MIS Quarterly

RESEARCH ARTICLE

NUDGING MOODS TO INDUCE UNPLANNED PURCHASES IN IMPERFECT MOBILE PERSONALIZATION CONTEXTS[1]

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By tracking consumers' browsing and purchase history, web personalization generates taste-matched recommendations for each consumer to stimulate purchases. In addition to taste-matching, mobile personalization matches recommendations to a consumer's physiological need and current location. These two additional features, referred to as need-matching and location-matching, are believed to be enablers of unplanned purchases. However, mobile advertisers may not be able to generate recommendations that meet all personalization criteria. Hence, mobile recommendations may be imperfect. We examine two questions in relation to imperfect recommendations. First, how do we use a descriptor to promote such recommendations? Second, what personalization criterion should be downplayed to induce unplanned purchases? Drawing upon the theory of mood congruence, we theorize that the effect of imperfect recommendation on consumers' unplanned purchases depends on their mood. We conducted three field experiments to test our hypotheses. Our findings indicate that (1) consumers in positive moods are more likely to form an urge to buy than those in negative moods, and this difference is larger when the descriptor is partial than when it is complete (Experiment 1); (2) need-matching is more influential on urge to buy for consumers in negative moods than for those in positive moods (Experiment 2); and (3) for taste-and-need-matched recommendations, location-matching exerts a stronger effect on the urge to buy for consumers in negative moods than for those in positive moods (Experiment 3). We validated the relevance of our research findings to practice through interviews with senior executives in personalization solution providers. Pathways for enhancing practical impacts of this line of research are recommended.

Keywords: Mobile personalization, imperfect recommendations, mood, unplanned purchase, mood congruence

Introduction

By tracking consumers' browsing and purchase history, web personalization generates taste-matched recommendations to stimulate purchases (Tam and Ho 2005, 2006). In addition to taste-matching, mobile personalization can identify each consumer's physiological need (Lai et al. 2009), detect his or her location (Kenteris et al. 2009; Lee et al. 2009), and then use this information to generate recommendations. Physiological need (hereafter referred to as *need*) and location capture consumers' contexts. Context is any information that can be used to characterize the situation of a person that is considered relevant to the interaction between the person and an object (i.e., mobile recommendation, in our case) (Dey 2001; Hong et al. 2009). Need-matching and location-matching are context-awareness approaches that adapt responses from a

[1]Andrew Burton-Jones was the accepting senior editor for this paper. Heshan Sun served as the associate editor.

The appendices for this paper are located in the "Online Supplements" section of the *MIS Quarterly*'s website (http://www.misq.org).

technology—mobile personalization—to satisfy situational requirements in an optimal manner (Dey 2001). These two features are believed to be enablers of unplanned purchases. It is, however, less trivial to generate a recommendation that can simultaneously match a person's taste, need, and location.

Consider the following scenario. Imagine that it is Anna's first trip to Chicago. It is now noon, and Anna is searching for a place to have lunch. Having learned from her prior transactions, the mobile advertiser[2] knows that Anna likes Japanese food—whenever a Japanese restaurant recommendation was sent to her, she readily accepted it. Today, however, the closest Japanese restaurant is three kilometers away from where Anna is currently located. Even though the mobile advertiser knows that Anna needs food, it cannot provide a recommendation that simultaneously matches her taste and location; that is, any recommendation would be *imperfect*. In this case, should the mobile advertiser recommend the distant Japanese restaurant to Anna or should it recommend a nearby restaurant that Anna may not like? How should the mobile advertiser present this imperfect recommendation to Anna? Should it even consider giving up this business opportunity and not give any recommendation to avoid irritating Anna? In response to the unanswered questions faced by mobile advertisers (as illustrated in the above scenario), the overarching objective of our research is to examine how to prepare and present imperfect recommendations to stimulate consumers' unplanned purchases.

The effectiveness of imperfect recommendations hinges on how consumers differentially weigh the strengths and weaknesses of imperfect recommendations in information processing. Prior research has revealed that *prepurchase mood* (hereafter referred to as *mood*) directs consumers' information processing to various product attributes, consequently changing their decision-making (Meloy 2000; Shen and Ball 2011). Hence, we anticipate that when consumers are presented with imperfect recommendations with different tradeoffs regarding personalization criteria, mood plays a pivotal role in differentiating the effectiveness of these imperfect recommendations in inducing unplanned purchases.

The first objective of our research is to examine the interplay between mood and the selection of a personalization criterion to downplay in order to enhance the likelihood of accepting an imperfect recommendation. Prior research on mobile personalization has examined how each of the *individual* personalization criteria (taste-matching, need-matching, and location-matching) influences consumer behavior on *planned purchases* (e.g., Lai et al. 2009; Li and Du 2012; Zheng et al. 2011). However, to our knowledge, no research has examined the combined effects of these personalization criteria, particularly in cases where the mobile advertiser cannot simultaneously meet all personalization criteria (taste, need, and location), and subsequently tradeoffs have to be made. Further, as noted, prior personalization research has focused on *planned purchases*; it remains unclear whether the findings on planned purchases can be generalized to unplanned purchases. Our research attempts to address these voids in the literature by explicitly investigating which personalization criterion mobile advertisers should downplay in the unplanned purchase contexts.

The second objective is to examine how the interplay between mood and ways to present imperfect recommendations influences unplanned purchases. Intuitively, the pleasant features of a recommendation should always be highlighted to attract consumers, but how should mobile advertisers inform consumers about the *unfulfilled* personalization criteria? One possible way is to (honestly) tell consumers about the imperfection of the recommendation; another way is to hide it. We refer to the former presentation approach as *a complete descriptor* and the latter as *a partial descriptor*. We compare how consumers in different moods react to the two types of descriptors when making unplanned purchase decisions.

Drawing on mood congruence theory, we develop three sets of hypotheses to examine the impacts of interplay between mood and the criterion to downplay and the interplay between mood and tradeoff descriptors on consumers' unplanned purchases based on imperfect recommendations. We test our hypotheses using three field experiments.

Our research has both theoretical and practical significance. Theoretically, we enrich our understanding of the effects of mobile personalization on unplanned purchases. Since unplanned purchasing is a fundamental aspect of consumer behavior, particularly in the mobile commerce context, adding different facets of consumer behavior to prior research that focuses largely on planned purchase is significant for e-commerce research. Moreover, prior research has been confined to examining the individual effects of each personalization strategy on consumer behavior—our research extends the focus to the combined effect of multiple personalization criteria when they must be traded off against each other.

Given that as much as 60 percent of sales are unplanned (LaCour 2013), by illuminating the effectiveness of context-aware personalization to induce unplanned purchases, we urge mobile advertisers, as well as merchants who are considering an investment in context-aware personalization, to more thoroughly assess not only potential benefits but also possible

[2] In this paper, we refer to parties who are involved in mobile personalization as "mobile advertisers." These parties include merchants, mobile operators, advertisers, and product promoters.

drawbacks. Our empirical evidence on whether and how mood influences unplanned purchases can inform technology designers about the potential value of mood detection and analysis technologies. Overall, we aim to make personalization research more ecologically valid and useful for practitioners.

Background

Types of Unplanned Purchases

An unplanned purchase is a sudden and spontaneous purchase with no pre-shopping intention to buy a specific product category or a specific product (Beatty and Ferrell 1998). The literature often uses unplanned purchase synonymously with impulse purchase. Indeed, most earlier literature simply equated the two terms—both unplanned purchase and impulse purchase referred to a buying action undertaken without a need having been previously recognized or a buying intention formed prior to entering the store (e.g., Clover 1950; Engel et al. 1978; West 1951). In the 1980s, research efforts began to differentiate the two terms, proposing that while impulse purchases are unplanned, not all unplanned purchases are made on impulse (Iyer 1989; Piron 1993). In our research, we prefer to use the term *unplanned purchase* to better reflect the types of purchase decisions that we intend to investigate in our context, because mobile personalization may offer a recommendation matched to an individual's prior transactions, and hence the purchases may not be made purely on impulse.

Parboteeah et al. (2009) have identified four types of unplanned purchase. The first type—*a pure unplanned purchase*—occurs with the least planning of the four. It is a purchase that does not fit with a person's regular buying pattern and is one that the person has never before considered. The second type of unplanned purchase is *a suggestive unplanned purchase*, which occurs when a person sees a product or its advertisement, and this creates a desire for the product. A *reminder unplanned purchase* occurs when a person is reminded of the need for a product once the product is presented. Finally, a *planned unplanned purchase* happens when a person does not plan exactly what will be purchased, but actively seeks out and takes advantage of promotions.

The extent of the unplanned nature of the four types of unplanned purchase does not affect our theoretical development; however, the practical challenge of triggering an unplanned purchase increases with the extent of its unplanned nature. Our research context is mobile personalization, in which a mobile advertiser gives product recommendations based on a consumer's prior purchase history (his or her taste), taking into consideration the consumer's current need and location. Therefore, our research context involves both *suggestive unplanned purchases* and *reminder unplanned purchases*.

The following two sections elaborate on unplanned purchases. The first presents the role of context awareness in unplanned purchases. The second describes the two pathways in which characteristics of imperfect recommendations influence unplanned purchases.

Context Awareness

Context awareness discovers a person's context, and uses this to personalize the recommendation. Knowing consumers' *spontaneous* preference (henceforth referred to as *preference*) is a core principle of personalization. A preference is a behavioral tendency that exhibits itself not so much in what the person thinks about the object, but how he or she acts toward it—whether he or she approaches it, takes it, and ultimately buys it (Slovic et al. 2007; Zajonc 1980; Zajonc and Markus 1982). People often do not have well-defined preexisting preferences; rather, these preferences are revealed only when they are selecting among available products. People construct their preferences on the spot when the external environment prompts them to decide (Slovic 1995; Slovic et al. 2007). The notion of a constructed preference implies that an unplanned purchase is highly contingent on the construction process, which itself is susceptible to the influence of external stimuli. As Bettman et al. (1998) noted, "One important property of this viewpoint is that preferences will often be highly context dependent" (p. 188). It follows then that *context awareness* (e.g., need identification and location detection, in our research) is a basic premise of any personalization strategy to trigger an unplanned purchase.

In the following subsections, we will discuss two context-awareness strategies—need-matching and location-matching—together with taste-matching. Since personalization researchers often use "taste" and "need" together, we first discuss the two terms and the related personalization strategies. Following that, we discuss location and location-matching. Appendix A provides a review of IS journal articles published from 2006 to 2016 that consider or examine at least one of the three personalization strategies.

Taste-Matching and Need-Matching

The concept of *taste* is a cornerstone of personalization research. It is often used conjunctively with "preferences" (e.g., Ho et al. 2011; Johar et al. 2014). Unlike a preference, which is a behavioral tendency, taste captures a general inclination. It reflects an individual's personal and cultural patterns of likes or dislikes. Taste is self-evident and beyond dispute (Scherer 2005). Thus, an individual's judgments of taste involve low cognitive processes (Gronow 1997; Kant 2009). In a study of food consumption, Gronow (1997) remarked that "we do not usually make mistakes in our judgments of the taste of food and drink, [and] we are equally unerring in our judgments of taste in general" (p. 9).

In the personalization literature, taste is regarded as an individual's subjective assessment of a product (Benlian et al. 2012) or perceived quality of an experience for goods depending more on subjective attributes (Benlian et al. 2012). Individual taste "can be very specific" (Ghoshal et al. 2015, p. 205). Taste-matching aims to offer a product to meet an individual's aesthetic taste (Benlian 2015). Since taste is a subjective assessment, in taste-matching, there is no single set of objective criteria that captures all aspects of an individual's taste and ranks individual products in a given product category (Adomavicius et al. 2013). Collaborative filtering and data mining of customer transactions are typical methods to understand and model an individual's taste. Prior research has often chosen hedonic products to study taste-matching, for instance, music in Benlian (2015), Ghoshal et al. (2015) and Oestreicher-Singer and Zalmanson (2013), movies and DVDs in Ghoshal et al. (2015) and Zhang et al. (2011), and TV shows and jokes in Adomavicius et al. (2013).

Need, on the other hand, is a personal circumstance in which something is required rather than just desirable. It is synonymous with *requirement*. Compared with taste, need is a more complex construct because an individual possesses many kinds of need. Prior research on personalization has examined task need (Adomavicius et al. 2011; Kohler et al. 2011; Qiu and Benbasat 2009; Wang and Benbasat 2007, 2009), emotional need (Benlian et al. 2012; Qiu and Benbasat 2009), motivational need (Benlian et al. 2012), information need (Benlian et al. 2012), and physiological and psychological needs (Kohler et al. 2011).[3]

In the personalization literature, need-matching makes a recommendation to fulfill an individual's specific requirements (Adomavicius et al. 2011; Kohler et al. 2011; Parboteeah et al. 2009; Qiu and Benbasat 2009; Wang and Benbasat 2007, 2009). Some researchers have studied need-matching at the product-attribute level; that is, to suggest methods for identifying all attributes of a product important to fulfill an individual's specific requirements (Komiak and Benbasat 2006), and capture the relative weights among these attributes (Xu et al. 2014). Prior studies related to need-matching have selected high-involvement or utilitarian products to be the study context; for instance, apartment searching (Hess et al. 2009), air tickets for a specific travel itinerary (Adomavicius et al. 2011; Kohler et al. 2011), laptops for friends (Al-Natour et al. 2011), and digital cameras with specific functions (Komiak and Benbasat 2006; Wang and Benbasat 2007, 2009). Among various need types, our research focuses on physiological needs. Given that breakthrough technology is able to detect people's physiological conditions (e.g., heart rate and body temperature) (Banos et al. 2014), we foresee that more mobile applications will be developed to detect or predict people's physiological needs.

Location-Matching

Definitions of location-matching used in prior research on personalization are unambiguous: location-matching offers a product recommendation that is available in close proximity to consumers' current geographical place or position (Wattal et al. 2009; Xu et al. 2012; Zou and Huang 2015). Prior research reveals that consumers are more likely to accept location-matched recommendations than unmatched recommendations (Constantiou et al. 2014; Ho 2012). Today's global positioning system (GPS) receivers give highly accurate estimations of a mobile user's location. For example, Garmin® GPS receivers are accurate to within 15 meters on average. Newer Garmin® GPS receivers with wide area augmentation system capability can improve accuracy to less than three meters on average. Despite the availability of GPS, in practice, mobile advertisers may not be able to offer recommendations in close proximity to consumers' current locations because products that match their taste and need may not be available nearby.

Full or Partial Mediation by Urge to Buy

Figure 1 depicts our unplanned purchase model, simplified from Beatty and Ferrell (1998). The three personalization strategies described in the previous section are stimuli that trigger unplanned purchase. As illustrated in Figure 1, urge to buy may fully or partially mediate the effects of a stimulus on a consumer's unplanned purchase action. The indirect effect occurs when a stimulus increases consumers' positive affect or reduces their negative affect. In Beatty and Ferrell, *shopping enjoyment* enhances a consumer's positive affect, and so triggers the urge to buy. The direct effect occurs when the stimulus is related to situational factors that enable or inhibit the act of unplanned purchase. *Money availability* is an example.

[3]In the description of taste-matching, researchers identified hedonic need (Benlian 2015; Kohler et al. 2011), which is a need for pleasingness and interestingness.

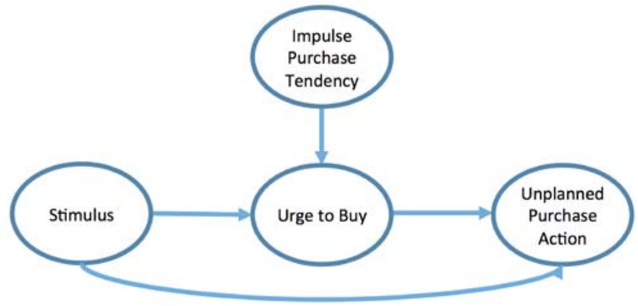

Figure 1. Unplanned Purchase Model

We predict that tradeoff descriptors influence unplanned purchase action through a full mediation by urge to buy. Among the three personalization strategies, location-matching is predicted to influence unplanned purchase action through a partial mediation by urge to buy, whereas the other two are predicted to go through a full mediation by urge to buy. These concepts are explained in detail in the following paragraphs.

Tradeoff descriptors divert consumers' information processing, encouraging them to think more about either those recommendation features that are matched to their taste and context, or those features that are unmatched. The matched features may excite them, whereas the unmatched features may frustrate them (Tam and Ho 2005). This may result in either positive affect (for the former case), leading to an increase in urge to buy, or negative affect (for the latter case), leading to a decrease in urge to buy. Since descriptors are textual or graphical information and do not enable or inhibit a consumer's behavior, they are predicted not to exert any direct effect on unplanned purchase action.

Next, we discuss any possible *direct* effect on unplanned purchases by each of the three personalization strategies. We argue for a direct effect of location-matching on unplanned purchases, because when a recommended product is in proximity to a consumer's location, the consumer will not be constrained by his or her time availability or inaccessibility of transportation method to reach the recommendation, enabling the unplanned purchase. Conversely, taste-matching and need-matching do not influence any situational factors that enable or inhibit consumers in reaching the recommendation or enhance their ability to afford the purchase of the recommendation. Hence, we do not expect these two personalization strategies to exert a direct effect on the unplanned purchase action.

Finally, we discuss any possible *indirect* effect on unplanned purchases by each of the three personalization strategies. Prior research has shown that people are more likely to select a taste-matched recommendation than select a random product because it arouses a feeling of pleasure and excitement (Tam and Ho 2005, 2006). This feeling of pleasure and excitement is a kind of positive affect, which elicits the urge to buy. Similarly, when consumers have an unfulfilled need, they become frustrated or even annoyed (Kohler et al. 2011). Need-matched recommendations address their current need, relieving frustration or annoyance, and this reduces their negative affect and enhances their urge to buy. The extent of location-matching affects the effort required to buy the recommended product. If the recommendation is not available in close proximity, people feel frustrated as they are asked to travel to buy the recommended product (Ho 2012), resulting in negative affect. Overall, the three strategies either increase positive affect or reduce negative affect; therefore, all three are expected to enhance the urge to buy, which in turn leads to unplanned purchase.

Hypotheses Development

Theory of Mood Congruence

The theory of mood congruence is grounded in the premise that people tend to recall events from their memory that are consistent with their current mood (Schwarz and Clore 2003; Wells et al. 2011). People in positive moods are susceptible to recalling pleasant events, whereas those in negative moods are susceptible to recalling unpleasant events. Since people associate the recalled events in processing, their judgment is biased by their current mood. This phenomenon is referred to as *mood-as-information* (Schwarz and Clore 2003). Mood congruence has been found to hold even when factors that cause the specific mood are unrelated to the object under assessment (i.e., the recommendation, in our case) (Hsee and Weber 1997). Because of mood congruence, people in positive moods often make an optimistic judgment, whereas those in negative moods often make a pessimistic judgment.

The associative network theory provides an explanation as to the cause of mood congruence (Bower 1981). The theory models human memory as a network—past events and mood at the time that the event occurred are stored in memory nodes that are linked to other related events or concepts. Mood operates at the automatic level and influences the accessibility of different concepts in memory by biasing memory retrieval, perceptions, judgments, and evaluations. A positive mood turns on other memory nodes of mood in a similar valence as a consequence of recognition rules, and spreads activation to nodes associated with them (Clark and Teasdale 1985). Therefore, people in positive moods associate the stimulus with their pleasant experiences in the past and assess it optimistically. Similarly, people in negative moods associate the recalled unpleasant experiences with the stimulus and assess it pessimistically.

How do people form an urge to buy? Unplanned purchase is a type of decision-making under uncertainty. Without careful deliberation and prior intention, consumers may be uncertain if their preferences at the point of unplanned purchase are inconsistent with their later preferences (Miao 2011). This uncertainty is salient particularly when recommendations are imperfect. Prospect theory reveals that, when making an uncertain decision, people assess two estimations: (1) the perceived value of an outcome and (2) the likelihood that the outcome will occur (Kahneman 2003; Kahneman and Tversky 1979). In unplanned purchases, when receiving a recommendation, consumers estimate the perceived value of the recommendation and the likelihood that a positive outcome will result from its purchase. The perceived value of the recommendation depends on its relevance to consumers' tastes and context. The estimation of the likelihood is based on prior events, such as experience with products similar to the recommendation, and experience with the mobile advertiser's previous recommendations. The multiplication outcome of the two estimations is then compared with a threshold, which varies with individual consumer characteristics (such as impulse-purchase tendency) and situational factors (such as money availability). The greater the positive difference between the multiplication outcome and this threshold, the more likely that a recommendation will trigger an urge to buy.

We continue the earlier example about a restaurant recommendation made for Anna on her first trip to Chicago. A Japanese restaurant (matched to her taste) that is three kilometers away from her current location (not matched to her location) is suggested to Anna prior to the lunch break (matched to her need). Anna is uncertain that the effort of traveling three kilometres for a Japanese restaurant is justifiable. She estimates the likelihood of having a good lunch in the recommended restaurant based on her experience with similar restaurants and her experience with the recommended restaurants from the same mobile advertiser. She also estimates the perceived value of the recommendation—she likes Japanese food and she is hungry, but the restaurant is a bit far away.

How does mood influence the above estimations? Mood congruence predicts that consumers in positive (negative) moods will be more optimistic (pessimistic) about the likelihood that a positive outcome will result from the purchase of a recommendation. Further, given the same "imperfection" of a recommendation, because of the mood congruence effect, consumers in positive moods are more likely to assign a higher perceived value to the imperfect recommendation than those in negative moods. This explains the direct effect of mood on the urge to buy that has been observed empirically in prior research (e.g., Silvera et al. 2008). Our research is interested in how mood *moderates* the effects of tradeoff-related variables on the urge to buy.

Tradeoff Descriptors for Imperfect Recommendations

Product descriptors present the features of a product to attract consumers. However, when a recommendation is imperfect, mobile advertisers can choose to use a *complete* descriptor that presents both the matched (pleasant) features and unmatched (unpleasant) features of the recommendation, or a *partial* descriptor that hides the unmatched features.

Our research focuses on the interaction between consumer mood and descriptor type on urge to buy. To elaborate, a partial descriptor omits information about unpleasant features; for instance, if a recommendation is far away from a consumer's current location, a partial descriptor will not mention any information on the travel distance. When consumers face omitted information, they are likely to make an inference about the missing attribute to make choice decisions (Edward et al. 2011). These inferences occur spontaneously (Gunasti and Ross 2009). Prior research reveals that mood is an important cue in triggering spontaneous inferences (Fehr-Duda et al. 2011). When receiving a recommendation with a partial descriptor, because of mood congruence, consumers' mood affects their inference about the omitted information. Consumers in positive moods perceive the omitted information as positive and have a higher perceived value of the purchase outcome, whereas those in negative moods perceive the omitted information as negative and have a lower perceived value of the purchase outcome. Hence, the influence of mood is strong when a partial descriptor is given. In contrast, a complete descriptor provides consumers with all information about pros and cons of a recommendation. They can readily rely on the information made available by the recommendation, rather than the information retrieved from their memory (which is subject to the valence of the consumer's mood), to make their inference. Hence, the influence of mood is weak.

H1: *There is an interaction between mood and descriptor type on urge to buy, such that the effect of mood is stronger when the descriptor is partial than when the descriptor is complete.*

Tradeoffs Between Taste-Matching and Need-Matching

Taste-matching is seen as superior with respect to hedonic dimensions and need-matching is seen as superior with respect to utilitarian dimensions. Hedonic dimensions are characterized by affective and experiential pleasure, while utilitarian dimensions are primarily instrumental and functional (Dhar and Wertenbroch 2000). Hedonic dimensions are easily imaginable, sensory- and imagery-evoking (Hassenzahl 2001), and salient (Shiv and Huber 2000). By contrast, to assess utilitarian dimensions, people have to undergo deliberate higher-order processes in reasoning to understand what their needs are, how to fulfill their needs, and whether the product can fulfill their needs (Miao 2011). Since the processing of hedonic dimensions occurs in a relatively automatic manner (Johar 2006), they are processed before their utilitarian counterparts. Despite the fact that hedonic dimensions are processed first, utilitarian dimensions are more influential in determining consumer preferences in situations that foster justification (Böhm and Pfister 1996), such as negative moods.

As explained previously, according to the theory of mood congruence, consumers in negative moods recall more unpleasant events from their memories and are more pessimistic. This guides them to make a more cautious or calculative decision. They search for reasons to justify their choices (Shafir et al. 1993) and engage in normative evaluations of the purchase (Miao 2011). Since utilitarian dimensions provide justifiable arguments for decision-making (Dhar and Wertenbroch 2000) and often dampen cognitive conflict and potential regret (Miao 2011), consumers in negative moods weight utilitarian dimensions more highly than hedonic dimensions in unplanned purchase. Consequently, for consumers in negative moods, utilitarian dimensions exert a stronger effect on urge to buy than do their hedonic counterparts.

In contrast, consumers in positive moods are optimistic. They are not as cautious and calculative as their counterparts in negative moods. In unplanned purchase, they require fewer reasons than those in negative moods, and as a result, they stop processing at an early stage, and some may in fact only process hedonic product dimensions (Johar 2006; Shiv and Huber 2000). The implication is that the relative influence of need-matching vis-à-vis taste-matching on urge to buy is weaker for consumers in positive moods than for those in negative moods.

H2: *The relative importance of need-matching vis-à-vis taste-matching on urge to buy is stronger for consumers in negative moods than for consumers in positive moods.*

Tradeoffs Between Taste-and-Need-Matching and Location-Matching

When a recommendation only matches consumers' location but not their taste and need, this recommendation has no effect on urge to buy. As explained, close proximity to the recommended product does not produce positive affect; it only avoids frustrating consumers when asking them to travel a long distance to buy the recommendation (Ho 2012). Close proximity to a recommendation that is unwanted and unnecessary cannot arouse an urge to buy. This prediction is evident in our daily experience: we walk in a shopping mall and see many random products, but they do not trigger an urge to buy. Therefore, regardless of consumer mood, a recommendation that matches *only* location but *not* taste or need cannot trigger an urge to buy.

H3a: *When a recommendation does not match a consumer's taste or need, location-matching has no effect on the urge to buy.*

Conversely, when a recommendation matches consumers' taste and need, the extent of location-matching interacts with consumer mood to influence urge to buy. Because of mood congruence, consumers in positive moods are optimistic (Schwarz and Clore 2003; Wells et al. 2011) and may be willing to take a risk. Hence, consumers in positive moods are likely to pay less attention to the shortcoming that they are required to travel further to buy the recommended item. By contrast, mood congruence predicts that consumers in negative moods are pessimistic (Schwarz and Clore 2003; Wells et al. 2011) and unwilling to take a risk. Thus, they are less likely to form an urge to buy a location-unmatched recommendation.

H3b: *When a recommendation matches a consumer's taste or need, there is an interaction between location-matching and consumer mood, such that the effect of location-matching is stronger on consumers in negative moods than on those in positive moods.*

Common Setup of the Three Experiments

A Preexperiment Survey to Prepare for the Main Experiments

Our main experiments are based on snack recommendations. Before conducting the main experiments, we conducted a preexperiment survey to understand students' taste and need for snacks. We recruited 131 students (47 males and 84 females) from a public university. We collected information about their favorite snack categories, flavors, and brands. In the main experiments, we used this information to generate taste-matched recommendations. In addition, we asked the preexperiment subjects about the circumstances in which they needed a snack. They indicated that they sometimes needed a snack in the late afternoon break but rarely in the morning break. Furthermore, they preferred fresh juices, smoothies, and bottled juices in summer, and chewy bars and hot beverages in winter. Hence, when preparing need-matched recommendations, we took the time and temperature of the day into consideration. We purposely conducted the main experiments in both semesters of a year to take advantage of the wide temperature range of the city[4] in which we conducted the study. This helped us easily offer a snack to meet people's psychological needs under different temperature conditions. Table 1 gives an overview of the field experiments.

Procedures of the Main Experiments

In the main experiments, we recruited students from the same public university. To minimize the testing effect, the subjects in the main experiments had not participated in the pre-experiment survey. Each subject would receive USD$15 for his or her participation. During the registration, students completed a short questionnaire on their demographics, snack tastes, and impulse-purchase tendencies. They were informed that a merchant planned to launch a personalized mobile service in the near future, and that they would be requested shortly to take part in the service test and then give feedback on this new service. We also asked subjects to upload their class timetables to identify a free time for the service test. If subjects agreed to evaluate this new service, they would continue with the field experiment. After the briefing, none of the subjects dropped out of the study.

[4]In the fall semester, the average temperature in the afternoons was 43° F (6° C); in the spring semester, the average temperature in the afternoons was 90° F (32° C).

On the day of the field experiment, our system sent messages to the subjects' mobile phones. The first message was sent five minutes after they started their class break. It contained one question: "How positive or negative is your mood right now? (1 = very negative; 9 = very positive)" After five minutes, the second message was sent, recommending a snack. It showed a picture of a recommended snack and asked subjects a question: "How strong (or weak) is your urge to buy this recommendation? (1 = weak; 9 = strong)" (Figure 2). In the evening of the experiment day, the subjects received an auto-email and were asked to complete a web survey in which they reported their mood and urge to buy at the time they received the recommendation. It also asked if they had actually purchased the snack.

We conducted three pilot studies, each with 20 subjects, to check if our personalization system functioned properly. The subjects completed an open-ended questionnaire to report any system malfunctions and offer suggestions to improve the flow of the main experiments. Overall, the pilot subjects reported that they received all the mobile messages at the correct time. The process of receiving and viewing mobile recommendations was error-free. The main experiments followed the same procedures as those of the pilot studies.

Manipulation

Tradeoff Descriptors

We included two types of tradeoff descriptors: complete and partial. The complete descriptor presented the full information of the recommendation, including both pleasant and unpleasant features. An example of such a descriptor to a subject who did not like hot drink was: "Even though you don't like hot tea, isn't it good to have one on such a freezing day? Get it at the nearby Gods Cafe." The partial descriptor only presented the pleasant features of the recommendation, for example, "How about drinking hot tea on such a freezing day? Get it at the nearby Gods Cafe." We controlled for the description length (constraining it to between 15 and 25 words).

The Three Personalization Strategies

Our research examines three personalization strategies: taste-matching, need-matching, and location-matching. In the following, we describe the manipulation of each of the personalization strategies. Appendix B shows the survey instruments we used in the manipulation checks. The results of manipulation checks will be presented in the data analysis section of the corresponding studies.

Table 1. An Overview of the Three Experiments

Focus	Manipulation	Controlled For
Experiment 1: Types of tradeoff descriptors	We manipulated the type of tradeoff descriptor accompanying the recommendation. The descriptor was either complete or partial.	• We controlled for the extent of location-matching. All subjects received location-matched recommendations. • The length of descriptors was controlled to lie between 15 and 25 words.
Experiment 2: Tradeoff between taste-matching and need-matching	We manipulated taste-matching and need-matching, such that the recommendation matched a subject's taste but mismatched his or her need, or it mismatched a subject's taste but matched his or her need.	• The extent of taste-matching and need-matching were sent in *opposite* directions. • We controlled for the extent of location-matching. All subjects received location-matched recommendations. • Complete descriptors were used.[a]
Experiment 3: Tradeoff between location-matching and other criteria	We manipulated the relation between location-matching and the other two personalization criteria.	• The extent of taste-matching and need-matching were sent in the *same* direction. • Complete descriptors were used.

[a]In Experiments 2 and 3, we chose to use a complete descriptor, because the findings of Experiment 1 indicated that partial descriptors led to a stronger urge to buy than complete descriptors. Therefore, a complete descriptor would serve as a more conservative test of our hypotheses. That is, if the hypothesized relationships were found to be statistically significant with a complete descriptor, the results would be even more salient if a partial descriptor were used.

Figure 2. A Sample of Recommendations Generated by Our System

We based the manipulated taste-matching on subjects' indicated snack categories, and combined the information about snack flavors and preferred brands from the preexperiment survey to generate taste-matched recommendations. Taste-matched recommendations came from the subject's favorite snack categories, flavors, and brands, whereas taste-unmatched recommendations were randomly selected from the snack list.

To manipulate need-matching, we considered the temperature of the experiment day, the time at which the recommendation was sent, and the number of consecutive classes the subject had taken on the experiment day. These contextual variables informed us about the subjects' physiological need. Subjects who received need-matched recommendations would have snacks matched to their physiological need, thus capturing their degree of hunger and thirst. Conversely, need-unmatched recommendations were not aimed at easing subjects' physiological need, or were sent at a time when subjects did not need snacks.

To manipulate location-matching, we collected location information of vending machines and stores on campus. For high location-matching conditions, the recommended snack was available from vending machines or stores within 50 meters from the subjects' locations. For low location-matching conditions, the recommended snack was only available in a supermarket 400 meters away from the campus.

Mood

We did not manipulate subjects' mood; rather, we let subjects' mood emerge naturally. Before we sent the subjects a recommendation, we asked them to report their current mood. To increase the variance of mood, we ran the experiment in two rounds. The first round of the experiment was conducted in the first week of the semester, and the second round in the middle of the semester. Our rationale was that at the beginning of the semester most students would be relaxed and energetic, and thus be likely to have a relatively positive mood. By mid-semester, because of assignment deadlines and quizzes, many of them would be stressed and tired. Their stress and fatigue would likely induce a relatively negative mood. We asked the subjects to report their mood in two ways: (1) via mobile message (right before receiving the recommendation) and (2) via a web survey (in the evening of the experiment day).

Dependent and Control Variables

Our experiment included two dependent variables: (1) urge to buy and (2) unplanned purchase action. For urge to buy, we collected a numeric response from each subject after they received the recommendations. Subjects' responses via mobile devices were instantaneous, but the instruments were single-item because of the limited input capability of mobile phones. Thus, on the evening of the experiment day, we asked the subjects in a web survey to recall their urge to buy and report it via a multi-item instrument adapted from Cole and Sherrell (1995). We used a yes/no question to capture subjects' unplanned purchase action. Additionally, if students collected a receipt of purchase or took a photo of the purchased snack, they could collect \$1 from us. The receipt or the photo of the purchased snack provided evidence of their actual behavior.

Nine control variables were included in our data analysis. There were six control variables for urge to buy: (1) impulse-purchase tendency, (2) current temperature of the city, and physiological conditions that captured (3) how hungry and (4) how thirsty a subject was, (5) perception of how unhealthy a snack was, and (6) health awareness. The items for impulse-purchase tendency were adapted from Beatty and Ferrell (1998). As our recommendations were snacks, and some students might have health concerns regarding snack food, we controlled for subjects' perceived (un)healthiness of snack food and their health awareness.

In addition, we included three control variables for the unplanned purchase action: (1) a subject's time availability to buy the recommended snack, (2) money availability, and (3) mobile phone usage. The first two control variables followed Beatty and Ferrell's study. We included mobile phone usage as it influenced users' reactions to mobile ads. When delivering novel products or services, heavy users are often promotion targets (Ho 2012).

Experiment 1: Tradeoff Descriptors

Experiment Design and Checks

Experiment 1 examined the effectiveness of the two types of descriptors (complete versus partial) in promoting imperfect recommendations in unplanned purchase. We adopted a two (descriptor: complete versus partial) by two (tradeoff type: taste-matched-but-need-unmatched versus need-matched-but-taste-unmatched) design. We controlled for location-matching, such that all subjects received location-matched recommendations. This resulted in four treatment groups. See the previous section on experiment setups for the details of manipulation.

We checked the manipulation of taste-matching using three questions on a nine-point Likert scale. The subjects who received a taste-matched recommendation (6.81) gave a higher score on taste-matching than those who received an unmatched recommendation (3.96). The difference in the two means was significant ($p < .01$). We checked the manipulation of need-matching via another four questions using a nine-point Likert scale. The subjects who received a need-matched recommendation (7.33) perceived that it matched their need more closely than those who received an unmatched recommendation (2.72). The difference in the two means was significant ($p < .01$). Our manipulations were deemed to be successful. Appendix C presents the results of construct validation. All constructs show good psychometric properties.

Table 2. Descriptive Statistics for Experiment 1 (N = 472)

	Mood	Dependent Variables	Need-Matched and Taste-Unmatched (N = 257)	Taste-Matched and Need-Unmatched (N = 215)	Both Groups
Complete Descriptor	Positive Mood[a] (N = 137)	Sample Size (N)	70	67	137
		Urge to Buy[b, c]	4.70 (2.22) [Mobile]	3.12 (1.64) [Mobile]	3.92 (2.11) [Mobile]
			2.23 (.84) [Web]	5.04 (1.55) [Web]	3.61 (1.87) [Web]
		Buy or Not?	16%	34%	25%
	Negative Mood (N = 109)	Sample Size (N)	60	49	109
		Urge to Buy	2.00 (.84) [Mobile]	2.82 (1.04) [Mobile]	2.37 (1.02) [Mobile]
			1.88 (.78) [Web]	3.27 (1.51) [Web]	2.50 (1.35) [Web]
		Buy or Not?	5%	8%	6%
Partial Descriptor	Positive Mood (N = 135)	Sample Size (N)	75	60	135
		Urge to Buy	5.62 (2.60) [Mobile]	5.83 (1.59) [Mobile]	5.71 (2.20) [Mobile]
			4.11 (1.01) [Web]	5.39 (1.73) [Web]	4.68 (1.51) [Web]
		Buy or Not?	24%	22%	23%
	Negative Mood (N = 91)	Sample Size (N)	52	39	91
		Urge to Buy	3.19 (2.55) [Mobile]	3.49 (1.13) [Mobile]	3.32 (2.06) [Mobile]
			2.61 (1.01) [Web]	3.46 (1.63) [Web]	2.97 (1.37) [Web]
		Buy or Not?	2%	10%	5%

[a] To construct Table 2, we split the sample into two groups, based on whether they were in positive moods or negative moods. In the path model, we treated moods as a continuous variable. We did the same for Table 3 and Table 4.
[b]Mean (s.d.).
[b][Mobile] for data collected via mobile messages; [Web] for the web survey data.

Subjects

In all, 573 students registered for Experiment 1, of which 543 completed it. On the experiment day, 27 were not on campus, so we discarded these data points. As a result, we had 516 usable data points (299 females and 217 males).

Data Analysis

Table 2 presents the descriptive statistics. The two variables—mood and urge to buy—were captured via both mobile messages and the web survey. About 8% (41 out of 545) of the subjects did not reply to the two mobile messages, but all of them completed the web survey. We used 504 (545 – 41) data points to conduct two correlation tests to compare the mobile and web responses—one correlation test for mood and the other for urge to buy. The correlation for mood was .51 ($p < .01$) and the correlation for urge to buy was .31 ($p < .01$). Since H1 focused on subjects in either positive or negative moods, we discarded 73 subjects who consistently reported having neutral moods in both their mobile and web responses. Thus, the data analysis focused on 472 (545 – 73) subjects (276 females and 196 males).

To gain an overview of the interaction effect between descriptors and a subject's mood on his or her urge to buy, we used Mplus 6.0 to run a path analysis.[5] Our initial analysis included a three-way interaction effect of descriptor type, personalization criterion (i.e., taste-matching versus need-matching), and subjects' mood. The three-way interaction effect was found to be nonsignificant on urge to buy ($b = -.016$, $t = -.23$, $p > .1$). Hence, we removed it and re-ran the path analysis. Figure 3 shows the results of the model without the three-way interaction.

Confirmatory factor analysis (CFA) tests how well the proposed factor structure fits the data. Fit is evaluated using the RMSEA, CFI, TLI and WRMR,[6] as in Kline (2010). The fit

[5] In all three experiments, we performed two sets of analyses, one using the data collected from the mobile messages and the other using the web-survey data. The two sets of results are remarkably similar, and thus, the rest of the paper reports the set of results based on the data collected from the web survey. For those subjects who did not reply to the web survey, we used their mobile message responses to replace their missing data.

[6]WRMR was proposed by Muthén and Muthén (2010). It is suitable for models with categorical outcomes.

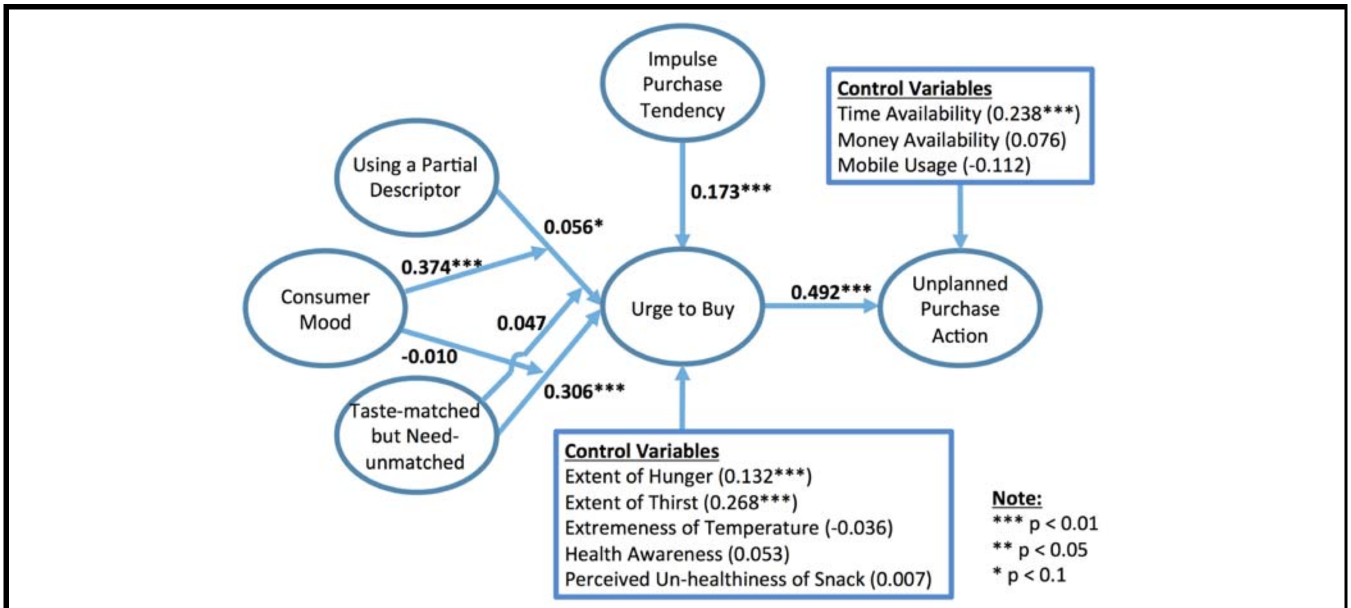

Figure 3. Experiment 1 Results

indices of the proposed factor structure were as follows: CFI = .97, TLI = .94, WRMR = .75, and RMSEA = .02. The CFI (greater than the cutoff of .9), TLI (greater than the cutoff of .9), WRMR (less than the cutoff of .9), and RMSEA (less than the cutoff of .08) were all satisfactory, thus demonstrating a good model fit. The R-squares of the dependent variables were satisfactory—.61 for urge to buy and .25 for unplanned purchase action. We coded a partial descriptor as "1" and a complete descriptor as "0." Our results show that the interaction effect of descriptor type and mood was significant ($\beta = .37$, $t = 3.56$, $p < .01$), supporting H1. When the recommendation came with a partial descriptor, the difference in urge to buy between subjects in positive moods (4.68) and those in negative moods (2.97) was 1.71. When the recommendation came with a complete descriptor, the difference was 1.11 (3.61 – 2.50). This provides evidence that the influence of mood on urge to buy is stronger when the descriptor is partial than when it is complete.

Experiment 2: Tradeoffs Between Taste-Matching and Need-Matching

Experiment Design and Checks

Experiment 2 examined the effect of the tradeoff between taste-matching and need-matching on unplanned purchase by consumers in different moods. There were two treatment groups. One group received recommendations that were high in need-matching but low in taste-matching, whereas the other group received recommendations that were low in need-matching but high in taste-matching. (See above for the details of manipulation.)

In our manipulation checks, the subjects who received a taste-matched recommendation (7.62) gave a higher score on taste-matching than those who received an unmatched recommendation (3.74). The difference in the two means was significant ($p < .01$). The subjects who received a need-matched recommendation (6.14) perceived that it matched their need more closely than those who received an unmatched recommendation (2.12). The difference in the two means was significant ($p < .01$). Our manipulations were deemed to be successful. Also, we followed the procedures in Appendix C to perform construct validation. All constructs show good psychometric properties.

Subjects

In Experiment 2, 309 students completed the registration, of which 277 finished the study. One subject indicated that he or she had not brought his or her mobile phone on the experiment day, and 29 subjects indicated that they were not on campus. Hence, they were disqualified from the experiment, resulting in 247 usable data points (156 females and 91 males).

Table 3. Descriptive Statistics for Experiment 2 (N = 203)			
		Need-Matched but Taste-Unmatched (N = 87)	**Taste-Matched but Need-Unmatched (N = 116)**
Positive Mood (N = 111)	Sample Size (N)	44	67
	Urge to Buy[a]	3.33 (1.57) [Mobile][b]	5.04 (1.55) [Mobile]
		2.57 (2.28) [Web]	5.14 (1.64) [Web]
	Buy or Not?	6%	34%
Negative Mood (N = 92)	Sample Size (N)	43	49
	Urge to Buy	1.50 (.89) [Mobile]	2.82 (1.04) [Mobile]
		1.62 (.85) [Web]	3.27 (1.51) [Web]
	Buy or Not?	8%	8%

[a]Mean (s.d.) .
[b][Mobile] for data collected via mobile messages; [Web] for the web survey data.

Data Analysis

Table 3 presents the descriptive statistics. The two variables—mood and urge to buy—were captured through both mobile messages and the web survey. About 26% (64 out of 247) of subjects did not reply to our mobile messages and 3% (7 out of 247) did not complete the web survey. We used the remaining data points to conduct two correlation tests to compare the two sets of responses—one correlation test for mood and the other for urge to buy. For mood, the correlation was .43 ($p < .01$)[7]; for urge to buy, the correlation was .25 ($p < .01$). Since H2 concerned the unplanned purchase action of consumers in either a positive mood or a negative mood, we removed 26 subjects who consistently reported having a neutral mood in both mobile messages and the web survey. Also, 18 subjects gave inconsistent responses. We discarded these 44 (26 + 18) responses. The path model analysis employed 203 usable data points (121 females and 82 males). Figure 4 shows the path model for Experiment 2.

The results of CFA tests suggested that the proposed factor structure has a reasonably good fit with the data (CFI = .99, TLI = .99, WRMR = .71, and RMSEA = .03). The R-squares of the dependent variables were satisfactory—.63 for urge to buy and .26 for unplanned purchase action. H2 focuses on the tradeoff between need-matching and taste-matching. Taste-matching was coded as "1" and need-matching was coded as "0." The moderation by mood was positive ($\beta = .70$, $t = 5.33$, $p < .01$), indicating that mood differentiated the effects of the tradeoff between need-matching and taste-matching on subjects' urge to buy.

To examine the data more closely, we split our sample into two groups (positive mood and negative mood) and ran two regressions. First, we used the 111 subjects who reported a mood valence greater than 5 to perform a multiple regression with urge to buy as the endogenous variable. Regarding control variables, impulse-purchase tendency ($\beta = .31$, $t = 4.72$, $p < .01$) exerted a significant positive effect on urge to buy. The rest of the control variables were found to be nonsignificant. The results show that subjects in positive moods formed a stronger urge to buy a taste-matched imperfect recommendation (5.14) than a need-matched imperfect recommendation (2.57) ($\beta = .75$, $t = 11.36$, $p < .01$).[8] Next, we conducted a similar regression as above, except that we used the 92 subjects who reported a mood valence less than 5. Contrary to our prior prediction, although the results showed that the coefficient of need-matching was significant ($\beta = .22$, $t = 2.22$, $p < .05$), subjects in negative moods formed a stronger urge to buy taste-matched imperfect recommendations (3.27) than need-matched imperfect recommendations (1.62).

As reported in Figure 4, mood moderates the effect of taste-matched imperfect recommendations (versus need-matched imperfect recommendations) on subjects' urge to buy. Table 3 shows that the difference in subjects' urge to buy given the two types of imperfect recommendations was greater for subjects in positive moods than for those in negative moods. Specifically, the difference for subjects in positive moods was

[7]The web survey presented 24 basic mood categories. For each basic mood category, we asked subjects to report (yes/no) if they experienced it at the time right before receiving the recommendation. We coded "yes" as +1 for positive moods, "yes" as −1 for negative moods, coded "no" as 0 for all mood types. We summed up these 24 numbers and calculated the correlation between this sum and the mood valence reported in the mobile messages.

[8]Further, given that the coefficient of mood (which is a continuous variable in the model) on urge to buy was nonsignificant ($\beta = -.02$, $t = -.35$, $p > .1$), there was no evidence that a high level of positive mood would lead to a strong urge to buy.

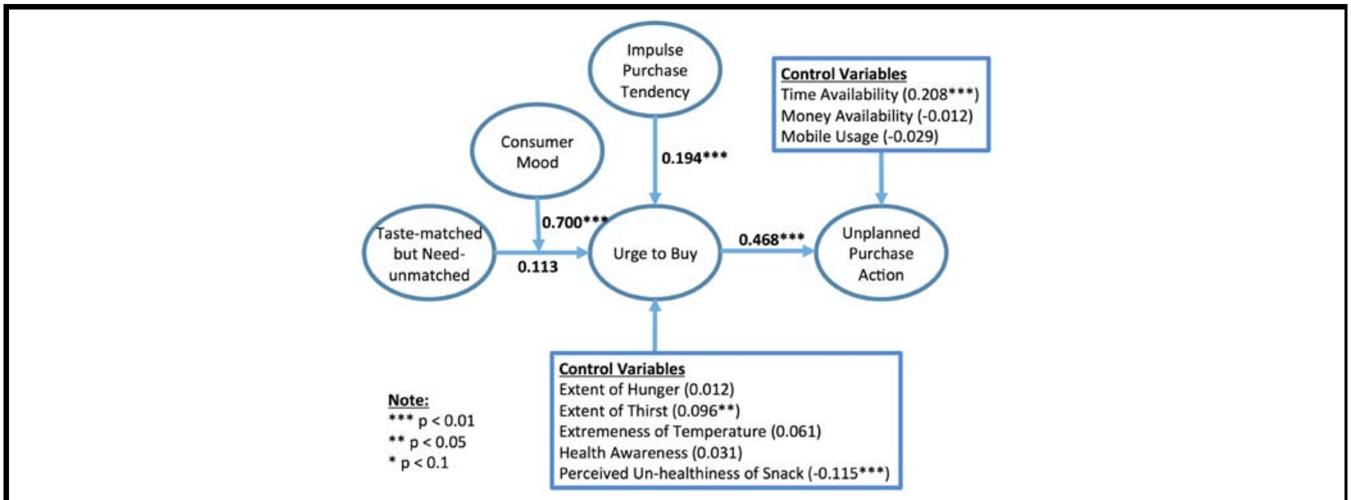

Figure 4. Experiment 2 Results

2.57 (5.14 − 2.57) and that for subjects in negative moods was 1.65 (3.27 − 1.62). Although both groups tended to form a stronger urge to buy taste-matched imperfect recommendations than to buy need-matched imperfect recommendations, these relative differences imply that the relative importance of need-matching to taste-matching increases when subjects were in negative moods. H2 was supported.

Why did the subjects in negative moods not form a stronger urge given need-matched imperfect recommendations as we expected? To probe further into this surprising finding, we explored the results of the second regression analysis further. The coefficient of mood (which was a continuous variable in the model) on urge to buy was negative ($\beta = -.19$, $t = -.1.92$, $p = .059$). The effect was marginally significant, probably because the sample size was small. This negative coefficient indicates that the more extreme the negative mood, the stronger the urge to buy created by taste-matched (but not need-unmatched) recommendations. This motivated us to investigate if the predictions from the theory of mood congruence can be applied to people in extreme negative moods. In doing so, we split the subjects in negative moods into subgroups according to their mood arousal. The subjects used a nine-point Likert scale to report their mood (1 = very negative, 5 = neutral, 9 = very positive). In the experiment, no subjects selected "1." The means of urge to buy for subgroups which selected "2," "3," and "4" in answering the mood question were 3.22, 2.95, and 2.39 respectively. Those with a high arousal had a stronger urge to buy taste-matched imperfect recommendations than those with a low arousal.

In sum, the relative importance of need-matching vis-à-vis taste-matching on urge to buy was stronger for subjects in negative moods than for those in positive moods. However, when subjects' moods were highly negative, taste-matched imperfect recommendations created a stronger urge to buy than need-matched imperfect recommendations.

Experiment 3: Tradeoff Between Location-Matching and Taste-and-Need-Matching

Experiment Design and Checks

Adding to Experiment 2 that controlled for the effect of location matching on unplanned purchase, Experiment 3 examined the effect of tradeoff in relation to location-matching on unplanned purchase. We manipulated the extent of location-matching and the extent of taste-and-need-matching, giving a two (location-matching: high versus low) by two (taste-and-need-matching: both high versus both low) design. See the section on the experiments' setup for the details of manipulation for taste-matching, need-matching, and location-matching.

We used the questions in Appendix B to check our manipulations. The subjects in the high location-matching condition (6.47) perceived the recommendation as being in closer proximity than those in the low location-matching condition (2.07). The difference in the two means was significant ($p < .01$). The subjects who received a taste-and-need-matched recommendation (7.42 for taste-matching and 6.32 for need-matching) evaluated the recommendation more highly than those who received an unmatched recommendation (1.51 for taste-matching and 1.34 for need-matching). Two t-tests showed that the differences were significant (both with $p < .01$). Our manipulations were successful. Also, we followed the procedures in Appendix C to perform construct validation. All constructs show good psychometric properties.

Subjects

There were 298 students registered for Experiment 3. As in Experiment 2, on the day of the experiment, we sent recommendations to their mobile phones. Thirteen subjects indicated that they were not on campus that day, and 29 subjects did not respond to our mobile messages and the web survey. As a result, there were 256 usable data points (170 females and 86 males).

Data Analysis

Table 4 presents the descriptive statistics. Out of the 256 subjects, 46 did not reply to our mobile messages and three did not complete the web survey, but none missed both responses. We used the complete data set to conduct two correlation tests—one test for mood and the other for urge to buy. For mood, the correlation of the two modes of response was .48 ($p < .01$). For urge to buy, the correlation was .27 ($p < .01$). All subjects gave consistent responses about their mood across the two surveys. Figure 5 depicts the path model.

The results of CFA tests suggest that the proposed factor structure has a reasonably good fit with the data (CFI = .97, TLI = .93, WRMR = .72, and RMSEA = .04). The R-squares of the dependent variables were satisfactory: .61 for urge to buy and .40 for unplanned purchase action. The interaction effect between location-matching and the other two personalization criteria (taste-matching and need-matching, which were always in the same direction in Experiment 3) was found to be significant and positive ($\beta = .58$, $t = 8.02$, $p < .01$), indicating that subjects formed a strong urge when they received a recommendation matching all three criteria.

H3a and H3b focus on the tradeoff between location-matching and the other two personalization criteria. We conducted two regressions to test these two hypotheses. To test H3a, we focused on the 113 subjects who received both taste- and need-*unmatched* recommendations. We ran a regression to predict the subjects' urge to buy. The predictors included a binary variable representing location-matching, the subject's mood, and their interaction effect. The control variables included the subject's impulse-purchase tendency, extent of hunger, extent of thirst, extremeness of temperature, health awareness, and (un)healthiness awareness of snack. Among these control variables, impulse-purchase tendency ($\beta = .32$, $t = 3.90$, $p < .01$), extent of thirst ($\beta = .26$, $t = 2.48$, $p < .05$) and (un)healthiness awareness ($\beta = -.17$, $t = -2.08$, $p < .05$) were found to be significant. Location-matching was found to be nonsignificant in influencing subjects' urge to buy ($\beta = -.10$, $t = -.46$, $p > .1$). According to Table 4, regardless of whether the recommendation was location-matched (5%) or unmatched (5%), the likelihood of unplanned purchase was equally low. There was no evidence that location-matching motivated subjects to spontaneously buy an unwanted and unnecessary recommendation. Hence, H3a was tenable.[9] In addition, mood and the interaction between mood and location-matching were both nonsignificant.

To test H3b, we focused on the 143 subjects who received taste-and-need-*matched* recommendations. We ran a similar regression on these 143 subjects. Among the control variables, impulse-purchase tendency ($\beta = .17$, $t = 5.14$, $p < .01$) was found to be significant. Regarding the predictors, mood ($\beta = .22$, $t = 5.02$, $p < .01$) and location-matching ($\beta = 1.33$, $t = 15.20$, $p < .01$) exerted a significant positive effect on a subject's urge to buy. H3b looked at the interaction effect of mood and location-matching. The interaction effect was significant ($\beta = -.59$, $t = -6.32$, $p < .01$). This negative coefficient indicated that the effect of location-matching on urge to buy was stronger for subjects in negative moods (3.88 = 7.35 − 3.47) than for those in positive moods (2.16 = 4.90 − 2.74). H3b was supported.

Discussion

Key Findings

In this study, we set out to develop a broader understanding of personalization by investigating *imperfect* recommendations—situations that mobile advertisers constantly face. Drawing on the theory of mood congruence, we theorized that consumer mood might play a pivotal role in affecting the effectiveness of imperfect recommendations in stimulating consumers' urge to buy the recommended product and their ultimate purchase action. We conducted three field experiments to test three sets of hypotheses. Our approach promised a more complete understanding of the effectiveness of personalization in mobile commerce when advertisers are

[9]Prior to conducting Experiment 2, we estimated that for a sample size of around 100 and assuming a medium effect size, the power of the statistical test would be higher than the recommended value of 0.8.

Table 4. Descriptive Statistics for All Subjects in Experiment 3 (N = 256)

			Taste-and-Need-Matched (N = 143)	Taste-and-Need-Unmatched (N = 113)
Location-Matched (N = 127)	Positive Mood	Sample Size (N)	42	31
		Urge to Buy[a, b]	5.33 (1.12) [Mobile]	3.91 (1.82) [Mobile]
			4.90 (.85) [Web]	1.91 (.82) [Web]
		Buy or Not?	21%	6%
	Negative Mood	Sample Size (N)	27	27
		Urge to Buy	6.99 (1.68) [Mobile]	3.78 (1.76) [Mobile]
			7.35 (.40) [Web]	2.19 (.38) [Web]
		Buy or Not?	39%	4%
Location-Unmatched (N = 129)	Positive Mood	Sample Size (N)	42	29
		Urge to Buy	3.12 (1.01) [Mobile]	1.89 (.78) [Mobile]
			2.74 (.45) [Web]	1.46 (.55) [Web]
		Buy or Not?	19%	4%
	Negative Mood	Sample Size (N)	32	26
		Urge to Buy	3.73 (1.21)	2.13 (1.10) [Mobile]
			3.47 (.69) [Web]	2.05 (.82) [Web]
		Buy or Not?	6%	6%

[a]Mean (s.d.).
[b][Mobile] for data collected via mobile messages; [Web] for data collected via the web survey.

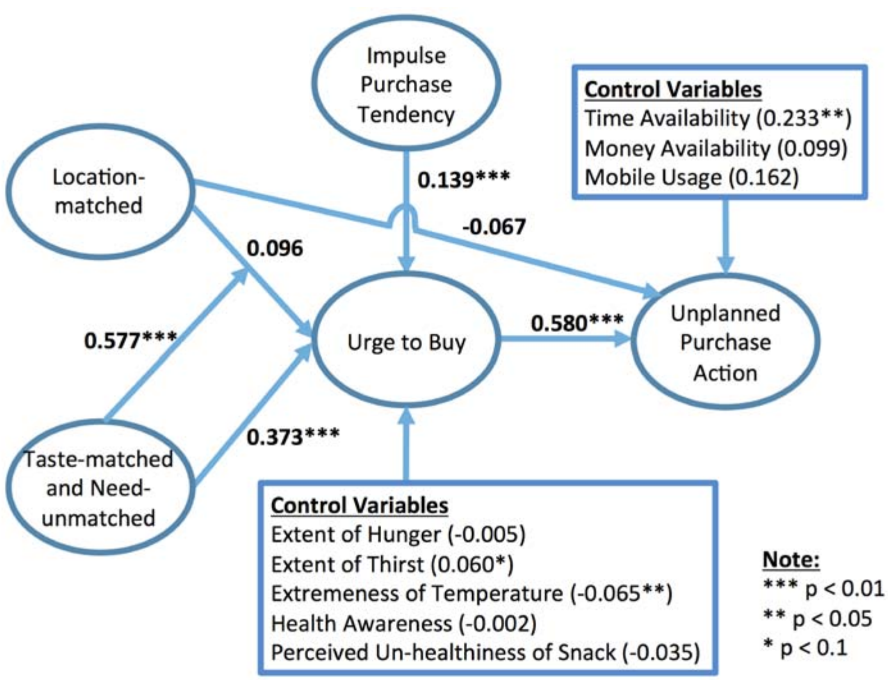

Figure 5. Experiment 3 Results

forced to provide imperfect recommendations. Our research has important theoretical and practical implications, as discussed in the next section.

Theoretical Contributions

Our research extends the literature in three ways. First, we study the effectiveness of personalization in *unplanned purchase*, in contrast to *planned purchase*, which has been examined in prior research. For instance, Moon et al. (2008) used lab experiments to study intention to purchase when processing recommendations of search goods (computers) vs. versus experience goods (sunglasses), and Ho and Bodoff (2014) asked subjects to select gifts for their friends and examined how personalization influenced their decision-making. These experiments had a planned, forced-choice setting—subjects were tasked to "buy" a product that was not for immediate use at the time of purchase; hence, their *need* was predefined and their *location* was irrelevant to decision-making. This prior research built on attitude-to-behavior models and used theory, such as consumer search theories (Moon et al. 2008) and the elaboration likelihood model (Ho and Bodoff 2014), to study the antecedents of consumers' attitudes toward a personalization agent and their intentions to select from the personalized list of products. These models are predominantly viewed as being cognition-based structures that are derived from consumers' processing of recommendation attributes and engaging in self-generated cognitive reasoning. The extant literature can thus explain planned purchases, but not spontaneous unplanned purchases, which might arise in response to mobile recommendations. Our research adds to the understanding of the effectiveness of personalization by broadening the research scope of personalization from planned to unplanned purchase, by taking into account consumers' context, and by investigating how consumers' context and recommendations influence their unplanned purchase.

The second contribution to the literature is that we extend the discussion on personalization effectiveness by shifting the research focus to *imperfect* recommendations. In prior studies, researchers often selected a small set of personalization criteria and discussed how a recommendation that fulfills all the selected personalization criteria influences consumer behavior. For instance, Ho and Bodoff focused on personalization quality. They found that the mean value of personalization quality influenced consumers' depth of processing of recommendations, and its variance influenced their breadth of processing. It is almost a truism that offering a recommendation matched to all the selected criteria is a precondition for successful personalization, determining the strategic impact of personalization on firm performance (Zhang et al. 2011). In practice, however, such a perfect recommendation may not exist, and, consequently, merchants may have to offer imperfect recommendations. It has been found that the provision of imperfect recommendations may result in feelings of deception (Xiao and Benbasat 2011), and subsequent distrust in personalization agents (Chau et al. 2013; Komiak and Benbasat 2008). However, researchers have not explored how imperfect recommendations can be carefully prepared to minimize these adverse effects in order to trigger consumers' unplanned purchases.

Adding to prior research, we investigate how imperfect recommendations can arouse consumers' urge to buy, which, in turn, leads to unplanned purchase. We examine how tradeoffs should be presented to increase the likelihood of unplanned purchase (H1). Also, we examine two combinations of personalization criteria tradeoff—between taste-matching and need-matching (H2) and between location-matching and taste-and-need-matching (H3a and H3b)—and the moderating effects of mood, in which consumers become biased by pleasant features of recommendations in their decision making. Our research is one of the very first studies to investigate the conditions in which imperfect recommendations remain attractive to consumers. Our research not only opens up a new avenue of inquiry, but also provides a foundation for future research examining imperfect recommendations.

The third way our research extends the literature is by introducing an affective variable—mood—to the personalization research. Mood directs consumers' information processing to various attributes of personalized recommendations and, thus, it moderates the effectiveness of imperfect recommendations on consumer unplanned purchases. Since mood congruence exerts a stronger influence on consumers when the descriptor contains "missing" information, when consumers have a positive mood, a partial descriptor is more effective than is a complete descriptor (H1). Mood informs researchers about the conditions under which we would predict which of the two product dimensions (hedonic versus utilitarian) to dominate. Our empirical analysis reveals that negative mood drives consumers to focus on need-matching. In particular, the relative weight of need-matching and taste-matching changes with consumer mood (H2), and location-matching exerts a stronger effect on consumers in negative moods than on those in positive moods (H3b). Our findings confirm the claim by Zhang (2013) that mood "can even have more explanatory power than cognition under certain circumstances" (p. 248). Overall, we have demonstrated that mood can explain a significant portion of the variance in consumer behavior in reacting to imperfect recommendations. It echoes the remark by Zajonc and Markus (1982, p. 124) that "preferences are themselves primarily affectively based behavioral phenomena." Our findings provide the impetus for a new line of research investigating how mood differentiates consumers' decisions toward imperfect recommendations.

Practical and Managerial Implications

We validated the relevance of our research findings to practice through two practitioner symposiums, which involved senior executives from the personalization solution industry and the search engine marketing industry. In total, there were 60 participants. In both symposiums, the participants first presented their current projects and we then presented ours. We openly discussed the opportunities and challenges of personalized mobile services. Appendix D provides a summary of insights shared by these participants. We followed the guidelines on applicability checks by Rosemann and Vessey (2008). Overall, the participants found the findings to be important, accessible, and applicable to their contexts. In the following paragraphs, we will discuss the practical implications of our study by drawing from the findings of our field experiments in corroboration with the interview sights of the two practitioner symposiums.

The first implication is the guideline on applying context-awareness personalization to stimulate unplanned purchase. Context awareness plays a significant role in mobile personalization. For instance, Wal-Mart developed a software application with the ability to search and analyze social media applications (like Twitter or Facebook) in real-time to discover *user taste*. Amazon analyzes users' clickstreams within a session to identify their *current need*. Facebook uses computer IP addresses and/or GPS to detect *user location*. Despite industry investment in context-awareness personalization, it might have only helped merchants gain an increase of 19% in sales (Questback 2015). To probe into this issue, we conducted field experiments to examine whether context-aware personalization influences unplanned purchases. The results of all experiments confirm that personalized recommendations can trigger unplanned purchase actions. If so, what is wrong? In our open exchanges with practitioners, we believe that the current GPS is very well-developed and that location detection is considered very implementable, but need identification is far from satisfactory. This echoes the call and predictions of a McKinsey report on the need to incorporate smart phones with need-identification features: "future smart devices will incorporate new mobile sensor types, such as biometric, pressure, and environment sensors, along with the ones currently in most smart phones" (Atluri et al. 2012, p. 6). We, therefore, call for the industry to further develop new techniques to better identify user needs to maximize the effect of context-aware personalization.

A second practical implication is the guidelines to merchants on the promotion of *imperfect* recommendations to consumers. To date, the focus and aim of personalization has been to maximize the extent to which a recommendation and a user's taste (and context) match in order to generate a *perfect* recommendation. To this end, merchants invest in pattern recognition and data mining technologies, at great cost. However, they often focus on one personalization strategy of interest and neglect the opportunities and threats brought by considering multiple personalization strategies at the same time in generating one recommendation. Subsequently, they overlook possible conflict among personalization strategies. Our study highlights this practical problem: despite the advancement in pattern recognition and data mining technologies, generating a perfect recommendation may be infeasible in some cases. Our findings show that in certain situations consumers are willing to take an imperfect recommendation, and that mood exerts a subtle influence. Our study provides mobile advertisers with guidelines on how to promote imperfect recommendations to consumers under different contexts with different descriptors to maximize the effectiveness of the recommendations in inducing unplanned purchases. This fundamentally shifts the mindset of only generating perfect recommendations but giving up opportunities when perfect recommendations cannot be found. This shift in orientation provides a new stream of revenue for mobile advertisers.

Further, our study highlights the pivotal role of mood in promoting imperfect recommendations in unplanned purchases. Nowadays, mobile applications give recommendations on music according to the user's mood (Brennan 2017). Few practitioners have thought about integrating mood detection with other personalization strategies to generate recommendations in unplanned purchases, because it may appear to practitioners that it is difficult, if not impossible, to gain knowledge of a consumer's current mood. The recent breakthroughs in voice pitch analysis, electromyography, and eye-based measurements to capture a user's moods in real-time are not yet widely adopted in industry. We believe that personalizing imperfect recommendations according to mood will be realized in the future. Our study echoes the view of Corley and Gioia (2011): that research ought to take a prescience orientation by leading technological development. We believe that once it has been established that mood plays a pivotal role in the effectiveness of imperfect recommendations—by knowing consumers' mood, mobile advertisers can generate more revenue—hardware and software developers will not hesitate to further invest in mood detection technologies.

Future Research and Limitations

Our research is not without limitations. First, our sample frame may limit the generalizability of the findings. We invited university students to participate in the three field experiments. Although university students are active mobile phone users, the findings of the study would be more representative if our sample included people with different profiles. Future research could be conducted to examine how consumers with different characteristics (i.e., job types, household income, and personalities) react to personalization. Second, the study setting involved low-involvement products (i.e., a snack of $5). Future research could explore the effectiveness of personalization for promoting unplanned buying of different types of products. One natural additional direction for future research would be to examine how consumers react to personalized recommendations offering high-involvement products.

Conclusions

Our research examines how imperfect recommendations from mobile personalization influence consumers' unplanned purchase. We extend the model of Beatty and Ferrell (1998) and Wells et al. (2011), theorizing a pivotal role of mood on influencing consumers' unplanned purchase toward imperfect recommendations. Our extended model illustrates that mood influences consumers to weigh differently the various personalization criteria in their purchase decisions. Theoretically, our research adds to the personalization literature by providing a more complete picture of not only whether and how personalization stimulates unplanned purchase, but also on the moderating role of mood on consumers' unplanned purchase in the face of imperfect recommendations. Practically, our research provides mobile advertisers with guidance on how to more effectively steer consumers to spontaneously purchase the products recommended by imperfect recommendations.

Acknowledgments

The work described in this article was supported by the grants from the Australian Research Council, Australia (Project DP0879736), the Research Grants Council of the Hong Kong Special Administrative Region, China (Project CityU 11503814), and City University of Hong Kong Strategic Research Grant (Project 7004780).

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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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