Experience Overijssel

Optimal tourist experience and density in Overijssel via social interaction in the conversational recommender system, Travel With Zoey

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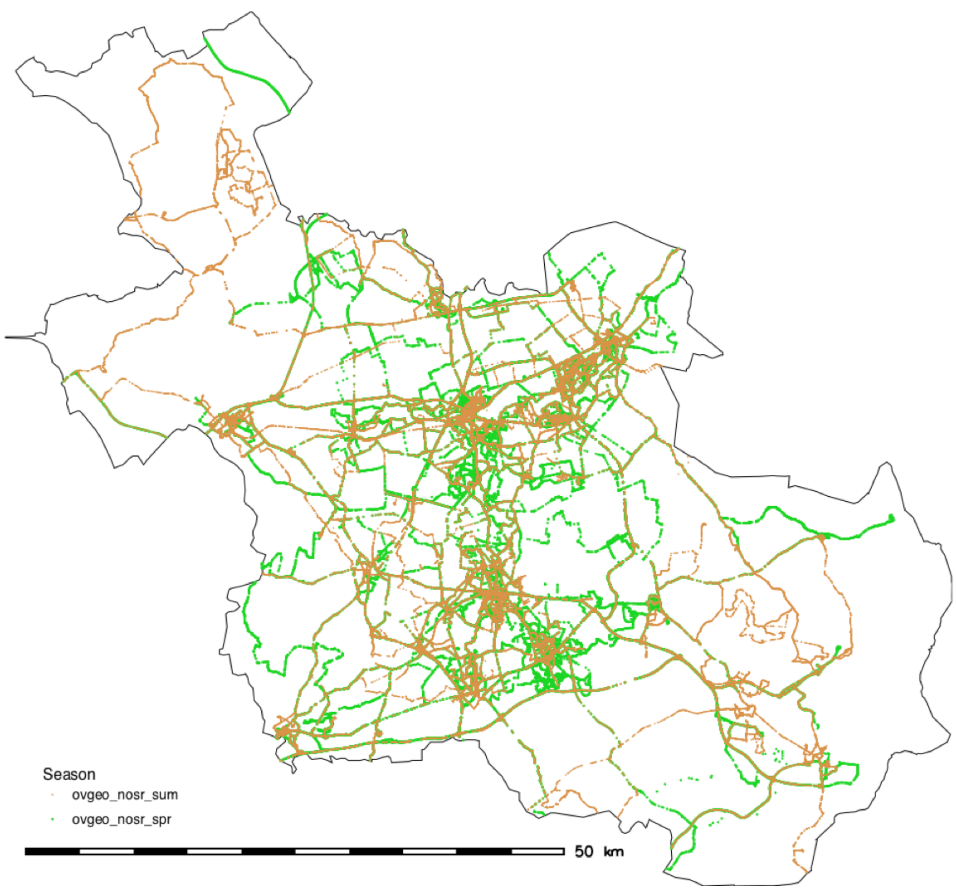

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Summary

Tourists often congregate in just a handful of popular attractions, leaving worthy alternative locations empty. It is assumed that marketing information about which attractions are preferable drives this behavior. We tested this assumption in a field experiment in May, July, and August 2021 in which about 150 visitors across 10 vacation parks in Overijssel reported their experience, quality of life, and evaluation of various parts of their vacation. We collected data before, during, and one week after their vacation. Additionally, participants recorded their location while traveling throughout their vacation using GPS.

Participants were randomly assigned to one of four experimental conditions. A baseline group was asked to download a typical destination marketing app, where a passive map displays attraction tips, with the tips assumed to offer the best experience somehow highlighted (experience-driven). Another group was offered a similar app, but this time with the least-visited locations highlighted (policy-driven). The other two groups were offered a WhatsApp contact to chat with. On the other end of the contact was Travel With Zoey, a conversational recommender system which provides a dialogue with tourists delivering highly personalized destination tips. While initial selection of possible tips is automated, human Travel With Zoey employees customize each message, making customers feel heard and attended to.

There were no significant differences between the four groups in vacation experience, vacation evaluation, or quality of life. There were striking differences between the groups in spatial behavior, however. Compared to users of the passive app with experience-driven tips, all other groups, but especially the two policy-driven groups, were more likely to be present at lesser-known attractions, and less likely to be present at experience-driven attractions. Furthermore, regardless of tips, participants evaluated the conversational recommender system as significantly more personal, more socially present, and more recommendable than the passive app.

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Introduction

A well-known alleged cause of tourist crowding is that information sources, such as guidebooks, review sites, and social media, tend to steer tourists to a relatively small number of attractions. This information provision urging relatively many people to visit relatively small areas leads to overtourism, which is degrading to the tourist experience but preventable. At the same time, other places where tourist could have enjoyable experiences, remain undiscovered and suffer, to some degree, from undertourism. Important in existing visions for restarting/resetting tourism after the pandemic is bringing these under-/and over-visited places more into balance. From the Perspective 2030 we gather the following vision on Tourism in the Netherlands:

> Perspective 2030, the vision for tourism in the Netherlands, is about the changing role of tourism. Heading up to 2030, we expect a 50 percent increase in the number of international tourists. This requires a new approach that prioritises the common interests of visitors, companies and residents. The goal is for every Dutch person to benefit from tourism. Five priorities are central for achieving this ambition:
>
> - Benefits and burdens are in balance, more benefits from tourism than burdens;
> - All of the Netherlands is attractive: put more cities and regions on the map as attractive destinations;
> - Accessible and achievable: easily accessible cities and regions;
> - Sustainability is a must: a living environment with less waste and pollution;
> - A hospitable sector: the Netherlands as a welcoming destination (NBTC, 2019).

The project aimed specifically at the second point—how to inform tourists about lesser-known locations so that they actually visit them, and so that those visits are at least as enjoyable as the visits they would have while less-informed.

Information is provided to tourists in a way that leads to over- and undertourism. New models of information provision to tourists, including recommender systems such as apps and chatbots, have so far not succeeded in changing the situation. Therefore, new policy-driven models of tourist information, as well as hyper-personalized information delivery using conversational recommender systems, have been developed. It is unknown if these are effective in spreading tourists while maintaining or even increasing the quality of the experience. A conversational recommender system is "a software system that supports its users in achieving recommendation goals through a multi-turn dialogue" (Jannach, Manzoor, Cai, & Chen, 2021, p. 2).

Travel With Zoey, a highly personalized conversational recommender system, provides services to customers of ANWB and TUI, among others. Their customers are proactively provided with tips that match their preferences. The service of Travel with Zoey is based on a combination of artificial intelligence and human-to-human interaction, whereby the customers not only receive tips that are personal and customized but also receive these in a WhatsApp conversation that feels 'natural' (as if they are talking to a friend that is giving advice on where to go). The tips come from a digital catalogue, organised in such a way that an optimal match can be made between traveller and content. The tips are proactively offered, but Travel with Zoey also responds to request by the customers themselves, e.g. when they ask Zoey what they can do this afternoon or the next day. Behind the scenes, the delivery of the content is mostly but not fully automated, so that human employees of Travel with Zoey are involved in making each interaction significantly more smooth, natural, and personalized than a chatbot could. There is an emphasis on empathy, wherein Travel with Zoey aims to make customers feel heard and attended to. Finally, any experiences at attractions that customers talk about in their conversation with Zoey are taken by Travel with Zoey employees as input for optimizing future recommendations.

In this project we utilized the conversational model of delivering destination information as an experimental intervention to provide tips to a sub-group of visitor participants in one specific destination, Overijssel. Furthermore, we investigated the effectiveness of prioritizing tips based on the policy of the DMO to direct visitors to certain places while reducing the pressure on others. We were guided by the following question:

Does a conversational recommender system, as exemplified by Travel with Zoey, spatially direct tourists to the places destination managers would like them to go, and how is their vacation experience changed as a result?

Methods

Design

As we wanted to measure the specific and direct effects of conversational recommender systems and the information therein on vacation behaviors and experiences, we used a true experiment with random assignment, like a clinical trial, which is the only research design that supports conclusions about an intervention **causing** a particular outcome (Bryman, 2016; Trochim & Donnelly, 2005). Two independent variables were manipulated: whether participants were invited to use a conversational recommender system or a conventional, passive, non-conversational equivalent app; and whether they received destination information (basically, tips about worthwhile attractions to visit) prioritized for the quality of their experience, or prioritized according to destination management policy, namely emphasizing lesser-visited attractions. Thus, participants were randomly assigned to receive destination information in one of four conditions:

- Experience-driven tips via a conventional passive map app;
- Policy-driven tips via a conventional passive map app;
- Experience-driven tips via a personalized conversation on WhatsApp;
- Policy-driven tips via a personalized conversation over WhatsApp;

The databases of attractions contained the same, approximately 400 tips for the policy-driven as well as experience-driven conditions. However, some of the tips are considered "premium" and have priority. On the passive map-based apps, priority tips were in color, whereas non-priority tips were grey. In the conversational recommender system, priority tips were given priority when multiple tips or responses were possible. A different, mutually exclusive set of attractions was given priority in the experience-driven conditions and in the policy-driven conditions. In the experience-driven conditions, the list of priority attractions was curated by Travel With Zoey on the basis of tourist demand and feedback. In the policy-driven conditions, the list of priority attractions was curated by Marketing Oost on the basis of destination policy, which calls for spreading tourists to less-visited attractions. Only one attraction out of over 400 was given priority in both conditions.

Data collection

We collected data twice, once during May 2021 and once during July and August 2021. Participants were approached based on booking a vacation at one of 10 (spring) or 8 (summer) vacation parks that chose to cooperate with the project. We asked vacation parks to connect us to participants via reservation software which could segment bookings by dates of visit and communicate with the resulting segment by email. Not a lot of reservations tools could do this, but we found out that BookingExperts has this feature. Knowing this, we contacted vacation parks who were using BookingExperts and asked them for permission to email guests coming in May or June. With the vacation parks on board, we send out an email and setup up a mail automation in MailChimp for upcoming bookings. Thus, we could continue to sample as last-minute bookings came in. We subquently created a flow of emails in MailChimp based on events (upcoming dates, completing first survey) for the data collection-related messages to be as timely as possible.

If would-be visitors to these parks agreed to participate, we sent them an intake questionnaire including a statement of informed consent. The intake survey assessed demographics and baseline quality of life. When their vacation was approaching within 5 days, they received email instructions to install a GPS tracking app (Sesamo) as well as installing the correct app (Nienke's Tips / Saar's Tips) or WhatsApp contact for the condition they have been assigned to.

After installing Sesamo, participants also began receiving daily questionnaires measuring their vacation experience. Items included emotions, novelty, social interactions, personal insight, and personal transformation. In the spring data collection, we also included two scales measuring the experience of using either the conversational recommender or the passive app, namely social presence and personalization. Participants could indicate if they were filling out the daily questionnaires on the last day of their vacation, in which case they were also asked to evaluate their vacation with a grade and intent to recommend, and their life satisfaction. These evaluation variables were asked one more time, in a follow-up questionnaire one week later.

Analyses

We analyzed the data in five stages. First, we described the experience and evaluation variables for the sample as a whole. Then, we examined differences on experience and evaluation between the four conditions (experience-driven/passive, policy-driven/passive, experience-driven/conversational, policy-driven/conversational) using conditional group means and one-way analysis of variance. The third and fourth stage of data analysis aimed to assess if participants in different conditions visited different locations.

In the third stage, we processed GPS data by first eliminating any data points not between date of arrival and date of departure or located outside of Overijssel. To analyze spatial patterns of participant distribution we transformed the participant point locations captured by GPS to continuous density representation using bivariate kernel density estimates (Petrasova et al., 2019). The kernel density maps were computed for participants grouped by recommender system conditions and experience-driven and policy-driven conditions. We then mapped differences in kernel densities between recommender system conditions (passive vs. conversational) separately for experience-driven and policy-driven conditions.

The last stage of data analysis involved modeling spatial presence or absence of participants within spatial buffers generated around the attractions (20 meters for point attractions and 100 meters for area-type attractions) as a function of experimental condition. In other words, we modeled the odds that each datapoint collected came from a participant in one of the experimental conditions. Data were nested within participants (as the same people tend to visit the same places, and with GPS, there are always many data points coming from a single person, usually spatially near each other). A multilevel logit model was used. We ran three models with different types of attractions as the outcomes: non-priority attractions,

attractions which had experience-driven priority, and attractions which had policy-driven priority. Finally, we also used these attraction presence variables as predictors of emotions to explore if participants enjoyed their vacation more on days when they spent more time at a specific type of attraction.

The experience-driven passive condition was the reference group for all analyses, meaning all other conditions were always compared to this one, because an experience-driven passive map-based app is the current default option used by many DMO's.

Limitations

When originally planned, the study aimed to collect data from about 1000 participants between 1 April and 1 June of 2021, under the assumption that there would be many advance as well as last minute bookings during this period, and conditions favorable for vacationing, as this is a period with many vacation days in the Dutch school and work calendars. This did not turn out to be the case. Data collection was only possible from 1 May, and attractions as well as restaurants were closed due to COVID-19-related lockdowns. Many people were hoping for some perspective on the situation before booking a vacation. At the last minute, when they might still have booked, the weather turned out to be extremely unfavorable, a genuine outlier in terms of wet and cold. Thus, we ended the spring data collection in mid-June with only about 150 active participants, and only 60 or so who had completed every stage of the research. We thus initiated a second data collection at the end of July and beginning of August, during much more favorable conditions. The only issue with the second data collection, which more than doubled the sample size, is that it could have gone on longer than it did. The sample might then have increased by a handful of participants, and by recording more daily data of participants who were still on vacation.

The vacation parks at which we sampled do not comprise a probability sample of accommodation bookings or of vacation parks in Overijssel. Some vacation parks we approached declined to participate in one or both data collections because their guests already get a lot of email from them. Our continuous email flow was additional to their own emails and could be confusing for the guests. We excluded participants which visited the holiday park with a "jaarplaats." We made this decision consciously, as such visitors know the region well and would therefore not be a target for destination information in practice. More generally, one might ask how representative our sample was of tourists that marketersare hoping to reach with information. Not every tourist will seek out or pay attention to destination information. In that sense, it is likely that the same tourists which downloaded information for an experiment like this one would also download information purely for use during their vacation. The average age of participants reflects the average age of pandemic-era visitors to Overijssel, as well. Nevertheless, we cannot rule out the possibility that participants were different from the population of potential users of destination information. Furthermore, our participants maybe have been different in ways that made them more susceptible to change their behavior in response to the information provided.

The data collection was extremely complex and demanding for a work of field research in tourism, which carries certain advantages and disadvantages. The data are obviously very rich and contain a great depth of possible explanatory variables. Furthermore, they made it possible to combine a postdoc, master theses, and a DDL subsidy, making the project even possible in the first place. However, participant burden was high. The response rate would doubtless have been higher if we did not ask for so many questionnaire response occasions and software installations from each participant. Nevertheless, it seemed worthwhile to us every once in a while to "put everything together" in terms of variables and occasions to measure, and do smaller, more simple studies—perhaps with bigger samples—in between. This project felt like the right moment to "put everything together."

Analyzing a phenomenon as complex as spatial behavior also brings limitations. We chose to use a buffer approach to measure participants' spatial behavior in relation to attraction locations, meaning when data points were within a certain minimum distance of an attraction, we counted them as being "at" that attraction, as a reasonably simple and accurate estimate. It is not a perfect measure however. Every single data point within a buffer does not mean that the participants visited the attraction, just that they were close - they might have been just passing by. Combining buffers with kernel densities or more precisely the per participant time data would address this issue. For area-type attractions the boundary polygons or trails would be needed to get more accurate estimate of the visitors.

Findings

Descriptive statistics

An initial group of 269 participants filled in the recruitment form and intake questionnaire. Random assignment led to a relatively even division across the four experimental groups (experience-driven passive n=71 ; policy-driven passive n=65; experience-driven conversational n=61; policy-driven conversational n=72). Of these, 268 filled in at least one daily questionnaire and 132 filled in a daily questionnaire on the last day of their vacation. The exit questionnaire received 197 responses. The responses between the different questionnaires presented to each participant do not overlap fully. The sample as measured by the intake questionnaire was over three-quarters female (76%) with a mean age of 44 years (sd = 11 years). A large majority went on vacation with either their partner (14%) or family (79%). The average age fits almost exactly with previous national research on visitors to Overijssel. Previous research also shows that relatively even proportions of men and women visit Overijssel, however. The current sample therefore does not reflect the population in gender.

Participants generally enjoyed their vacations, the destination, and the recommender system. On average participants graded their vacation with a 7.77 (sd = 1.25) and were quite likely to recommend their vacation park (mean = 8.10, sd = 1.67) and Overijssel (mean = 8.38, sd = 1.15). They were also mildly positive about the technology used to recommend tips (mean = 6.08, sd = 2.71). Average daily positive emotions were approximately normally distributed, with a mean of 3.19 on a 5-point scale (sd = 0.58). Negative emotions were extremely positively skewed, as usual for tourism datasets, with very few participants reporting much of any negative emotion at all (mean = 1.31, sd = 0.28).

Differences between groups

There were remarkably few differences in experiences and outcomes between groups. The groups were statistically similar in positive emotions on vacation, overall grade of vacation, life satisfaction, positive feelings in daily life, intent to recommend Overijssel, and intent to recommend their accommodation. There were modest differences in negative emotions on vacation, with conversational recommender users experiencing about 0.1 lower negative emotions on a 5 point scale, and negative feelings in life in general a week after vacation, which were 0.1 lower for passive app users which had received policy-driven tips. A somewhat larger difference was in the experience of novelty, which was 0.4 on a 5-point scale higher for experience-driven conversational recommender users, though not for policy-driven users. This is intriguing as it seems likely that policy-driven tips are to less familiar, thus more novel, attractions.

There were large differences between groups in evaluations of recommender systems. The passive app with either kind of tips earned about a 5 on the last day of vacation and 5.5 one week later (11 point scale ranging from 0 to 10). The conversational recommender, on the other hand, earned a a 6.7 (experience-driven) to 7.3 (policy-driven) on the last day of vacation and 7.8 (experience-driven) to 7.1 (policy-driven) one week later. It is intriguing that there were differences between experience-driven and policy-driven information here, and that these differences were in opposite directions when comparing the last-day and week-later surveys. Differences between tourists' experiences aggregated by recommender system are summarized in Table 1.

Table 1. Differences in recommender systems

	Scale	Passive	Conversational
Positive emotions on vacation	1-5	3.15	3.24
Negative emotions on vacation	1-5	1.31	1.27
Intent to recommend Overijssel	0-10	8.32	8.55
Intent to recommend vacation park	0-10	8.17	8.05
Intent to recommend the recommender system	**0-10**	**4.83****	**7.00****
Life Satisfaction	1-7	5.68	5.83
Personalization*	**1-5**	**2.86****	**3.52****
Social presence*	**1-10**	**3.46****	**7.23****
Intent to recommend Overijssel after 1 week	0-10	8.34	8.42
Intent to recommend vacation park after 1 week	0-10	8.38	8.17
Intent to recommend the recommender system after 1 week	**0-10**	**5.58****	**7.54****
Life Satisfaction after 1 week	1-7	5.60	5.83

** On these variable, statisically significant differences between groups were unlikely to occur by chance.

* Based only on the May data.

In the spring data we also measured two alleged mechanisms by which the conversational recommender system is favored to a passive app: personalization and social presence. Here also there were substantial differences, with the conversational recommender system scoring 1.48 higher on personalization on a 5-point scale, and 3.68 higher on social presence on a 5-point scale. These findings are further discussed in the Master of Science in Leisure and Tourism theses of Liselotte de Graaf and Koen Verstraten, respectively (Appendices). Personal insight and personal transformation data are not included in this report but available in the presentation to the 7 Experiences Summit of 2021 (Appendices).

Spatial distribution between groups

As a whole, participants were most present near the vacation parks, but spread out over the entire province of Overijssel, including all its major cities and motorways as well as side roads. Maps, and subsequent spatial analyses, are based on data from the 6 campings that had at least 10 participants per experimental group. On a map showing locations visited by at least one participant from each group (Figure 1), it is evident that all groups were present on roads around the campings, as well as between the campings and Enschede. Meanwhile the most visited areas (highest kernel densities of data points) are concentrated around the campings, Deventer, and Zwolle (Figure 2).

Figure 1. Locations visited by at least one participant from all four groups.

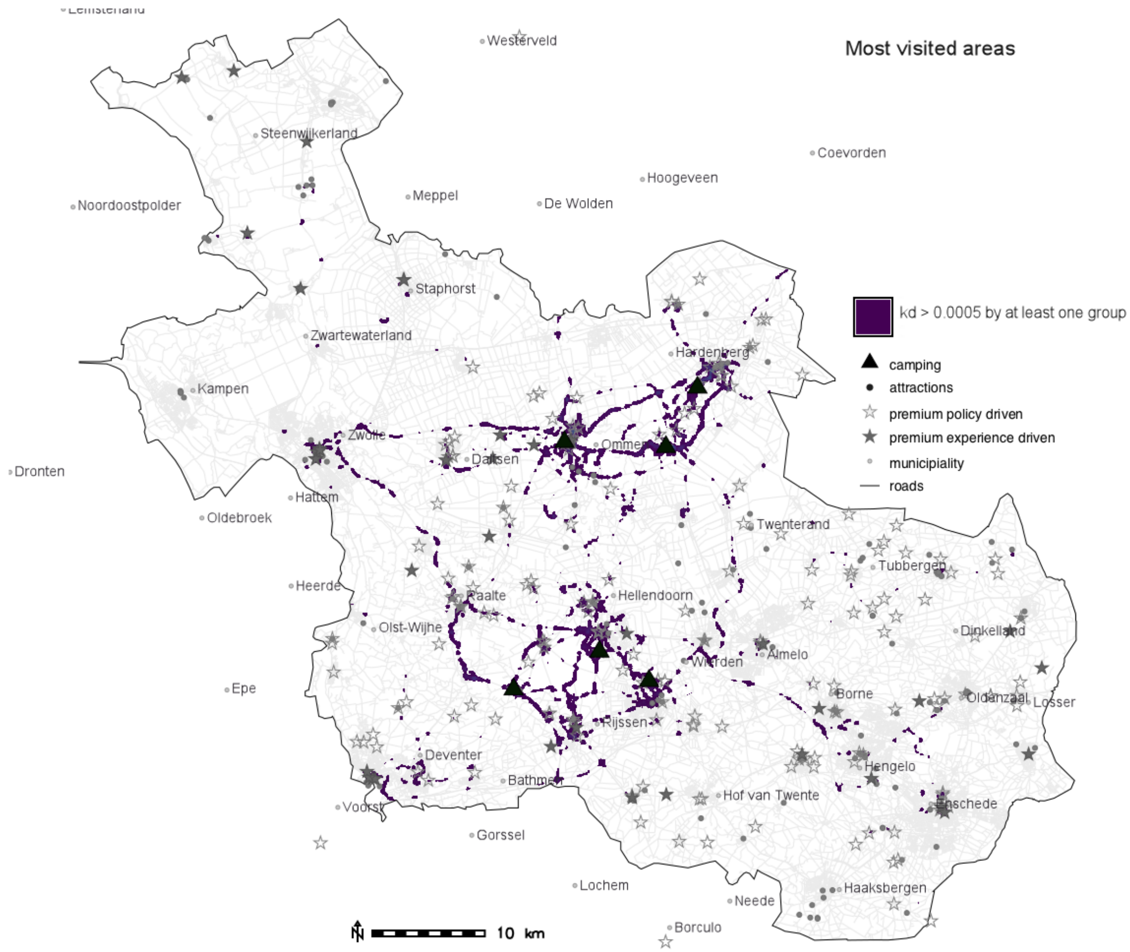

Figure 2. Most visited locations.

Unlike differences in reported experience and evaluations, the differences between groups in terms of where they went were rather dramatic. We also made maps showing locations where only one of the four groups was present (Figures 3 and 4). Patterns here are difficult to discern, but there are substantial segments of provincial roads around Zwolle, Kampen, Staphorst, Tubbergen, and Enschede that were only visited by a single group. This points to different groups aiming at different attractions. Furthermore, descriptive statistics show that the different groups covered different proportions of the geographic area of Overijssel. While experience-driven passive and policy-driven conversational groups visited about two-thirds of visited areas (and thus, 16% of the total area of Overijssel), the policy-driven passive group visited only one-third (and thus only 9% of Overijssel; Table 2).

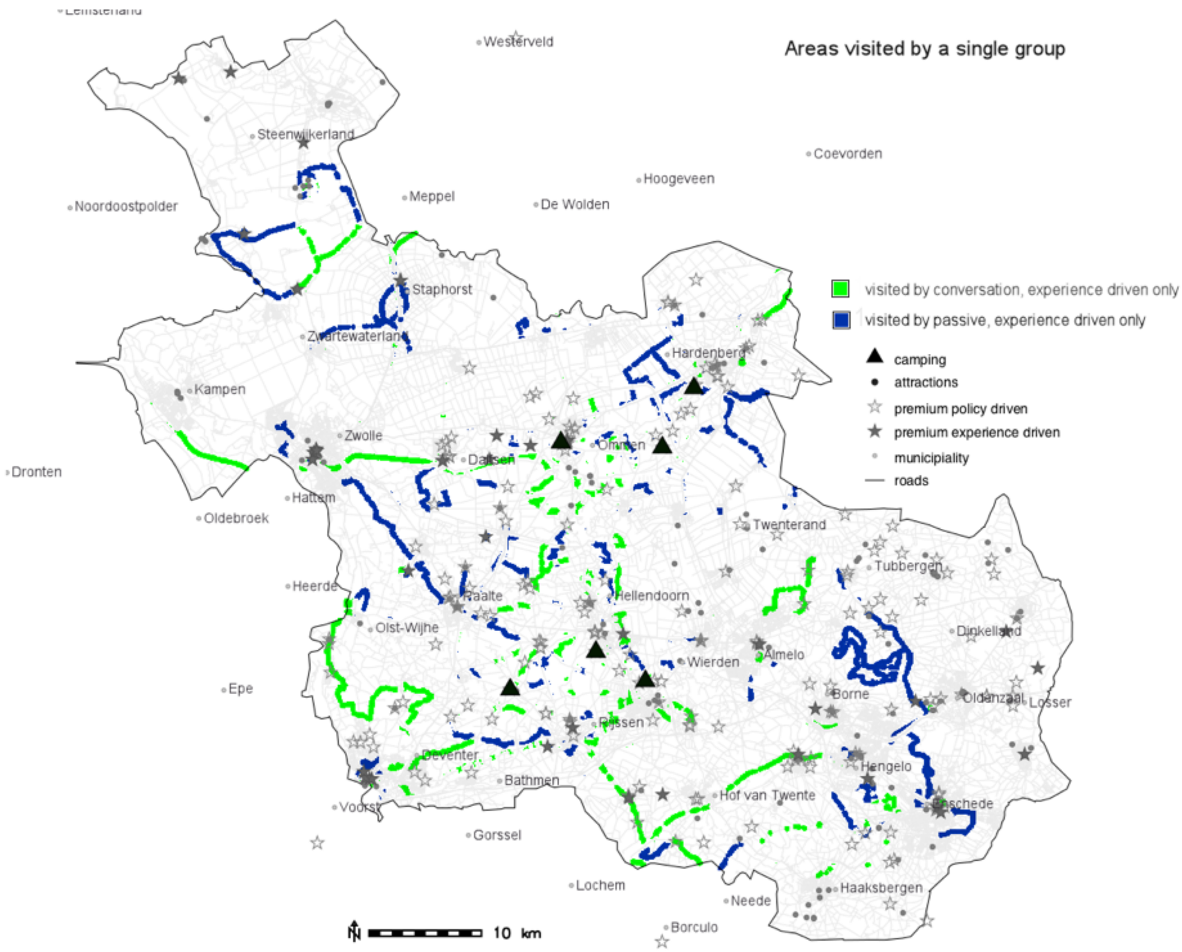

Figure 3. Locations visited exclusively by each of the 2 experience-driven groups.

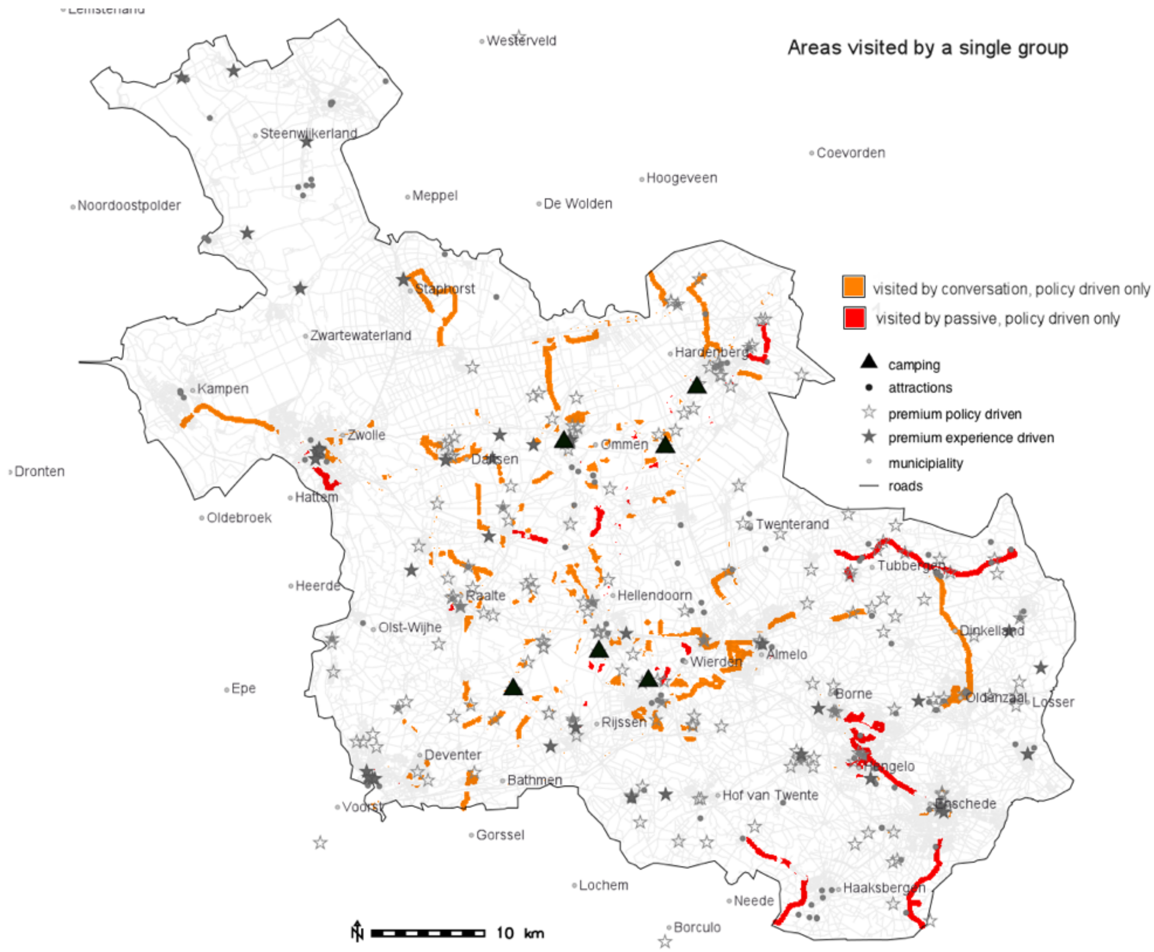

Figure 4. Locations visited exclusively by each of the 2 policy-driven groups.

Table 2. Coverage of Overijssel by each group

Group	% of visited area that was visited by this group	% of visited area that was visited **only** by this group	% of Overijssel visited by this group
Experience-Driven Passive	66%	13%	17%
Policy-Driven Passive	36%	4%	9%
Experience-Driven Conversational	56%	10%	14%
Policy-Driven Conversational	61%	10%	15%

Maps of kernel density differences showed that experience driven participants were more present just east of Ommen, just west of Almelo, and on the north side of Zwolle. They were also more present on the north side of the municipality of Tubbergen. Policy driven participants, on the other hand, were more present west of Ommen and in the municipalities of Rijssen-Holten and Hardenberg (Figure 5).

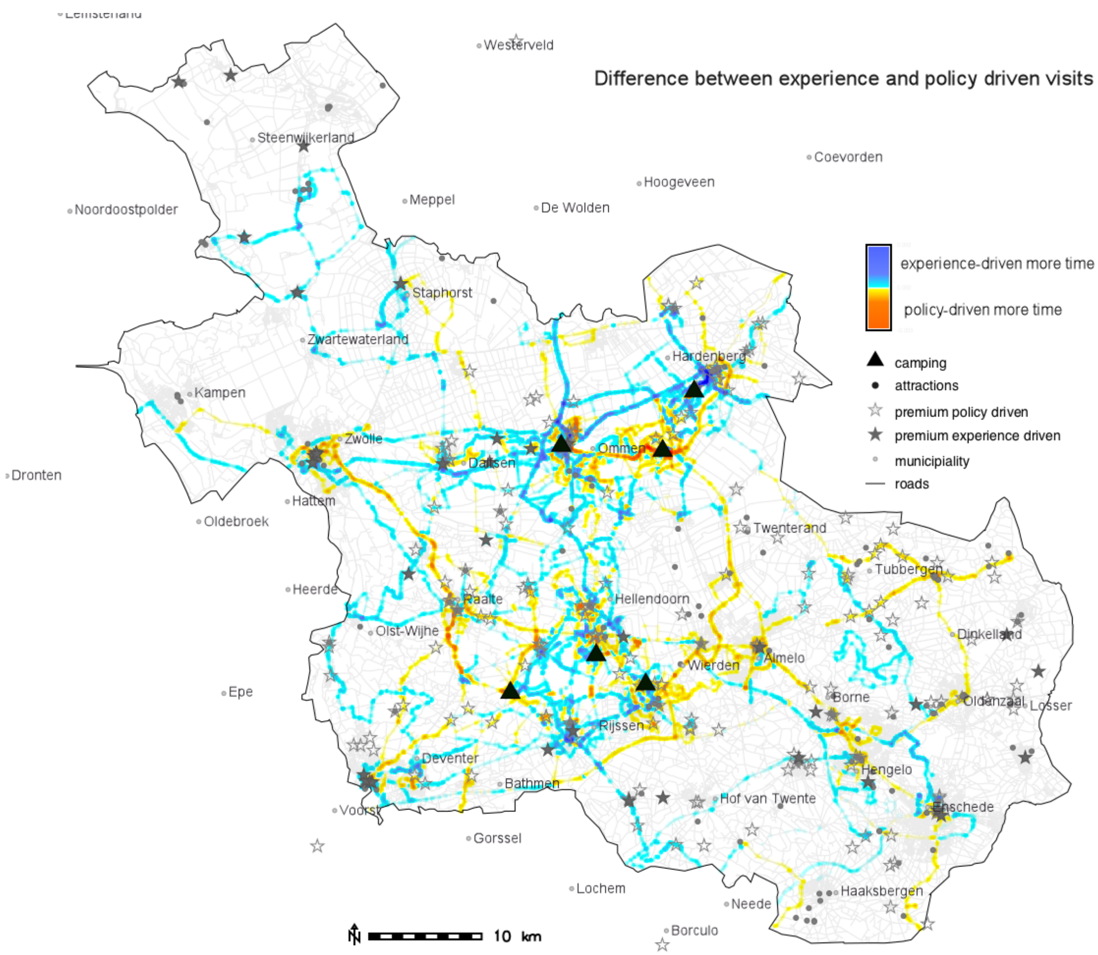

Figure 5. Difference between experience-driven and policy-driven participants

Dividing experience-driven and policy-driven participants into two separate maps, we examine differences between the recommender systems. Experience-driven participants using the passive app were more present in Enschede, Raalte, and Staphorst, comprising 57% of the visited locations on this map, while they were more present around Rijssen-Holten and south of Hardenberg if used the conversational recommender, comprising 43% of the visited locations on this map (Figure 6; Table 3).

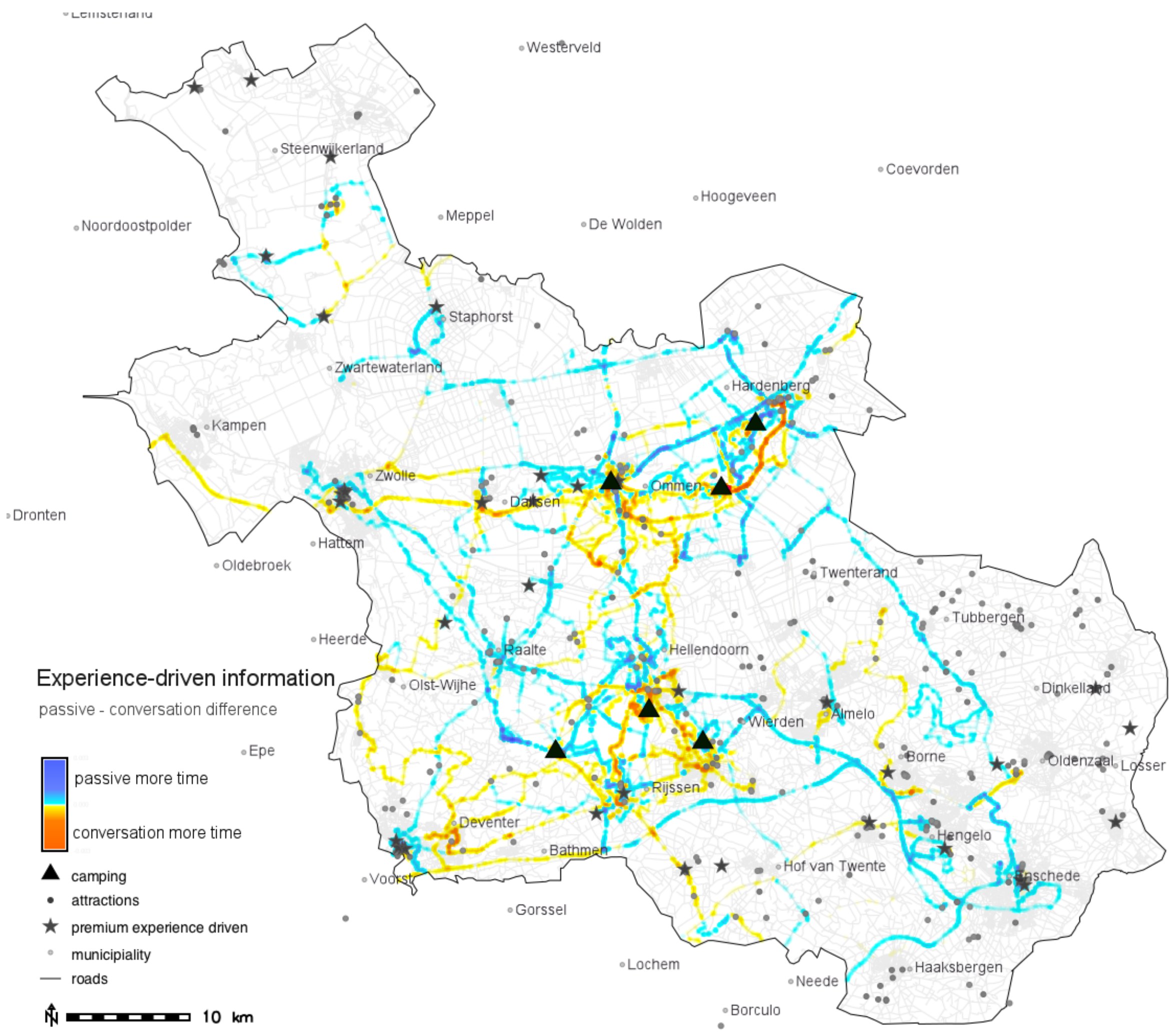

Figure 6. Difference between passive and conversational experience-driven participants

Policy driven participants, on the other hand, showed almost the opposite pattern. They were present south of Hardenberg and around Tubbergen if using the passive app, comprising just 21% of the visited locations on this map, but more present around Raalte, Rijssen-Holten, and Ommen if using the conversational recommender, an overwhelming 79% of visited locations (Figure 7; Table 3).

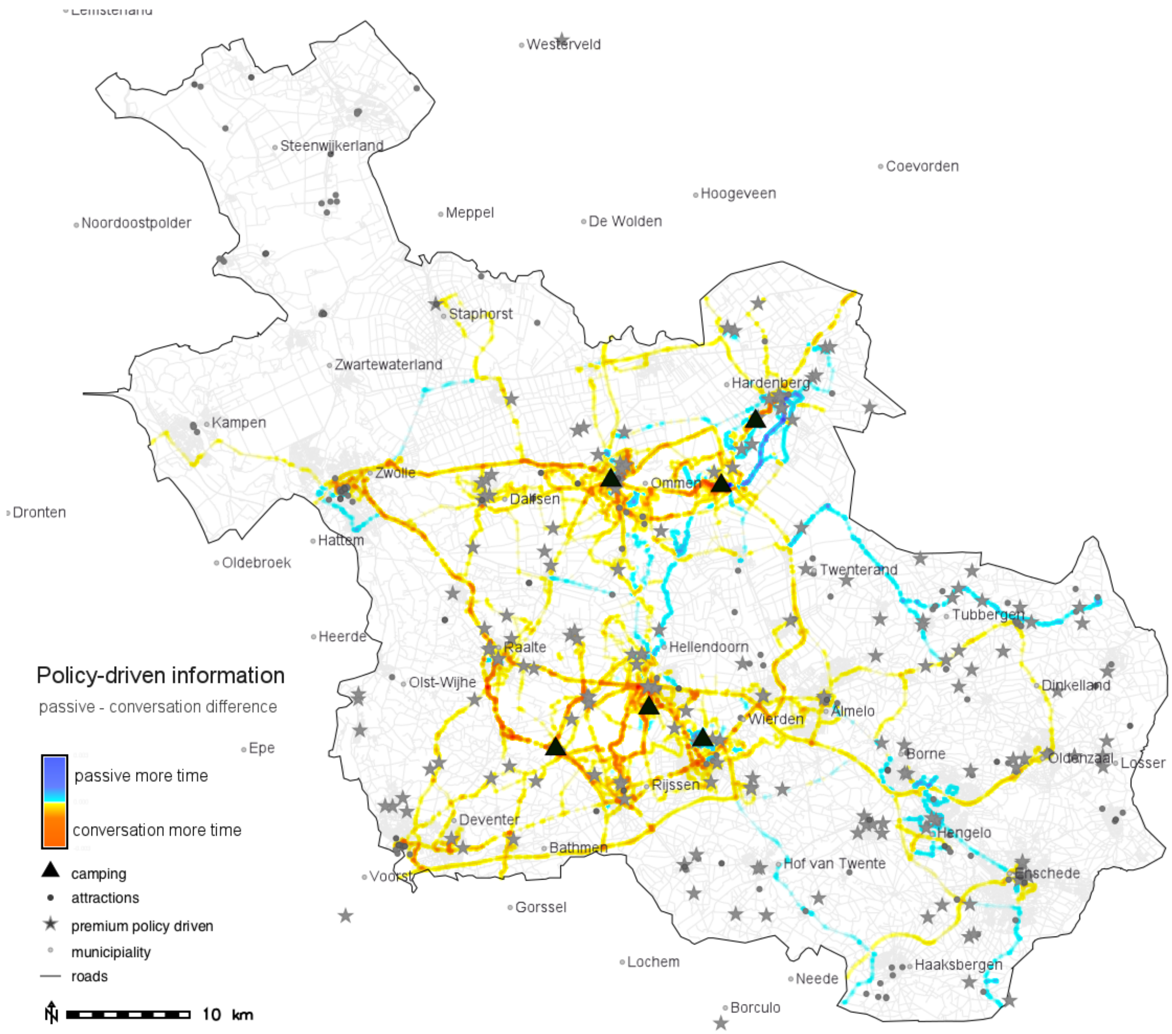

Figure 7. Difference between passive and conversational policy-driven participants

Table 3. Comparison of area attributable to passive compared to conversational group participants within type of tips

Groups	% area	Area [square km]
Within experience-driven participants (Fig. 2)		
More presence of passive group	57%	391.39
More presence of conversational group	43%	292.26
Within policy-driven participants (Fig. 3)		
More presence of passive group	21%	125.47
More presence of conversational group	79%	468.145

Statistical models assessing number of points at attractions of various types (non-premium, premium policy-driven, premium experience-driven) as a function of group confirm and quantify that tourists in different groups not only went to different places, but went ***to the locations where the information was urging them***. There were no differences between groups in presence at non-premium attractions. At premium experience-driven attractions, there was no significant difference in the behavior of conversational recommender users, but passive app users who received policy-priority tips were only 0.12 times as likely to be recorded at experience-driven attractions as passive app users getting experience-priority tips. In other words, participants who got policy-driven tips visited experience-driven attractions 88% less. At policy-driven attractions, participants getting policy-driven tips were 1.8 (passive app) to 2.0 (conversational recommender) times as likely to be present at premium policy-driven attractions, as participants getting experience-driven tips by passive app. Interestingly, conversational recommender users getting experience-driven tips were ***also*** 1.5 times more likely to be present at ***policy-driven*** attractions (approaching significant at $p = 0.06$). These odds ratios minus 1 are illustrated in the following graph, where bars above 0 represent greater likelihood of data points compared to those of experience-driven passive participants, and bars below 0 represent lower likelihood. See also table 4.

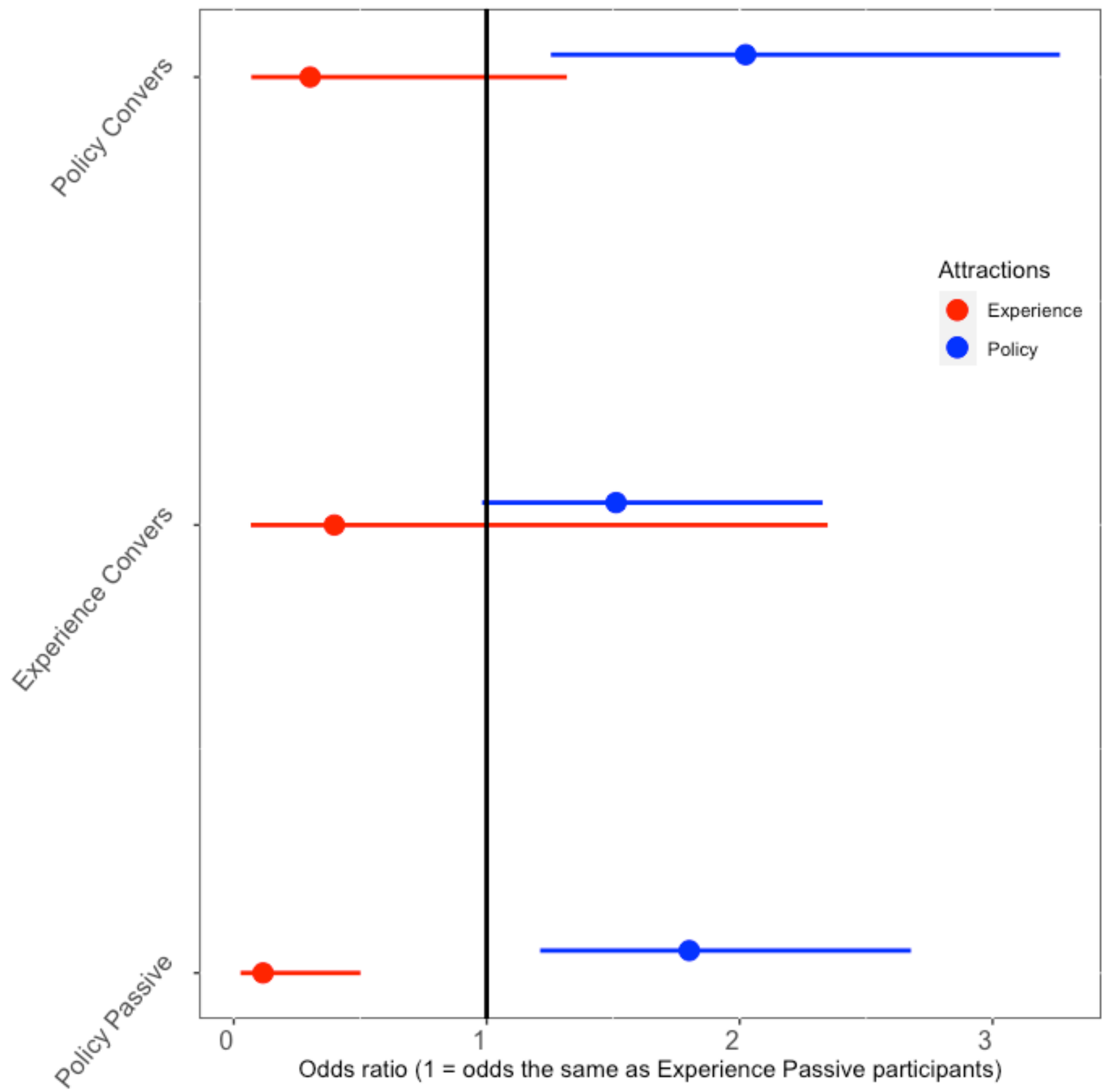

Figure 8. Odds ratios of each group compared to Experience-drived passive group of presence at attraction types.

Note: Horizontal lines represent 95% confidence intervals for odds ratios. When these intersect 1 (the black vertical line), the odds ratio is not statistically different from 1 (equal odds).

Table 4. Effect of recommender systems and destination information on spatial presence, expressed as odds ratios of experimental groups to reference (experience-driven passive) group

	Group	Odds Ratio	Standard Error
Experience-driven attractions			
	(Intercept)	0.00	0.46
	Policy-driven passive	**0.12****	**0.75**
	Experience-driven conversational	0.40	0.91
	Policy-driven conversational	0.30	0.75
Policy-driven attractions			
	(Intercept)	0.01	0.13
	Policy-driven passive	**1.80****	**0.20**
	Experience-driven conversational	1.51	0.22
	Policy-driven conversational	**2.02****	**0.24**
Non-premium attractions			
	(Intercept)	0.00	0.23
	Policy-driven passive	0.89	0.36
	Experience-driven conversational	1.18	0.34
	Policy-driven conversational	1.26	0.33

** On these variables, statisically significant differences between groups were unlikely to occur by chance.

Experience over space

Consistent with differences between groups, which show slightly attenuated negative emotions for some groups, there were no links between spatial behavior and positive emotions found, but some modest connections between spatial behavior and negative emotions. Days when participants spent relatively more time in non-premium attractions featured more negative emotions. In contrast, days with more time at experience-driven locations featured fewer negative emotions. Thus, it could be said that the **most negative** days had the most time at non-premium attractions, **average** days had the most time at policy-driven attractions, or at no attractions at all, and the **least negative** days had the most time at experience-driven attractions (Table 5). This finding makes a clear argument for curating attraction information carefully, because attractions which are not prioritized in any way are apparently associated with some negative emotions.

Table 5. Effects of presence at attractions compared to presence at non-attraction locations on daily emotions.

Outcome variable	Predictor	Coefficient	Standard Error
Positive emotions			
	(Intercept)	3.278	0.046
	Time at policy-driven attractions	-0.006	0.004
	Time at experience-driven attractions	0.021	0.015
	Time at non-premium attractions	-0.009	0.007
Negative emotions			
	(Intercept)	1.128	0.009
	Time at policy-driven attractions	0.000	0.001
	Time at experience-driven attractions	**-0.008****	**0.003**
	Time at non-premium attractions	**0.008****	**0.002**
	Policy-driven conversational	1.26	0.33

** On these variables, effects on daily emotions were unlikely to occur by chance.

Conclusions, recommendations, and considerations

The findings of the present project offer an unambiguous conclusion: giving participants policy-driven information spread them to the locations that Marketing Oost policy prefers without degrading their experience. A second, equally clear conclusion is that a conversational recommendation system slightly improved this process while being far more valued by participants. Finally, a somewhat more subtle conclusion is that premium experience-driven attractions somewhat improve the vacation experience. These conclusions suggest several recommendations.

First, DMO's should critically examine where tourists obtain information. It is clear from the present study that tourists' information strongly affects their behavior. They respond to digital recommender systems, whether passive or active, by visiting different types of attractions. Herein the most advanced conversational systems are likely to be the most powerful, because they personalize and socially engage tourists better. Thus, DMO's are encouraged to actively communicate where they wish tourists to go, and deactivate communication about locations where they would like to reduce crowding. This is likely to be effective within a passive recommender system. It may be more active with a conversational one.

There is a stronger reason for adopting conversational recommenders, however. DMO's often couple their brand to a variety of information sources and recommender solutions. The quality of the recommender might then end up reflecting back on the perceived quality of the destination. We did not test the extent to which participants saw the recommender system as a Marketing Oost product or reflective of the Marketing Oost brand, an issue that deserves further research. The conversational recommender was clearly experienced more positively, however. If the co-branding of a recommender system is a concern, we recommend based on the present study the adoption of a conversational recommender system. Its higher positive ratings may reflect better on the destinations if it is co-branded properly.

We also recommend to carefully select premium attractions based on experience quality. Experience driven premium locations performed the best. Reputation and cultural importance are very dynamic and difficult-to-grasp reasons in today's market, where experience quality is quickly communicated between tourists on review sites and social media. Thus, we urge DMO's to critically evaluate the quality of the experience at attractions they are recommending, and implement their marketing policies keeping tourists' experiences in mind. It is not just a policy of spreading tourists, or just asking what they will most enjoy, that will bring about the most manageable destination over the long term. Rather, it is the intersection of policy and tourist experience that is most promising.

Finally, we recommend destinations to make decisions based on data, such as those in the present project. Collecting and analyzing these data requires investment in an appropriate data software infrastructure, but it is possible to start small, scale up to projects like this one, and further yet to 'true' big data. Certainly ***any*** methodologically rigorous research on tourist behavior and experience is bound to lead to better destination management decisions than pure intuition.

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Appendices (Supplied separately)

Master of Science Thesis by Liselotte de Graaf

Master of Science Thesis by Koen Verstraten

Abstract for 7 Experiences Summit by Ward et al.

Presentation to 7 Experiences Summit by Ward et al.

Experience Overijssel update presentation

Experience Overijssel final presentation to BUas R&D Day November 2021

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