MIS Quarterly

RESEARCH ARTICLE

NUDGING MOODS TO INDUCE UNPLANNED PURCHASES IN IMPERFECT MOBILE PERSONALIZATION CONTEXTS

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Appendix A

Information Systems Journal Articles on Taste-, Need-, and Location-Matching and Tradeoffs in Personalization

We reviewed articles published between 2006 and 2016 related to taste-matching, need-matching, location-matching, and personalization tradeoffs. Publications were collected from the six major IS journals (*MIS Quarterly*, *Information Systems Research*, *Journal of Management Information Systems*, *Journal of the Association for Information Systems*, *European Journal of Information Systems*, and *Information Systems Journal*). We included two additional journals—*Decision Support Systems* and *Information and Management*—because one of their objectives is to publish articles on new and advanced developments in the field of IS.

	Context	Construct(s) Related to Our Research and Its Operational Definition	Research Objectives	Findings
Adomavicius et al. (2013)	Online shopping	**Taste-matching** offers a user's preferred product from a product category and there is no objective criterion to rank individual products in the given category. Their study used TV shows and jokes as examples of taste-matching.	Examines how the recommendations by recommendation agents (RAs) influence the formation of user preference.	The RA rating serves as an anchor for users' constructed preference. The effect is sensitive to users' perceived reliability of the RA.
Adomavicius et al. (2011)	Online shopping	**Need-matching** offers a recommendation that fulfills a user's specific requirements; e.g., a person needs a travel package for a specific date to go on vacation to a particular place with his/her family.	Presents a recommendation query language REQUEST (and associated algebra), which allows users to formulate recommendations in ways satisfying their individual needs.	Provides a series of examples to illustrate how users can customize their recommendations using REQUEST queries.

	Context	Construct(s) Related to Our Research and Its Operational Definition	Research Objectives	Findings
Al-Natour et al. (2011)	Online shopping	The authors suggest that online RAs offer products matched to a user's **interest** and **need**, but did not define or differentiate the two terms. Their experiment task focused on need. Subjects were asked to select a laptop for a friend based on the friend's needs, which were given as a set of requirements.	Examines the effects of perceived personality similarity (PPS) and perceived decision process similarity (PDPS) of an RA on user beliefs.	PDPS influences user beliefs (enjoyment, social presence, trust, ease of use, and usefulness), and the effects of PPS are largely mediated by PDPS.
Benlian (2015)	Online shopping	**Taste-matching** offers a product that matches a user's aesthetic tastes and hedonic needs. The author used music as an illustrative example.	Preference fit and perceived enjoyment are two mechanisms that differentiate effects of content and design personalization on users' willingness to pay for offerings.	A combination of content and design personalization cues is not effective in increasing preference fit and users' willingness to pay.
Benlian et al. (2012)	Online shopping	The authors suggest that perceived quality of an experience good depends more on subjective attributes that are a matter of personal **taste**. They also describe different kinds of **needs**, e.g., emotional need, motivational need, and information need.	Examines the differential effects of provider recommendations (PRs) and consumer reviews (CRs) on user beliefs, which in turn, influence continued RA usage and product purchase intentions.	PRs increase perceived usefulness and perceived ease of use, while CRs increase trust and perceived affective quality, resulting in different mechanisms operating for RA reuse and purchase intentions.
Chen et al. (2016)	Social network	Estimates home **locations** of social network users at the city level.	A social tie factor graph model is proposed to estimate a Twitter user's city-level location based on his or her following network, user-centric data, and tie strength.	An experiment shows that the proposed method significantly outperforms several state-of-the-art methods.
Cheng et al. (2011)	Micro-blogging [N]	Describes a method to extract useful information from micro-blogging sites to meet users' **preferences**. However, the paper does not explicitly define preferences.	A framework is proposed to increase usefulness of information extracted from micro-blogging sites by generating recommendations with an analysis of information diffusion pattern among micro-blogs.	Compared to benchmark approaches, the proposed diffusion-based recommendation framework results in more balanced and comprehensive recommendations.
Constantiou et al. (2014)	Mobile services	**Location**-based services provide location-related information to meet a person's **need** (not defined). Car navigation software, fitness applications, and city guides are used as examples of LBS.	A framework is developed to analyze users' decisions to use LBS, focusing on the cognitive processes involved in the decision-making.	The decision to use LBS can be made either via a comparative mode, based on the LBS value in relation to other options, or an intuitive mode, in which experiences trigger heuristics.
Ghoshal, Kumar, and Mookerjee al. (2015)	Online shopping	The authors did not provide a definition of taste or **taste-matching**. They used music and movies as illustrative examples.	Models the strategic behavior of users who make repeated purchases at two competing firms: one with personalization and another without, and examines how RAs affect prices and profits of firms under competition.	Users should distribute their purchases across both firms to maximize surplus over a planning horizon. The RA can influence the price and profit of not only the personalizing firm but also the non-personalizing firm.

	Context	Construct(s) Related to Our Research and Its Operational Definition	Research Objectives	Findings
Ghoshal, Menon, and Sarkar (2015)	Method development	Throughout the paper, the authors used the word **preference**, and did not explicitly explain how preference relates to either **taste** or **need**.	Proposes a framework to compare alternative combinations of rules with an aim of improving the quality of recommendations.	An experiment shows that the recommendations generated by the proposed approach are more accurate than those made by some state-of-the-art benchmarks.
Hess et al. (2009)	Online services	The authors used the terms **preference** and **need**, but did not explicitly define them. The experiment subjects were asked to select an apartment with the assistance of an RA, which asked questions such as to "specify their preference for each apartment" and "select the apartment that best meets your need."	Examines how interface features of an RA can be designed to increase social presence of the RA.	RA personality, vividness, and computer playfulness affect social presence, which in turn, increases user trust in the RA.
Ho (2012)	Mobile shopping	**Location-matching** has two dimensions: location accuracy and location precision. The concept of location precision exists only in a longitudinal setup.	Examines the effects of location-matching on users' intention to take a mobile recommendation.	Initial perceptions of location-matching enhance intrinsic and extrinsic motivations, which in turn enhance intention to use mobile services in the long run.
Ho and Bodoff (2014)	Online shopping	Throughout the paper, the authors used the term **preference**, but did not explicitly explain how it relates to **taste** or **need**. The website of Study 2 recommended books relevant to a student's major. The website of Study 3 recommended music tracks.	Uses depth of processing from an elaboration likelihood model and breadth of processing from consumer search theory to develop a model of user attitude toward an RA and user behavior.	Both the number of sampled items so far and the depth of processing of each influence user attitude toward an RA, which in turn influences item selection and any further item sampling.
Ho et al. (2011)	Online shopping	Throughout the paper, the authors used the term **preference**, and did not explicitly explain how it relates to **taste** or **need**. The website of Study 2 recommended books relevant to a student's major. The website of Study 3 recommended music tracks.	Focuses on timing personalization and examines user responses to differences in presentation timing and recommendation type, and the interaction between the two.	Recommendation quality improves, but the probability of considering and accepting a given recommendation diminishes over the course of the session.
Jabr and Zheng (2014)	Online shopping	The authors did not specify any individual dimensions of personalization. They studied typical RAs and their joint effect with online reviews to influence users' shopping decision.	Examines the joint effect of user reviews and an RA on online sales.	Those products with higher centrality within the resulting network of referrals are associated with higher sales. These sales gains are hampered by improvements in the reviews of competing products.
Johar et al. (2014)	Online shopping	The phrase "tastes and preferences" is often used in the article; however, the authors did not provide a definition of **taste-matching**.	Examines what proportion of the offer set should be targeted toward immediate sales and what proportion toward learning the user's profile for a profit-maximizing firm.	Factors for firms deciding how to vary the size and composition of the offer set include uncertainty in the length of the period, the length of the engagement period, and the frequency of visits.

	Context	Construct(s) Related to Our Research and Its Operational Definition	Research Objectives	Findings
Kohler et al. (2011)	Online shopping	**Need-matching** matches a recommendation to a person's specific requirement (e.g., preferred arrival date of a trip), as well as physiological and psychological needs. However, the article also gives examples of need, such as preferred theme of a vacation, which is more hedonic in nature.	Examines how temporal distance moderates the effectiveness of the two approaches—a concrete feature-based approach or an abstract consumer-needs approach—to interact with users.	Congruency between consumption timing (immediate versus distant) and RA communication design (concrete versus abstract) alter the perceived transparency of the RA process.
Komiak and Benbasat (2006)	Online shopping	**Need-matching** offers a recommendation matched to a user's personal needs, including identifying all product attributes important to that particular user, capturing the relative importance among different product attributes, and helping novice users by mapping their shopping goals to product attribute specifications.	Examines the effects of perceived personalization on cognitive trust and emotional trust in an RA, and the impact of two types of trust on the intention to adopt the RA.	Perceived personalization increases both types of trust. Emotional trust plays an important role beyond cognitive trust in determining users' intention to adopt the RA.
Komiak and Benbasat (2008)	Online shopping	**Need-matching** offers a recommendation matched to a user's personal needs. In the experiment, the subjects were asked need-based questions (e.g., "what do you need this product for") so that the RA could link subjects' personal needs to the product attribution specifications.	Delineates trust-building and distrust-building processes and collects and analyzes the concurrent verbal protocols from an experiment to test a process theory.	Trust-building processes are different from distrust-building processes. This may suggest that some RA features should be designed to increase trust, and others to decrease distrust.
Liu et al. (2010)	Content industry	The article indicates that **taste-matching** can increase the quality of personalized content, but does not define taste or taste-matching.	Identifies the optimal resource allocation policies in the context of personalized content generation when the website receives multiple user requests.	The website can deliver an optimally personalized version of content to the user with a long delay, or a suboptimal version more quickly. A policy that determines optimal batch lengths is identified.
Oestreicher-Singer and Zalmanson (2013)	Content industry	The authors did not provide a definition of **taste-matching**. They used favorite music as an illustrative example. Also, music was their data collection context.	Proposes an approach that capitalizes on users' social behavior on the website and elicits payment from users.	Willingness to pay increases with users' participation on the website. It is more strongly linked to community participation than to the volume of content consumption.
Parboteeah et al. (2009)	Online shopping	**Need-matching** matches a recommendation to a user's current task need.	Examines whether and how recommendations matched to users' current tasks will increase the likelihood of impulse purchase.	Adapting web content to match users' current tasks increases their urge to buy and the likelihood of online unplanned purchase.
Parsons and Ralph (2014)	Method development	The authors used the term **preference**, but did not explicitly define it.	Presents an approach to generate recommendations. The approach uses item-viewing time to reveal user preferences for items. It models item preference as a weighted function of preferences for item attributes.	The proposed approach generated estimated item ratings consistent with explicit item ratings and assigned high ratings to products that reflect revealed preferences of users.

	Context	Construct(s) Related to Our Research and Its Operational Definition	Research Objectives	Findings
Pathak et al. (2010)	Online shopping	The authors suggested that online RAs offered products matched to a person's **taste** and **need** but they did not define or differentiate the two terms.	Examines how RAs affect sales by considering the indirect effect of recommendations on sales through retailer pricing, potential simultaneity between sales, and recommendations, and a comprehensive measure of the strength of recommendations.	Recommendations not only improve sales but also provide added flexibility to retailers to adjust their prices.
Provost et al. (2015)	Mobile network	The authors did not provide a definition of **taste-matching**. They wrote "users with similar tastes" and "users with similar interests and tastes" but did not define taste or differentiate it from interests.	Proposes a design that uses location data from mobile devices to build a "geo-similarity network" (GSN) among users with similar tastes.	70%–80% of the time the same user is connected to him/herself in the GSN, and the GSN neighbors of visitors to a wide variety of publishers are substantially more likely to visit those same publishers.
Qiu and Benbasat (2009)	Online shopping	The primary role of an RA is to help users complete the cognitive task of identifying a specific product that best meets cognitive **needs** from among hundreds of alternatives. RA interfaces should be carefully designed to meet users' emotional needs.	Examines the effects of applying anthropomorphic interfaces on users' perceived social relationship with a technological and software-based artifact designed for electronic commerce contexts.	Using humanoid embodiment and human voice-based communication enhances perceived social presence of an RA, which enhances trusting beliefs, perceived enjoyment, and ultimately, intentions to use the RA.
Sheng et al. (2008)	Privacy concern	The authors used the term, **preference**, but did not explicitly define it. In their conclusion, they wrote "**needs** or preferences" without further clarifications.	Examines how personalization and context can impact users' privacy concerns as well as intention to adopt ubiquitous commerce applications.	The effects of personalization on users' privacy concerns and adoption intention are situation dependent.
Tam and Ho (2006)	Online shopping	Content relevance approximates the extent of personalization. Their first experiment asked subjects to select a laptop, which was **need** related, while their second experiment asked subjects to download a music track they like, which was **taste** related.	Develops a model of web personalization. The influence of an RA is mediated by two variables—content relevance and self-reference—and moderated by goal specificity.	Content relevance, self-reference, and goal specificity affect the attention, cognitive processes, and decisions of web users.
Wang and Benbasat (2007)	Online shopping	**Need-matching** offers a recommendation that enhances users' task performance. Their experiments asked subjects to select a digital camera that met a set of task requirements.	Examines the effects of three types of explanations about an RA—how, why, and trade-off explanations—on users' trusting beliefs in an RA's competence, benevolence, and integrity.	"How" explanations increase users' competence and benevolence beliefs; "why" explanations increase benevolence beliefs; and tradeoff explanations increase integrity beliefs.
Wang and Benbasat (2009)	Online shopping	**Need-matching** offers a recommendation that enhances users' task performance. Their experiments asked subjects to select a digital camera with a particular requirement, i.e., to take pictures beyond the immediate vicinity or from very far away.	Extends the effort–accuracy framework of cognition by considering the perceived strategy restrictiveness of RAs.	The perceptions of cognitive effort, advice quality, and perceived strategy restrictiveness exert a significant influence on users' intentions to use an RA.

	Context	Construct(s) Related to Our Research and Its Operational Definition	Research Objectives	Findings
Wattal et al. (2009)	Content delivery	The authors indicate that **taste** is what a user likes and **location-matching** is the physical distance between a user and a recommendation.	Examines how personalization interacts with a firm's horizontal and vertical product differentiation. It also considers how different market structures lead to different equilibriums when firms adopt personalization.	Personalization by one firm leads to higher profits for both if product quality and misfit costs are high and the firms offer similar products ex ante. Personalization by both firms is profitable only if the technology is effective or if both product quality and misfit costs are low.
Wei et al. (2006)	Online document-clustering	An RA offers online documents matched to users' **need** and **preference**. The authors gave an example—some people use topic domains to categorize research articles, whereas others use research methods. Since no definitions are provided for need or preference, it is unclear if the above example refers to need or preference.	Combining two representation methods (feature refinement and feature weighting) with two clustering methods (precluster-based hierarchical agglomerative clustering (HAC) and atomic-based HAC), the study establishes four personalized document-clustering techniques.	The proposed personalized document-clustering techniques improve clustering effectiveness, as measured by cluster precision and cluster recall.
Xiao and Benbasat (2015)	Online shopping	The authors regarded users' **need** and **preference** as user requirements of a product, but they did not explicitly differentiate the two terms. They used digital cameras as the context of their experiments.	Examines how the availability and design of warning messages can enhance users' performance (in terms of correct detection of biased RAs (hits) and incorrect detection (false alarms)) in detecting biased RAs).	A warning message without accompanying advice increases hits at the cost of increased false alarms. By contrast, including in warning messages risk-handling advice increases hits and decreases false alarms.
Xu et al. (2011)	Privacy concerns	The extent of **location-matching** is the mobile operator's accuracy of location detection.	Explores the personalization–privacy paradox in location-aware marketing. It extends the privacy calculus model with considerations of user characteristics and two personalization approaches (covert and overt).	The effects of personalization on privacy risk/benefit beliefs vary with the two personalization approaches, and user characteristics moderate the parameters and path structure of the privacy calculus model.
Xu et al. (2012)	Location services	**Location-matching** offers a recommendation sufficiently close to the current location of a user. The authors used a web-based experiment and did not operationalize location-matching with physical distance/travels.	Clarifies the nature of control in the context of information privacy and generates insights into the effects of different privacy assurance approaches on context-specific concerns for information privacy.	Perceived control over personal information is a key factor affecting context-specific concerns for information privacy in the context of location-based services.

	Context	Construct(s) Related to Our Research and Its Operational Definition	Research Objectives	Findings
Xu et al. (2014)	Online shopping	**Need-matching** offers a recommendation that matches a user's weighting of different attributes of a product (such as hard drive and memory of a laptop).	Proposes an RA interface design that interactively illustrate tradeoffs among product attribute values to improve users' perceived product diagnosticity and perceived enjoyment, which in turn influence perceived decision quality and perceived decision effort.	Perceived enjoyment and perceived product diagnosticity follow an inverted U-shaped curve as the level of tradeoff transparency increases. Although users spend more time understanding attribute tradeoffs, they are more efficient in selecting a product.
Zhang et al. (2011)	Online shopping	**Taste-matching** offers a product interesting to users. The authors used a hedonic product, favorite DVDs, as an illustration. The term **need** appeared a few times in the article, but the authors did not provide a definition.	Draws on the household production function model in the consumer economics literature to explain the mechanisms through which RAs influence users' store loyalty in electronic commerce.	Higher quality RAs are associated with greater value derived by users from the online product brokering activity in terms of higher decision-making quality, which positively influences repurchase intention.
Zou and Huang (2015)	Mobile shopping	**Location-matching** provides an offer close to the geographic location of the user.	examines how location-based services act as a couponing channel and an infomediary to change the way people use information for purchase decision-making. It combines price dispersion with horizontal differentiation to examine the impact on retail competition.	The optimal strategy is for neither or both retailers to adopt, depending on the size of the uninformed segments and reach of services. The location identification feature leads to greater demand at the initial stage, but limits the equilibrium profit level in subsequent pricing stages.

Appendix B

Questionnaire Items

Manipulation Check for Taste-Matching (1 = Strongly Disagree; 9 = Strongly Agree)
1. I like [the recommended snack].
2. [The recommended snack] is my favorite snack.
2. [The recommended snack] is what I wanted.

Manipulation Check for Need-Matching (1 = Strongly Disagree; 9 = Strongly Agree)
1. I was thinking of having a snack at the time of receiving the mobile recommendation.
2. I needed a snack at the time of receiving the personalized mobile services.
3. I received the personalized mobile recommendation during my class break.
4. It was good to have [the recommended snack] on such a (hot/cold) day.

Manipulation Check for Location-Matching (1 = Strongly Disagree; 9 = Strongly Agree)
1. The personalized mobile services provided a recommendation close to where I was.
2. The personalized mobile services recommended a snack that was available in a nearby shop.
3. The snack recommendation was available in a shop that was close to where I was.
   Also, estimate the distance between the location where you received the personalized mobile services and the nearest shop that sold the snack: ______________ meter.

Impulse Purchase Tendency
1. I often buy things spontaneously.
2. "Just do it" describes the way I buy things.
3. I often buy things without thinking.
4. "I see it, I buy it" describes me.
5. "Buy now, think about it later" describe me.
6. Sometimes I feel like buying things on the spur-of-the-moment.
7. I buy things according to how I feel at the moment.
8. I carefully plan most of my purchases.
9. Sometimes I am a bit reckless about what I buy.

Moods
You had a class from XXX to YYY. Recall your moods at the time after you finished the class (i.e., RIGHT BEFORE you received the snack recommendation). In the following, there are 24 basic mood types. For each mood type, select yes or no to indicate if you experienced it at that time.

Affection, Lust, Longing, Joy, Zest, Contentment, Pride, Hope, Relief, Surprise, Irritability, Frustration, Rage, Disgust, Envy, Suffering, Sadness, Disappointment, Shame, Isolation, Pity, Panic, Anxiety, and Boredom.

Urge to Buy (1 = Strongly Disagree; 9 = Strongly Agree)
Recall what you felt RIGHT AFTER you saw the snack recommendation:
1. I felt an irresistible urge to purchase the recommended snack.
2. I experienced an uncontrollable drive to buy the recommended snack.
3. The desire to purchase the recommended snack was beyond my control.

Purchase Decision
Did you buy the recommended snack after receiving the personalized mobile services from us?
1. Yes
2. No

Appendix C

Construct Validation for Experiment 1

As a first item-culling step, we tested the model variables for univariate and multivariate threats to normality. None of the variables exceeds the < 3.0 threshold for acceptable skewness and the < 10.0 threshold for acceptable kurtosis (Kline 2010). Thus, we concluded that no variable exhibited significant departure from normality. As a second item-culling step, we performed a principal components factor analysis to check whether impulse-purchase tendency (IPT) and urge to buy met the two criteria: (1) items are loaded higher on their own construct than on another construct, and (2) item loading is at least .70 on their own construct. Table C1 confirms that all items passed the second item-culling step.

Table C1. Factor Analysis for Experiment 1

	IPT	Urge
IPT1	.952	.102
IPT2	.966	.101
IPT3	.953	.105
IPT4	.982	.095
IPT5	.969	.101
IPT6	.940	.103
IPT7	.910	.021
IPT8	.932	.057
IPT9	.760	-.076
Urge1	.046	.977
Urge2	.065	.959
Urge3	.084	.944

Note: IPT was captured in the registration survey, and urge to buy (Urge) was captured in the evening survey on the recommendation day.

We further examined the construct reliabilities, the convergent validities of measures associated with individual constructs, and the discriminant validities between constructs. First, we assessed the construct reliabilities. The reliabilities of IPT and urge to buy were .979 and .913. As all reliabilities were above the recommended threshold of .70, the first criterion was met. Second, we assessed the convergent validity, which involved two steps. In the first step, we confirmed that the average variance extracted (AVE) values for all constructs were higher than the recommended threshold of .5 (Table C2). In the second step, we checked all item loadings with their corresponding constructs and confirmed that all loadings were significant at the $p < .01$ level. Thus, the convergent validity was reasonably satisfactory. Third, we assessed the discriminant validity. We checked whether the square roots of the AVE values were greater than the off-diagonal correlations. Table C2 confirmed that the discriminant validity was reasonably satisfactory.

Table B2. AVE and Correlations

	IPT	Urge to Buy
IPT	**.877**	
Urge to Buy	.101	**.878**

Note: Diagonal entries (bold) are the square root of the AVE.

Appendix D

Practitioner Symposiums to Validate Research Relevance to Practice

We validated the relevance of our research findings to practice through open exchanges with senior executives of personalization solution providers and in the search engine marketing industry. Considering the importance of timeliness in research, we followed the guidelines by Stewart et al. (2007) to conduct symposiums for collecting group feedback from a number of practitioners, rather than interviewing individual practitioners. In the two practitioner symposiums, we presented our research project and sought feedback from senior executives, with a total of more than 50 participants. Among them, there were chief executive officers (CEOs) and directors of personalization teams of personalization solution providers and in the search engine marketing industry in Hong Kong and China. We told the participants that we wanted to seek their feedback to enhance the industry value of the extension of the current project. We also told them that we wanted to learn what they were doing and look for collaboration opportunities. We encouraged them to give us direct comments and new ideas. We started the symposium by outlining the design and the findings of the research project, followed by an open discussion between the research team and the participants. Each symposium lasted for about 90 minutes. Overall, the participants at the symposiums found our findings surprising yet interesting. Most importantly, they believed that our findings are important and implementable.

We follow the guidelines on applicability checks by Rosemann and Vessey (2008) to explore the relevance of this research project to practice. In the following, we present the insights shared by these senior executives under the three dimensions of the applicability checks: importance, accessibility, and applicability (Rosemann and Vessey 2008).

Importance

The importance of research to practice encompasses "whether the characteristics or process under consideration can be controlled within the organization, whether it focuses on a key management issue, whether it addresses a real-world problem, and whether it is timely" (Rosemann and Vessey, 2008, p. 3). In our study, the characteristics of interest are imperfect recommendations, context awareness (i.e., need-matching and location-matching), and the moderating role of mood, while the process of interest is unplanned purchase.

Both groups of participants in the symposiums considered context awareness personalization to be a timely, real-world problem. Also, they indicated that personalized recommendations were far from perfect. The CEO of a personalization solution provider described his personal experience with mobile recommendations: he occasionally received mobile messages suggesting he buy women's products while driving on a road near a shopping mall. In his opinion, the recommendation was irrelevant to his need and the (driving) situation restricted him from taking any purchase action. Both groups of participants advocated that, given the prosperity of ubiquitous commerce, location-matching was a core strategy of personalization for both mobile and web applications. The CEO of the personalization solution provider recognized the potential of applying context-aware personalization to unplanned purchase. However, neither group of participants explicitly commented on need-matching. In addition to the application of context awareness to online marketing, they raised the possibility of applying it in the transportation sector to give personalized safety alerts to drivers and the healthcare industry to shorten patients' waiting time in hospital by forwarding patients to the closest clinics with the required medical specialists.

Regarding mood, both groups of participants had not thought about the *moderating* role of moods in personalization. The personalization team from the search engine marketing industry considered mood personalization to be of timely importance, but they had not explicitly considered its application in unplanned purchase. In their research labs, they had recently implemented voice-based mood detection software modules, incorporating these into search engines to detect and enhance (if relevant) searchers' mood. In the future, they planned to launch services that recommend music matched to users' mood and that would send short messages to cheer up people in negative moods. However, so far, they focused on mood personalization per se but had not yet thought about integrating mood personalization with other personalization strategies.

The CEO of the personalization solution provider indicated that his development team had not thought about the role of mood in the personalization process. He was interested in our research findings and asked us to present the details of the experiment and data analysis. After listening to our findings, he commented that it was easy for merchants to manipulate consumers' moods and he believed that the quality of personalization could be significantly enhanced with the consideration of mood. In sum, both groups of participants found it surprising that moods play a pivotal role when considering tradeoffs in imperfect recommendations and that personalization to an individual's mood could be an important extension of the current personalization technologies.

Notably, in the two symposiums, our senior executive participants emphasized that the key to success for context-aware services was "users"—to think from a user's perspective and to focus on the users. We believe that this feedback is very valuable to personalization researchers.

Accessibility

Accessibility of research to practice encompasses "whether the research is understandable, readable, and focuses on results rather than the research process" (Rosemann and Vessey, 2008, p. 3). In the symposiums, we prepared a set of presentation slides that described our research objectives, what other researchers had done, our experiment design, data collection and analysis, and the key findings. Since practitioners are less likely to be interested in the theory, we did not mention mood congruence theory. However, we did briefly mention that our research idea was grounded on a well-tested cognitive processing phenomenon that people in positive moods are susceptible to recalling pleasant events, whereas those in negative moods are susceptible to recalling unpleasant events. The participants found that our presentation was easy to understand.

In both symposiums, the participants spontaneously asked for our statistical analyses. Based on their request, we then presented some detailed tables of descriptive statistics and charts. Also, we described and explained the interaction effect between mood and personalization tradeoffs. Although our verbal descriptions used terms such as *hypotheses* and *test of significance*, the participants had no difficulty understanding statistical details. After listening to our findings, both groups of participants even suggested that we perform more comparisons to further corroborate and strengthen our findings. We thus concluded that our findings are understandable and hence accessible to practitioners.

Applicability

Applicability of research to practice encompasses "whether the published article is complete, whether it provides guidance and/or direction, and whether it provides concrete recommendations" (Rosemann and Vessey, 2008, p. 3). After listening to our presentation, participants agreed that our findings clearly point to the important role of mood in making imperfect recommendations for unplanned purchase. They also recognized the need to treat positive and negative moods differently. They believed that our findings on partial versus complete descriptors as well as how to make tradeoffs under positive versus negative moods were clear and appropriate to be readily implemented to extend their product offerings. Some participants even suggested that, in addition to unplanned purchase, our findings could be applicable to recommendations on online dating and healthcare services.

In the symposiums, we spent much time discussing the consideration of mood in the personalization process. Participants from the personalization solution provider were initially skeptical about the feasibility of detecting users' moods; however, on explaining that several research labs (e.g., MIT Media Lab) are currently developing mood detection devices, these participants became excited about the applicability of the findings to their products. The participants from the search engine marketing industry, on the other hand, had no difficulty accepting the feasibility of detecting users' moods because they had recently developed a voice-recognition program that is able to detect users' moods based on voice pitch. They believed that our findings could be readily integrated into their existing product line.

In summary, the feedback that we received from the practitioners through the two symposiums was positive and encouraging. The participants were surprised yet excited about our findings. Most importantly, they could understand our findings and viewed them as important and implementable.

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