypotheses. Section 4 deals with experiment design. Section 5 describes the manipulation of variables. Section 6 shows our experimental results. Section 7 discusses the results, and Section 8 concludes.

2. Literature and theory

2.1. On the definition and dimensions of personalization

The dimensions of personalization should be identified to investigate their effectiveness. Since the dimensions of personalization vary depending on the scope and concept of personalization, it is necessary to define the concept of personalization and its related terms prior to identifying the dimensions. The process of using a customer's information to deliver a targeted solution to that customer is known as personalization, or one-to-one marketing (Peppers and Rogers 1997). However, although many articles have been written about personalization, there is still some confusion among researchers about what the term actually means (Sunikka and Bragge 2008). According to Fan and Poole (2006), personalization means different things to different people in different fields. This makes it difficult to relate personalization studies to one another and to accumulate knowledge about personalization.

To clarify the meaning of personalization, it is necessary to explore the term, customization, which is often used interchangeably with personalization. While some researchers use these two terms to discuss the same concept, most researchers suggest that there are differences between them. Some researchers (Murthi and Sarkar 2003, Arora et al. 2008) have viewed personalization as the point when a firm decides—usually based on previously collected customer data—which marketing mix is most suitable for an individual customer. Book and music recommendations on Amazon.com are a good example of personalization. Customization, however, occurs when a customer proactively specifies one or more elements of his or her marketing mix. MyYahoo at Yahoo.com allows users to specify elements of their home page, which is an example of customization (Arora et al. 2008). That is, personalization is regarded as a system or firm-initiated concept, and customization as a user or customer-initiated concept.

Meanwhile, other researchers view personalization in a broad sense and see customization as a sub-concept of personalization. Fan and Poole (2006) define personalization as a process that changes the functionality, interface, information access, content, and distinctiveness of a system in order to increase its personal relevance to an individual or a category of individuals. In relation to their definition, they regard customization as one approach to implementing personalization. Sunikka and Bragge (2008) insist that personalization should be the umbrella term that includes mass customization and customization, following the suggestion of Poulin et al. (2006) who see personalization as a more generic and open concept. They term customization as user or customer-initiated personalization, and personalization in a narrow sense as system or firm-initiated personalization.

This study follows others that regard personalization as a more generic concept, such as Blom (2000) and Fan and Poole (2006). We term personalization in a narrow sense as system-initiated personalization and customization as user-initiated personalization. In this study, therefore, personalization is defined as a process that changes all the marketing mix including the core product or service, website and mode of communication to increase personal relevance to an individual, by employing Riemer and Totz’s (2001) personalization performance system.

The dimensions of personalization will now be identified to investigate their effectiveness. There are various dimensions in the implementation of personalization and all of them have many options. A few studies (Instone 2000, Wu et al. 2003, Fan and Poole 2006, Sunikka and Bragge 2008) provide frameworks for personalization by suggesting dimensions of personalization. For example, Fan and Poole (2006) suggest the three dimensions of personalization implementation in an extensive literature review and thereby provide a 4 × 2 × 2 dimensional framework. Previous studies are listed in Table 1 for comparison. However, there are some problems in the studies, especially for their classification of different dimensions. First, there is no theoretical background for classifying the object of personalization (what is personalized) although many researchers have explained the variations of personalized offerings. Adomavicius and Tuzhilin (2005) claim that these offerings include content (e.g., web pages and links), product and service recommendations (for products, e.g., books, CDs, and vacations), e-mail, information searches, dynamic prices, and products for individual consumers (e.g., custom CDs). Fan and Poole (2006) distinguish four aspects of information systems that can be personalized: the information itself (content), how the information is presented (user interface), the media through which information is delivered (channel and information access), and what users can do with the system (functionality). Yet, their explanation is limited to information systems or lacks a background to the classification, which make the offerings not mutually exclusive and collectively exhausted.

Second, the target of personalization (“to whom to personalize”) does not match the option of individual or group very well (see Table 1). It is more proper that the to whom to personalize question should be raised when deciding whether a customer should receive personalized treatment. For example, if a company or system does not have sufficient information about a customer’s

<table>
<thead>
<tr>
<th>Study</th>
<th>Dimension</th>
<th>Options</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wu et al. (2003)</td>
<td>“who does personalization”</td>
<td>Explicit // implicit</td>
</tr>
<tr>
<td>Fan and Poole (2006)</td>
<td>“what is personalized”</td>
<td>Content // interface</td>
</tr>
<tr>
<td></td>
<td>Aspects of personalization (“what is personalized”)</td>
<td>Content // user interface // functionalty // channel &amp; information access</td>
</tr>
<tr>
<td></td>
<td>Target of personalization (“to whom to personalize”)</td>
<td>Individual // group</td>
</tr>
<tr>
<td>Sunikka and Bragge (2008)</td>
<td>“who does the personalization”</td>
<td>The user (explicit) // the system (implicit)</td>
</tr>
<tr>
<td></td>
<td>Object of personalization</td>
<td>Intangibles // tangibles</td>
</tr>
</tbody>
</table>

1 Fan and Poole (2006) provided representative definitions of personalization from the various disciplines of marketing, e-commerce, cognitive science, social science, computer science, architecture/environmental psychology, and information science.
preferences, or if a customer does not have stable preferences, the company should decide whether it provides a personalized product or service to that customer at that moment. Moreover, the option of individual or group corresponds to one-to-one personalization or one-to-N personalization that represents the level of personalization.

Third, the terms explicit and implicit are confused with the terms user-initiated and system-initiated (see Table 1). The explicit method is used when providers directly ask customers for preference information such as ratings; the implicit method is used when providers learn about customers’ preferences indirectly, from purchase history data or web usage mining. Previous studies, such as Wu et al. (2003) and Fan and Poole (2006) use explicit for user-initiated personalization and implicit for system-initiated personalization. However, system-initiated personalization does not always use an implicit method. If a system or a firm explicitly asks customers about their preferences and personalizes their e-mail or website to the preference of each customer, it cannot be an implicit personalization. The terms explicit and implicit are strongly related to the methods of collecting and learning customer preferences. Therefore, separating the dimension of the preference learning method from that of the personalization subject is necessary.

Taking these into consideration, this study proposes four dimensions for implementing personalization: (a) what is personalized (object of personalization); (b) how far things are personalized (personalization level), (c) who does the personalization (subject of personalization), and (d) how to learn about customer preferences (preference learning method for personalization).

In terms of the first dimension (the object of personalization), Riemer and Totz’s (2001) study is noteworthy. In it, the authors suggest a personalization performance system from the viewpoint of an online marketing mix. They distinguish between three personalization-related performance layers: a products and services layer as the center of the system, a website layer as the relevant mediating channel, and a communication layer. Their proposed frame covers many aspects of personalization, from the core product or service to modes of communication. By modifying their system and considering the online marketing mix with regards to e-services, this research distinguishes four layers of personalization objects—a product or service layer, a website layer, a communication layer and a price layer. A product or services layer consists of the sub-layers core product or service and additional offers. A website layer comprises sub-layers called website content and interface, and sub-layers called communication channel and attributes that organize the communication layer. In the price layer, pricing can be personalized through personalized pricing schedules or price discrimination strategy. With this scheme, all the possible personalization objects in the previous literature are covered. For example, Ansari and Mela’s (2003) on-site and external personalization corresponds to the website layer and the communication layer.

The second dimension, the level of personalization, can be one-to-all (standardization, not personalization), one-to-N (micro personalization, segment marketing), or one-to-one. The terms one-to-one or one-to-N are more widely used than individual or group in a few previous studies. This dimension should therefore be regarded as the level of personalization, that is, how far things are personalized, as described in Arora et al. (2008).

The third dimension, the subject of personalization, can be user or customer-initiated, or system firm-initiated. The distinction between user-initiated personalization and system-initiated personalization is exactly matched with the one between the narrow sense of personalization and customization. Customers may not be satisfied with the personalized offers provided by a system or a firm while they may feel burdened about the user-created personalization designed by making use of customizing tools for themselves. Therefore, this dimension would be related to customers’ perceived quality and, moreover, to customers’ satisfaction towards personalized offers and should be regarded as an important aspect for implementing personalization.

The fourth dimension (how to learn about customer preference) is related to preference learning methods for personalization. Providers who wish to learn about customer preferences can use either the explicit or implicit method. Developers and marketers, who are to provide personalized services, should consider this dimension because elements related to this dimension include not only the requirements or components of back-end personalization systems such as databases and servers, but also customers’ involvement, which can affect customers’ efforts or privacy concerns. For example, too much explicit user involvement usually turns users away (Instone 2000).

The framework for personalization suggested in this research incorporates these four dimensions, as shown in Table 2. The personalization strategy in this study is the combination of options selected from each dimension.

### 2.2. Previous studies on the effectiveness of personalization

Many researchers have investigated the effectiveness of personalization. Studies from the area of computer science have traditionally measured the performance of personalization systems, such as recommender systems, with accuracy metrics (e.g., mean absolute error, precision, and recall) by comparing the lists from a system and with the users of the system.

Studies in IS or cognitive science have revealed the impact of personalization on the user cognitive process. For example, Ho (2006) argues that personalization cannot attract new users from high-involvement sites such as network games and online chat rooms. However, the perceived usefulness of personalization is a significant factor in attracting new users. Tam and Ho (2006) also investigate the impact of web personalization on user information processing and decision outcomes. They conceptualize the widely practiced personalization strategies into two variables of content-relevance and self-reference and investigate their impacts on user information processing that consists of attention, cognitive

### Table 2

Proposed framework for personalization.

<table>
<thead>
<tr>
<th>Dimension</th>
<th>Options</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Level</strong></td>
<td>One-to-all (market level)</td>
</tr>
<tr>
<td>Subject</td>
<td>User (customer)</td>
</tr>
<tr>
<td>Preference learning method</td>
<td>Explicit</td>
</tr>
<tr>
<td>Object</td>
<td>Core product or service</td>
</tr>
<tr>
<td>Product</td>
<td>Website content</td>
</tr>
<tr>
<td>Website (Place)</td>
<td>Communication channel</td>
</tr>
<tr>
<td>Promotion</td>
<td>Pricing schedule</td>
</tr>
<tr>
<td>Price</td>
<td></td>
</tr>
</tbody>
</table>
processing, decision, and evaluation. Komiak and Benbasat (2006) examine the effects of perceived personalization and familiarity on cognitive trust and emotional trust in the context of the technology acceptance theory.

Studies on customer satisfaction index (CSI) models, such as the American Customer Satisfaction Index (ACSI) (e.g., Fornell et al. 1996) and the European Customer Satisfaction Index (ECSI) (e.g., Johnson et al. 2001) reveal that personalization and customization experience results in customer satisfaction, which is a factor of customer loyalty. Ball et al. (2006) revise the original ECSI model and investigate the effect of service personalization on loyalty. They show service personalization has an effect on loyalty, and that effect is both direct and indirect.

2.3. Critique of the previous studies and research question

For all the studies mentioned above, little is known about how best to design personalization with its various dimensions. Immediate objectives of personalization are to understand and deliver highly focused, relevant offerings matched to users’ needs and contexts (Albert et al. 2004). But then, since its long-term objective is to generate more business opportunities (Ho 2006), there are other important measures that are interesting to managers in a business context, such as customer satisfaction and customer loyalty. Computer science studies are unable to capture the more complex and subtle aspects of personalization such as customer lifetime value because they have investigated the effects of various personalization strategies using accuracy-based metrics. Studies in IS and cognitive science, such as Ho (2006), Tam and Ho (2006), and Komiak and Benbasat (2006), failed to investigate the effects of various personalization dimensions in a business context. Further, although studies in human–computer interaction (HCI) have examined the user perception of interface features (Kumar et al. 2004), there has been no empirical research that investigates the impact of personalization dimensions using comprehensive personalization metrics such as customer satisfaction and loyalty. In contrast, marketing studies such as CSI models have not understood the various dimensions of personalization that can seriously affect business success.

Consequently, little is known about the effectiveness of personalization dimensions with regards to the more complex and subtle aspects of personalization. In other words, there has been no empirical study that compares and contrasts various personalization strategies that are varied in their dimensions in a business context. This absence of information has made service providers design and develop personalization strategies for their services without considering the impact on customer retention, as measured by customer satisfaction and loyalty. If the relationship between each personalization dimension and its impact on customer satisfaction and loyalty could be identified, there would be considerable increases in not only the efficiency of personalization—in areas such as cost, time, and effort for implementing and maintaining personalization—but also in the effectiveness of personalization, in areas such as customer retention.

This study will identify the effects of each personalization dimension listed in Table 2 on customer satisfaction and customer loyalty. However, since the proposed framework was designed to cover all conceivable areas of services, there are too many possible strategies for effective study. To clarify the experimental results, this study confines the experiment of this research to a web personalization context of the e-services where personalization has become more important (Cho et al. 2007, Kwon et al. 2009a,b). Hence, the main objects of personalization are limited to the website layer in Table 2, including content and interface. Learning preference implicitly requires too much time to provide satisfactory personalized offers, so that this experiment uses only the explicit preference learning method, which reduces the dimensions considered in this experiment.

This study also will answer the question of how best to design personalization. Who personalizes what and to what extent? Does this appear to increase customer satisfaction or customer loyalty, based on the empirical evidence?

2.4. Customer satisfaction, loyalty and retention

Over the past few decades, research has found that offers customized for individual customer’s preferences can provide superior value. Therefore, the importance of personalization has been emphasized and new tools and management approaches have been introduced designed to enable providers to better serve and satisfy the wants of individual customers. In other words, the fundamental objective of personalization lies in increasing the customer retention rate by providing competitive value to customers.

However, the phenomenon of customer retention, which indicates whether a customer continues to do business with a service provider or purchases the same brand repetitively, encompasses a degree of fuzziness; it represents a theoretical construct that cannot be observed directly (Gerpott et al. 2001). A number of previous studies have revealed that concepts of satisfaction and loyalty have emerged as strong predictors of customer retention (Eshghi et al. 2007). The concepts of satisfaction and loyalty may be used to refer to similar underlying behavior, however, a distinction exists between meanings and sequences.

Customer loyalty is defined as a customer’s intention or predisposition to repurchase from the same firm (Edwardsson et al. 2000). This means that loyalty encompasses intended behavior (Gustafsson and Johnson 2002), a fact that is strongly related to the concept of customer retention. According to studies on customer loyalty (e.g., Zeithaml et al. 1996), loyal customers forge bonds with a company and behave differently from non-loyal customers. From an e-service provider’s perspective, customer loyalty has been recognized as a key path to profitability (Srinivasan et al. 2002).

Customer satisfaction refers to customers’ overall evaluation of their purchase and consumption experience (Edwardsson et al. 2000, Johnson and Fornell 1991). Several studies (e.g., Bolton 1998, Bolton et al. 2000) have shown that satisfaction affects customer retention, and satisfaction is generally assumed to be a significant determinant of repeat sales, positive word-of-mouth, and customer loyalty. Satisfied customers return and buy more, and they tell other people about their experiences (Fornell et al. 1996), which leads to a stronger competitive position, resulting in higher market share and profit (Fornell 1992).

Personalization works to increase customer loyalty directly, as well as indirectly, by improving customer satisfaction. For this reason, this study adopts customer satisfaction and customer loyalty as measures of customer retention and investigates the effect of a variety of personalization strategies. On these measures.

3. Hypotheses development

3.1. Personalization object and its effect on customer retention

Although there have been studies on investigating the effect of personalization on aspects of customer retention, such as customer loyalty, there has been little research on the influences of personalization objects, including content and interface, on customer retention. For example, Ball et al. (2006) investigate the effect of service personalization on loyalty, however, they only reveal the effect of personalization itself and do not consider the variation of personalization objects. Srinivasan et al. (2002) identify customization (personalization) as an antecedent of e-loyalty, but do not
separate customized objects by regarding a website as one object, for which it is difficult to provide practical implication for marketers or developers. Liang et al. (2007) investigate the relationship between personalized content and customer satisfaction, while Chang and Chen (2008, 2009) examine the impact of customer interface quality on customer satisfaction and loyalty. These papers have contributed to the field in that they found the influences of each of the personalization objects. On the other hand, since there has been no research on comparing the effectiveness of the personalization objects simultaneously, it is hard to figure out the effectiveness of each personalization object and the interaction effects between them. This study hypothesizes that the effects of personalization strategies will be varied with respect to the objects of personalization. More specifically, there will be differences between the effects of content personalization and interface personalization strategy. This leads to our first hypothesis:

**Hypothesis 1 (Effects of Personalization Strategies Hypothesis).** The effects of personalization strategies vary with respect to the objects of personalization – content and interface.

Meanwhile, the impact of content personalization, for example, might be varied with the levels of interface personalization since customers may feel that a website is already personalized, regardless of the levels of content personalization, which indicates how well the website’s interface is tailored to them. In case of the subjects of personalization, for instance, the impact of content personalization might be varied with reference to the subject of interface personalization. This is because customers may think that a website is significantly personalized, regardless of the subject of content personalization, when they can modify the website’s interface as they please. Therefore, although there has been no previous research on these interactions, the effects of content and interface personalization may be interactive with reference to the levels and subjects of personalization. This leads to:

**Hypothesis 2a (Interaction Effects for Levels of Personalization Hypothesis).** There are interaction effects between the objects of personalization – content and interface – with reference to the levels of personalization.

**Hypothesis 2b (Interaction Effects for Subjects of Personalization Hypothesis).** There are interaction effects between the objects of personalization – content and interface – with reference to the subjects of personalization.

### 3.2. Personalization level and its effect on customer retention

One of the key issues of personalization research is how far a firm should go towards the ultimate goal of one-to-one marketing (Arora et al. 2008). The research on these issues can be classified into two categories: supportive and doubtful. Ansari and Mela (2003) state that the content targeting method can potentially increase the expected number of customer click-throughs by 62%. Arora and Henderson (2007) show that customization at an individual level can enhance the efficiency of embedded premium. However, Zhang and Wedel (2007) state that the incremental benefits of one-to-one promotions over one-to-N (segment level) and one-to-all (market level) promotions are small in general, especially in offline stores. Malthouse and Elsner (2006) also provide support for one-to-N personalization. Nonetheless, there has been little research on the issue, which considers the variation of the objects of personalization in view of customer retention.

In dealing with this issue, we could consider two related theories or principles of least effort and information overload. According to the principle of least effort, suggested by Zipf (1949), each individual will adopt a course of action that will involve the least average work from the person. The theory predicts that information seekers will minimize effort required to obtain information. From the theory, it is evident that accurate content and interface personalization, which reduce the effort needed by a customer, would increase customer satisfaction and loyalty.

Information overload means users are given more information than they can handle within the time available. Users are unable to locate what they need most (Herbig and Kramer 1994) and also fail to use the relevant information (Wilson 1995) due to the information overload. Ho and Tang (2001) assert that there are three factors that arouse information overload: information quantity, information quality, and information format. And information technology has been suggested a useful way of alleviating information overload. For example, Berghel (1997) describe five ways to deal with it: search engines, information agency, information customization, brand identification, and information push. We, therefore, could conclude that personalized services can increase customer satisfaction and loyalty by reducing information overload when such services can provide accurate content and interface personalization. Liang et al. (2007) and Chang and Chen (2008) state that content personalization and interface personalization can lead to higher customer satisfaction. However, they do not consider the level of personalization.

From the perspective of the theories mentioned above, this study assumes that the effects of personalization strategies will increase as the personalization level goes towards the one-to-one marketing level, irrespective of the objects of personalization, which leads to:

**Hypothesis 3a (One-to-N vs. One-to-All Content Personalization Strategy Hypothesis).** A one-to-N content personalization strategy is more effective than a one-to-all content strategy.

**Hypothesis 3b (One-to-N vs. One-to-All Interface Personalization Strategy Hypothesis).** A one-to-N interface personalization strategy is more effective than a one-to-all interface strategy.

**Hypothesis 3c (One-to-One vs. One-to-N Content Personalization Strategy Hypothesis).** A one-to-one content personalization strategy is more effective than a one-to-N content personalization strategy.

**Hypothesis 3d (One-to-One vs. One-to-N Interface Personalization Strategy Hypothesis).** A one-to-one interface personalization strategy is more effective than a one-to-N interface personalization strategy.

### 3.3. Personalization subject and its effect on customer retention

Although previous studies into the effectiveness of personalization have produced different results, user-initiated personalization (customization) seems to be more effective with customer satisfaction than system-initiated ones with respect to the subjects of personalization. Instone (2000) insists that user-initiated personalization should not be too strongly emphasized because too much explicit user involvement usually turns users away. However, Nunes and Kambil (2001) agree that visitors to various e-commerce sites would rather customize a site themselves than have it automatically personalized for them. Arora et al. (2008) assert that an obvious potential advantage of user-initiated personalization is greater customer satisfaction although its long-term impact has not been analyzed. These considerations would coincide with the belief that the customer’s participation in the personalization process may increase customer satisfaction, based on user involvement theory. Yet, the comparison between user-initiated and
system-initiated personalization with regards to different person- 
alized objects, has not yet been examined. This study hypotheses 
that user-initiated personalized is more effective than system-
initiated personalized, regardless of the objects of personaliza-
tion. This leads to:

**Hypothesis 4a** (User-Initiated vs. System-Initiated Content Personal- 
alization Hypothesis). User-initiated content personalization is more 
effective than system-initiated content personalization.

**Hypothesis 4b** (User-Initiated vs. System-Initiated Content Personal- 
alization Hypothesis). User-initiated interface personalization is more 
effective than system-initiated interface personalization.

The hypotheses are summarized in Fig. 1.

4. Experiment design and participants

4.1. Experimental design

This experiment design includes two sets of experiments, Set A and Set B. We employ a $3 \times 3$ factorial design for Set A and a $2 \times 2$ factorial design for Set B to investigate the hypotheses, as depicted in Table 3. The two independent variables in each set are the ob-
jects of personalization: content personalization and interface person-
Alization. There may be an interaction between these two variables, which is why the factorial design is employed. Each vari-
able in Set A is made up of three levels constructed by the dimen-
sion of personalization level: one-to-all, one-to-N and one-to-one 
system-initiated. Each variable in Set B has two levels constructed 
by the dimension of personalized subject: one-to-one system 
initiated and one-to-one user-initiated. Since one-to-N user-
initiated personalization is an extremely rare case except on those

sites that require collective intelligence, such as Wikipedia.com, 
it was omitted in this experiment. All the variables are between-
subject factors.

The experiment was conducted via a news portal service since 
people frequently visit news portals. This study tested the pro-
posed framework by implementing a news portal site that employs 
various personalization strategies. The implemented news portal 
site emulated the MyYahoo service at Yahoo.com to some degree, 
since the personalization strategies already in practice are thought 
to be more implicative.

4.2. Participants

An e-mail message that invited participants in this experiment 
was sent to 8340 randomly selected members of Naver.com, a 
leading portal site in Korea. Four hundred and thirty-nine mem-
bers agreed to participate. Every participant was given a reward 
for completing the given tasks. Their average age was 28.7, and 
53% of them were male. Participants were randomly assigned to 
each of the cells in Table 3. All of them already had experience with 
the use of internet news portals; however, 67 members did not 
accomplish the tasks.

4.3. Experimental procedure

The experimental procedure proceeded as follows:

1. **Joining stage** : At the start of the experiment, the participants 
were asked to access the implemented news portal site and to 
join its membership. At the time of joining, participants 
were randomly assigned to one of the cells in Table 3.

2. **Input stage** : The participants of each cell were then required 
to provide information needed for personalization, such as 
demographic, requested rating, and preference information.

3. **Usage stage** : All participants of each cell were asked to access 
the implemented news portal site via simple user verifica-
tion. They were required to access and use the news portal 
site as frequently as possible for 4 weeks. Previous similar 
studies have provided only 1 week to measure participants’ 
satisfaction and loyalty on a website. Khalifa and Liu 
(2002) gave an online questionnaire to respondents a week 
after their membership registration and said this period of 
time, a week was adequate to allow the new members to 
become familiar with the Internet-based services. This 
experiment provided a quadrupled duration in order to 
allow participants to become more familiar with the person-
alized sites. Participants who were assigned to user-initi-
ated personalization were required to customize the content 
or the interface of the website.

4. **Evaluation stage** : After 4 weeks of use, all participants were 
asked to answer the same questionnaire about their satisfac-
tion and loyalty.

5. Manipulation of variables

5.1. Independent variables

The two independent variables in this experiment are content 
personalization and interface personalization. Each variable has 
three levels for Set A and two levels for Set B. Detailed explanations 
for the methods used in each level of each variable are as follows:

1. **One-to-one user-initiated content personalization strategy** 

   **[CU]**: A one-to-one user-initiated content personalization 
   (CU) was implemented by allowing users to select or dese-
   lect the contents on a customized web news portal site, as...
shown in Fig. 2. Fifteen major newspaper agencies in Korea, twelve news headline services of several famous Korean portal sites (e.g., “Best Click News on Naver.com”), and the Yahoo.com news headline services of eight news categories, such as politics, finance, and sports, were offered. Each news content box contained the option of modifying the number of articles in each box (from 1 to 10) and the presentation form of articles (title only, image only, title and image, or title and partial content).

(2) One-to-one system-initiated content personalization strategy [CO] or [CS]: A one-to-one system-initiated content personalization (CO for Set A and CS for Set B) is realized by recommending the news articles to a target user by implementing a well-known collaborative filtering (CF) method by listing them. There have been many studies of news recommender systems using content-based filtering (CBF). The CBF method requires the extraction of keywords from news articles or the mining of the target user’s web use; however, these techniques require too much server load in analyzing news keywords, or web usages, and too much time devoted to learning about users’ preference, in order to produced satisfactory results. In addition, most of the studies of news recommender systems that used CBF have been conducted not by a real-time news feed but by news collection. In contrast, this study employed the CF method to reduce server load and to make real time recommendation possible. The CF method has a problem with scalability in the presence of many users; however, the relatively small number of users in this experiment made it possible to recommend news articles with a small calculation load. A detail for the CF method in this experiment is explained in Appendix A. The news articles that were recommended for a specific user were listed in the “Recommended News for You” content box with the explanation, “Users who are similar to you have read these articles,” as shown in Fig. 3. In addition to this news recommendation, the categorical news content box of a specific user that the target user had marked “interesting” at the input stage was presented on the screen. Through recommending articles and presenting user-specific news categories, CO or CS personalization was implemented for each user.

(3) One-to-N system-initiated content personalization strategy [CN]: A one-to-N system-initiated content personalization (CN) is realized by recommending (or listing) the favored news articles of a group of users. It is necessary to form a user group with similar preferences. To do this, users who were assigned to this strategy were asked to rate a set of 30 news articles randomly selected from 1 (not interesting) to 5 (very interesting) at the input stage. The ratings of those users who were assigned to this strategy were factor-analyzed first, which produced twelve factors. A K-means cluster analysis was executed by the factors, and the users were classified into six clusters. The users in a cluster are assigned to a user group. The users’ ten highest-ranked articles were recommended. The recommended news articles for a group of users were listed in the “Recommended News for You” content box with the explanation, “Users who are similar to you have read these articles.” Through recommending group-specific articles, CN personalization was implemented for each user.

(4) One-to-all content strategy [CA]: One-to-all content strategy (CA) was constructed as shown in Fig. 4. It had neither a CU tool nor CS personalization. The content boxes from eight famous newspaper agencies in Korea and the Yahoo.com news headline services of eight news categories, such as politics, society, finance, and entertainment, were provided in this strategy, which is almost same as the content on the default news page of MyYahoo.

(5) One-to-one user-initiated interface personalization strategy [IU]: One-to-one user-initiated interface personalization strategy (IU) is implemented by allowing users to alter page
6. One-to-one system-initiated interface personalization strategy [IO] or [IS]: One-to-one system-initiated interface personalization strategy (IO for Set A and IS for Set B) is achieved by tailoring the layout and appearance of the site according to the target user’s preferences. The key to personalizing an interface is the accurate prediction of user preferences. These have been analyzed at a variety of levels and in various dimensions by many research communities (Price et al. 2006). Although many technologies for interface personalization from disciplines such as human–computer interaction (HCI) have been developed, it is difficult to apply them in a real-time environment because they require a heavy server load and a relatively long time to learn about customer preferences. For this reason, a conjoint analysis was employed to extract the customers’ preferences in this experiment. A detail for the conjoint analysis in this experiment is explained in Appendix B. The combination of skin and layout that showed the highest utility from the analyses was provided to the news portal’s interface for the target user. In this way, IO (or IS) personalization was implemented for each user.

7. One-to-N system-initiated interface personalization strategy [IN]: One-to-N system-initiated interface personalization strategy (IN) is implemented by tailoring the layout and appearance of the site according to the preferences of a group of users. A conjoint analysis was employed to extract user preferences in this experiment. Every participant in this strategy was asked to rate his or her preference for the 46 presented interface bundles, as in the case of IO or IS. To achieve one-to-N personalization, in contrast to one-to-one personalization, it is necessary to cluster customers with similar preferences. To do this, the preference ratings of those users who were assigned to IN were factor-analyzed first, which produced fourteen factors. A K-means cluster analysis was executed by the factors, and the users were classified into five clusters. Then, part-worths of each attribute’s levels were estimated using the preference ratings of the users in each cluster. Finally, the combination of skin and layout that showed the highest utility in each cluster was provided as the news portal’s interface to all the users in the cluster. Thus, IN personalization was implemented for users in each cluster.

8. One-to-all interface strategy [IA]: A standard interface was provided in the one-to-all interface strategy (IA), as shown in Fig. 4. It had neither an IU tool nor IO personalization. It had three equally spaced columns, a fixed skin called Green Tea, and a normal font size, which was the default interface of the MyYahoo news service.

5.2. Dependent variable

In this research, customer satisfaction and customer loyalty were selected as a response variable, as mentioned earlier. All variables were measured using multiple indicators, as shown in Table 4. Customer satisfaction is operationalized through three survey measures: an overall rating of satisfaction, the degree to which performance falls short of or exceeds expectations, and a rating of performance relative to the customer’s ideal good or service in the category. These measures are identical to those used in the ACSI, the ECSI, and the Korean National Customer Satisfaction Index (KCSI). To operationalize customer loyalty, we used the measures suggested in the National Customer Satisfaction Index model of Johnson et al. (2001). These were based on Zeithaml et al. (1996). The measures in this experiment are likelihood of retention, likelihood of speaking favorably about the site to others, and likelihood of recommending the site to others.

5.3. Control variables

A personalization experiment that uses a web news portal might be affected by the characteristics of its participants (e.g., prior knowledge about personalized web services) and stimulus (e.g., brand name of service) (Hong et al. 2004). Multiple methods were used to control the effects of potentially confounding var-

<table>
<thead>
<tr>
<th>Measurement variables for satisfaction and loyalty.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Latent variable</td>
</tr>
<tr>
<td>Customer satisfaction</td>
</tr>
<tr>
<td>2. Expectancy disconfirmation (performance that falls short of or exceed expectations)</td>
</tr>
<tr>
<td>3. Performance versus the customer’s ideal news portal service</td>
</tr>
<tr>
<td>Customer loyalty</td>
</tr>
<tr>
<td>5. Likelihood of speaking favorably about the website to others</td>
</tr>
<tr>
<td>6. Likelihood of recommending the website to others</td>
</tr>
</tbody>
</table>

Note: Measures used are either a seven-point Likert type from strongly agree to strongly disagree, or a seven-point semantic differential scale with the anchors “not at all likely” and “very likely”.
ables in order to improve the study's internal validity. Individual differences, including personality, cognitive style, and personal web experiences, were controlled by randomly assigning participants to experimental conditions (Park et al. 2007).

In an experiment of this kind, it is also necessary to control other variables that might alter customer satisfaction and loyalty, such as brand effect and prior knowledge about personalized services (Park et al. 2007). Although the news portal service in this experiment was brand-free, it adapted some technologies and user interfaces of the MyYahoo service. There is some possibility that prior experience with the MyYahoo service could influence the experiment's results, so the participants had to assert that they had not previously used the MyYahoo service. Since prior knowledge about personalized websites may affect satisfaction or loyalty, the participants were asked to reply to questions about their prior knowledge. This was measured by an item with seven-point Likert-type anchors ranging from "I've never experienced or heard of it" to "I know it well." This prior knowledge was used as a covariate variable in this experiment.

With the random assignment of participants to each group, controlling variables, and a covariate, it is believed that the effects of confounding factors were minimized and controlled.

6. Experimental results

6.1. Manipulation check

We conducted two pre-tests to check whether the manipulations of the independent variables, the levels of personalization and the subjects of personalization, are effective prior to the main experiment. First, we measured perceived personalization (Wolfinbarger and Gilly 2003) to check the manipulation of personalization level in terms of content and interface. Sixty graduate students participated in the pretest and they were randomly assigned to one of the personalization levels, one-to-all, one-to-N, and one-to-one level, of content and interface. The participants answered the manipulation check question for perceived personalization. We used a seven-point Likert-type scale to indicate agreement or disagreement (7 being highly agree) with the following statement based on that used in Song and Zinkhan (2008): "The content (or interface) of the news site understands my specific needs."

In terms of content, the average perceived personalization of one-to-all, one-to-N, and one-to-one were 3.21, 4.48, and 5.16, respectively. There were significance differences in the perceived personalization from the results of one-way analysis of variance (ANOVA) test ($F(2, 57) = 74.163, p < 0.01$). Mean differences between one-to-all and one-to-N ($t(38) = -8.097, p < 0.01$), one-to-N and one-to-one ($t(38) = -4.032, p < 0.01$), and one-to-all and one-to-one ($t(38) = -12.114, p < 0.01$) were all statistically significant, according to post hoc multiple comparisons. The average perceived personalization of one-to-all, one-to-N, and one-to-one were 2.98, 4.63, and 5.47, respectively, in the case of interface. Participants also showed significant differences in their perceived personalization with respect to the level of personalization ($F(2, 57) = 87.174, p < 0.01$). Mean differences between one-to-all and one-to-N ($t(38) = -8.770, p < 0.01$), one-to-N and one-to-one ($t(38) = -4.404, p < 0.01$), and one-to-all and one-to-one ($t(38) = -12.679, p < 0.01$) were all statistically significant. Thus, support was found for our manipulation of personalization levels with respect to the personalization object.

Second, we also checked the performance of user-initiated personalization tool for the main experiment. If our personalization tool does not meet the average quality of the currently used tools such as MyYahoo, the personalized offers could not satisfy custom-ers who used it. We have let 20 graduate students, who have had no experience of using MyYahoo service, experience both tools in the test: MyYahoo service, one of the most popular personal home page tools and our personalization tool. They were asked to allocate seven scale points to the following sentence: "This tool for content (or interface) personalization is enough to satisfy my specific needs."

The average values for content personalization tool of MyYahoo and ours were 5.68 and 5.50, respectively. There was no significant difference between the two ($t(38) = 0.702, p = 0.487 > 0.05$). In terms of interface, those of MyYahoo and ours were 6.18 and 5.95, respectively. There was no significant difference between the two, either ($t(38) = 1.381, p = 0.175 > 0.05$). That is, our tool was proved to be adequate for being used as a personalization tool competitive with MyYahoo. Thus, the results showed that the manipulations of the levels and the subjects of personalization are effective.

6.2. Results

There was a total of 439 participants in this experiment. The replies from 67 users that were not fully answered were excluded from the data set. The final data set comprises 372 observations: 281 observations for Set A and 121 observations for Set B, of which 30 observations in [CS_IS] overlap with [CO_IO] in Set A.

Customer satisfaction and customer loyalty had single-factor structures when the three items in each variable were factor analyzed. The factors of customer satisfaction and loyalty were generated with an eigenvalue of 2.30 and 2.14 and Cronbach’s zs of 0.855 and 0.832, respectively. The mean values of the three items in each variable were used in subsequent analyses. Table 5 presents the mean and standard deviation of customer satisfaction and customer loyalty for each strategy. The sample size of each cell was over the recommended minimum of 20 per cell and was approximately equal across groups, which resulted in the desired power levels (Hair et al. 2005).

For this factorial design, nine groups for Set A and four groups for Set B were involved in testing the assumption of homoscedasticity, as shown in Table 6. The multivariate test (Box M) has an insignificant value, allowing us to accept the null hypothesis of homogeneity of variance–covariance matrices at the .05 level in each set. The univariate tests for the two dependent variables were also non-significant in both sets. With the multivariate test (Box M) and univariate tests showing no significance, the assumption of homoscedasticity was fully met.

6.2.1. Results for Set A

Fig. 6 portrays each dependent variable across the groups in the Set A, and Table 7 contains the multivariate analysis of covariance (MANCOVA) results for testing both the interaction and main effects of the Set A.

In this experiment, prior knowledge about the web personalization was used as a covariate; however, as shown in Table 7, the covariate is not statistically significant in either the multivariate or univariate tests. Fig. 6 also indicates the non-parallel pattern around which an interaction may exist. As we can see in each graph, the gaps between interface personalization levels decrease as the content personalization level moves toward CO, and the CO level has smaller differences among lines than do the other two levels of content personalization. The differences among the levels of interface personalization are seen to differ based on how content is personalized. Also, as the interface personalization moves toward CO, the differences

---

2 About 15.2% or 67 participants did not accomplish the entire experiment since they were randomly selected and not compulsorily but voluntarily participated.
among the levels of content personalization are shown to be smaller, meaning that the impact of content personalization weakens. Since the lines cease to run parallel but not cross in a significant way, the interaction is ordinal. The multivariate effect of the interaction of content and interface personalization is significant by all four tests, as shown in Table 7a. Univariate tests for each dependent variable in Table 7b are also significant; therefore, statistical tests confirm what was indicated in Fig. 6. A significant ordinal interaction effect occurs between content and interface personalization. Therefore, the Interaction Effects for Levels of Personalization Hypothesis (H2a) is accepted.

With a significant ordinal interaction, it is necessary to assess whether both independent variables still have significant effects when considered simultaneously and separately. Both content personalization and interface personalization have a significant impact on customer satisfaction and loyalty, both as a set and individually. 

### Table 5
Descriptive statistics of customer satisfaction and loyalty.

#### (a) Experiment Set A (subject of personalization: system-initiated personalization)

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Interface[I]</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>One-to-All[A]</td>
<td>CA_IA</td>
<td>4.11</td>
<td>.558</td>
<td>5.01</td>
<td>4.55</td>
</tr>
<tr>
<td></td>
<td>CN_IA</td>
<td>4.60</td>
<td>.771</td>
<td>5.14</td>
<td></td>
</tr>
<tr>
<td></td>
<td>CO_IA</td>
<td>4.91</td>
<td>.683</td>
<td>4.96</td>
<td></td>
</tr>
<tr>
<td>One-to-N[N]</td>
<td>CA_IN</td>
<td>3.148</td>
<td>.650</td>
<td>5.14</td>
<td>5.275</td>
</tr>
<tr>
<td></td>
<td>CN_IN</td>
<td>5.01</td>
<td>.583</td>
<td>5.14</td>
<td></td>
</tr>
<tr>
<td></td>
<td>CO_IN</td>
<td>5.14</td>
<td>.576</td>
<td>5.275</td>
<td></td>
</tr>
<tr>
<td>One-to-One[O]</td>
<td>CA_IO</td>
<td>4.73</td>
<td>.560</td>
<td>5.01</td>
<td>5.275</td>
</tr>
<tr>
<td></td>
<td>CN_IO</td>
<td>5.01</td>
<td>.583</td>
<td>5.14</td>
<td></td>
</tr>
<tr>
<td></td>
<td>CO_IO</td>
<td>5.14</td>
<td>.576</td>
<td>5.275</td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>4.665</td>
<td>.650</td>
<td>4.998</td>
<td>5.116</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(.558)</td>
<td>(.571)</td>
<td>(.576)</td>
<td>(.590)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>N = 3</td>
<td>N = 30</td>
<td>N = 31</td>
<td>N = 94</td>
</tr>
<tr>
<td></td>
<td></td>
<td>N = 2</td>
<td>N = 31</td>
<td>N = 94</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>N = 9</td>
<td></td>
<td>N = 31</td>
<td></td>
</tr>
</tbody>
</table>

#### (b) Experiment Set B (personalization level: one-to-one personalization)

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Interface[I]</td>
<td></td>
<td>CS_IS</td>
<td>CU_IS</td>
</tr>
<tr>
<td>System-initiated[S]</td>
<td>CS_IS</td>
<td>5.310</td>
<td>5.333</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(.579)</td>
<td>(.566)</td>
</tr>
<tr>
<td></td>
<td>N = 30</td>
<td>N = 30</td>
<td>N = 60</td>
</tr>
<tr>
<td>User-initiated[U]</td>
<td>CS_IU</td>
<td>5.881</td>
<td>5.910</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(.574)</td>
<td>(.572)</td>
</tr>
<tr>
<td></td>
<td>N = 31</td>
<td>N = 30</td>
<td>N = 61</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td>5.600</td>
<td>5.722</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(.640)</td>
<td>(.597)</td>
</tr>
<tr>
<td></td>
<td>N = 61</td>
<td>N = 60</td>
<td>N = 121</td>
</tr>
</tbody>
</table>

Note: Numbers in the parentheses are standard deviations.


Table 6
Multivariate and univariate measures for testing homoscedasticity.

<table>
<thead>
<tr>
<th>Design: Intercept + Content + Interface + Content + Interface + Prior Knowledge.</th>
</tr>
</thead>
<tbody>
<tr>
<td>(a) Box’s test of equality of covariance matrices</td>
</tr>
<tr>
<td>Box/M</td>
</tr>
<tr>
<td>Set A</td>
</tr>
<tr>
<td>Set B</td>
</tr>
<tr>
<td>(b) Levene’s test of equality of error variances</td>
</tr>
<tr>
<td>F</td>
</tr>
<tr>
<td>Set A</td>
</tr>
<tr>
<td>Set A</td>
</tr>
<tr>
<td>Set B</td>
</tr>
<tr>
<td>Set B</td>
</tr>
</tbody>
</table>

Note: Tests the null hypothesis that the error variance of the dependent variable is equal across groups.

6.2.2. Results for Set B

Fig. 7 portrays each dependent variable across the groups in Set B, and Table 9 contains the MANCOVA results for testing both the interaction and main effects of Set B. Prior knowledge about the web personalization used as a covariate is not statistically significant in either the multivariate or univariate tests for Set B, as in the case of Set A.

The differences among the levels of interface personalization are seen to differ based on how content is personalized as indicated in Fig. 7. However, the multivariate effect of the interaction of content and interface personalization is not significant in all four tests, as shown in Table 9a. Univariate tests for each dependent variable in Table 9b are also not significant; therefore, statistical tests confirm that a significant interaction effect does not occur between content and interface personalization with reference to the subject of personalization. Therefore, the Interaction Effects for Subjects of Personalization Hypothesis (H2b) is not supported in this experiment.

Only interface personalization has a significant impact on customer satisfaction and loyalty, both as a set and separately, as demonstrated by the multivariate and univariate tests in Table 7a and b. The impact of content and interface personalization can be compared by examining the relative effect sizes indicated by $\eta^2$ values. The effect size of interface personalization is almost one and a half times that of content personalization. It supports the Effects of Personalization Strategies Hypothesis (H1). This implies that although research on personalization has focused on content personalization, the impact of interface personalization is in no way negligible. Also, the results for Tukey’s HSD and Scheffe’s post hoc tests for content personalization and interface personalization are shown in Table 8.

When content personalization of the CA and CN levels are considered, there are significant differences between the two levels in terms of satisfaction and loyalty. Considering interface personalization of the IA and IN levels, the differences between the two levels are statistically significant in cases of satisfaction and loyalty. Therefore, a one-to-N personalization strategy is superior to one-to-all strategy. This suggests that the One-to-N vs. One-to-All Content Personalization Strategy Hypothesis (H3a) and the One-to-N vs. One-to-All Interface Personalization Strategy Hypothesis (H3b) are supported.

When interface personalization of IN and IO levels are considered, there are significant differences between the two levels in cases of satisfaction and loyalty. However, after taking into consideration content personalization of CN and CO levels, they do not significantly differ in cases of satisfaction and loyalty. This means that one-to-one content personalization does not significantly improve customer value compared to one-to-N content personalization, while one-to-one interface personalization does compared to one-to-N interface personalization. Therefore, the One-to-One vs. One-to-N Content Personalization Strategy Hypothesis (H3c) is not supported, but the One-to-One vs. One-to-N Interface Personalization Strategy Hypothesis (H3d) is supported in this experiment.

6.2.3. Selection of personalization strategy

In terms of interface personalization, every personalization level improves as the level moves from one-to-all to one-to-one. User-initiated one-to-one personalization is superior to any other interface personalization strategy. Although every other content personalization strategy improves customer value compared to one-to-all content strategy, they do not significantly differ from each other, irrespective of the levels or subjects of personalization. Thus, the most recommended combination of content and interface personalization that leads to customer satisfaction and loyalty in this experiment are one-to-one user-initiated interface person-
alization and content personalization strategy other than one-to-
all content strategy.

This experiment measures the effects of personalization strate-
gies by examining customer retention in terms of customer satis-
faction and loyalty. However, the purpose of personalization may
determine how best to characterize the personalization strategies.
In other words, since providers may personalize their products or
services for other purposes, such as increasing customer visits to
the site or improving the amount of sales, the recommended per-
sonalization strategy may be varied with respect to the purpose.

7. Discussion

7.1. Implications

Several important practical implications can be identified
from the experimental results. First, the importance of interface
personalization should be emphasized more regarding the object
of personalization. Up to the present, there has been much effort
to personalize content according to a user’s preferences, such as
recommender systems; however, in this experiment, interface
personalization is shown to significantly improve customer satis-
faction and loyalty, and it has an impact greater than that of
content personalization. This implies that if the content is not
easily personalized, such as “cold start” cases where customer
preference information is not enough to provide personalized
offers, interface personalization can be a good alternative to pur-
sue in order to improve customer satisfaction and loyalty. Yet,
the generalization of this result—“interface personalization is al-
ways more effective than content personalization”—seems to re-
quire additional experiments. In this experiment, the participants
did not have any mission of news searching during the experi-
ment, which made them in a low-involvement status. If the par-
ticipants had a mission to search for specific information or to

### Table 7
Multivariate and univariate tests for group differences in experiment Set A.

<table>
<thead>
<tr>
<th>(a) Multivariate tests. Effect</th>
<th>Value</th>
<th>F</th>
<th>Hypo. df</th>
<th>Error df</th>
<th>Sig</th>
<th>Partial Eta Sq</th>
<th>Noncent. parameter</th>
<th>Observed power</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept Pillai’s Trace</td>
<td>.959</td>
<td>3155.568</td>
<td>2.000</td>
<td>270.000</td>
<td>.000</td>
<td>.959</td>
<td>6311.135</td>
<td>1.000</td>
</tr>
<tr>
<td>Wilks’ Lambda</td>
<td>.041</td>
<td>3155.568</td>
<td>2.000</td>
<td>270.000</td>
<td>.000</td>
<td>.959</td>
<td>6311.135</td>
<td>1.000</td>
</tr>
<tr>
<td>Hotelling’s Trace</td>
<td>23.375</td>
<td>3155.568</td>
<td>2.000</td>
<td>270.000</td>
<td>.000</td>
<td>.959</td>
<td>6311.135</td>
<td>1.000</td>
</tr>
<tr>
<td>Roy’s Largest Root</td>
<td>23.375</td>
<td>3155.568</td>
<td>2.000</td>
<td>270.000</td>
<td>.000</td>
<td>.959</td>
<td>6311.135</td>
<td>1.000</td>
</tr>
<tr>
<td>Prior knowledge</td>
<td>.006</td>
<td>.865</td>
<td>2.000</td>
<td>270.000</td>
<td>.422</td>
<td>.006</td>
<td>1.729</td>
<td>.198</td>
</tr>
<tr>
<td>Wilks’ Lambda</td>
<td>.994</td>
<td>.865</td>
<td>2.000</td>
<td>270.000</td>
<td>.422</td>
<td>.006</td>
<td>1.729</td>
<td>.198</td>
</tr>
<tr>
<td>Hotelling’s Trace</td>
<td>.006</td>
<td>.865</td>
<td>2.000</td>
<td>270.000</td>
<td>.422</td>
<td>.006</td>
<td>1.729</td>
<td>.198</td>
</tr>
<tr>
<td>Roy’s Largest Root</td>
<td>.006</td>
<td>.865</td>
<td>2.000</td>
<td>270.000</td>
<td>.959</td>
<td>.006</td>
<td>1.729</td>
<td>.198</td>
</tr>
<tr>
<td>Content</td>
<td>.166</td>
<td>12.292</td>
<td>4.000</td>
<td>542.000</td>
<td>.000</td>
<td>.083</td>
<td>49.166</td>
<td>1.000</td>
</tr>
<tr>
<td>Wilks’ Lambda</td>
<td>.834</td>
<td>12.856</td>
<td>4.000</td>
<td>540.000</td>
<td>.000</td>
<td>.087</td>
<td>51.422</td>
<td>1.000</td>
</tr>
<tr>
<td>Hotelling’s Trace</td>
<td>.200</td>
<td>13.418</td>
<td>4.000</td>
<td>538.000</td>
<td>.000</td>
<td>.091</td>
<td>53.670</td>
<td>1.000</td>
</tr>
<tr>
<td>Roy’s Largest Root</td>
<td>.200</td>
<td>27.032</td>
<td>2.000</td>
<td>271.000</td>
<td>.166</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Interface</td>
<td>.252</td>
<td>19.552</td>
<td>8.000</td>
<td>542.000</td>
<td>.000</td>
<td>.126</td>
<td>78.208</td>
<td>1.000</td>
</tr>
<tr>
<td>Wilks’ Lambda</td>
<td>.740</td>
<td>20.950</td>
<td>8.000</td>
<td>540.000</td>
<td>.000</td>
<td>.134</td>
<td>83.800</td>
<td>1.000</td>
</tr>
<tr>
<td>Hotelling’s Trace</td>
<td>.322</td>
<td>22.351</td>
<td>8.000</td>
<td>538.000</td>
<td>.000</td>
<td>.142</td>
<td>89.404</td>
<td>1.000</td>
</tr>
<tr>
<td>Roy’s Largest Root</td>
<td>.326</td>
<td>44.163</td>
<td>8.000</td>
<td>271.000</td>
<td>.246</td>
<td></td>
<td>88.326</td>
<td>1.000</td>
</tr>
<tr>
<td>Content + Interface</td>
<td>.056</td>
<td>1.955</td>
<td>8.000</td>
<td>542.000</td>
<td>.050</td>
<td>.028</td>
<td>15.639</td>
<td>.812</td>
</tr>
<tr>
<td>Wilks’ Lambda</td>
<td>.944</td>
<td>1.962</td>
<td>8.000</td>
<td>540.000</td>
<td>.049</td>
<td>.028</td>
<td>15.696</td>
<td>.814</td>
</tr>
<tr>
<td>Hotelling’s Trace</td>
<td>.059</td>
<td>1.969</td>
<td>8.000</td>
<td>538.000</td>
<td>.048</td>
<td>.028</td>
<td>15.752</td>
<td>.816</td>
</tr>
<tr>
<td>Roy’s Largest Root</td>
<td>.050</td>
<td>3.403</td>
<td>4.000</td>
<td>271.000</td>
<td>.010</td>
<td>.048</td>
<td>13.611</td>
<td>.849</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>(b) Tests of between-subjects effects Source</th>
<th>Dependent variable</th>
<th>Type III sum of squares</th>
<th>df</th>
<th>Mean square</th>
<th>F</th>
<th>Sig</th>
<th>Partial Eta Sq</th>
<th>Noncent. parameter</th>
<th>Observed power</th>
</tr>
</thead>
<tbody>
<tr>
<td>Corrected Model</td>
<td>Satisfaction</td>
<td>39.033</td>
<td>9</td>
<td>4.337</td>
<td>13.196</td>
<td>.000</td>
<td>.305</td>
<td>118.764</td>
<td>1.000</td>
</tr>
<tr>
<td></td>
<td>Loyalty</td>
<td>44.467</td>
<td>9</td>
<td>4.941</td>
<td>15.438</td>
<td>.000</td>
<td>.339</td>
<td>138.944</td>
<td>1.000</td>
</tr>
<tr>
<td>Intercept</td>
<td>Satisfaction</td>
<td>1754.503</td>
<td>1</td>
<td>1754.503</td>
<td>5338.328</td>
<td>.000</td>
<td>.952</td>
<td>5338.328</td>
<td>1.000</td>
</tr>
<tr>
<td></td>
<td>Loyalty</td>
<td>740</td>
<td>2</td>
<td>3.700</td>
<td>38.197</td>
<td>.000</td>
<td>.105</td>
<td>76.393</td>
<td>1.000</td>
</tr>
<tr>
<td>Prior</td>
<td>Satisfaction</td>
<td>267</td>
<td>1</td>
<td>267</td>
<td>812</td>
<td>.368</td>
<td>.003</td>
<td>.812</td>
<td>.146</td>
</tr>
<tr>
<td></td>
<td>Loyalty</td>
<td>.002</td>
<td>1</td>
<td>.002</td>
<td>.007</td>
<td>.931</td>
<td>.000</td>
<td>.007</td>
<td>.051</td>
</tr>
<tr>
<td>Knowledge</td>
<td>Satisfaction</td>
<td>25.108</td>
<td>2</td>
<td>12.554</td>
<td>38.197</td>
<td>.000</td>
<td>.220</td>
<td>76.393</td>
<td>1.000</td>
</tr>
<tr>
<td></td>
<td>Loyalty</td>
<td>23.277</td>
<td>2</td>
<td>11.638</td>
<td>36.366</td>
<td>.000</td>
<td>.212</td>
<td>72.733</td>
<td>1.000</td>
</tr>
<tr>
<td>Content + Interface</td>
<td>Satisfaction</td>
<td>3.161</td>
<td>4</td>
<td>.790</td>
<td>2.404</td>
<td>.050</td>
<td>.034</td>
<td>9.617</td>
<td>.688</td>
</tr>
<tr>
<td>Error</td>
<td>Satisfaction</td>
<td>85.067</td>
<td>271</td>
<td>.329</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Loyalty</td>
<td>86.729</td>
<td>271</td>
<td>.320</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>Satisfaction</td>
<td>6942.700</td>
<td>281</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Loyalty</td>
<td>6903.510</td>
<td>281</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Corrected total</td>
<td>Satisfaction</td>
<td>128.101</td>
<td>280</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Loyalty</td>
<td>131.196</td>
<td>280</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: Design: Intercept + Content + Interface + Content + Interface + Prior Knowledge.

* Computed using α = .05.
* Exact statistic.
* The statistic is an upper bound on F that yields a lower bound on the significance level.
* Computed using α = .05.
* $R^2 = .332$ (adjusted $R^2 = .310$).
* $R^2 = .339$ (adjusted $R^2 = .317$).
buy products in e-shops, the importance of content personalization might increase.

Second, as far as the level of personalization is concerned, the importance of one-to-one content personalization could be emphasized less. One-to-one content personalization does not improve customer value more significantly than one-to-N content personalization. This implies that if one-to-one content personalization requires too much time, cost, or effort, one-to-N content personalization (called “segment marketing” in marketing literature) may be a good alternative. Meanwhile, because the impact of content personalization is influenced by the level of interface personalization, the consideration of content personalization separately from interface personalization may be biased.

Third, incentives are needed to increase user participation in the personalization process, considering the subject of personalization. According to the results, user-initiated personalization of content and interface makes customers more satisfied or loyal. However, most of the users of e-services have a tendency to feel that self-initiated personalization is somewhat bothersome, which results in a relatively small number of users participating in self-initiated personalization provisions. Thus, it is necessary for various marketing promotions to provide incentives that lead to users to self-initiated personalization in order to increase customer satisfaction and loyalty.

7.2. Limitations of the experiment

In spite of the aforementioned implications, this study has two limitations to be discussed. The first limitation regards the measurement of customer loyalty. We measured customer satisfaction with the measures of CSI models like the ACSI and the ECSI, which are same. However, we measured customer loyalty with Johnson et al. (2001)’s study based on Zeithaml et al.’s (1996), instead of using the loyalty measures in the CSI models. Customer loyalty in the ACSI model has two measures that are repurchase likelihood and price tolerance. In terms of the ECSI, the loyalty measures include likelihood of retention, likelihood of recommending the company or brand, and whether the amount customers are likely to purchase will increase. Meanwhile, Johnson et al. (2001) suggested the measures for loyalty, likelihood of retention, likelihood of speaking favorably about the company (website) to others, and likelihood of recommending the company (website) to others.

Therefore, we selected loyalty measures from Johnson et al. (2001) because loyalty measures of the CSI models are not proper to a news service that is made freely available to the public. Meanwhile, Oliver (1999) suggested that loyalty has four phases of cognitive, affective, conative and action loyalty. The measured loyalty in this experiment seems mainly focus on the behavioral intention. It may not correspond to the action loyalty phase but to the conative loyalty phase. If measures for action loyalty phase like the number of revisits were included, more practical implications would be obtained.

Second limitation of the experiment is related to the personalization technologies used to compare different levels of personalization. Personalization level is one of the personalization technologies used to compare different levels of personalization. Personalization level is one of the personalization technologies used to compare different levels of personalization. Personalization level is one of the personalization technologies used to compare different levels of personalization.

A second limitation of the experiment is related to the personalization technologies used to compare different levels of personalization. Personalization level is one of the personalization technologies used to compare different levels of personalization. Personalization level is one of the personalization technologies used to compare different levels of personalization.
method as a tool for one-to-one level personalization. Therefore, implementing one of the recommender systems for one-to-one level personalized marketing seems to be natural. However, there might be a difference in the effectiveness of personalization technologies. Although there have been studies on comparing the effectiveness of CF, CBF and hybrid methods, there still has been lack of research in view of customer satisfaction or loyalty. Fan and Poole (2006) considered the dimension for personalization implementation that can seriously affect customer satisfaction and/or customer loyalty, thereby determining business success. In contrast, marketers focus on how to manage customer relationships by delivering unique values and benefits to each customer. Most studies of personalization systems by computer scientists have focused too much on personalization technologies without considering unique values and benefits to each customer. Most studies of personalization systems by computer scientists have focused too much on personalization technologies without considering the fundamental objectives of personalization, which results in passing over the managerial effect of personalization. In contrast, marketers have not recognized the various aspects of personalization implementation that can seriously affect customer satisfaction and/or customer loyalty, thereby determining business success.

The key contribution of this study is its provision of an interdisciplinary framework that enables personalization system develop-
ers to understand the more general aspects of personalization effectiveness and allows marketers to consider the dimensions of personalization implementation from a strategic viewpoint. This research identified the four important dimensions for implementing personalization: subject, object, level, and learning method. Personalization strategies were classified by these dimensions. An experiment for investigating the effects of each strategy on customer retention—customer satisfaction and customer loyalty—was completed. It revealed the interaction between content personalization and interface personalization, the importance of interface personalization, and the optimal personalization strategy, which consists of one-to-one user-initiated interface personalization and one-to-N or one-to-one content personalization in the case of a news portal site.

The directions for future research are as follows. First, since the results in this paper are confined to the context of web personalization, another empirical study could be undertaken to compare a larger number of personalization strategies. For example, an analysis including other objects of personalization such as e-mail, is needed. Second, more practical variables for measuring customer loyalty can be developed and employed. Although this study follows the surveyed measures in marketing literature, measures from both the survey and the web log analysis—such as number of visits, duration times, or click-to-buy—may provide more insight to developers or marketers. Third, since the most highly recommended personalization strategy may be dependent on the purpose of personalization, additional studies that examine the effects of different personalization strategies in view of other purposes, such as increasing customer visits or improving sales, could be followed.

Appendix A. Detailed explanation for personalization by collaborative filtering

The CF firstly selects neighbors with item ratings similar to those of the target users, and subsequently recommends the items preferred by those neighbors. The rating similarity between two users is measured by Pearson’s correlation coefficient. The similarity between users \( u \) and \( v \) (denoted by \( UserSim_{u,v} \)) is calculated using Eq. (A1). In this experiment, to reduce the sparseness problem and the scalability in finding neighbors, users who were assigned to this strategy were asked to rate a set of 30 news articles randomly selected from 1 (not interesting) to 5 (very interesting) at the input stage. Neighbors to a specific user were selected by the rating similarities using Eq. (A1), and users in this strategy were asked to rate five randomly selected news articles at every login stage to keep neighbors up-to-date.

\[
UserSim_{u,v} = \frac{\sum_{i=1}^{m} (R_{u,i} - \bar{R}_{u})(R_{v,i} - \bar{R}_{v})}{\sqrt{\sum_{i=1}^{m} (R_{u,i} - \bar{R}_{u})^2 \sum_{i=1}^{m} (R_{v,i} - \bar{R}_{v})^2}}
\]

(A1)

where:

- \( R_{u,i} \): user \( u \)'s rating for item \( i \)
- \( R_{v,i} \): user \( v \)'s rating for item \( i \)
- \( M \): number of co-rated items

The rating of the target user \( a \) for an item \( i \) is estimated by aggregating the ratings of the top 10 neighbors with that of the target user for the news article, seen in Eq. (A2). In this experiment, if a user read a news article, the user's rating of the article is 1; if not, it is 0. The 10 articles that had been highly ranked by the equation and not read by a target user were recommended.

\[
P_{\text{Estimated}} = \bar{R}_{i} + \frac{\sum_{a=1}^{N} UserSim_{a,u}(R_{a,i} - \bar{R}_{u})}{\sum_{a=1}^{N} UserSim_{a,u}}
\]

(A2)

Appendix B. Detailed explanation for personalization by conjoint analysis

A conjoint analysis is an experimental procedure for assessing values, which are called part-worths of attributes. The analysis was originated in marketing studies such as Green and Srinivasan (1990) and is the most widely applied methodology for measuring and analyzing consumer preferences. It assumes that a unit is a bundle of attributes and that the unit’s value is the sum of the part-worths of those attributes.

The utility of a user interface \( i \) to target user \( u \), \( U_{ui} \), is a sum of the part-worth of attributes by a regression form, as follows:

\[
U_{ui} = \sum_{n=1}^{N} \sum_{m=1}^{M} p_{um}x_{um} + \epsilon_{ui},
\]

where:

- \( U_{ui} \): the target user \( u \)'s evaluation of an interface \( i \) (known);
- \( p_{um} \): part-worth of attribute \( n \) level \( m \) to the target user \( u \) (unknown);
- \( x_{um} \): 1, if the \( m \)th level of the \( n \)th attribute is present in an interface \( i \), and 0 otherwise (known);
- \( N \): the number of attributes
- \( M \): the number of levels in the \( n \)th attribute

A user in the IO (or IS) personalization of this experiment can customize his or her user interface by changing the skin of web pages, the layout of the screen, or the size of the font; however, since font size can easily be modified on the web browser, the personalization of font size is not very meaningful. Thus, in this experiment, a user interface with normal font size was regarded to have two attributes: skin of the web pages, and screen layout. There were 40 levels of web page skins and six levels of screen layouts. Thus, Eq. (B1) can be rewritten as seen below:

\[
U_{ui} = \sum_{m=1}^{40} p_{um}x_{um} + \sum_{m=1}^{6} p_{um}x_{um} + \epsilon_{ui},
\]

(B2)

where:

- \( U_{ui} \): the target user \( u \)'s evaluation of an interface \( i \) (known);
- \( p_{um} \): part-worth of \( n \)th level of skin and layout to the target user \( u \) (unknown);
- \( x_{um} \): 1, if the \( m \)th level of the skin or layout is present in an interface \( i \), and 0 otherwise (unknown);
- \( \epsilon \): is the random error with normal distribution

The number of possible interface bundles is \( 40 \times 6 = 240 \); however, it is not necessary to rate all 240 interfaces, since there are only 46 unknowns \((p_{um}, p_{um})\) in the regression equation. If an orthogonal experiment design is employed, ratings on 46 (=40 + 6) interface sets make the part-worths of each user calculated by a regression analysis. Thus, to estimate the 46 unknowns \((p_{um}, p_{um})\), 46 interface bundles (one for each interface concept) were presented to every participant assigned to this strategy for their preference rating. Then, every user’s part-worth of attributes in this strategy was estimated. The combination of skin and layout that showed the highest utility was provided to the news portal’s interface for the user.

References

Fornell, C., Johnson, M. D., Anderson, E. W., Cha, J., and Bryant, B. E. The American
Hair, J. F., Black, B., Babin, B., Anderson, R. E., and Tatham, R. L.
Gustafsson, A., and Johnson, M. D. Measuring and managing the satisfaction–
Gerpott, T. J., Rams, W., and Schindler, A. Customer retention, loyalty, and
Fan, H., and Poole, M. S. What is personalization? Perspectives on the design and
Cho, J., Kwon, K., and Park, Y. Collaborating filtering using dual information sources.
Chang, H. H., and Chen, S. W. Consumer perception of interface quality, security, and
Bolton, R. N. A dynamic model of the duration of the customer’s relationship with a
Chang, H. H., and Chen, S. W. The impact of customer interface quality, satisfaction and
Blom, J. Personalization: A taxonomy. In CIIF 2000 Conference on Human Factors in
Ball, D., Coelho, P. S., and Vilares, M. J. Service personalization and loyalty. Journal of
Berghel, H. Cyberspace 2000: dealing with information overload. Communications of the
Blom, J. Personalization: A taxonomy. In CIIF 2000 Conference on Human Factors in