

AN APPROACH TO DERIVE USER PREFERENCES FROM MULTIPLE-CHOICE QUESTIONS IN ONLINE REVIEWS

Research in Progress

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Abstract

Digital trace data from social media provide large amounts of information on individuals, their behavior, and their interactions with each other. Social media data have been employed to study personality, social networks, and other phenomena. However, employing social media data for research causes some issues: for example, data have to be transformed to fit analytical methods, and data may have been shaped by the social media information systems through which they were produced. In turn, the ways in which these issues are accounted for significantly affects research results. This study contributes to the methods used to analyze social media data by proposing a method to compute frequency measures on users' preferences (formally comparable to survey items) from answers to multiple-choice questions in online reviews that are repeatedly given by users over time. I evaluate the method by computing travel motivations from online travel reviews and comparing my results to findings on travel motivations obtained through classic surveys. Since both results are very similar, I conclude that my approach is appropriate and should be tested for other domains and datasets. I discuss the limitations of the method and the evaluation and these issues can be alleviated in further research.

Keywords: social media; online reviews; multiple-choice questions; user preferences

1 Introduction

Which information about users/consumers/individuals can be derived from social media, and how can this be done reliably? These and related questions are topics of ongoing research. For example, several approaches have been proposed to derive an individual's personality traits from his or her user profile, status messages, likes, and other types of user-generated content published on Facebook, Twitter, blogs, community sites, and other social media sites (Adali and Golbeck, 2012; Golbeck et al., 2011; Gao et al., 2013; Gou et al., 2014; Lima and de Castro, 2014; Ortigosa et al., 2014). Another example is the application of data from social media sites in the field of social network analysis (SNA) (for an overview and discussion see Howison et al., 2011; Kane et al., 2014).

Social media are—in the broadest meaning of the term—“social interactions built on a multitude of digital media and technologies, which allow users to create and share content and to act collaboratively” (Schoder et al., 2013, p. 10). Social media data are said to document “effective behavior in contrast to stated or postulated behavior” (Schoder et al., 2013, p. 10) and may thus also qualify as “digital trace data” (Howison et al., 2011). They can provide large amounts of information on many individuals, they may systematically document certain human (inter)actions over time, and they are often available inexpensively. Therefore, it seems to be a promising idea to use digital trace data from social media and other information technology (IT)/information systems (IS) products and services to derive insights about individuals, their personalities, and their behavior (including interactions with each other), and doing so is equally interesting for researchers and practitioners (Kaplan and Haenlein, 2010; Kietzmann et al., 2011; King, 2011; Lazer et al., 2009, 2014).

However, several scholars have emphasized, for example, that digital trace data might be biased statistically and semantically in several ways; that data must be processed and interpreted with careful consideration of the context of their creation; and that existing methods, assumptions, concepts, and theories have to be checked for their applicability to digital trace data (Howison et al., 2011; Kane et al., 2014; Ruths and Pfeffer, 2014; Tufekci, 2014).

Hence, the aim of this study is to contribute to the methods used for the analysis of digital trace/social media data by developing a computational method to derive measures of user preferences from answers to multiple-choice (MC) questions in online reviews. Such MC answers are given repeatedly over time in binary coding (e.g., MC answer checked: yes/no/yes/no/no/yes). This structure differs from survey items, which are usually collected at discrete points in time and on scales (e.g., item agreed at +2 on a scale from -3 to +3). Converting the former structure to the latter poses some problems for which I propose a possible solution. I test the method using a dataset of online travel reviews published on a large international online travel community by deriving measures of individuals' travel motivations from MC questions like "Visit was for?" Unlike many other studies that also employ social media data, I also evaluate the method by comparing the results derived from travel reviews to empirical results on travel motivations obtained in another study through classic surveys. Since both results (from online travel reviews and from classic surveys) are very similar, I conclude that the proposed method has some potential and should be further evaluated, for example, on different datasets.

The following literature review introduces the emerging field of research on digital trace/social media data, especially online reviews, and the problems and challenges associated with these data. Section 3 describes the research problem and the proposed method to solve it. Section 4 details the procedure used to evaluate the method, including how the social media sample was constructed, how measures of travel motivations were computed, and how these measures were evaluated against empirical results from Pearce and Lee (2005). The results on travel motivations and evaluation are presented in Section 5. The final section concludes and discusses steps to further evaluate the proposed method.

2 Literature Review

2.1 Social Media Data for Research

Howison and colleagues define digital trace data as "records of activity (trace data) undertaken through an online information system (thus, digital)" (2011, p. 769). Trace data are further described as *found* (as opposed to purposefully created for research), *event-based* (i.e., not summary), and hence *longitudinal* (i.e., created in the course of events over time, not, for example, in surveys) data (Howison et al., 2011, pp. 769–770). They are digital because they "are both produced through and stored by an information system" (Howison et al., 2011, p. 770). Although the definition was originally developed in the context of SNA from digital trace data, it generally pertains to much of the data produced and stored in social media applications and must not be restricted to data that qualifies for SNA. It may include, for example, data from blogs, wikis, content communities (e.g., YouTube), and other forms of social media. Indeed, Kane and colleagues (2014) argue that it may not be appropriate to view social network sites as a specific class of social media site but rather to speak of social media networks that draw upon some features of social media sites.

Social media are only one (though probably the most prominent) of several relatively new sources of "rich" data on humans (King, 2011). Other sources are, for example, ubiquitous smart devices (González et al., 2008), web-based applications (Brockmann et al., 2006), e-mail (Wise, 2014), and similar products and services based on IT and IS. In general, the digitization of everyday life gives rise to countless (big) databases (King, 2011). Hence, digital trace data is also an appropriate term to capture the nature of the even wider array of data that are generally stored in IT-/IS-based (not necessarily online) techno-social systems (Vespignani, 2009) and that are the basis for recent streams of research like "reality mining" (Eagle and Pentland, 2006; Pentland, 2009), "big data analysis" (George et al., 2014), and "computational social science" (Lazer et al., 2009).

However, employing digital trace data—including data from social media and other IT/IS-based products and services—to study human personalities and behavior must be done with care. Ruths and Pfeffer (2014) discuss several ways in which data from social media sites may possibly be subject to biases, which researchers should quantify and account for as much as possible. Howison and colleagues (2011) explain how digital trace data from IS have to be preprocessed and interpreted purposefully and contextually by the researcher in order to be applicable to a research problem and for the researcher to infer insights about investigated phenomena or concepts. Unfortunately, these issues are often neglected (Tufekci, 2014): for example, several studies focus on only one dominant social media site, filter data a dependent variable (e.g., successful hashtag), use absolute measures in the absence of a denominator, over-interpret the meaning of data/measures, or import methods from other fields without discussing their applicability. These and other issues have led to more or less prominent failures in the use of digital trace/social media data (Lazer et al., 2014).

Generally, the fact that data are collected by an IS raises questions as to how the system and its features are used *in practice*, which the researcher has to understand in order to be able to interpret data and results adequately and to study certain phenomena through the lens of digital trace data (Howison et al., 2011; Kane et al., 2014; Tufekci, 2014). Hence, existing concepts, theories, and methods might not be immediately transferable to digital trace data, making it necessary for the researcher to take time to consider whether and how they can (or must) be adapted.

Besides these and other epistemological issues of using digital trace data, several scholars also raise concerns regarding the privacy rights of individuals who are depicted in the data, unequal possibilities for researchers to access and handle complex datasets and methods, and hence the difficulty or even impossibility of reproducing and verifying the findings of earlier studies (boyd and Crawford, 2012; King, 2011; Lazer et al., 2009).

While this study cannot resolve all of the abovementioned issues of the analysis of digital trace data, it responds to some concerns, especially calls for greater methodological transparency and rigor in the analysis of digital trace/social media data (Ruths and Pfeffer, 2014) by proposing a new method for a specific problem and conducting a first evaluation of the method.

2.2 The Case of Online Reviews

There has been great scientific interest in online reviews over the last years. With respect to the creation of reviews, researchers have studied people's motivations to share information through online word of mouth (e.g., through reviews) (Cheung and Lee, 2012; Kang and Schuett, 2013; Munar and Jacobsen, 2014) and their propensity to review very popular versus less popular products (Dellarocas et al., 2010). Research also shows that reviewers and their reviews are influenced (i.e., biased) by earlier/existing reviews of a product or service (Aral, 2014; Ma et al., 2013) and that reviews and ratings differ when done through mobile/non-mobile devices or with more/less time lapse since product or service consumption (Piccoli and Ott, 2014).

When reviews are consumed, different characteristics of the review (e.g., specific emotions expressed, language, rating, or valence) affect its perceived helpfulness (Mudambi and Schuff, 2010; Piccoli and Ott, 2014) and credibility (Cheung et al., 2012; Jensen et al., 2013), the likelihood of being voted as helpful by readers (Kuan et al., 2015), and its impact on conversion rates/sales (Chevalier and Mayzlin, 2006; Ludwig et al., 2013). Compared to product recommendations from the seller, online consumer reviews are perceived to be more affective and trustworthy (especially for experience goods) but less easy to use and useful (especially for search goods) (Benlian et al., 2012). Combining both features (i.e., sellers' product recommendations and consumers' online reviews) increases competition among products, and more central products gain higher sales though a positive and homogeneous set of reviews reduces this effect for less central products (Jabr and Zheng, 2014). Companies should carefully consider the optimal mix of product information from consumers (e.g., reviews) and from sellers (e.g., product attributes) in their marketing communication (Chen and Xie, 2008) because, for example, consumer reviews seem to have a greater impact on consumer decisions for products that are

less popular (Zhu and Zhang, 2010) or brands that are weaker (Ho-Dac et al., 2013). Wittingly or unwittingly, independent hotels with small owners and small management teams already seem to behave accordingly and “push” their online image through fake positive reviews as opposed to branded hotel chains, which tend to avoid such behavior (Mayzlin et al., 2014). Detecting these fake reviews is also a topic of ongoing research (for example, Kugler, 2014).

Some studies investigate techno-social recommender-and-review systems as a whole by assessing, for example, the biasing impact of changing product prices over time on consumers’ perceived value as expressed through reviews and ratings (Li and Hitt, 2010) or—vice versa—the effect reviews have on price competition between firms (Li et al., 2011). However, the impact of these systems goes even farther: they constitute new algorithmic apparatuses of valuation—“transforming user-generated content into ‘trusted advice’” (Orlikowski and Scott, 2014, p. 885)—that are different from traditional formulaic apparatuses of valuation and have repercussions for respective industries, business, and management teams (Jeacle and Carter, 2011; Scott and Orlikowski, 2012; Orlikowski and Scott, 2014).

This study adds to the growing body of work on online reviews by proposing a method to transform answers to MC questions in online reviews to measures formally comparable to scaled survey items. The necessity of doing this depends on the research question. If one is interested in, for example, a customer’s experience with a product, a review would already be summary data (experiences summarized by the customer) and subject to, say, content analysis. However, if one is interested in features of the customer (or the product, seller, etc.) that are expressed through multiple online reviews, it becomes necessary to aggregate data from reviews into summary data in some way. This is a common issue when dealing with digital trace data because data often exist in structures and formats that do not immediately fit analytical methods or research questions (e.g., longitudinal data and cross-sectional methods). Rather, they have to be transformed in some way (see Howison and colleagues (2011) and Kane and colleagues (2014) for detailed discussions in the case of SNA).

3 Proposed Method

For reasons of comprehensibility, I explain the proposed method using the example of online travel reviews, travel motivations, and respective MC questions that are also used for my evaluation of the method. Nevertheless, the method is not specific to the tourism domain and can also be used in other domains. Specifically, I focus on the following three MC questions that users may answer when writing a travel review to an online travel community (all answers are listed in Table 2):

- “Visit was for?” (e.g., “Leisure,” “Quality time with family”)
- “Traveled with?” (e.g., “Solo traveler,” “With friends”)
- “I selected this hotel as a top choice for” (e.g., “Outdoor/adventure,” “Golf”)

A user can answer these questions for every travel review he or she writes. From the multiple answers a user gives over time in each review, the aim is to derive a measure of how important a certain occasion (“Visit was for”), travel companion (“Traveled with”), or hotel feature (“I selected this hotel as a top choice for”) is for this user. These measures are interpreted to reflect travel motivations compared to those obtained, for example, from surveys.

Data on travel reviews (and hence MC questions as part of them) are longitudinal event-based data that require transformation to summary data. This implies some difficulties, which I explain with the resolution presented in my approach. First, one may not simply use absolute numbers on a certain answer to an MC question (e.g., how many times has a user stated that “Visit was for: Quality time with family”) because such numbers will be higher on average for a user who has written more reviews even though that does not necessarily mean that this answer reflects a preference that is more important to this user. In other words, comparing absolute numbers for one answer across multiple

users who have written different numbers of travel reviews ignores the relative importance of this answer to the user. Hence, one should use a relative measure instead of an absolute measure. Specifically, I use the absolute number for a certain answer (to one of the three MC questions) in relation to the user's total number of answers to this MC question.

Second, a user with only a few reviews may not have had the opportunity yet to express his or her preferences on all possible answer options. In this case, relative numbers for those answer options would give them a disproportionately high weight. Consider, for example, two users who have written two and 20 reviews, respectively. The first user may have answered "Quality time with family" once and the second 10 times. The remaining one and 10 times, respectively, go to other answers for the question "Visit was for." In both cases, "Quality time with family" would be measured as 50% important even though the information for the second user is much more significant due to several other answer options to this question that he or she used with a frequency lower than 50%. Conversely, the first user might also have other travel motivations that he or she has not yet expressed through travel reviews. Therefore, I introduce an adjustment factor, which is the number of *distinct* answers a user stated for one question divided by the total number of answer options for this question. The idea behind this adjustment is that the importance of one type of preference is more significant when it is contrasted to many other types than what it would be if it was contrasted to only a few other types.

In formal terms, let x_{iqa_q} be the absolute number of times user i stated answer a_q (e.g., "Quality time with family") to question q (e.g., "Visit was for") from the set of possible answers A_q . Then Equation 1 gives the corresponding relative adjusted frequency measure \hat{x}_{iqa_q} (henceforth only termed frequency measure) for which the first term is the relative frequency and the second is the adjustment term.

$$\hat{x}_{iqa_q} = \frac{x_{iqa_q}}{\sum_{a_q \in A_q} x_{iqa_q}} \times \frac{|\{a_q \in A_q : x_{iqa_q} > 0\}|}{|A_q|} \quad (1)$$

Lastly, since a user cannot state an answer less than zero times, it is very likely that these frequency measures are not normally distributed. Hence, one should investigate the distribution type of the frequency measures and conduct an appropriate transformation to the normal distribution since this is one key prerequisite for many methods in inferential statistics, including t-test for the significance of group differences. One should also consider a z-transformation to the standard normal distribution to make absolute levels of frequency measures for different answers comparable.

For a given set of reviews, the resulting variable measures the average degree to which a user agrees on a specific MC answer below or above the average community user. If reviews cover a specific period, the variable can be interpreted as the user's average agreement to the answer in this period.

4 Evaluation

The basic idea for evaluating the proposed method is to calculate frequency measures for a set of online reviews and MC questions from different users of an online review site and compare the results to findings from classic surveys. If the results from the online reviews and surveys match, there would be strong indications that the method is appropriate. Ideally, the group of users and survey participants would be identical and MC questions and answers would match survey items exactly. However, before putting forth the effort to collect survey data, it is reasonable to use appropriate existing survey results as a first evaluation. I chose online travel reviews for a first evaluation for two reasons. First, there is already a body of literature on online travel reviews to draw from and to relate to (Jeacle and Carter, 2011; O'Mahony and Smyth, 2010; Orlikowski and Scott, 2014; Scott and Orlikowski, 2012). Second, suitable survey results already exist from Pearce and Lee (2005). They developed a paper-based questionnaire comprising 74 items on different travel motivations. In November and December 2000, individuals at Australian shopping centers, express coach terminals, and airport boarding gates were asked

to express the importance of each of the items. Based on the responses from this survey sample, the wide array of items was reduced to 14 latent motive dimensions using principal component analysis. Participants were also asked to indicate their travel experience in terms of domestic and international trips. Based on their results, Pearce and Lee were able to confirm the proposition that travelers with low travel experience are motivated by different travel motivations than travelers with high travel experience. I use these quantitative results on differences in travel motivations due to travel experience as a benchmark.

The evaluation of the proposed method was conducted in three steps. First, based on a large dataset of users and travel reviews from an online travel community, I constructed a sample of users and reviews (“online sample”). Second, for every user in the online sample, I computed frequency measures of the MC answers. Third, I evaluated the proposed method by comparing the results of the frequency measures from the online sample to travel motivations from the survey sample.

4.1 Constructing the Online Sample

The basis for the online sample is a dataset of about 3.87 million users and 7.89 million travel reviews from a large international online travel community collected in 2010. As Ruths and Pfeffer (2014) mention, possible sample biases in social media data should be assessed and accounted for if possible. Accordingly, I restricted users to those who (1) had a fully filled-out user profile (e.g., age, gender, nationality) to be able to assess demographic bias and (2) had written at least 10 reviews (non-business trips; see below). While this number is arbitrary, it is obvious that a minimum number of reviews is required to be able to calculate frequency measures based on travel reviews. From this restricted set of 19,317 users, a random sample of about 10% (1,913 users) was drawn in order to be able to compute significance tests for group differences. See Table 1 for the assessment of demographic bias of the online sample compared to the survey sample.

Sample	N	Age (%) (years)			Gender (%)		Nationality (%)		
		Young	Intermediate	Older	Male	Female	Australia	UK	Other
Survey	940	23.0 (2–24)	58.7 (25–50)	18.3 (> 50)	46.9	53.1	55.8	22.6	21.6
Online	1,913	3.7 (13–24)	72.8 (25–49)	23.5 (> 50)	46.5	53.5	3.9	21.6	74.5

Table 1. Comparison of samples' demographics

Further, only those 36,577 reviews were used that (1) had been written by one of the selected users (otherwise, they could not have been used in the analysis) and (2) indicated an answer other than “business” for the question “Visit was for” because Pearce and Lee only investigated pleasure trips.

4.2 Computing the Variables for Travel Motivation

For every user in the online sample, the proposed method was used to compute frequency measures for each MC answer found in his or her travel reviews. If a user had never used a certain answer at all, this was treated as a missing value. Since the distributions for most of the frequency measures resembled a log-normal distribution, I transformed them to a standard normal distribution first using a natural logarithmic transformation and then a z-transformation. Some MC answers were excluded from further analysis because they either had to do with business trips (“Traveled with: clients/customers” and “I selected this hotel as a top choice for: business meeting/event”) or because they could not be interpreted in a meaningful way (answer “other” for each of the three MC questions), resulting in 27 MC answers for further analysis. These are interpreted as travel motivations of the users in the online sample.

4.3 Evaluation of Differences in Travel Motivations

Pearce and Lee (2005) investigate differences in travel motivations for two different levels of travel experience, namely high versus low. Using information on the date of travel and the country visited extracted from the travel review, I employed the following heuristic to calculate the number of travel events as a proxy for a user's travel experience: a travel review is counted as a travel event only if no other travel review from the same user to the same country and within the same month of the year (e.g., March 2008) has yet been counted. The resulting measure may not match perfectly with users' actual travel experience, but it is arguably a good proxy in the absence of a more sophisticated approach. To construct groups of high and low travel experience, I separated the online sample into two clusters of approximately equal size based on their number of travel events. Then, I assessed differences in the frequency measures between the two clusters using two-sided t-tests for independent samples. To evaluate the approach, I assigned each frequency measure to the semantically most similar travel motivation from Pearce and Lee (2005) and checked whether the direction of the difference was identical—that is, if a motivation is more important to users with more (fewer) travel events, is it also more important for people with higher (lower) travel experience in the survey sample.

5 Results

Table 2 presents (1) the results of comparing users with high and low numbers of travel events (higher mean highlighted bold), (2) the corresponding travel motivation and level of travel experience for which it is more important (Pearce and Lee, 2005), and (3) an indication of whether the results match. For example, I found that the frequency measure for the answer “Honeymoon” to the question “Visit was for” was significantly higher for online travel community users with fewer travel events than for users with many travel events. Compared to travel motivations in Pearce and Lee (2005), “Honeymoon” was closest to “Romance.” Since Pearce and Lee also find that “Romance” (as a travel motivation) is significantly more important to travelers with low travel experience, both findings match.

For 22 out of 27 answers (81.5%), the results match between both samples. Three answers (11.1%) produced results contrary to Pearce and Lee (2005). For two answers, no corresponding travel motivation could be found. Though differences in frequency measures between users with low and high travel experience (i.e., number of travel events) were not always significant, the overall tendency is that differences in motivations according to travel experience derived from MC questions using the proposed approach resemble those from the survey sample quite well.

6 Discussion

I proposed a method to derive measures of user preferences from answers to MC questions in online reviews that are then formally comparable to survey items. The method was then successfully evaluated using a set of online travel reviews and comparing the calculated user preferences (i.e., travel motivations) to existing survey results. I conclude that the method has some potential and should be further evaluated. Other researchers may employ the method in cases for which scaled measures are needed but only longitudinal binary data on MC questions from, for example, a social media dataset are available. Hence, this method adds to the methods to process digital trace data to study human behavior and personality. It can help researchers and practitioners better leverage digital trace data from social media in, for example, automated marketing research (Lee and Bradlow, 2011).

One may argue that the importance of travel motivations also depends, for instance, on the season of the year and that Pearce and Lee's theory should be extended. Nevertheless, this does not affect this study because I compare answers on average levels of importance for travel motivations (from Pearce and Lee) to average levels of importance calculated from longitudinal data on MC questions.

While the survey sample from Pearce and Lee (2005) enabled a first evaluation of the method, their sample is not an ideal benchmark for two reasons. First, while the travel reviews were easily restricted

to pleasure trips, the comparison of both samples' demographics (see Table 1) revealed that there were substantial differences with respect to age and nationality due to differences between the online travel community's user base and the population surveyed by Pearce and Lee. Therefore, further research should either switch to other more similar samples or re-sample from the online travel community population to obtain an online sample that is more similar to the survey sample. Second, since answers to the MC questions and survey items were taken from existing datasets (an existing online travel community and Pearce and Lee (2005)), they are not identical but sometimes ambiguous or semantically overlapping. Future research should compare data from (non-overlapping) MC answers to data from identical survey items. Nevertheless, even for identical surveys conducted in different forms (e.g., online versus paper-based surveys), people may respond differently (Fang et al., 2014). Hence, it may be necessary to combine other source of information on travel motivations in a mixed-method approach (Behrendt et al., 2014).

Answer	Few Travel Events			Many Travel Events			sig.	Corresponding Motivation and Level of Travel Experience for Which This Motivation Is Higher ‡	Match	
	N	Mean	Std. Dev.	N	Mean	Std. Dev.				
Visit was for? (One answer per online travel review at most)										
Leisure	786	-.06	.94	734	.07	1.06	.014	Escape/relax	L ^{ns}	No
Quality time with family	505	.01	.87	590	-.01	1.10	.664	Relationship	L ^{ns}	Yes
Romantic getaway	391	.00	.87	487	.00	1.09	.940	Romance	L	No
Hobbies/interest/culture	294	.08	.92	398	-.06	1.06	.083	Pers. development	L	Yes
Quality time with friends	222	.15	.87	336	-.10	1.07	.002	Relationship	L ^{ns}	Yes
Honeymoon	62	.26	.99	71	-.23	.95	.004	Romance	L	Yes
Personal event	162	.17	.84	270	-.10	1.07	.003	Romance	L	Yes
Traveled with? (One answer per online travel review at most)										
Solo traveler	156	.16	.82	216	-.12	1.10	.006	Isolation	L ^{ns}	Yes
With colleagues	10	.37	.96	27	-.14	1.00	.181	Relationship	L ^{ns}	Yes
With spouse/partner	806	-.10	.82	752	.11	1.16	.000	Romance	L	No
With friends	301	.17	.88	379	-.13	1.07	.000	Relationship	L ^{ns}	Yes
Family with young children	184	.10	.83	187	-.10	1.13	.063	Relationship	L ^{ns}	Yes
Family with teenagers	148	.07	.91	145	-.07	1.08	.261	Relationship	L ^{ns}	Yes
Extended family	237	.21	.91	284	-.18	1.04	.000	Relationship	L ^{ns}	Yes
Large group/tour	57	.45	.84	113	-.23	1.00	.000	Relationship	L ^{ns}	Yes
I selected this hotel as a top choice for? (Multiple answers per online travel review)										
Great food/wine	449	-.06	.89	560	.05	1.08	.069	Host-site involvmt.	H	Yes
Shopping	409	.02	.84	540	-.02	1.10	.534	-	-	-
Outdoor/adventure	447	.14	.85	473	-.13	1.11	.000	Stimulation	L	Yes
Theme/amusement park	145	.21	.90	175	-.18	1.04	.000	Stimulation	L	Yes
Beach/sun	519	.10	.85	588	-.09	1.11	.001	-	-	-
Museums/cultural/hist. sites	560	-.15	.91	628	.13	1.06	.000	Host-site involvmt.	H	Yes
Spa	162	.06	.82	256	-.04	1.10	.285	Escape/relax	L ^{ns}	Yes
Skiing/winter sports	47	.47	.76	67	-.33	1.02	.000	Pers. development	L	Yes
Concerts/music festival	134	.25	.81	209	-.16	1.08	.000	Stimulation	L	Yes
Golf	53	.28	.77	79	-.19	1.09	.004	Pers. development	L	Yes
Gambling/casinos	83	.11	.93	123	-.07	1.04	.200	Stimulation	L	Yes
Sporting event	72	.20	.76	143	-.10	1.09	.018	Stimulation	L	Yes

‡ L: Low, H: High, ^{ns}: Differences not significant in Pearce and Lee (2005)

Table 2. Differences in travel motivations according to travel experience

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