Journal of Services Marketing

Recommendations as personalized marketing: insights from customer experiences

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Recommendations as personalized marketing: insights from customer experiences

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Abstract

Purpose – The purpose of this paper is an exploratory study of customers' "lived" experiences of commercial recommendation services to better understand customer expectations for personalization with recommendation agents. Recommendation agents programmed to "learn" customer preferences and make personalized recommendations of products and services are considered a useful tool for targeting customers individually. Some leading service firms have developed proprietary recommender systems in the hope that personalized recommendations could engage customers, increase satisfaction and sharpen their competitive edge. However, personalized recommendations do not always deliver customer satisfaction. More often, they lead to dissatisfaction, annoyance or irritation.

Design/methodology/approach – The critical incident technique is used to analyze customer satisfactory or dissatisfactory incidents collected from online group discussion participants and bloggers to develop a classification scheme.

Findings – A classification scheme with 15 categories is developed, each illustrated with satisfactory incidents and dissatisfactory incidents, defined in terms of an underlying customer expectation, typical instances of satisfaction and dissatisfaction and, when possible, conditions under which customers are likely to have such an expectation. Three pairs of themes emerged from the classification scheme. Six tentative research propositions were introduced.

Research limitations/implications – Findings from this exploratory research should be regarded as preliminary. Besides, content validity of the categories and generalizability of the findings should be subject to future research.

Practical implications – Research findings have implications for identifying priorities in developing algorithms and for managing personalization more strategically.

Originality/value – This research explores response to personalization from a customer's perspective.

Keywords Customer satisfaction, Personalization, Critical incidents, Consumer preference, Recommendation agent

Paper type Research paper

An executive summary for managers and executive readers can be found at the end of this issue.

Introduction

Recommendation agents programmed to "learn" customer preferences and make personalized recommendations of products and services (Gershoff and West, 1998; West *et al.*, 1999) are considered a very useful tool for personalized marketing, i.e. targeting each customer individually in marketing (Rust and Chung, 2006; Simonson, 2005). Some leading service firms have developed proprietary recommender systems in the hope that making personalized recommendations could engage customers and increase customer satisfaction, thus sharpening the competitive edge of their businesses (Netflix Annual Report, 2010; Amazon Annual Report, 2010).

For all its potentials to enhance customer satisfaction, the practice of making personalized recommendations has met with both successes and challenges (Flynn, 2006; Shen and Ball, 2009). In some instances, personalized recommendations may actually lead to customer *dis*satisfaction, even annoyance or irritation (Iacobucci, 2006, p. 582):

> I love Amazon.com; I really do. I think "amazon" should be pronounced: a-maz'-in(g). Yet, it's quite difficult to opt out of their overriding, tailored recommendation format. When I browse for books, I want to know everything that's out there, not someone's heuristic of what they think I'll like. Algorithms based on similarity, within genre, or frighteningly to other customers with whom I probably share no other qualities, assume that customers want assistance drilling down to find more, similar products. A different assumption underlies the segment that reads voraciously and eclectically to be transported to different worlds, via travel essays of Bryson or Theroux, popular science writings on fractals or space worms, international collections of sublime prayers, or a barf check on the popular business press books. I might be a difficult case for Amazon, in that, as a final insight into my psyche, I find these questions to be of equal importance: "Will this new multivariate book explain concepts more clearly to my doctoral students than books I've assigned previously?" and "Will Stephanie Plum choose Morelli or Ranger?" Nevertheless, I didn't ask Amazon to track my preferences. Indeed, I wish they'd stop. I am an efficient and effective expert in this category, and I don't need some computer hack salesperson? sales entity? suggesting what I'd enjoy. Further, the recommendations need to be based on a better mix of the similarity between profile pattern (correlation) and profile height (distance measures), because currently we're

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Journal of Services Marketing
28/5 (2014) 414–427
© Emerald Group Publishing Limited [ISSN 0887-6045]
[DOI 10.1108/JSM-04-2013-0083]

This research was funded by a Research and Creative Projects Award from the State University of New York at New Paltz.

Received 2 April 2013
Revised 6 July 2013
Accepted 15 September 2013

also bombarded with simple volume-based offerings: "Dawn, we recommend the latest Harry Potter", or worse, an Oprah read.

Is this disclosure of dissatisfaction merely "a difficult case" or fairly common among customers who have interacted with personalized recommendations? What are the major sources of (dis)satisfaction with a service firm's recommendations? These questions are fundamental to personalized marketing – a topic highly relevant to managers and academics.

To online service firms embracing personalization as part of their core competitive strategy, (dis)satisfaction with agent recommendations is not without consequences. First, customer (dis)satisfaction may have an immediate impact on sales transactions in the current service episode. While satisfied customers are more likely to be engaged and to proceed to placing orders, dissatisfied customers may simply drift away from the current episode, or even to a competitor's Web site (which is just a click away). Second, customer (dis)satisfaction may also affect their overall experiences with the service firm, which may in turn exhibit its impact on customer retention and long-term profitability. Furthermore, with customers of ever increasing technology savvy, marketing of personalized products and services is becoming a business necessity. A solid understanding of sources of customer (dis)satisfaction with recommendation services may help the development of recommendation algorithms and may have broader implications for service firms hoping to be more adaptive in their individual marketing strategies.

Service researchers have studied personalized marketing in interpersonal service encounters under the rubrics of service customization (Bettencourt and Gwinner, 1996; Gwinner *et al.*, 2005), service personalization (Mittal and Lassar, 1996; Surprenant and Solomon, 1987) and service relationships (Ball *et al.*, 2006; Gwinner *et al.*, 1998). However, personalization through recommendation agents often does not involve the intervention of service employees; rather, it is driven by information technologies such as algorithms, databases, data mining and artificial intelligence. The potential for recommendation agents to create customer benefits by learning preferences and personalizing services is not fully understood (Dabholkar and Sheng, 2012; Rust and Chung, 2006; Shen and Ball, 2009). Some researchers have even questioned the core assumption of personalized marketing that customers have preferences that marketers can reveal by building a learning relationship (Kramer, 2007; Simonson, 2005). Drawing on the rich tradition of constructive choice theories (Bettman *et al.*, 1998; Slovic, 1995), this research argues that preferences are constructed at the time when decisions are being made – customers often do not have stable preferences to be retrieved and applied to decisions. The notion of preference construction casts into serious doubt whether preference learning and personalization can add any value to service research. Indeed, research on recommendation agents has shifted its theoretical focus from preference learning to the context in which preferences are constructed (Aksoy *et al.*, 2006; Cooke *et al.*, 2002; Häubl and Murray, 2003; Kramer, 2007). For instance, Kramer (2007) argued that, as preferences are often ill-defined, consumers will evaluate personalized recommendations based on how easily they can identify their stated preferences. He demonstrated experimentally that measurement tasks that allow consumers to "see through" the construction of their preferences increase the likelihood of agent recommendations being chosen, a finding he refers to as the "task transparency effect".

Although the notion of constructed preference is well-accepted in research, little is known about how customers experience preference construction under the aid of recommendation agents. Yet, how customers "live" the personalization experiences of recommendation agents may be interesting to researchers who wish to further investigate whether and when preference learning and personalization by recommendation agents could add value to customers – a question fundamental to personalized marketing and service research. Analyzing customer experiences of and articulating customer expectations for agent recommendations may offer a new angle to review the theorization of personalized marketing and may potentially enrich our understanding of preference learning and preference construction.

To identify sources of customer (dis)satisfaction with agent recommendations, I conducted an exploratory study of critical (dis)satisfaction incidents as narrated by customers who had interacted with agent recommendations in their relationship with a service firm. An exploratory approach is warranted because the topic of customer (dis)satisfaction with agent recommendations has scarcely been examined in previous research, as discussed above. Taking the customer's perspective is appropriate for the specific objective of this research, which is to understand sources of customer satisfaction or dissatisfaction with recommendation services. The critical incident technique is a research method that has been successfully applied to study other research problems (Bitner, 1990; Gremler, 2004; Keaveney, 1995; Meuter *et al.*, 2000). I collected and content-analyzed critical incidents and experiences narrated by customers to answer these questions: From the customer's perspective, what are the major sources of (dis)satisfaction with agent recommendation services? What are the underlying customer expectations driving their (dis)satisfaction?

In the rest of the paper, I first discuss the critical incident technique and the procedures I followed in the collection and analysis of critical (dis)satisfaction incidents. I then present the classification scheme developed to account for all the (dis)satisfaction incidents, discuss coding results, identify themes emerging from these incidents and suggest tentative research propositions. Finally, I discuss the managerial and theoretical implications of this research.

Research methodology

Critical incident technique

The critical incident technique is a qualitative research method that enables researchers to collect and analyze incidents or occurrences of interest, and develop classification schemes to help addressing practical problems (Bitner, 1990; Flanagan, 1954; Gremler, 2004). Marketing and consumer researchers find it an especially valuable tool when the research objective is to develop understanding of behavior of interest in the marketplace. Gremler (2004) identified 106 articles in major journals of marketing research that had used this research tool. For instance, service researchers have used it to explore customer (dis)satisfaction with service encounters (Bitner, 1990; Bitner *et al.*, 1994; Meuter *et al.*, 2000), incidents that precede service switching (Keaveney, 1995) and retail failures and recoveries (Kelley *et al.*, 1993). Following

Gremler's (2004) advice, as the critical incident technique is widely accepted in research, the rest of my discussion will focus on the operational procedures I used to conduct the research. Interested researchers may refer to Gremler (2004) for a comprehensive review of the critical incident technique.

Defining critical incidents

In this research, a critical incident is an episode of service interaction between a customer and his/her service firm that takes place via the firm's proprietary recommender system to which the customer attributes his/her (dis)satisfaction. That is, an interaction episode must meet two requirements simultaneously to qualify as a critical incident. First, the interaction episode must take place via the company's proprietary recommender system (e.g. clicking to view recommended items, rating recommended items). Thus, failure to receive shipments of orders placed from Amazon.com should not be considered a qualified incident because it involves the company's delivery system, not its recommender system. Second, an interaction episode must result in a customer's satisfaction or dissatisfaction (i.e. the valence must be unambiguously positive or negative). Thus, merely explaining to other customers how to use Netflix's recommender system should not be considered a qualified incident because no satisfaction or dissatisfaction can be observed. For an example of qualified incident, a customer may express satisfaction when Amazon.com recommends a book he/she enjoys reading and would not have found otherwise. Alternatively, a customer may express dissatisfaction when Netflix recommends a movie that turns out to be a total disappointment.

Data collection

Research on critical incidents starts with collecting customer narratives of their own service experiences. Although narratives of critical incidents are often obtained through personal interviews or surveys in previous research (Keaveney, 1995; Meuter *et al.*, 2000), narratives of customer (dis)satisfaction with personalized recommendation services may be more often communicated among members of online communities (e.g. in online discussion groups or via Web blogs), and can be observed in a naturalistic way following the netnography approach (Kozinets, 2002; 2010). Such critical incidents, recorded as they occur or immediately after and collected by researchers from online discussion groups and personal blogs, may be more accurate than those obtained at a later time of data collection by prodding customers with interviews or survey questions (Kozinets, 2010). Although this netnography approach makes it difficult to collect reliable customer demographics data, previous research has suggested that this should not be a major concern if the research objective is to gain research insights (Bitner *et al.*, 1990, 1994). With this consideration in mind, I decided to adopt the naturalistic netnography approach in data collection and analysis (Kozinets, 2002, 2010), by observing and selecting communications that take place in online communities without interrupting their flow.

Personalized recommendation services are available from a number of service firms. I selected three service firms (Amazon, Netflix and Apple in its iTunes) whose proprietary recommender systems have been in operation for a relatively extended period. To collect data, I searched through Google for online discussion groups and blogs under key words such as "Amazon recommendations", "personalized recommendations", "Netflix recommendations", "Netflix movie recommendation system", "iTunes Genius" or "Genius recommendations". The narratives collected for this research were mostly from online discussion groups (e.g. rec.arts.sf.written) or personal blogs (e.g. http://safle.org/wordpress/2011/11/23/amazon-recommendations-and-useless-algorithms.html).

To ensure the quality of data collection, returned search results were initially screened by the researcher based on the judgment of whether the narratives meet the qualification requirements discussed earlier – narratives would be screened out if they did not pertain to using the company's recommender system or if they involved neutral stance (e.g. how-to-use instructions) or ambiguous experiences (e.g. reporting both positive and negative responses to the same service episode). I also checked whether narratives read like written by average customers holding conversations in discussion groups or monologs in blogs over their user experiences of the firm's recommendation service. Narratives that appear on company-sponsored Web sites or that read like written by business executives or algorithm developers were discarded. I exercised caution regarding privacy and copyrights, limiting my search to Web sites or blogs that existed in the public domain and did not place restrictions on the academic use of content.

In preparation for data coding, I again read discussion threads or blog posts individually as well as in their original contexts to determine, using the criteria discussed above, whether they were qualified critical incidents – disqualified incidents were again discarded and qualified incidents were highlighted as either satisfactory incidents or dissatisfactory incidents.

Sample size was determined by following the benchmark numbers of previous studies (Bitner *et al.*, 1990; Gremler, 2004; Keaveney, 1995; Meuter *et al.*, 2000). In this research, 426 qualified narratives were collected from 358 online group discussion participants and bloggers, for a total of 650 qualified incidents. A discussion participant or a blogger may post multiple narratives, so the number of discussion participants or bloggers is smaller than the number of narratives (358 vs 426). Similarly, a narrative may consist of one or more qualified critical incidents, so the number of narratives is smaller than the number of critical incidents (426 vs 650). For more detailed distribution across the three service firms, see Table I.

Table I Participants/bloggers, narratives and critical incidents by service firms

Service Firm	Number (%) of discussion participants/ bloggers	Number (%) of narratives	Number (%) of critical incidents
Amazon.com	115 (32)	140 (33)	212 (33)
Netflix.com	121 (34)	154 (36)	263 (40)
Apple's iTunes	122 (34)	132 (31)	175 (27)
Total	358 (100)	426 (100)	650 (100)

Data analysis

Unit of analysis

The unit of analysis is a critical incident – an episode of interaction with the recommendation service that results in satisfaction or dissatisfaction (no distinction was made between high and moderate levels in satisfaction or dissatisfaction).

As customers record their user experiences naturalistically, a narrative may record a customer's response to one discrete interaction episode (e.g. viewing a recommended item and finding it to be offensive) or several discrete interaction episodes (e.g. viewing a recommended item and finding it to be poorly related to his/her true preference; rating the recommended item as a poor recommendation; and receiving recommendations better aligned with his/her preference). This is not uncommon, as previous research has documented that a narrative may involve two or more critical behaviors (Keaveney, 1995). Sometimes, a narrative may report a cumulative response to multiple discrete interactions of the same type. For example, rating a movie after watching it is a discrete interaction with the recommendation service. However, rating 1,000 movies after viewing each of them in a period of five years and finding it really easy to do is a cumulative response based on multiple episodes of similar interaction with the recommendation service. In this research, a cumulative response is treated as one critical incident.

Classification scheme development and inter-rater reliability

An iterative inductive delineation process (Bitner *et al.*, 1990; Gremler, 2004) was followed to develop a classification scheme that could account for all the critical incidents. I first read and reread each of the 650 qualified incidents that resulted in satisfaction (38 per cent, or 248 incidents) or dissatisfaction (62 per cent, or 402 incidents) alone and in combination with its original context to allow commonalities to emerge. Then, a classification scheme was drafted with definition for each of the categories. Moving on to the third stage, I started to sort each identified incident into a category of the classification scheme drafted in the previous stage, making minor modifications to the category definitions when necessary until I felt confident that the categories in the classification scheme were able to account for all qualified critical incidents and that each critical incident had been sorted into a correct category.

To test the reliability of the classification scheme, two business students were recruited as coders (coder A and coder B). They first received training to familiarize themselves with the classification categories previously developed by the researcher. They then used the classification scheme to independently code all the satisfactory and dissatisfactory incidents. The two coders agreed in 82.92 per cent of the critical incidents in the designation of categories. Coder A agreed with the researcher in the designation of 81.69 per cent of the incidents, while coder B agreed with the researcher in the designation of 80.15 per cent of the incidents. The inter-judge reliability is considered acceptable.

Results

The classification scheme

Following the procedures described above, a classification scheme with 15 categories has been developed to account for all the 650 incidents. In Table II, all categories except the "other" category in the classification scheme are each illustrated with an exemplary incident.

Number and per cent of critical incidents by category

Table III is a summary report of the number and percentage of critical incidents that fall into each of the categories. Customer discussion of personalized recommendations is concentrated (79.6 per cent of all incidents) in the eight topic areas of *algorithm* (Is the recommendation algorithm superior or inferior?), *discovery* (Do recommendations help me find valuable items I would not find otherwise?), *convincing connection* (Are recommendations connected to my preference in a convincing manner?), *privacy* (Does the system violate my privacy?), *accuracy* (Do recommendations match my preference?), *customer knowledge* (Do recommendations indicate that the company has good knowledge of the customer?), *sales motive* (Does the company only make recommendations out of self-interested motive?) and *product knowledge* (Do recommendations indicate that the company has good knowledge of the products it recommends?). The higher proportion of dissatisfaction incidents (402 of 650, or 61.8 per cent) than that of satisfaction incidents (248 of 650, or 38.2 per cent) suggests that overall customer experiences with agent recommendations might be in the negative region.

Table IV is a ranking of the most discussed categories, the top satisfying and dissatisfying categories and the top winning and losing categories. The categories most discussed (79.6 per cent of all critical incidents) are, in order of frequency, algorithm (16.3 per cent), discovery (13.2 per cent), convincing connection (10.3 per cent), privacy (10.2 per cent), accuracy (9.1 per cent), customer knowledge (7.4 per cent), sales motive (6.9 per cent) and product knowledge (6.3 per cent).

Interestingly, 77.3 per cent of all dissatisfaction incidents are related to *algorithm* (the recommendation algorithm is perceived to be inferior), *convincing connection* (recommendations are not connected to the customer's preference in a convincing manner), *discovery* (recommendations are repetitive and do not help the customer discover valuable items), *sales motive* (the company only makes recommendations out of self-interested motive), *customer knowledge* (recommendations indicate the company has poor knowledge of the customer), *product knowledge* (recommendations indicate the company has poor knowledge of the products it recommends), *privacy* (the recommendation system is a violation of privacy) and *accuracy* (recommendations match the customer's preference). Dissatisfaction incidents are dominant when it comes to *convincing connection*, *product knowledge*, *sales motive* and *customer knowledge*. Incidents are almost exclusively dissatisfactory in *sub-accounts* (the recommendation system does not separate the preference profiles of users who share the account), *redundancy* (making redundant recommendations), *propriety* (recommendations are embarrassing or inappropriate) and *availability* (the system cannot generate any recommendations when needed).

Table II Illustrative incidents for categories in the classification scheme

Categories of (dis)satisfac-tion sources	Satisfaction incidents	Dissatisfaction incidents
Accuracy	"The Amazon.com recommendation engine knows me fairly well [. . .] I've been their customer for almost 15 years, and the books they try to sell me genuinely reflect my passions: Spanish-language literature, personal essays, travel, business and marketing, children books and books related to World's Fairs" Available at: http://aguahispanicmarketing.com/lost-in-the-jungle/; Posted by anonymous on 6/30/11 (accessed 27 March 2012)	"[. . .] it seems that I'm not the only one irritated by Netflix's recommendations[. . .] Is there a way for me to use Netflix's rating system in a way that will cause the system to recommend movies that truly match my tastes, or should I forget about it?" Available at: http://ask.metafilter.com/185224/Do-you-know-anything-about-Netflix-ratings; Posted by partner to media & arts on 5/6/2011 (accessed 17 March 2012)
Discovery	"[. . .] I utilize [. . .] (Netflix) electronic recommendations when choosing films, and I find that this is one of the best ways to discover films that I honestly would not have discovered on my own" Available at: http://themotionpictures.wordpress.com/2012/04/07/5-ways-i-choose-films/; Posted by Lindsey on 4/7/12 (accessed on 21 April 2012)	"[. . .] these recommendations are based on the idea of 'more of the same'. So if you like one British comedy show, you get recommended more British comedies [. . .] I think that if you just follow the recommendations, you might end up just reading the same thing over and over" Available at: http://christinarosendahl.wordpress.com/2012/01/12/are-recommendations -bad-for-you/; Posted by Christina R. on 1/12/12 (accessed on 12 February 2012)
Convincing connection	"Netflix definitely got more linear with its recommendation this week. The connection between St. Elmo's Fire and About Last Night are pretty clear: Brat-Pack actors, similar plot lines, beautiful twenty-something's having some sex" Available at: www.secretly-important.com/category/52-weeks-of-netflix/; Posted by jaimemnavarro on 10/6/11 (accessed on 24 February 2012)	"(iTunes Genius) suggests other music [. . .] nebulously, tenuously or debatably related to that music. If you like hearing the preternaturally visionary melancholia of Elliott Smith, I will advise you to purchase 'The A Team' by Ed Sheeran, who honestly does share more with Smith than initials, and is in no way a derivative and cynical unit-shifting cipher disguised as a songwriter" Available at: http://hairyapplefeed.blogspot.com/2011/08/itunes-genius-where-your-heart-should.html Posted by HairyAppleMen on 8/4/11 (accessed on 29 March 2012)
Algorithm	"[. . .] how they make the magic happen [. . .] Netflix looks at the movies you rate, (anonymously) finds other users who've given the same movies the same ratings, and then recommends other movies that they rated highly. They then classify these recommendations into categories based on traits associated with the movies" Available at: www.entertainedorganizer.com/2011/08/what-netflix-has-taught-me-about-myself.html; Posted by Patrick on 8/11/11 (accessed on 24 February 2012)	"iTunes recommendations seem to be rather run-of-the-mill collaborative filtering recommendations based upon the wisdom of the crowds [. . .] recommendations seem to be artist-based and not album or track-based[. . .] the Genius just picks tracks from similar artists regardless of how well the track is representative for the artist" Available at: http://synthese.wordpress.com/2008/09/10/genius-itunes-recommender/ Posted by Andre Vellino on 9/10/08 (accessed on 29 March 2012)
Voluntary participation	"I happily spend a bit of time entering my ratings of just about every book I've ever read, just for fun" Available at: rec.arts.sf.written; Posted by Brian Charles Kohn on 3/27/10 (accessed on3 February 2012)	"I have spent a number of hours rating the stuff I own (telling Amazon that I both already own and what star ranking I give it) and checking off'not interested'[. . .] The downside is that it takes time" Available at: http://boards.straightdope.com/sdmb/showthread.php?t=518189 Posted by phreesh on 5/21/09 (accessed on 9 February 2012)
User control	"By rating a lot of books and putting books on my wishlist [. . .] I've got this doing a pretty good job of recommending stuff to me [. . .] It does an especially decent job keeping up with new books by authors I like and new books about my professional interests" Available at: http://boards.straightdope.com/sdmb/showthread.php?t=518189; Posted by Harriet the Spry on 5/20/09 (accessed on 24 February 2012)	"I have such an eclectic browsing history and have purchased so many gifts through Amazon that my recommendations are utter crap and after tinkering around with the 'fix this recommendation' feature, I haven't been able to fix a thing" Available at: www.thecompulsivereader.com/2012/01/reading-rants-balancing-amazon-and.html; Posted by The Compulsive Reader on 1/2/12 (accessed on 2 February 2012)
Sales motive	"[. . .] Genius also has some recommendations from the iTunes store but it certainly isn't a pushy salesman. You can preview the purchasable music from within a sidebar or simply slam the section shut if you aren't in the mood to kick start our economy"	"I don't know why I am not as comfortable with the similar Amazon system. I suspect it is because every time I look there, they make recommendations that are obviously based on what they have been paid to promote"

(*continued*)

Table II

Categories of (dis)satisfac-tion sources	Satisfaction incidents	Dissatisfaction incidents
Product knowledge	Available at: http://usedwigs.com/itunes-genius/; Posted by Todd Marrone on 9/19/08 (accessed on 29 March 2012) "(brick and mortar bookstores) sales staffs not as knowledgeable as the mythology suggests. Amazon's recommendation engine is worlds better than anybody I ever met in a bookstore, especially if you understand how it works (and how it's biased) and tweak it" Available at: http://mhpbooks.com/48750/when-will-big-publishers-speak-out-about-amazon/; Posted by TwoTooth on 2/2/12 (accessed on 22 February 2012)	Available at: rec.arts.sf.composition/; Posted by Ian Montgomerie in 11/08 (accessed on 9 February 2012) "'Genius' is of no use to those whose taste in music goes beyond a fairly narrow range. On my Macs it can't make a playlist based on Vladimir Horowitz playing Chopin. This is not esoteric stuff[. . .]" Available at: comp.sys.mac.system/; Posted by Davoud on 9/17/08 (accessed on 29 March 2011)
Customer knowledge	"Since I do most of my reading on my Kindle, Amazon has a good record of the books I like. To find new books to read, I usually look at their recommendations for me. Chuck Klosterman, Chelsea Handler, Tina Fey, Stephen Clarke, Amy Sedaris, Kathy Griffin, Augusten Burroughs, Sarah Silverman, Elizabeth Gilbert [. . .] the list varied quite a bit" Available at: http://everythingisblooming.wordpress.com/2011/10/21/on-amazon-recommendations/; Posted by Ashley on 10/21/11 (accessed on 2 February 2012)	"(Amazon) top recommendation is Dan Brown's turgid 'The Lost Symbol'. I cannot for the life of me think why Amazon's algorithms would recommend this [. . .] My best guess is it is based on my browsing history because I have looked at all the Dan Brown books on Amazon. What Amazon failed to spot is that I did not just look at the books–I reviewed them" Available at: http://safle.org/wordpress/2011/11/23/amazon-recommendations-and-useless-algorithms.html; Posted by Stephen on 11/23/11 (accessed on 2 February 2012)
Propriety	N.A.	"Steve Wozniak just sent me this hilarious screenshot [. . .] It's from the Genius Recommendations in the movie section of the iTunes Store: If you bought the PBS documentary Steve Jobs: One Last Thing you will like Hitler: A Career. His comment in the mail: 'Someone at Apple has a sense of humor" Available at: http://gizmodo.com/5898202/if-you-bought-steve-jobs-one-last-thing-youll-like-hitler-a-career-says-itunes-genius; Posted by Jesus Diaz on 4/1/12 (accessed on 3 April 2012)
Privacy	"Did you not read the 'Genius' agreement? Apple collects a list of music content but it does not collect the information that would link it to an identity" Available at: comp.sys.mac.system/; Posted by Davoud on 9/10/08 (accessed on 29 March 2011)	"[. . .] i had a friend who download music from torrent never been caught but when he turn it the Guinness bar on about a week later his isp email him saying that some company reported that he has download nusic of torrent site and they would not apriciate it if does that again" Available at: www.ifans.com/forums/threads/genius-piracy-detection.97237/; Posted by jaywurld on 5/6/10 (accessed on 7 April 2012)
Redundancy	N.A.	"I also wish that it would stop recommending other editions of things that I already own" Available at: http://arstechnica.com/civis/viewtopic.php?f=2&t=20840; Posted by Chicago Burbs on 2/26/10 (accessed on 18 March 2012)
Sub-accounts	N.A.	"I just wish there was a way to segregate my wife's recommendations and likes from mine. She spends considerably more time with Netflix than I do, so whenever I go to look for something the recommendations and estimated ratings aren't exactly in line with my tastes" Available at: http://arstechnica.com/civis/viewtopic.php?f=23&t=1146591; Posted by Chris FOM on 6/4/11 (accessed on 15 February 2012)
Availability	"IIRC, John Siracusa was complaining a lot at the beginning of Genius that the feature would be useless for collections that weren't mostly iTMS purchases, and this has not been the case at all" Available at: http://musicmachinery.com/2011/05/14/how-good-is-googles-instant-mix/; Posted by Zachary Pennington on 5/17/11 (accessed on 29 March 2012)	"Alas, Genius still has no recommendations for my new copy of Taylor Swift's 'Speak Now,' which I confess I did buy from Amazon MP3 instead of iTunes" Available at: http://forums.macrumors.com/showthread.php?t=1041524 Posted by 6502a on 11/1/10 (accessed on 29 March 2012)

Journal of Services Marketing
Volume 28 · Number 5 · 2014 · 414–427

Table III Classification of critical satisfaction/dissatisfaction incidents

Categories of (dis)satisfaction sources	*N* (%) of satisfaction incidents	*N* (%) of dissatisfaction incidents	*N* (%) of critical incidents
Accuracy	29 (11.7)	30 (7.5)	59 (9.1)
Discovery	52 (21.0)	34 (8.5)	86 (13.2)
Convincing connection	14 (5.6)	53 (13.2)	67 (10.3)
Algorithm	43 (17.3)	63 (15.7)	106 (16.3)
Voluntary participation	23 (9.3)	10 (2.5)	33 (5.1)
User control	12 (4.8)	16 (4.0)	28 (4.3)
Sales motive	11 (4.4)	34 (8.5)	45 (6.9)
Product knowledge	9 (3.6)	32 (8.0)	41 (6.3)
Customer knowledge	15 (6.0)	33 (8.2)	48 (7.4)
Propriety	0 (0.0)	15 (3.7)	15 (2.3)
Privacy	35 (14.1)	31 (7.7)	66 (10.2)
Redundancy	0 (0.0)	20 (5.0)	20 (3.1)
Sub-accounts	0 (0.0)	22 (5.5)	22 (3.4)
Availability	1 (0.0)	7 (1.7)	8 (1.2)
Other	4 (1.6)	2 (0.4)	6 (0.9)
Total	248 (100)	402 (100)	650 (100)

In contrast, 73.4 per cent of satisfaction incidents are related to *discovery* (recommendations help the customer discover valuable items he/she would not find otherwise), *algorithm* (the recommendation algorithm is perceived to be superior), *privacy* (the system does not violate the customer's privacy), *accuracy* (recommendations closely match the customer's preference) and *voluntary participation* (the customer enjoys participation). Satisfaction incidents are dominant when it comes to *voluntary participation*, *discovery* and *privacy*.

Customer expectations by category

Included in Table V is customer expectation for each category of incidents.

Patterns or commonalities in customer expectations would naturally emerge as the classification scheme was developed. In the process of understanding and articulating customer expectations, I also attempted to illustrate customer expectations with typical instances (satisfaction vs dissatisfaction) and, when possible, explore the conditions under which these expectations are likely to occur. For example, for the *discovery* category, customer expectation is illustrated with the question: "Do recommendations help me find valuable items I would not find otherwise?" Typical instances exemplify moments of satisfaction or dissatisfaction:

> The customer will be satisfied if recommendations are related to his/her interest, offering variety in recommendations or even challenging him/her, in order to find great things to enjoy. The customer would be dissatisfied if recommendations are repetitive – "more of the same things", "over and over again" – thus failing to help him/her find great things to enjoy.

When it is possible, I also suggest the condition under which the expectation is likely to arise: "When a customer has an interest to be further defined through exploration".

For all other categories, see Table V.

Emerging themes and research propositions

The research also attempts to identify more abstract, higher-level themes across categories of incidents and to develop tentative propositions for future research. When Table V is closely examined, three pairs of themes seem to emerge from the 14 categorized sources of (dis)satisfaction

Table IV Rankings of critical incident categories

Top satisfying categories (by per cent in all satisfaction incidents):
1. Discovery: 21.0
2. Algorithm: 17.3
3. Privacy: 14.1
4. Accuracy: 11.7
5. Voluntary participation: 9.3

In total: 73.4

Top winning categories (by per cent of satisfaction incidents within a category):
1. Voluntary participation: 23/33 = 69.7
2. Discovery: 52/86 = 60.5
3. Privacy: 35/66 = 53.0

Most discussed categories (by per cent of all critical incidents):
1. Algorithm: 16.3
2. Discovery: 13.2
3. Convincing connection: 10.3
4. Privacy: 10.2
5. Accuracy: 9.1
6. Customer knowledge: 7.4
7. Sales motive: 6.9
8. Product knowledge: 6.3

In total: 79.6

Top dissatisfying categories (by per cent in all dissatisfaction incidents):
1. Algorithm: 15.7
2. Convincing connection: 13.2
3. Discovery: 8.5
4. Sales motive 8.5
5. Customer knowledge: 8.2
6. Product knowledge: 8.0
7. Privacy: 7.7
8. Accuracy: 7.5

In total: 77.3

Top losing categories (by per cent of dissatisfaction incidents within a category):
1. Sub-accounts: 22/22 = 100.0
2. Redundancy: 20/20 = 100.0
3. Propriety: 15/15 = 100.0
4. Availability: 7/8 = 87.5
5. Convincing connection: 53/67 = 79.1
6. Product knowledge: 32/41 = 78.0
7. Sales motive: 34/45 = 75.6
8. Customer knowledge: 33/48 = 68.8

Journal of Services Marketing
Volume 28 · Number 5 · 2014 · 414–427

Table V Customer expectations by category

Customer expectation by category	Typical instances	Condition under which the expectation is likely to arise
Accuracy: "Do recommendations match my preference?"	A recommendation being accurate ("right on ") results in satisfaction, whereas a recommendation being inaccurate ("way off ") results in dissatisfaction. Dissatisfaction will be worse if a recommendation is something the customer obviously dislikes ("the opposite ")	When a customer knows clearly what s/he wants, or when, where, how and at what price s/he wants it
Discovery: "Do recommendations help me find valuable items I would not find otherwise?"	The customer will be satisfied if recommendations are related to his/her interest, offering variety in recommendations or even challenging him/her, in order to find great things to enjoy. The customer would be dissatisfied if recommendations are repetitive–"more of the same things", "over and over again"–thus failing to help him/her find great things to enjoy	When a customer has an interest to be further defined through exploration
Convincing Connection: "Are recommendations connected to my preference in a convincing manner?"	The customer will be satisfied if there is a convincing connection between the recommendation and his/her previous purchases or interests. For example, recommending accessory items or items often purchased together is considered helpful and good service ("in case I forget"). The customer will be dissatisfied if the connection is perceived as unconvincing, hard to understand or even funny	When a customer lacks the technology savvy about recommendation agents
Algorithm: "Is the recommendation algorithm superior or inferior?"	Satisfaction results from perceived superiority (e.g. if the company adopts a customer-centered approach in learning customer preferences–inferring preferences from the customer's ratings, reviews or using data integrated across multiple venues where customer preferences are revealed — and is able to present a true picture of the customer). Dissatisfaction results from perceived inferiority (e.g. if the company adopts a company-centered approach–inferring preferences solely from the company's internal data such as search and purchase, whereas the customer also purchases in other places–thus have a fragmented picture of the customer)	When the customer has the technology savvy about recommendation agents
Voluntary participation: "Can I participate if I choose to?"	The customer will be satisfied if he/she has fun in participating (e.g. "it was fun"), can claim ownership (e.g. "I have rated 3000 movies") or claim achievement (e.g. "my time investment was worth it") through participation. The customer will be dissatisfied if he/she finds participation requirement to be more than he/she is willing to commit and is thus "time-consuming", "effortful", "burdensome" or "not worth it"	N.A.
User control: "Do I have some control over which recommendations to receive or not to receive?"	The customer will be satisfied if he/she has some degree of control over what types of recommendations to receive or not to receive, and to be able to take actions to correct dissatisfactory recommendations by providing feedback (e.g. "I own it", "Don't use this for future recommendations", "Not interested")	N.A.
Sales motive: "Does the company only make recommendations out of self-interested motives?"	The customer will be satisfied if the company makes recommendations based on his/her preferences, rather than only out of self-interested motives (e.g. to get sales, to manage inventories)	N.A.

(*continued*)

Table V

Customer expectation by category	Typical instances	Condition under which the expectation is likely to arise
Product knowledge: "Does the company have specialized knowledge in the products it recommends?"	The customer will be satisfied if they perceive a company as knowledgeable–trustworthy because it knows the stuff it recommends ("expert in these products "). The customer will be dissatisfied if the company is perceived as not knowledgeable ("not even knowing the stuff it recommends")	N.A.
Customer knowledge: "Does the company have knowledge of the customer when making recommendations?"	The customer will be satisfied if the company has good knowledge of his/her preferences when making recommendations. The customer will be dissatisfied if the company makes recommendations based on superficial understanding of the customer or makes stupid assumptions of the customer (e.g. in the cases of gift purchases, textbook purchases, random purchases, using other people's computers)	N.A.
Propriety: "Do recommendations violate social norms?"	The customer will be dissatisfied if a recommendation is found to be inappropriate, offensive, personally embarrassing or insulting to the customer's personal identity	N.A.
Privacy: "Does the system violate my privacy?"	The customer will be satisfied if his/her privacy (e.g. personally identifiable information) is secure with the company when using its recommender system. Dissatisfaction occurs if he/she has privacy concerns and feels insecure interacting with the company via its recommender system	N.A.
Redundancy: "Does the system make redundant recommendations?"	The customer will be dissatisfied if he/she receives redundant recommendations. Examples include: a customer who already owns an iPod gets recommended another iPod; a customer who has purchased a paperback copy of the book gets recommended a hardcover copy; a customer who has a particular song from Album A gets recommended that same song from Album B	N.A.
Sub-accounts: "Does the system separate the preference profiles of users sharing the account?"	The customer will be dissatisfied if his/her personal profile or preferences are mixed with those of others who shared the same account, messing up with otherwise personalized recommendations	N.A.
Availability: "Does the system have recommendations available for me when I need them?"	The customer will be dissatisfied if recommendations, when sought, are not available	N.A.

based on the overall directions of focal customer expectations in each category (Table VI).

Theme Pair 1: decision outcome versus decision process

Consumer decision-making may be understood in terms of two aspects: decision outcome and decision process. Among the categories of the classification scheme, *accuracy* (the expectation that recommendations should match the customer's preference) and *discovery* (the expectation that recommendations should help the customer find valuable items he/she would not find otherwise) seem to be directed at the *outcome* aspect (i.e. what recommendations to receive). In contrast, *convincing connection* (the expectation that recommendations should be connected to the customer's preference in a convincing manner) and *algorithm* (the expectation that the recommendation algorithm should be superior) seem to be directed at the *process* aspect (i.e. how to relate recommendations to customer preference).

Theme Pair 2: customer's role versus marketer's role

Response to recommendation systems seems to be inherently relational, as customers expect ongoing support in many upcoming (rather than one isolated) decision tasks. For example, customers participate now (e.g. by writing many reviews and rating many items) in anticipation of receiving quality recommendations in the future. If customers take a transactional approach to using recommender systems, they should provide preference information only when required for the current decision task and should have this preference information deleted when the decision task is completed. Although customers may take a transactional approach, my research found that this is not the case for customers who use recommender systems. The relational nature is more clearly evident in Theme Pair 2 (defining the roles of relationship partners) and Theme Pair 3 (articulating norms in the relationship) than in Theme Pair 1.

Table VI Emergent themes for personalized marketing

Emergent themes	Categories of (dis)satisfaction sources
Pair 1	
Decision outcome	Accuracy: "Do recommendations match my preference?"
	Discovery: "Do recommendations help me find valuable items I would not find otherwise?"
Decision process	Convincing Connection: "Are recommendations connected to my preference in a convincing manner?"
	Algorithm: "Is the recommendation algorithm superior or inferior?"
Pair 2	
Customer's role	Voluntary participation: "Can I participate if I choose to?"
	User control: "Do I have control over which recommendations to receive or not to receive?"
Marketer's role	Sales motive: "Does the company only make recommendations out of self-interested motives?"
	Product knowledge: "Does the company have specialized knowledge in the products it recommends?"
	Customer knowledge: "Does the company have knowledge of the customer when making recommendations?"
Pair 3	
Social norm	Propriety: "Do recommendations violate social or relational norms?"
	Privacy: "Does the system violate my privacy?"
Technology	Redundancy: "Does the system make redundant recommendations? "
	Sub-accounts: "Does the system separate the preference profiles of users sharing the account?"
	Availability: "Does the system have recommendations available for me when I need them?"

Among the categories, *voluntary participation* (the expectation that the customer should be able to participate if he/she chooses to) and *user control* (the expectation that the customer should have control over which recommendations to receive or not to receive) seem to be defining the *customer's role* in the recommendation service. On the other hand, *sales motive* (the expectation that the company should not make recommendations only out of self-interested motives), *product knowledge* (the expectation that the company have specialized knowledge in the products it recommends) and *customer knowledge* (the expectation that the company have knowledge of the customer when making recommendations) seem to pertain to the *marketer's role* in the recommendation service.

Theme Pair 3: social norm versus technology

As discussed above, Theme Pair 3 pertains to the social norms in this relationship even though it is completely technology-mediated. Among the categories, *propriety* (the expectation that recommendations should respect social norms) and *privacy* (the expectation that the system should respect the customer's privacy) seem to indicate that social norms should be respected, whereas *redundancy* (the expectation that the system should not make redundant recommendations), *sub-accounts* (the expectation that the system separate the preference profiles of users sharing the account) and *availability* (the expectation that the system should have recommendations available when needed) seem to be instances violating expectations regarding *technical* functioning.

Research propositions

The distinction between outcome expectations and process expectations as outlined in Theme Pair 1 suggests how recommendation agents could add value through personalization. Regarding the outcome aspect of decisions, customers will expect *accuracy* and *discovery* as recommendation benefits depending on their preference development:

P1a. Customers who have well-defined, stable preferences and good knowledge into their own preferences will expect accuracy benefit in recommendation outcomes.

P1b. Customers who do not have well-defined preferences and who clearly know their lack of well-defined preferences will expect discovery benefit in recommendation outcomes.

When it comes to the process aspect of decisions, customers will expect *algorithm* and *convincing connection* as recommendation benefits depending on their technology savvy about recommendation agents:

P2a. Customers who have the technology savvy about recommendation agents will expect algorithm benefit in recommendation process.

P2b. Customers who do not have the technology savvy about recommendation agents will expect convincing connection benefit in recommendation process.

Theme Pairs 2 and 3 jointly indicate that customers use recommendation agents in a relational manner, as they define roles of the service firm and the customer as relationship partners and expect the relationship to be governed by not only technical functionality but also by social norms:

P3a. Customers who use recommendation agents are committed to the learning relationship with the service firms.

What, then, is a primary motivation for customers to remain in such a learning relationship with the service firms? Customer expectations for *accuracy* and *discovery* (as outlined in *P1a* and *P1b* above) seem to suggest that customers who use recommendation agents may have an underlying motivation. That is, they have a subjective belief in their true preferences

Journal of Services Marketing
Volume 28 · Number 5 · 2014 · 414–427

that can be learned (if overt to themselves) or discovered (if hidden from themselves) with the aid of recommendation agents. Without recognizing such a motivation, their relational behaviors toward recommendation systems would be difficult to understand:

P3b. Customers who use recommendation agents are motivated by a subjective belief in their true preferences, regardless of whether preferences are overt to, or hidden from, themselves.

Discussion

This paper is an exploratory study of customers' "lived" experiences of commercial recommendation services. The critical incident technique was used to analyze 650 critical incidents collected from 358 online group discussion participants and bloggers. A classification scheme with 15 categories was developed, and all incidents were sorted into a category in the scheme. Categories in the classification scheme are illustrated with satisfactory incidents and dissatisfactory incidents. Each category (except the "other" category) is further defined in terms of an underlying customer expectation, typical instances of satisfaction and dissatisfaction and, when possible, conditions under which customers are likely to have such an expectation. Three pairs of themes emerged from the classification scheme. Tentative research propositions were introduced regarding how personalization with recommendation agents can create value to customers, whether and when customers are motivated to maintain a learning relationship with the service firm. Next, I will discuss the managerial and research implications of findings in this research.

Managerial implications

The research findings reported above may have useful implications for the development of recommendation algorithms. To enhance recommendation performance, much attention has been dedicated to finding the best prediction models (Ansari *et al.*, 2000; Gershoff and West, 1998; Iacobucci *et al.*, 2000) or methods – content-based filtering, collaborative filtering or hybrid methods – for making recommendations (Adomavicius and Tuzhilin, 2005; Linden *et al.*, 2003). While algorithm developers often delve deeply into data to spot patterns and have explored such topics as filtering methods, data scalability and recommendation stability (Adomavicius and Tuzhilin, 2005; Adomavicius and Zhang, 2012; Linden *et al.*, 2003), they tend to devote much less effort to finding out how customers think or feel when they use recommendation systems. This research suggests that these might be gaps of knowledge in the state-of-the-art in algorithm development and that customer perspectives should be incorporated to supplement the data-focused approach.

The higher proportion of dissatisfaction incidents (61.8 per cent of all incidents) suggests that more effort should be made to improve the overall customer experiences of agent recommendations. The most discussed categories, the top dissatisfying categories and the top losing categories point to some of the priorities for improvement. For example, the eight top dissatisfying categories are also the most discussed categories: *algorithm* (recommendation algorithms perceived as inferior), *convincing connection* (recommendations not connected to preference in a convincing manner), *discovery* (recommendations not helping the customer find valuable items), *sales motive* (the company only makes recommendations out of self-interested motive), *customer knowledge* (recommendations indicate that the company has poor knowledge of the customer), *product knowledge* (recommendations indicate that the company has poor knowledge of the products it recommends), *privacy* (the recommendation system is a violation of privacy) and *accuracy* (recommendations do not match the customer's preference). Among them, *convincing connection*, *product knowledge*, *sales motive* and *customer knowledge* are predominantly losing categories and may be considered the weakest links in recommendation services. These major gaps from the customers' perspective deserve the serious attention of algorithm development teams.

This research also adds new insights to how to incorporate customer perspectives in making recommendations. Providing explanations why the system recommends the suggested items (e.g. "We recommend this item because you like X") is an attempt to make the algorithm more "transparent" and to increase customer satisfaction and acceptance (Kramer, 2007; Pu *et al.*, 2012). However, although "explanations" may make the recommendation logic more "transparent", this research finds that they are not enough, particularly when customers lack the technology savvy about recommendation agents. What is needed is a *convincing connection* between the recommended item and previously revealed preference (as outlined in *P2a* and *P2b*). For example, recommending accessory items or items often purchased together is considered convincing. In contrast, unconvincing recommendations are often weird or difficult to understand, even if the recommendation algorithm is clearly transparent. For example, in Table II, the customer was dissatisfied by the recommendation of "The A Team" by Ed Sheeran based on liking of Elliott Smith because, according to the customer, their music styles should not go along together. Similarly, while there has been discussion on trust of recommendation agents (Komiak and Benbasat, 2006; Lam *et al.*, 2006), *product knowledge*, *sales motive* and *customer knowledge* have not been identified as possible antecedents of customer trust. Apparently, algorithm developers could benefit from a better understanding of customer expectations to deliver customer satisfaction and reduce customer dissatisfaction.

The research findings may also have implications for service firms hoping to be more adaptive in deploying recommendation systems as a core part of their competitive strategy. For example, service firms may use the categories in the classification scheme as a basis to develop a more comprehensive checklist to assess the performance of their overall personalized marketing effort based on the perception of customers. This research suggests that customer expectations should be inherently relational in that roles are being defined for relationship partners (Theme Pair 2) and norms are being articulated for the relationship (Theme Pair 3). When a recommender system is deployed as a personalized marketing tool, its performance is not just quality of recommendations as a consumer decision support – something that can be left to the discretion of the algorithm team. Rather, its performance should be a marketing management concern and should be assessed more comprehensively in terms of how effective the recommender system is as a marketing tool.

Research implications

By exploring customers' "lived" experiences of personalized recommendations, academic researchers may find a new angle – the customer's perspective – to examine theories of personalized marketing and to gain more nuanced understanding of preference learning and preference construction with the aid of recommendation agents. Previous research suggests that customers often do not have hidden or overt preferences that marketers can reveal by building a learning relationship. The extent to which customers can benefit from personalized recommendations (i.e. their satisfaction) should depend on:

- their preference development, i.e. whether they have well-defined and reasonably stable preference for marketers to learn; and
- their preference insight, i.e. whether they know their preference so that they can recognize and appreciate that recommendations are based on their revealed preference (Kramer, 2007; Simonson, 2005).

By taking the customer's perspective, this research contributes original insights into these issues fundamental to personalized marketing.

First, in terms of preference development and preference insight, which type(s) of customers should be more satisfied with personalized recommendations? Presumably, they should be customers who have well-defined and reasonably stable preferences and have good insight into their own preferences, e.g. customers who love Merlot wines and know their love for Merlot wines (Simonson, 2005). In this research, customer expectations for *accuracy* and *discovery* in recommendation outcomes seem to have an underlying logic in customer expectations (Table V) that provides only partial support for this reasoning. Consistent with previous research, customers who expect *accuracy* in recommendation outcomes tend to be those with well-defined, stable preferences and good knowledge into their own (overt) preferences as well. In contrast with previous research, however, customers who expect *discovery* in recommendation outcomes tend to be those who do not have well-defined (overt) preferences, who clearly know that they do not have well-defined (overt) preferences but who, nevertheless, believe that they have (hidden) preferences that can be discovered through self-exploration and with help from the recommendation agent. Although customers who expect *discovery* may look similar to Group 2 (customers who have poorly defined and unstable preferences and who know that they have poorly defined and unstable preferences) discussed in previous research (Simonson, 2005), they are actually different in that they believe that they have true (albeit hidden from themselves) preferences. This distinction can be found in *P1a* and *P1b*.

Second, previous research (Simonson, 2005) suggests that customers, regardless of their preference development and preference insight, may be unwilling to commit to a learning relationship with the recommendation agent for the following reasons. Customers with well-defined preference and good knowledge of their preference may be less dependent on the recommendation agent. On the other hand, customers with poorly defined preference or poor knowledge of their preference may get little benefit from using recommendation agents. In this research, customers seem to be able to stay fairly committed to a learning relationship with the recommendation agent, as outlined in *P3a* and evidenced particularly in emerging Theme Pairs 2 and 3 (Table VI). For instance, in Theme Pair 2, customers define roles as relationship partners, are willing to participate, hoping to take some control, expecting the relationship partner (the service firm) to be knowledgeable about the customer, to be more knowledgeable about the products it recommends and not to be driven only by sales motives. Similarly, in Theme Pair 3, customers articulate that the relationship should not only be governed by technical functionality but also by social norms involving propriety and respect for privacy. As indicated in the outcome benefits in Theme Pair 1, customers expect *accuracy* benefit or *discovery* benefit depending on their preference development. Customers seem to have a subjective belief in true preferences so that they should be able to benefit from personalized recommendations regardless of whether their preferences are overt to or hidden from themselves. This intuitively held belief might provide a primary motivation for customers to maintain a learning relationship with the service firm. Without recognizing such a motivation, relational behaviors in the use of recommendation systems would be difficult to understand. This underlying logic on the part of customers may have interesting implications for preference learning and preference construction. This insight is outlined in *P3b*.

Limitations and future research

Findings from this exploratory research should be regarded as preliminary. Besides, a few other limitations should also be recognized. First, the categorization scheme was developed and verified within one sample only and its content validity should be subject to more verification in future studies. One method that can be used to perform validity check of a classification scheme is to randomly split the sample into two subsets – one for the development of the classification scheme and the other for its confirmation (Gremler, 2004). However, this method is technically challenging to implement in this research because narratives are often situated in discussion contexts (e.g. discussion groups or follow-up comments to Web blog posts). Future studies based on different sets of data may be needed to further verify the validity of the categorization scheme. In addition, the reliability and validity of the categories should be subject to more tests by other researchers in future research. Second, the categorization scheme and its categories were developed in the context of personalized recommendation service. However, personalized marketing is not limited to only making recommendations. It is unclear whether these categories may be usefully extended to other service contexts (e.g. customization of physical products) or interfaces (e.g. mobile devices, GPS devices).

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