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**Using consumer feedback from location-based services in PoI recommender systems for people with autism**

**This is the author's manuscript**

*Original Citation:*

*Availability:*

This version is available <http://hdl.handle.net/2318/1854295> since 2022-06-22T11:34:02Z

*Published version:*

DOI:10.1016/j.eswa.2022.116972

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1 Using consumer feedback from location-based services in  
2 PoI recommender systems for people with autism

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## 8 **Abstract**

When suggesting Points of Interest (PoIs) to people with autism spectrum disorders, we must take into account that they have idiosyncratic sensory aversions to noise, brightness and other features that influence the way they perceive places. Therefore, recommender systems must deal with these aspects. However, the retrieval of sensory data about PoIs is a real challenge because most geographical information servers fail to provide this data. Moreover, *ad-hoc* crowdsourcing campaigns do not guarantee to cover large geographical areas and lack sustainability. Thus, we investigate the extraction of sensory data about places from the consumer feedback collected by location-based services, on which people spontaneously post reviews from all over the world. Specifically, we propose a model for the extraction of sensory data from the reviews about PoIs, and its integration in recommender systems to predict item ratings by considering both user preferences and compatibility information. We tested our approach with autistic and neurotypical people by integrating it into diverse recommendation algorithms. For the test, we used a dataset built in a crowdsourcing campaign and another one extracted from TripAdvisor reviews. The results show that the algorithms obtain the highest accuracy and ranking capability when using TripAdvisor data. Moreover, by jointly using these two datasets, the algorithms further improve their performance. These results encourage the use of consumer feedback as a reliable source of information about places in the development of inclusive recommender systems.

9 *Keywords:* sensory features from reviews, autism, recommender systems

## 10 **1. Introduction**

11 Most personalized recommender systems consider the individual user’s  
12 preferences and contextual conditions to select the Points of Interest (PoIs)  
13 that are suitable to the individual user (Adomavicius and Tuzhilin, 2015).  
14 However, when suggesting PoIs to people with Autism Spectrum Disorders  
15 (ASD), these systems should take into account that users have idiosyncratic  
16 sensory aversions to noise, brightness, and other features, which influence the  
17 way they perceive items, especially places (Robertson and Simmons, 2013).  
18 Aversions should therefore be considered to suggest PoIs that are at the same  
19 time interesting and compatible with the target user. This is crucial because  
20 what bothers people with autism has great importance in their daily choices  
21 and can determine a high level of stress and anxiety (Simm et al., 2016).

22 Mauro et al. (2020, 2022) propose to distinguish the role of user pref-  
23 erences and compatibility in PoI suggestion. The idea is to estimate the  
24 suitability of a place  $p$  for a user  $u$  by evaluating how much  $u$  is expected to  
25 like  $p$ , and how compatible  $p$  is with  $u$ , depending on  $u$ ’s sensory aversions.  
26 However, retrieving sensory data about PoIs is a real challenge because most  
27 geographical information servers, like OpenStreetMap<sup>1</sup> and Google Maps,<sup>2</sup>  
28 only provide data about properties of places such as their category, address  
29 and accessibility. Indeed, the crowdsourcing paradigm (Sui et al., 2013),  
30 where people actively provide information about places, can be used to gather  
31 the missing data. However, that approach covers limited geographical areas  
32 and requires a community willing to participate in the data collection, that

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<sup>1</sup><https://www.openstreetmap.org/>

<sup>2</sup><https://www.google.it/maps/>

33 is not simple to achieve. Therefore, to identify a sustainable information  
34 source, we investigate the usefulness of the reviews available in services such  
35 as Yelp<sup>3</sup> and TripAdvisor<sup>4</sup> to extract sensory data about places. Reviews  
36 report people’s experience with items (Ghose and Ipeirotis, 2011) and come  
37 as a by-product of the increasing usage of location-based services. However,  
38 to the best of our knowledge, they have always been employed to mine con-  
39 sumers’ opinions about the quality of services and products, overlooking their  
40 potential to provide sensory data about items. Moreover, existing feature ex-  
41 traction approaches focus on the identification of the most frequent opinions  
42 while we have to adopt a pessimistic feature identification approach to guar-  
43 antee that people with autism are not disturbed by sensory characteristics  
44 which might be rarely reported.

45 In this work we propose a model to extract sensory data about places for  
46 inclusive recommendation and we pose two research questions:

47 RQ1: *Does the feedback available in online item reviews collected by a*  
48 *location-based service provide useful sensory information about PoIs?*

49 RQ2: *How does the sensory information extracted from reviews impact*  
50 *recommendation performance in the personalized suggestion of places?*

51 To answer these questions, we developed a model for the extraction of  
52 sensory features from consumer feedback and we used it to build a dataset  
53 of sensory information about places from TripAdvisor reviews. The present  
54 paper describes this model and its integration within a recommender system  
55 by predicting the compatibility of sensory features with the user. This work

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<sup>3</sup><https://www.yelp.it/>

<sup>4</sup><https://www.tripadvisor.com/>

56 also compares the performance achieved by different recommender systems  
57 when they employ crowdsourced data, our TripAdvisor dataset, or both to  
58 suggest items to two user groups: ASD people, and people who did not previ-  
59 ously receive an autism diagnosis (we denote the latter as neurotypical). The  
60 evaluation results show that, with both groups, consumer feedback supports  
61 higher recommendation performance than crowdsourced information. The  
62 accuracy (Precision, Recall, and F1) and ranking capability (MAP, MRR) of  
63 the algorithms is almost always higher when using TripAdvisor data. More-  
64 over, accuracy, ranking capability, and rating prediction error (MAE, RMSE)  
65 decrease when jointly using the two datasets. Furthermore, the recommender  
66 systems that deal with both preferences and compatibility outperform those  
67 that only take preferences into account. These results encourage the use of  
68 consumer feedback as a reliable source of information in PoI recommenda-  
69 tion. They also show that it helps improving suggestions to both autistic  
70 and neurotypical people. This is relevant to the development of inclusive  
71 recommender systems and paves the way toward sustainable information ac-  
72 quisition models for PoI recommendation.

73 This work is framed in the PIUMA (Personalized Interactive Urban Maps  
74 for Autism)<sup>5</sup> project, which has the aim to develop novel digital solutions to  
75 help people with autism spectrum disorders in their everyday movements  
76 (Rapp et al., 2017). Sections 2 and 3 present the perceptual needs of autis-  
77 tic people and the related work. Section 4 describe the data collection and  
78 sensory feature extraction model. Section 5 outlines the recommendation

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<sup>5</sup>PIUMA involves a collaboration among the Computer Science and Psychology De-  
partments of the University of Torino and the Adult Autism Center of the City of Torino.

79 algorithms we tested and Section 6 describes the validation method we ap-  
80 plied. Sections 7 and 8 present and discuss the experimental results. Section  
81 9 describes limitations and future work, and Section 10 concludes the paper.

## 82 **2. Sensory issues of people with autism**

83 People with autism spectrum disorders differ in terms of cognitive ability.  
84 However, almost all of them show substantial hypo and hypersensitivity to  
85 environmental stimuli (Sensory Processor Disorder (Matsushima and Kato,  
86 2013; Robertson and Simmons, 2013)). These stimuli can be auditory, olfac-  
87 tory, and tactile. The brain seems unable to appropriately balance the senses  
88 (Robertson and Simmons, 2013). This means that people with autism ap-  
89 pear to react differently to sensory stimulations. A majority of them may be  
90 overwhelmed by environmental features that are easily managed by neurotyp-  
91 ical subjects. For example, many ASD people are hyper-sensitive to bright  
92 lights, or to certain light wavelengths, such as fluorescent lights. Several of  
93 them find some sounds, smells, and tastes overwhelming. Certain types of  
94 touch (light or deep) can cause uncomfortable feelings, as well. Thus, a per-  
95 son with autism might want to avoid places that negatively impact her/his  
96 senses (Robertson and Simmons, 2013). These sensory aversions can cause  
97 negative feelings like anxiety, fatigue, sense of oppression (Rapp et al., 2020).  
98 Due to these features, and to other peculiar characteristics, such as atypical  
99 social functioning, autistic people tend to have a reduced range of activities  
100 and are less likely to explore new environments (Smith, 2015). Therefore,  
101 they need a careful selection of places when moving in their city, or in a  
102 different area (Rapp et al., 2018). It is crucial to find places that satisfy

103 their sensory needs, focusing on aversions derived from their high sensitiv-  
104 ity to sensory stimulation. The technology could be used to support them  
105 because they have a positive attitude towards it, due to the predictability  
106 of the interaction. However, most ICT-based solutions assist people in or-  
107 ganizing their daily activities (Putnam and Chong, 2008), helping them in  
108 social interactions (Kientz et al., 2013; Grynszpan et al., 2014), and in emo-  
109 tion management (Simm et al., 2016; Boyd et al., 2016) but those solutions  
110 overlook space and sensory issues.

111 Most services that aim at supporting people with autism in moving around  
112 are simple informative websites. Autistic Globetrotting<sup>6</sup> and the Toerisme  
113 voor Autisme<sup>7</sup> provide information about places that is useful to ASD peo-  
114 ple. Moreover, recent research highlights the benefits of Virtual Reality in-  
115 terventions, such as computer-based simulations of reality where users can  
116 train specific skills needed to move around and travel, e.g., taking a bus  
117 (Bernardes et al., 2015), or a plane (Soccini et al., 2020). At the same time,  
118 each person with autism has unique sensitivities; thus, there is a high need  
119 to personalize solutions.

### 120 **3. Background and related work**

121 This section positions our work in the related one from three points of  
122 view: (i) general-purpose recommendation algorithms, (ii) recommender sys-  
123 tems targeted to people with autism, and (iii) methods applied to extract  
124 information about items from reviews.

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<sup>6</sup><http://autisticglobetrotting.com>.

<sup>7</sup><https://www.toerismevoorautisme.be/>

**Table 1:** Models and types of information used to personalize item suggestion. K-NN denotes K-Nearest Neighbors algorithm (Desrosiers and Karypis, 2011). MF is Matrix Factorization (Koren and Bell, 2011). CARS means Context-Aware Recommenders.

Citations	Algorithm	Recommendation Model	Evaluation dimensions	Information Sources (other than item ratings)
Lops et al. (2011)	CBF	vector distance	category, properties	item descriptions
Desrosiers and Karypis (2011) Koren and Bell (2011)	CF	K-NN, MF	items	-
Adomavicius and Kwon (2007) Zheng (2017) Jannach et al. (2014)	Multi-Criteria	K-NN or MF on multiple dimensions	properties	item metadata
Burke (2002) Gemmell et al. (2012) Cantador et al. (2011)	hybrid	weighted hybrid integration	category, properties	item descriptions, metadata, tags
Musto et al. (2011)	CBF	vector-distance	category, properties	item descriptions
Ardissono et al. (2003)	compatibility evaluation	T-Norm tuned by preference importance	category, properties	item metadata
Dragone et al. (2018)	constraint-based	constraint satisfaction	category, properties	metadata
Hernández-Rubio et al. (2019) Chen et al. (2015)	review-based	CF, CBF, etc.	categories, properties	item reviews
Dong et al. (2016)	review-based	CBF	categories, properties	item reviews
O'Mahony and Smyth (2018) Bao et al. (2014) Musat and Faltings (2015) Al-Ghossein et al. (2018) Zhao et al. (2015)	review-based	CF	categories, properties	item reviews
Musto et al. (2017)	review-based	MF on multiple dimensions	categories, properties,	item reviews
Chen et al. (2019)	review-based	neural networks	properties	item reviews
Shalom et al. (2019) Lu et al. (2018)	review-based	neural networks + CF	properties	item reviews
Adomavicius and Tuzhilin (2015)	CARS	KNN, MF	category, properties, user context	physical, temporal social dimensions
Baltrunas et al. (2011)	CARS	MF	category, properties, user context	data provided by users
Biancalana et al. (2013)	CARS, review-based	neural networks	category, properties, user context	social networks location-based services, item reviews

125 *3.1. Recommender systems - algorithms*

126 Recommender Systems are “software tools and techniques providing sug-  
127 gestions for items to be of use to a user” (Ricci et al., 2011). They assist

128 users in finding relevant information, products, and services by offering in-  
129 dividualized suggestions. Table 1 classifies these systems on the basis of the  
130 data about items they manage. Content-Based Filtering (CBF) (Lops et al.,  
131 2011), Collaborative Filtering (CF) (Desrosiers and Karypis, 2011; Koren  
132 and Bell, 2011), collaborative multi-criteria (Adomavicius and Kwon, 2007;  
133 Zheng, 2017; Jannach et al., 2014), and hybrid recommender systems (Burke,  
134 2002; Gemmell et al., 2012; Cantador et al., 2011) estimate item ratings on  
135 the sole basis of users’ preferences. Ardissono et al. (2003) model the compat-  
136 ibility of items with the user but they unify it with preferences. Analogously,  
137 constraint-based recommender systems (Dragone et al., 2018) model both  
138 compatibility and preferences as a Constraint Satisfaction Problem (Brails-  
139 ford et al., 1999). Differently, we separate preferences from compatibility  
140 with sensory features of items by modeling the latter as possible sources of  
141 discomfort rather than liking or disliking factors. This separation also distin-  
142 guishes our model from the recommenders that deal with negative preferences  
143 (Musto et al., 2011). In fact, it supports the specification of heterogeneous  
144 criteria to deal with user preferences and item compatibility.

145 Review-based recommender systems (Hernández-Rubio et al., 2019; Chen  
146 et al., 2015) leverage consumer feedback for their suggestions. They apply  
147 different methods to match items to users, such as content-based (Dong et al.,  
148 2016), collaborative (O’Mahony and Smyth, 2018; Bao et al., 2014; Musat  
149 and Faltings, 2015; Al-Ghossein et al., 2018; Zhao et al., 2015), multi-criteria  
150 (Musto et al., 2017), and neural ones (Chen et al., 2019), as well as hybrid  
151 solutions (Shalom et al., 2019; Lu et al., 2018). However, they uniformly treat  
152 all the item features extracted from the reviews as targets of user preferences.

**Table 2:** Recommender systems for users with autism spectrum disorders.

Citations	Recommendation Algorithm	User Features	Item Suggested	Target	Evaluation
Hong et al. (2012)	no algorithm	social issues	social behaviors	teenager	no
Costa et al. (2017)	case based	age, gender	daily activities	children	no
Premasundari and Yamini (2019)	association rules	symptoms (e.g., learning difficulties, fine motor skill dysfunction, language disorder,..)	food and therapies	children	usability
Ng and Pera (2018)	hybrid (collaborative, graph-based)	interest social skills emotional state	social games	adults	accuracy (no ASD subj.)
Banskota and Ng (2020)	collaborative filtering	interests, weakness	videogames	adults	accuracy (no ASD subj.)
Mauro et al. (2020)	content-based	interests, sensory aversions	POIs	adults	accuracy (no ASD subj.)

153 Context-aware recommenders consider different variables about the user  
154 and her/his context, specifically dealing with the time, location, and nearby  
155 people to provide just-in-time recommendations (Adomavicius and Tuzhilin,  
156 2015). Baltrunas et al. (2011) extend Matrix Factorization to recommend  
157 music in a car by considering the user’s preferences for the driving style,  
158 road type, and so forth. Biancalana et al. (2013) propose a neural recom-  
159 mender system that personalizes the suggestion of PoIs based on the user’s  
160 preferences, and on her/his location, transportation means, etc.. Similar to  
161 these works, we use contextual information about PoIs to steer the system’s  
162 suggestions, and we employ consumer feedback to build rich models of places.  
163 However, we model both user preferences and idiosyncratic aversions. While  
164 we use static data about PoIs to generate the recommendations, our model  
165 is based on a modular architecture that makes it seamlessly extensible to  
166 retrieve data in real-time from external data sources and sensors.

167 *3.2. Recommender systems - applications for autism*

168 Recommender systems specifically conceived for people with autism spec-  
169 trum disorders are rare. Table 2 summarizes the state-of-art.

170 Hong et al. (2012) propose to provide users with suggestions within a  
171 social network aimed at supporting the independence of young adults. How-  
172 ever, they focus on the organization of the social network, by relying on peer  
173 suggestions, instead of generating recommendations. Costa et al. (2017)  
174 develop a task recommender system that uses case-based reasoning to sug-  
175 gest the child’s daily activity to be performed (related to eating, keeping  
176 clean, etc.) based on age, gender, and time of day but it does not consider  
177 the child’s preferences. Moreover, the level of difficulty of the activities is  
178 manually set by the therapist. Premasundari and Yamini (2019) propose a  
179 food and therapy recommender system for autistic children based on their  
180 symptoms in different areas (social interaction and communication problems,  
181 speech deficits, etc.). The system targets parents and caregivers, rather than  
182 children, and has been exclusively evaluated from a usability viewpoint. Ng  
183 and Pera (2018) propose a hybrid game recommender for adult people with  
184 autism, based on collaborative and graph-based recommendation techniques.  
185 The system is only tested on neurotypical people. Banskota and Ng (2020)  
186 present, and empirically evaluate, a recommender system that suggests ther-  
187 apeutic games to adults with autism spectrum disorders. The system can  
188 improve users’ social-interactive skills, and takes their weaknesses into ac-  
189 count in the recommendations. Our work differs from the above ones in  
190 the application domain, and also because it employs aversions to sensory  
191 features, besides user preferences, to steer recommendation.

**Table 3:** Extraction of item features. LDA denotes Latent Dirichlet Allocation.

Citations	Purpose	Feature extraction algorithm	Extracted features	Information Sources
Lops et al. (2011)	content-based item recommendation	TF-IDF	item properties	item descriptions
Musat and Faltings (2015)	review-based item recommendation	faceted opinion extraction	item properties	item reviews
Dong et al. (2013)	review-based item recommendation	bi-gram and tri-gram analysis	item properties	item reviews
Bao et al. (2014)	review-based item recommendation	Non-negative Matrix Factorization	item properties	item reviews
McAuley and Leskovec (2013) Al-Ghossein et al. (2018)	review-based item recommendation	LDA	item properties	item reviews
Peña et al. (2020)	review-based item recommendation	ensemble methods	item properties	item reviews
Qi et al. (2016)	product properties identification	LDA + PageRank	item properties	item reviews
Korfiatis et al. (2019)	evaluation aspects identification	Structural Topic Models	evaluation aspects of items	item reviews
Paul et al. (2017)	review recommendation	double propagation	item properties	item reviews
Xu et al. (2017)	aspect extraction	Latent Semantic Analysis	item properties	item reviews
Tang et al. (2019)	aspect extraction	JABST	multi-grain aspects and opinions	item reviews

192 *3.3. Extraction of information about item features*

193 Table 3 classifies the feature extraction and review analysis models rele-  
 194 vant to our work. Content-Based Filtering (Lops et al., 2011) leverages item  
 195 descriptions for feature extraction. The features representing item properties  
 196 are typically taken from textual catalogs by applying statistical metrics such  
 197 as TF-IDF to identify relevant characteristics for the generation of vector  
 198 models describing items.

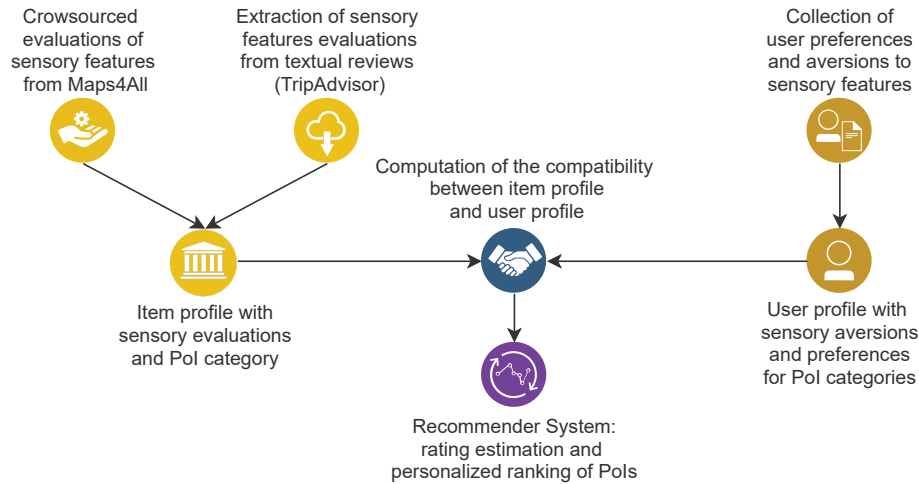
199 Review-based recommender systems use consumer feedback as a descrip-  
 200 tion of the experience with items (Ghose and Ipeirotis, 2011). They extract  
 201 aspects from reviews to identify both item properties and users’ opinions  
 202 on such properties, based on the sentiment emerging from online comments.  
 203 These systems adopt opinion mining techniques like faceted opinion extrac-

tion (Musat and Faltings, 2015), bi-gram and tri-gram analysis (Dong et al., 2013), Non-negative Matrix Factorization (Bao et al., 2014), Latent Dirichlet Allocation (LDA, see Blei and McAuliffe (2007)) (McAuley and Leskovec, 2013; Al-Ghossein et al., 2018) and *ensemble* methods (Peña et al., 2020). Further techniques are applied in review helpfulness analysis and in the extraction of sentiment about products and services. Qi et al. (2016) combine LDA with PageRank (Page et al., 1999) on terms to find relevant product properties and Korfiatis et al. (2019) apply Structural Topic Models to extract evaluation aspects from reviews. Paul et al. (2017) use double propagation (Qiu et al., 2011) and Xu et al. (2017) use Latent Semantic Analysis to derive aspects from reviews as latent topics. Tang et al. (2019) propose the JABST model to extract multi-grained aspects and opinions, and Mauro et al. (2021) analyze user and item biases for helpfulness evaluation.

We cannot adopt any statistical approaches to extract sensory data about places. In our context, the notion of “relevance” differs from the one used in information retrieval because we have to take a cautious approach to item suggestions. Rather than finding the most frequently occurring aspects of an item in its reviews, we aim at identifying specific sensory features, possibly reported by few users, which might reveal issues that dramatically impact ASD people. In other words, the notion of conformity, often adopted in the assessment of reliable data (Li et al., 2013), does not apply to our context.

#### 4. Data

As shown in Figure 1, which overviews the framework of our compatibility-aware recommendation model, we base the personalized suggestion of places



**Figure 1:** Framework for the compatibility-aware recommendation of places.

228 on the acquisition of item and user profiles that are matched to each other  
 229 by taking the user’s preferences and sensory aversions into account. In the  
 230 following sections we describe the techniques we developed to acquire the  
 231 data about users and places, corresponding to the upper layer of the figure.

232 *4.1. Data about users*

233 Recommender systems suggesting places to autistic people must work  
 234 under data scarcity. There is a low number of users who can be analyzed  
 235 to learn their interests: Elsabbagh et al. (2012) indicates that autism affects  
 236 about 1 in 100 people in Europe. ASD people are hard to contact because  
 237 they have interaction problems and a tendency to avoid new experiences.  
 238 Moreover, their attention problems cause difficulties in providing detailed  
 239 feedback about items (Murray et al., 2005). These factors hamper both  
 240 the acquisition of information about individual properties of users, and the  
 241 execution of massive tests to evaluate the systems targeted to them. For our

242 work, we employ a dataset that was collected by Mauro et al. (2020). We  
243 gathered data by means of a questionnaire in which we asked participants to  
244 rate in the [1, 5] Likert scale the following variables:

- 245 • Preferences for categories of PoIs associated with free time and daily  
246 activities, such as places for eating, doing sports, and so forth.<sup>8</sup>
- 247 • Aversions to sensory features of PoIs, and in particular to the  
248 **brightness, crowding, noise, smell** and **openness** of places.

249 The questions about aversions derive from the Sensory Perception Quotient  
250 test by Tavassoli et al. (2014) that supports the elicitation of basic hyper- and  
251 hyposensitivity to external factors from adults with and without autism. The  
252 questions have the following format (translated from the Italian language):  
253 “In a place, how much does it bother you: too much light, very low light, . . .”.  
254 Regarding **brightness** and **openness**, participants evaluated two extreme  
255 conditions, i.e., low or high levels, assuming that the middle ones are not  
256 problematic. As far as **crowding, noise** and **smell** are concerned, people  
257 were asked about their aversion to the highest level because the low levels of  
258 these features are usually well tolerated.

259 Besides the user information derived from the questionnaire, the dataset  
260 includes the overall ratings that participants gave to 50 PoIs located in Torino  
261 city center, and belonging to the categories of the questionnaire. In the  
262 following, we refer to this set of places as  $\Pi$ . Ratings are in a [1, 5] Likert

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<sup>8</sup> The categories are: restaurants, pubs and coffee shops, ice cream shops, museums and exhibitions, cinemas and theaters, squares, railway stations, malls and markets, comic shops, tech shops, clothing stores, libraries, bookshops.

263 scale, where 1 represents the lowest value and 5 is the highest one. As in  
264 typical user-ratings matrices, we mark unrated features, i.e., features about  
265 which the system has no information, with the “0” value. Two groups of  
266 people answered the questionnaire and rated the places:

- 267 • 20 ASD adults (from 22 to 40 years old, mean age 26.3, median 28; 11  
268 men, 9 women, 0 non-binary and 0 not declared) who are patients of  
269 the Autistic Adult center in Torino with medium- and high-functioning.  
270 This ratio is roughly consistent with the overall gender ratio of 3:1  
271 (man:woman) diagnosed with autism (Loomes et al., 2017).
- 272 • 128 neurotypical subjects (from 19 to 71 years old, average age: 28.1,  
273 median 23; 63 men, 65 women, 0 non-binary and 0 not declared) who  
274 are University students or contacts of this paper’s authors.<sup>9</sup>

275 The mean number of ratings provided by participants is 31.86 (Standard  
276 Deviation - SD=8.07) for autistic subjects and 39.34 (SD=10.52) for neu-  
277 rotypical ones. While the first group was fairly active in rating provision  
278 (the minimum number of ratings per user is 25), neurotypical participants  
279 varied much more, with a minimum number of ratings equal to 6. The ma-  
280 jor contribution of ASD people to data collection can be explained by their  
281 higher motivation to actively join in a collective goal that can bring benefits  
282 to other people, as well as to themselves, and which also impacts the sense  
283 of self-efficacy and empowerment.

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<sup>9</sup>We have no mean to know whether the subjects of this group belong to the autism spectrum or not. However, we expect that the neurotypical sample respects the proportion of the entire population. Thus, the group should include no more than 2 ASD people.

**Table 4:** Descriptive statistics of sensory feature evaluations concerning the places of set II. The table shows the minimum, maximum and mean (with Standard Deviation) number of evaluations received by features per PoI.

	Maps4All				TripAdvisor			
	Min	Max	Mean	SD	Min	Max	Mean	SD
<b>brightness</b>	0	9	3.14	1.26	0	42	2.56	6.50
<b>crowding</b>	0	9	3.14	1.26	0	299	47.1	74.39
<b>openness</b>	0	9	3.14	1.26	0	483	80.01	118.63
<b>noise</b>	0	9	3.14	1.26	0	36	3.72	6.93
<b>smell</b>	0	9	3.14	1.26	0	9	0.5	1.67

284 *4.2. Crowdsourced data about PoIs*

285 Mauro et al. (2020) retrieved the data about places from the Maps4All<sup>10</sup>  
 286 crowdsourcing platform, conceived to collect the evaluation of sensory fea-  
 287 tures. Maps4All provides ratings in the [1, 5] Likert scale; for each PoI, it  
 288 returns the mean values of the available ratings. The platform was used to  
 289 collect data in two experimental crowdsourcing sessions, during two lessons  
 290 at the Master degree in “Social Innovation and ICT” at the University of  
 291 Torino, in May and December 2019. We involved about 120 students in  
 292 these sessions, and we asked each of them to anonymously evaluate the sen-  
 293 sory features of at least three PoIs in Torino city center. Overall, the 50  
 294 places of set II, which we used in our experiments, received 785 sensory fea-  
 295 ture evaluations with coverage=49 (the sensory features were evaluated in 49  
 296 places of II). Henceforth, we denote the dataset we produced as “Maps4All”.

297 The left portion of Table 4 shows the descriptive statistics of Maps4All

<sup>10</sup><https://maps4all.firstlife.org>

	Min	Max	M_dist	Standard Deviation	+ve/-ve	M_diff
<b>brightness</b>	0	2.3333	0.9701	0.6448	+0.1046	-0.2228
<b>crowding</b>	0.0242	2.6667	1.0618	0.7809	+0.1250	-0.0398
<b>openness</b>	0.1667	2.4575	0.8952	0.5486	+0.2526	-0.0942
<b>noise</b>	0	3	1.2698	0.8758	+0.2760	+0.9442
<b>smell</b>	0	2	1.0181	0.6904	-0.4647	-1.0181

**Table 5:** Minimum, maximum and mean distance (with Standard Deviation) between the feature evaluations of Maps4All and TripAdvisor for the places of set  $MA \cap TA$ . Column +ve/-ve reports the correlation values between feature evaluations across datasets. M\_diff shows the difference between the mean values given to features in the datasets.

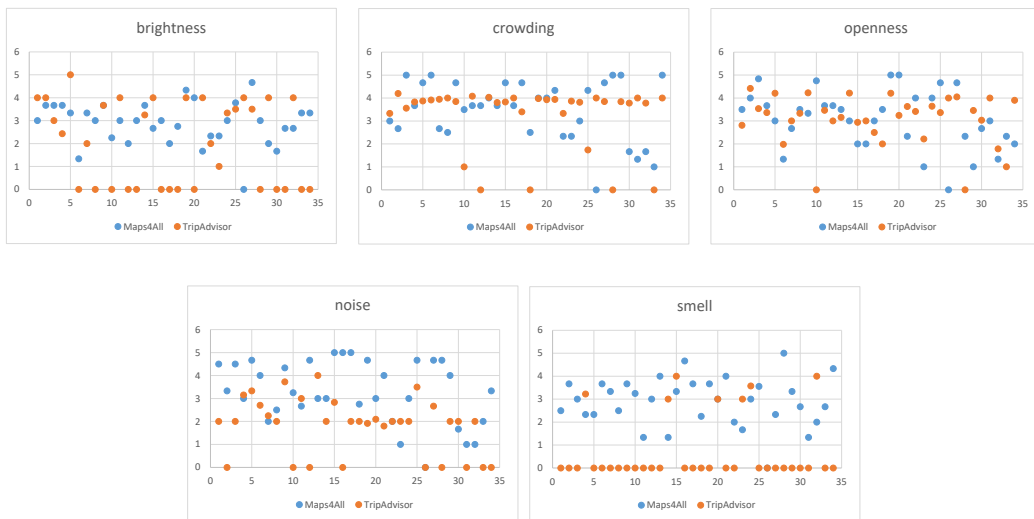
298 dataset. The minimum number of ratings received by sensory features is 0  
 299 because, in a given place, some features might not have been evaluated.

### 300 4.3. Consumer feedback about PoIs

301 We also retrieved sensory feature evaluations from consumer feedback  
 302 extracted from a location-based service, leveraging the spontaneous reviewing  
 303 activity carried out by its users. Specifically, we collected a dataset from  
 304 TripAdvisor by scraping from its website all the reviews of the places included  
 305 in set  $\Pi$  that were written until June 2020.<sup>11</sup> Only 34 places out of 50 were  
 306 mapped in the service but we extracted 6696 evaluations of sensory features  
 307 concerning them. The right portion of Table 4 shows the statistics about the  
 308 TripAdvisor dataset. Most sensory features have a definitely higher number  
 309 of ratings than in Maps4All; for instance, the mean number of ratings of  
 310 **crowding** and **openness** is 80.01 and 47.1, respectively, against 3.14.

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<sup>11</sup>In the analysis of consumer feedback we overlook the identity of the reviews' authors because we are not interested in considering the social relations among TripAdvisor users.



**Figure 2:** Sensory feature evaluations of the 34 PoIs mapped in both Maps4All and TripAdvisor ( $MA \cap TA$ ). The  $X$  axis represents PoIs, the  $Y$  axis denotes the mean feature values in  $[1, 5]$  obtained from the datasets (0 means unknown value).

311     TripAdvisor has lower coverage than Maps4All (**brightness**=20,  
312     **crowding**=30, **noise**=25, **smell**=7 and **openness**=32). In other words, in  
313     TripAdvisor fewer places received at least one evaluation of their sensory fea-  
314     tures. The most problematic feature is **smell**, which is only evaluated in 7  
315     places. These findings suggest that consumer feedback is a promising source  
316     of sensory data but multiple information sources might have to be integrated  
317     to extend its coverage of places.

#### 318 4.4. Comparison of feature values in the Maps4All and TripAdvisor datasets

319     We consider the 34 places that are mapped in both datasets. We denote  
320     this set of places as  $MA \cap TA$ . Figure 2 shows the feature values of these  
321     PoIs and highlights the data sparsity concerning **brightness** and **smell**,  
322     and partially **noise**. Table 5 shows that, on average, the distance between

323 the mean feature values provided by the two datasets is about 1, with a  
324 Standard Deviation that ranges from 0.55 to 0.88. Moreover, column `M_diff`  
325 shows that Maps4All provides higher mean values of `noise` than TripAdvisor.  
326 The opposite holds for `smell` and `brightness`, while the values of the other  
327 features are balanced.

328 According to Pearson correlation (column `+ve/-ve`), most feature values  
329 weakly correlate in a positive way in the two datasets. Differently, `smell` has  
330 a negative correlation (-0.4647) but this is not particularly relevant because  
331 TripAdvisor reviews provide little information about this feature.

#### 332 4.5. Extraction of sensory features from consumer feedback

##### 333 4.5.1. Creation of linguistic resources about sensory features

334 We could not find any linguistic resources for the analysis of sensory  
335 features in the Italian language, which is the target of our work. Therefore,  
336 three researchers from our University staff collaborated to build a *sensory*  
337 *features dictionary* that associates words to features, and to their values.  
338 We consider the following sensory features: `brightness`, `crowding`, `noise`,  
339 `smell`, and `openness`. These researchers also defined a *modifiers dictionary*  
340 that describes how adverbs and other grade modifiers positively or negatively  
341 change the values of features associated with words within the [1, 5] scale  
342 adopted in our model. When these researchers disagreed with each other,  
343 they discussed the outcome with us.

344 The *sensory features dictionary* is organized as a set of  $\langle w, f, f_w, d_w \rangle$   
345 tuples. Each tuple contains:

- 346 • A word  $w$  referring to a sensory feature  $f$  of our model. For instance,  
347 adjective “scuro” (dark) refers to `brightness`.

- 348 • The feature  $f$  which  $w$  references (**brightness**).
- 349 • The basic positioning of  $w$  in the  $[1, 5]$  scale of the values of  $f$ , denoted  
350 as  $f_w$ . For example, “dark” is associated with a value of **brightness**  
351 equal to 2 ( $brightness_{scuro} = 2$ ) to enable the mapping of expressions  
352 such as “very dark” to the minimum value of the scale.
- 353 • The positive or negative direction  $d_w$  of change with respect to the  
354 basic positioning  $f_w$ , when  $w$  is associated with a grade modifier such as  
355 “little”, “very”, and so forth. For instance,  $d_{scuro} = -1$  because a very  
356 dark place has lower **brightness** than a little dark one. Conversely,  
357 regarding “chiaro” (bright),  $d_{chiaro} = 1$  because low values (1, 2) denote  
358 dark places, while higher values (3, 4, 5) correspond to brighter places.

359 The *modifiers dictionary* contains a set of  $\langle m, impact_m \rangle$  pairs. Each pair  
360 specifies the impact of a grade modifier  $m$  (e.g., “tanto” - a lot, “poco” - a  
361 little, etc.) on the values of features associated with words. Let us assume  
362 that  $m$  modifies a word  $w$  associated with a feature  $f$ . Then,  $impact_m$   
363 indicates how much  $m$  changes the value of  $w$  with respect to the basic  
364 position  $f_w$ , in the direction specified by  $d_w$ . The impact of modifiers takes  
365 values in the  $[-2, 2]$  scale that makes it possible to model positive and negative  
366 impact having low (-1, 1) or high (-2, 2) strength. For example,  $impact_{tanto} =$   
367 1 means that, when this modifier is applied to a word expressing an increasing  
368 scale, such as “bright”, it increments the corresponding feature value by 1.  
369 Differently, “a little” has the opposite behavior, and its impact is -1.

#### 370 4.5.2. Extraction of sensory feature evaluations from reviews

371 We use standard Natural Language Processing techniques to retrieve the  
372 sensory information about places used for recommendation. Starting from  
373 the comments about a place  $i$ , we select the set  $REV_i$  of reviews expressed  
374 in Italian and we extract the users' perceptions about the sensory features  
375 of  $i$  in two steps: 1) for each review  $rev \in REV_i$ , we extract the references  
376 to sensory features occurring in  $rev$  and their values. 2) for each sensory  
377 feature, we assign  $i$  the mean value retrieved from all the reviews of  $REV_i$ .

378 To extract sensory data (step 1), we analyze each sentence of the reviews  
379 by navigating the tree obtained through dependency parsing and we look for  
380 the nodes that represent words  $w$  of the *sensory features dictionary*. For each  
381 node  $N$  of this type, we compute the value  $val_{f_w}$  of feature  $f$  as follows:

- 382 • If  $N$  is a leaf node, or its sub-tree does not include any modifiers,  
383  $val_{f_w} = f_w$  as specified by tuple  $\langle w, f, f_w, d_w \rangle$  in the dictionary.
- 384 • Otherwise (suppose that  $w$  is modified by  $m$ ), let  $\Delta = impact_m * d_w$   
385 represent the displacement with respect to the basic position of  $f_w$ .  
386 Then,  $val_{f_w}$  is obtained by normalizing  $(f_w + \Delta)$  in  $[1, 5]$ .

### 387 5. Compatibility-aware PoI recommendation

388 This section presents the lower level of the framework for the compatibility-  
389 aware recommendation of places shown in Figure 1. This portion of the  
390 framework is based on the work by (Mauro et al., 2020) and we outline it to  
391 make the present paper self-contained. Table 6 shows the notation we use.

**Table 6:** Notation used to describe the compatibility-aware PoI recommendation model.

Variable	Definition
$U$	Set of users $u$
$I$	Set of items $i$
$C$	Set of item categories $c$
$L$	Likert scale in $[1, v_{max}]$ . In the present work $v_{max} = 5$
$F$	Set of sensory features of items ( $f$ )
$F^\uparrow$	Set of sensory features such that the higher the value of $f$ , the stronger its negative impact on the user (e.g., <b>noise</b> )
$F^V$	Set of features whose extreme values make people uncomfortable while the middle ones are less problematic (e.g., <b>brightness</b> )
$\vec{\mathbf{i}}$	Vector storing the value of each feature $f \in F$ of an item $i$
$PREF_u$	User preferences for the categories of places
$R_u$	Set of ratings that a user $u \in U$ gave to the items of $I$
$a_{ufv}$	A user $u$ 's aversion to a value $v$ of a feature $f \in F$
$comp_{ufi}$	Compatibility of item $i$ with $u$ regarding $f$
$\hat{r}_{ui}$	Estimation of a user $u$ 's rating of item $i$

### 392 5.1. Item profiles

393 Each PoI  $i \in I$  (where  $I = \Pi$ ) is described by an item profile that specifies  
394 the category of places  $c \in C$  to which  $i$  belongs, and a vector  $\vec{\mathbf{i}}$  storing its  
395 feature values:  $\vec{\mathbf{i}}_f$  (in  $[1, v_{max}]$ ) denotes a feature value and we remind that, if  
396 that value is unknown, we set  $\vec{\mathbf{i}}_f = 0$  to denote the lack of knowledge. Feature  
397 values are extracted from the Maps4All and/or TripAdvisor datasets.

### 398 5.2. User profiles

399 The information about a user  $u \in U$  is stored in a user profile that  
400 specifies the following data types, expressed in the  $L$  scale:

- 401 • Her/his preferences  $PREF_u = \{p_c \mid c \in C\}$  for the categories of places.

- 402 • The sensory aversion to specific values of item features declared by  $u$ .  
 403 We denote  $u$ 's aversion to a value  $v$  of a feature  $f \in F$  as  $a_{ufv}$ ; e.g.,  
 404  $a_{uf5} = 5$  means that  $u$  is very disturbed by an item  $i$  such that  $\vec{\mathbf{i}}_f = 5$ .
  - 405 – For each  $f \in F^\uparrow$ , we assume that  $a_{uf1} = 1$ . Thus, the user  
 406 profile only stores a value  $a_{ufv_{max}}$  that specifies  $u$ 's aversion to the  
 407 maximum value of  $f$ .
  - 408 – For each  $f$  in  $F^V$ , the user profile stores two values that express  
 409  $u$ 's aversion to the minimum and maximum values of  $f$ .

410 In our work, the list of sensory aversions of a user  $u$  consists of  $\{a_{ubrightness1},$   
 411  $a_{ubrightness5}, a_{ucrowding5}, a_{unoise5}, a_{usmell5}, a_{uopenness1}, a_{uopenness5}\}$ . The user pro-  
 412 files are set to the user data described in Section 4.1.

### 413 5.3. Evaluation of the compatibility of an individual feature with the user

414 The aversion values stored in the user profiles correspond to the extreme  
 415 values that features can take. Thus, an interpolation method is needed to in-  
 416 fer a user  $u$ 's aversion for the other values of  $[1, v_{max}]$ . Assuming to represent  
 417 feature values in the  $X$  axis, and aversion in the  $Y$  axis of a plane:

- For each  $f \in F^\uparrow$ , and given  $a_{ufv_{max}}$  in  $u$ 's profile, we approximate  
 aversion as a line connecting point  $(1, 1)$ , to point  $(v_{max}, a_{ufv_{max}})$  to  
 represent the increment of aversion while the value of  $f$  increases:

$$line^\uparrow(x) = 1 + \frac{(a_{ufv_{max}} - 1)(x - 1)}{v_{max} - 1} \quad (1)$$

418 Therefore,  $u$ 's estimated aversion to  $f$  in  $i$  is  $ea_{ufi} = line^\uparrow(\vec{\mathbf{i}}_f)$ .

- For each  $f \in F^V$ , and given  $\{a_{uf1}, a_{ufv_{max}}\}$  in  $u$ 's profile,  $ea_{ufi} = \max(\text{line}^\uparrow(\vec{\mathbf{i}}_f), \text{line}_\downarrow(\vec{\mathbf{i}}_f))$ , where

$$\text{line}_\downarrow(x) = 1 + \frac{(x - v_{max})(1 - a_{uf1})}{v_{max} - 1} \quad (2)$$

419 connects  $(1, a_{uf1})$  and  $(v_{max}, 1)$  to represent the decrease in aversion  
 420 from low to middle values of  $f$ .

Similar to (Mauro et al., 2020), we compute the compatibility of a feature value  $\vec{\mathbf{i}}_f$  with a user  $u$  as the complement in  $[1, v_{max}]$  of  $u$ 's aversion to  $f$  because aversion can be described as the opposite of compatibility:

$$\text{comp}_{ufi} = v_{max} + 1 - ea_{ufi} \quad (3)$$

421 Notice that, if the reviews of  $i$  do not mention  $f$ , we pessimistically set  
 422  $\text{comp}_{ufi} = 1$ . Even though the lack of references to a feature could be inter-  
 423 preted as a lack of complaints about it, this assumption is reasonable when  
 424 dealing with neurotypical users who, given the low percentage of autistic peo-  
 425 ple in the population, are plausibly the authors of most reviews. Conversely,  
 426 we consider the sensory needs of users with autism spectrum disorders, whose  
 427 sensitivity is much higher. To prevent the risk of bothering them, we assume  
 428 that a feature whose value is unknown is an incompatible one.

#### 429 5.4. Aggregation measures

430 Before describing the recommendation algorithms we use, we outline the  
 431 aggregation measures they apply to integrate evaluation components for rat-  
 432 ing prediction. Depending on the recommendation model, evaluation com-  
 433 ponents can represent the compatibility values of the sensory features or the

434 preference of the user  $u \in U$  for the category of the item to be evaluated. Let  
 435 us consider a set of evaluation components  $\Omega = \{\omega_1, \dots, \omega_k\}$ , where  $\omega_j$  takes  
 436 values in  $[1, v_{max}]$  and represents an aspect of fit between item and user. We  
 437 compute the aggregated value  $y$  by applying one of the following measures:

- 438 • *Min*:  $y$  is the minimum value of set  $\Omega$ , meaning that the aggregated  
 439 value corresponds to the worst fit between item and user.
- 440 • *Ave*:  $y$  is the mean value of set  $\Omega$ , denoting average fit.
- 441 • *Cos*:  $y$  is a normalization in  $[1, v_{max}]$  of Cosine similarity between a  
 442 vector  $\vec{\omega}$  representing the values of evaluation components and a vector  
 443  $\overrightarrow{\mathbf{ideal}_u}$  whose values for the same components best match  $u$ 's profile.  
 444 The smaller the angle between  $\vec{\omega}$  and  $\overrightarrow{\mathbf{ideal}_u}$ , the better  $\Omega$  fits  $u$ .
- *RMSD*: the aggregated value is the complement in  $[1, v_{max}]$  of the Root  
 Mean Square Deviation between  $\vec{\omega}$  and  $\overrightarrow{\mathbf{ideal}_u}$ . This represents the  
 distance between the two vectors ( $\overrightarrow{\mathbf{ideal}_{u\omega}}$  is component  $\omega$  of  $\overrightarrow{\mathbf{ideal}_u}$ ):

$$y = 1 + v_{max} - \sqrt{\frac{1}{|\Omega|} * \sum_{\omega \in \Omega} (\omega - \overrightarrow{\mathbf{ideal}_{u\omega}})^2} \quad (4)$$

#### 445 5.5. Rating prediction

446 For each  $u \in U$  and  $i \in I$ , we estimate  $u$ 's evaluation of  $i$  ( $\hat{r}_{ui}$ ) by applying  
 447 the following algorithms described in (Mauro et al., 2020, 2022):<sup>12</sup>

- **Individual (Ind)** estimates item ratings by adapting the relative impact  
 of sensory features compatibility and user preferences to the individual

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<sup>12</sup>We did not consider any collaborative recommendation algorithms (Adomavicius and Kwon, 2007) because our datasets are too small to train them.

user because it seems that people with autism weight these factors in a personal way (Mauro et al., 2020):

$$\hat{r}_{ui} = \alpha * overallComp_{ui} + (1 - \alpha) * p_{uci} \quad (5)$$

448 where  $p_{uci}$  is  $u$ 's preference for the category  $c$  of item  $i$  and  $overallComp_{ui}$   
 449 is the overall compatibility of  $i$  with  $u$ , given  $i$ 's sensory features. More-  
 450 over,  $\alpha$  (in  $[0, 1]$ ) personalizes the balance between item compatibility  
 451 and user preferences. Section 6 describes how  $\alpha$  is obtained.

452 **Ind** computes  $overallComp_{ui}$  by combining the compatibility of the  
 453 sensory features of  $i$  with  $u$  using the aggregation measures of Section  
 454 5.4. In *Min* and *Ave*,  $\Omega = \{comp_{ubrightnessi}, \dots, comp_{uopennessi}\}$  and its  
 455 components are defined as in Equation 3. Regarding *Cos* and *RMSD*,  
 456 we found that mapping  $\Omega$  to feature values improves recommendation  
 457 performance. Thus,  $\vec{\omega} = \vec{\mathbf{i}}$  and  $\overrightarrow{\mathbf{ideal}}_{\mathbf{u}}$  is an ideal item that minimizes  
 458  $u$ 's aversions. For each  $f \in F$ ,  $\overrightarrow{\mathbf{ideal}}_{\mathbf{uf}}$  is the most compatible value of  
 459  $f$ , based on  $u$ 's estimated aversion to  $f$ .

- 460 • **C-only** is a setting of the **Ind** algorithm where  $\alpha = 1$  is used to predict  
 461 ratings on the basis of its compatibility with the user.
- 462 • **Pref-only** is a setting of **Ind** where  $\alpha = 0$  is used to evaluate items on  
 463 the basis of the user's preferences.
- 464 • **Multi-Criteria (MC)** computes  $\hat{r}_{ui}$  by fusing  $u$ 's preference for the cate-  
 465 gory of  $i$  ( $p_{uci}$ ) with the compatibility of each individual feature ( $comp_{ufi}$ ),  
 466 managing all such values as independent evaluation factors. It inte-  
 467 grates the individual values by applying the aggregation measures of

468 Section 5.4 by setting  $\Omega = \{p_{uci}, comp_{ubrightness}, \dots, comp_{uopenness}\}$ .  
469 MC differs from `Ind` because it applies the same aggregation function to  
470 all the evaluation parameters, while `Ind` distinguishes preferences from  
471 compatibility and supports the adoption of heterogeneous aggregation  
472 criteria to the two types of information. Incidentally, we deal with a  
473 single preference for the item category but the preference component  
474 might result from the integration of multiple item features.

## 475 6. Validation methodology

476 Our experiments pursue two main goals. Concerning research question  
477 RQ1, we are interested in evaluating the usefulness of the sensory data about  
478 places gathered from Maps4All and/or from TripAdvisor platforms. Regarding  
479 RQ2, we aim at understanding how the sensory data extracted from  
480 consumer feedback impacts recommendation performance and whether, by  
481 modeling both user preferences and item compatibility, we obtain higher  
482 performance compared to taking only one of these aspects into account. To  
483 satisfy these goals, we compare the performance of the recommendation algo-  
484 rithms by configuring them on each aggregation measure of Section 5.4. The  
485 algorithms determine whether compatibility and/or user preferences have to  
486 be used in rating prediction. The aggregation measures provide alternative  
487 data fusion methods.

488 We are also interested in checking whether the management of compatibil-  
489 ity information is relevant to both neurotypical and autistic users. Therefore,  
490 we test the algorithms on the datasets of users described in Section 4.1:

- 491 1. Users with autism spectrum disorders. We denote this dataset as AUT.

492 2. Neurotypical users. We denote this dataset as NEU.

493 For each recommendation algorithm, we specify the aggregation measure  
494 we apply by appending the two names. For example,  $\text{Ind}_{Cos}$  represents the  
495 application of the *Cos* aggregation measure to model *Ind*. In addition to the  
496 notation of Table 6, we define  $R$  as the overall set of item ratings provided  
497 by the users of  $U$  and  $\hat{R}$  as the set of estimated ratings.  $Relevant_u$  is the  
498 set of items that  $u \in U$  has positively rated:  $Relevant_u = \{i \in I \mid r_{ui} > 3\}$ .  
499  $Recomm_u$  is the set of items that the system suggests to  $u$ :  $Recomm_u =$   
500  $\{i \in I \mid \hat{r}_{ui} > 3\}$ , and  $k$  denotes the length of the suggestion list.

501 We analyze recommendation performance in terms of **Accuracy** (Preci-  
502 sion, Recall, and F1 metrics), **Ranking capability** (MAP and MRR), **Error**  
503 **in rating prediction** (MAE and RMSE) and **User coverage**. The last pa-  
504 rameter describes the percentage of users to whom the system recommends  
505 items. All metrics, except for MAE and RMSE, have to be maximized.

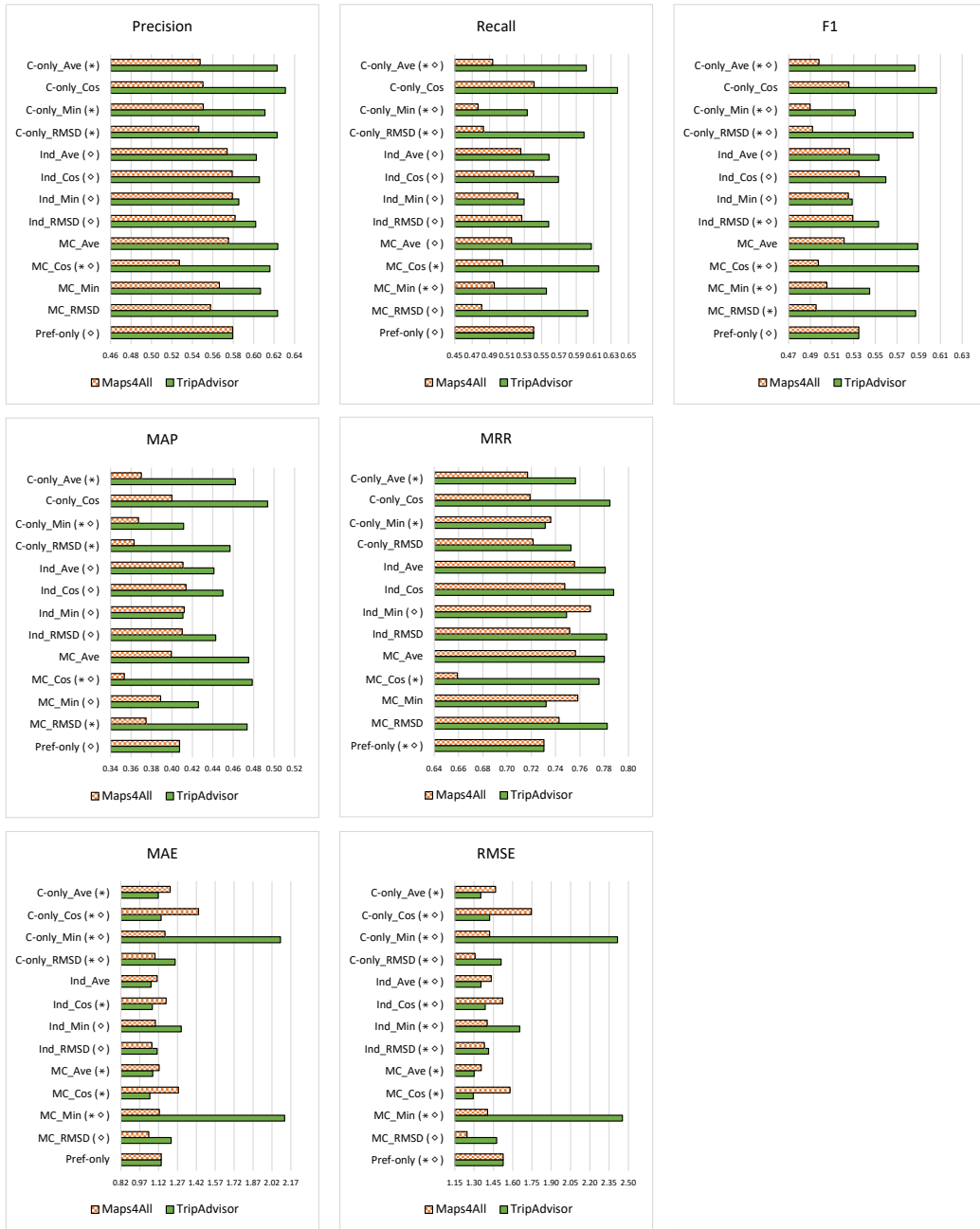
506 We perform a 5-fold cross-validation in which, for every fold, we use 80%  
507 as training set to find the best  $\alpha$  value for each individual user and 20% as  
508 test set. We are interested in optimizing performance with respect to the  
509 ranking of items in the recommendation lists. Thus, we run each model to  
510 find the best user-specific setting by optimizing its results for MAP using the  
511 Exhaustive Grid Search algorithm<sup>13</sup>. Notice that, to be sure that the other  
512 algorithms (*MC*, *C-only* and *Pref-only*, which do not need any training) are  
513 consistently evaluated, we run them on the same test sets used for *Ind*.

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<sup>13</sup>[https://scikit-learn.org/stable/modules/grid\\_search.html#exhaustive-grid-search](https://scikit-learn.org/stable/modules/grid_search.html#exhaustive-grid-search).



**Figure 3:** Comparison of performance results using Maps4All and TripAdvisor on the AUT dataset, based on the 50 PoIs of set II. Symbol “\*” denotes the statistical significance (t-test,  $p < 0.05$ ) of the difference between the best performing algorithm and the other ones on Maps4All. Similarly, “◊” denotes significance on TripAdvisor. See Table A.8.



**Figure 4:** Comparison of performance results using Maps4All and TripAdvisor on the NEU dataset, based on the 50 PoIs of set II. We use the same notation as in Figure 3. See Table A.9 for details.

## 514 7. Evaluation results

### 515 7.1. Comparing crowdsourced sensory information to consumer feedback

516 We first compare the recommendation performance of algorithms when  
517 they use either Maps4All or TripAdvisor for rating prediction, on the items  
518 of set  $\Pi$  (50 PoIs in Torino city center). We evaluate the algorithms assuming  
519 that the recommendation list has length 5 because longer lists would overload  
520 people with autism, due to their attention problems (Murray et al., 2005).

521 Figures 3 and 4 graphically summarize the performance results concerning  
522 the users of the AUT and NEU datasets. See Tables A.8 and A.9 for details.  
523 We omit the results concerning user coverage because it is 100% in all the  
524 cases. The figures group results by accuracy, ranking capability, and error  
525 metrics. Notice that the **Pref-only** algorithm achieves the same results on  
526 both datasets because it only uses preference information. Therefore, it does  
527 not depend on how sensory data about places is retrieved.

#### 528 7.1.1. Accuracy

529 Most algorithms obtain higher accuracy on TripAdvisor than on Maps4All.  
530 In the AUT dataset, this happens to 10 algorithms regarding Recall and  
531 F1. Moreover, it happens to 11 regarding Precision. In the NEU dataset,  
532 this happens to 12 algorithms. This means that, by relying on sensory fea-  
533 tures extracted from consumer feedback, the recommender system suggests  
534 a larger number of PoIs that the user appreciates. This might be due to  
535 the fact that, compared to the low number of evaluations received by each  
536 place in Maps4All, the TripAdvisor reviews provide a more extensive amount  
537 of data about items. While this finding does not discriminate performance

538 among algorithms, it encourages analyzing the online reviews collected from  
539 location-based services to build item profiles.

540 We now compare the performance of individual algorithms on TripAd-  
541 visor, where they achieve superior results, to investigate the impact of item  
542 compatibility and user preferences on the accuracy of recommendations:

- 543 • On the AUT dataset,  $MC_{Cos}$  has the highest F1 and Recall, and  $C-$   
544  $only_{Cos}$  is the second best. Moreover,  $MC_{Min}$  has maximum Precision,  
545 and  $MC_{Ave}$  is the second best. By focusing on F1, which summarizes  
546 accuracy, we can see that the difference between  $MC_{Cos}$  and most of the  
547 other  $C-only$  algorithms, which only use compatibility, is statistically  
548 significant. Similarly, the difference between  $MC_{Cos}$  and most of the  
549 other multi-criteria algorithms is significant. The accuracy of the  $Ind$   
550 algorithms is lower but the results are not statistically significant.
- 551 • In NEU,  $C-only_{Cos}$  achieves better results than the other algorithms  
552 in the three metrics, and  $MC_{Cos}$  is the second best in Recall and F1.  
553 The difference between F1 of  $C-only_{Cos}$  and the other algorithms is  
554 statistically significant.

555 On both AUT and NEU, these algorithms have higher accuracy than  $Pref-$   
556  $only$ , which is agnostic with respect to compatibility information, with sta-  
557 tistically significant differences on the NEU dataset.

558 Overall, the accuracy results support our hypothesis that compatibility  
559 information plays an important role in PoI recommendation.

560 *7.1.2. Ranking capability*

561 Most algorithms obtain better results when they use TripAdvisor than  
562 Maps4All. On the AUT dataset, this happens to 10 algorithms regarding  
563 MAP, and to 11 concerning MRR. On NEU, 11 algorithms have higher MAP  
564 and 9 have higher MRR. This finding supports the hypothesis that TripAdvi-  
565 sor is more effective than Maps4All in promoting items suitable for the user.  
566 Similar to the evaluation of accuracy, the algorithms that take both pref-  
567 erences and compatibility into account obtain higher results than Pref-only,  
568 which overlooks compatibility. However, the situation of the other algorithms  
569 is mixed and does not reveal a neat superiority of a specific way to combine  
570 these two types of information.

571 On the AUT dataset,  $\text{Ind}_{Cos}$  has the highest MAP and MRR on Maps4All,  
572 with a statistically significant difference of MAP compared to most C-Only  
573 and MC algorithms. However, on TripAdvisor, where algorithms perform  
574 better, the multi-criteria models achieve the best results:  $\text{MC}_{Cos}$  excels in  
575 MAP, and  $\text{MC}_{Min}$  in MRR (most results are not statistically significant).

576 On the NEU dataset, the Ind models achieve the best results on Maps4All.  
577 However, on TripAdvisor, C-only $_{Cos}$  has the best MAP, with a statistically  
578 significant difference compared to most of the other algorithms. Moreover,  
579  $\text{Ind}_{Cos}$  excels in MRR with poor statistical significance.

580 *7.1.3. Error in rating estimation*

581 Consumer feedback supports rating estimation in a less satisfactory way.  
582 On the AUT dataset, only 3 (respectively 5) algorithms obtain lower MAE  
583 (RMSE) when using TripAdvisor; the other ones work better on Maps4All.  
584 Moreover, on the NEU dataset, only 6 algorithms achieve lower rating esti-

585 mation errors on TripAdvisor than on Maps4All.

586 The comparison between algorithms provides mixed results, as well. On  
587 the AUT dataset with Maps4All data, the best model is  $\text{Ind}_{Min}$  with statis-  
588 tically significant difference compared to the other ones. The second best is  
589  $\text{Ind}_{RMSE}$  on both MAE and RMSE. We notice that the most pessimistic al-  
590 gorithms, which set item compatibility to the minimum one (e.g.,  $\text{C-only}_{Min}$   
591 and  $\text{MC}_{Min}$ ), have low performance.

592 Differently, on NEU, multi-criteria models work better than the other  
593 ones. The best algorithms are  $\text{MC}_{RMSE}$  on Maps4All, and  $\text{MC}_{Cos}$  in TripAd-  
594 visor. In both cases, the results are statistically significant.  $\text{Pref-only}$  is fairly  
595 good but, on both AUT and NEU, several algorithms that use compatibility  
596 information perform better than it.

#### 597 7.1.4. Overall performance

598 Concerning the accuracy and ranking capabilities, the best algorithms are  
599 the multi-criteria ones. Notice that the promotion of good items at the top of  
600 a recommendation list is a prior goal to be achieved because a low number of  
601 items can be realistically proposed to users in the autism spectrum disorder.  
602 Thus, the improvement of ranking capability obtained by extracting sensory  
603 data about places from reviews is a particularly relevant result. The results  
604 concerning the error metrics are mixed but they show a superiority of the  
605 models that take both user preferences and item compatibility into account,  
606 compared to those that use a single type of information.

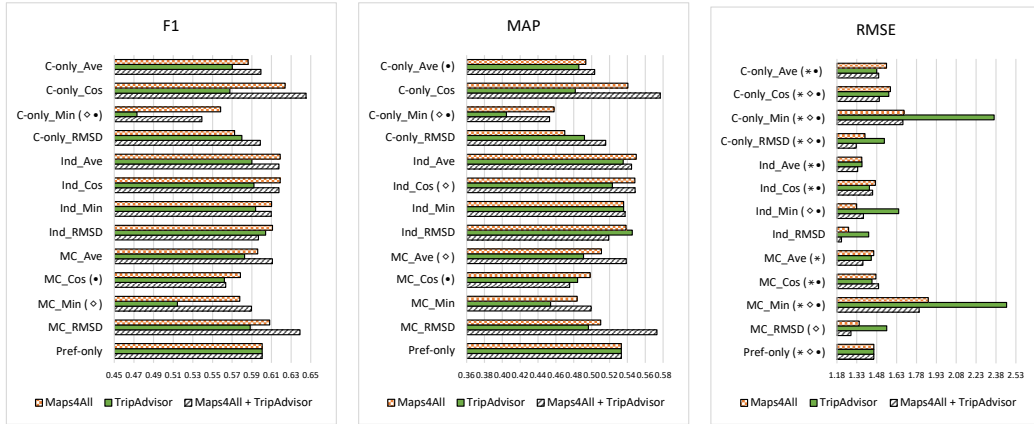
607 We found that rating estimation is not equally well-supported by con-  
608 sumer feedback. Indeed, we believe that this weak performance might be  
609 caused by a lack of data about PoIs. As discussed in Section 4.3, some sen-

610 sory features, such as `smell`, are poorly covered in TripAdvisor. Moreover,  
611 only 34 places out of the 50 of set  $\Pi$  are evaluated in TripAdvisor, against the  
612 49 of Maps4All. This means that the algorithms we tested on TripAdvisor  
613 frequently worked blindly, assuming by default a maximum incompatibility  
614 between individual features and the user. This aspect is likely responsible  
615 for the bad rating prediction results of the algorithms that use the *Min* ag-  
616 gregation strategy ( $C\text{-only}_{Min}$  and  $MC_{Min}$ ) because, if a single feature value  
617 is unknown, they propagate the incompatibility to the whole item. However,  
618 as discussed in Section 2, when suggesting places to autistic people, we have  
619 to avoid any possible source of discomfort and stress. Thus, our pessimistic  
620 approach to the estimation of sensory feature compatibility is a must. At the  
621 same time, we believe that rating estimation might be improved by facing  
622 data sparsity. For instance, multiple consumer feedback sources might be in-  
623 tegrated, such as different location-based services, with the aim of retrieving  
624 richer information about places.

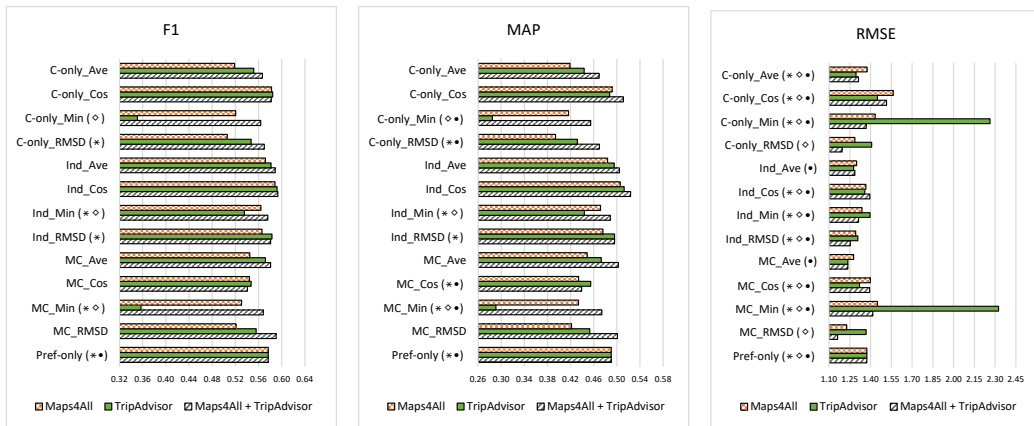
### 625 7.2. Integration of multiple data sources

626 To assess the usefulness of sensory data extracted from consumer feed-  
627 back, we shortly compare the performance achieved when separately using  
628 Maps4All or TripAdvisor data sources to that obtained when merging them  
629 in rating prediction ( $M+T$  model). In this case, instead of measuring perfor-  
630 mance on the whole set  $\Pi$  of places, we focus on its 34 places that are mapped  
631 by both data sources, i.e., on set  $(MA \cap TA)$  of Section 4.4. The reason for  
632 this choice is that we aim at understanding the usefulness of combining data  
633 sources when they can both provide at least partial information about places.

In the  $M+T$  model, we fuse data by computing the weighted average of



(a) AUT dataset. See Tables B.10 and B.11 for details.



(b) NEU dataset. See Tables B.12 and B.13 for details.

**Figure 5:** Comparison of performance results using data about PoIs from Maps4All, TripAdvisor, or by fusing them in the M+T model. All the results concern the 34 places of set  $MA \cap TA$ . Symbol “\*” denotes the statistical significance (t-test,  $p < 0.05$ ) of the difference between the best performing algorithm and the other ones on Maps4All. Similarly, “◊” (respectively “•”) denotes significance on TripAdvisor (resp. fusion of Maps4All and TripAdvisor).

feature values. In this way, we tune the impact of the two data sources in the estimation of feature values based the amount of available data about

sensory features. Moreover, if a single data source provides information about a feature, it compensates the lack of knowledge affecting the other one. For each  $i \in I$ , for each  $f \in F$ :

$$\vec{\mathbf{i}}_f = \frac{n_1 val_{f_{Maps4All}} + n_2 val_{f_{TripAdvisor}}}{n_1 + n_2} \quad (6)$$

634 where  $val_{f_{Maps4All}}$  (respectively  $val_{f_{TripAdvisor}}$ ) represents the value of  $f$  pro-  
 635 vided by Maps4All (resp. TripAdvisor) and  $n_1$  (resp.  $n_2$ ) is the number of  
 636 feature evaluations on which this value is based.

637 Figure 5 summarizes the accuracy, ranking capability, and rating pre-  
 638 diction error of algorithms by considering F1, MAP, and RMSE in the three  
 639 cases (only Maps4All, only TripAdvisor, M+T). We can see that 6 algorithms  
 640 (AUT dataset) and 9 algorithms (NEU dataset) improve their F1 when the  
 641 data retrieved from Maps4All and TripAdvisor is merged using Equation 6.  
 642 Moreover, in that case, 8 algorithms (AUT) and 10 algorithms (NEU) im-  
 643 prove their MAP. Furthermore, 8 algorithms (AUT) and 7 algorithms (NEU)  
 644 improve their RMSE. See Tables B.10, B.11, B.12, and B.13 for details.

645 Even though results are statistically significant in a few cases, they are  
 646 consistent with the hypothesis that recommendation performance can be im-  
 647 proved by combining different information sources to retrieve sensory feature  
 648 evaluations. We can explain this finding with the fact that the recommender  
 649 system leverages a larger amount of data and integrates missing information  
 650 by retrieving it from the source that provides it.

### 651 7.3. Analysis of the $\alpha$ weights for the *Ind* algorithms

652 The optimization of the *Ind* algorithms, which personalize the balance of  
 653 user preferences and compatibility to the individual user through the  $\alpha$  weight

	$\text{Ind}_{Ave}$		$\text{Ind}_{Cos}$		$\text{Ind}_{Min}$		$\text{Ind}_{RMSD}$	
	50 PoIs		50 PoIs		50 PoIs		50 PoIs	
	AUT	NEU	AUT	NEU	AUT	NEU	AUT	NEU
	Mean(SD)	Mean(SD)	Mean(SD)	Mean(SD)	Mean(SD)	Mean(SD)	Mean(SD)	Mean(SD)
Maps4All	0.180(0.282)	0.327(0.406)	0.230(0.365)	0.322(0.401)	0.200(0.304)	0.347(0.401)	0.180(0.271)	0.298(0.380)
TripAdvisor	0.260(0.299)	0.363(0.397)	0.310(0.373)	0.416(0.428)	0.285(0.328)	0.341(0.381)	0.305(0.329)	0.373(0.393)
	34 PoIs		34 PoIs		34 PoIs		34 PoIs	
Maps4All	0.275(0.392)	0.251(0.376)	0.320(0.440)	0.322(0.417)	0.235(0.356)	0.281(0.385)	0.280(0.375)	0.264(0.384)
TripAdvisor	0.315(0.369)	0.329(0.405)	0.315(0.398)	0.426(0.442)	0.310(0.346)	0.246(0.348)	0.325(0.370)	0.317(0.396)
Maps4All + TripAdvisor	0.335(0.430)	0.272(0.396)	0.535(0.479)	0.437(0.457)	0.380(0.435)	0.316(0.404)	0.445(0.444)	0.329(0.426)

**Table 7:** Average  $\alpha$  weights for the  $\text{Ind}$  algorithm.

654 of Equation 5, reveals interesting findings about the perception of places in  
655 the user population. As these algorithms achieve rather good performance  
656 in several evaluation metrics, they can provide evidence about how people  
657 weight these two types of information in the evaluation of places.

658 Table 7 shows the average  $\alpha$  weights for the different configurations of the  
659  $\text{Ind}$  algorithm. Surprisingly, in some cases, the  $\alpha$  weights are higher on the  
660 NEU dataset than on the AUT one. This supports the hypothesis that, to  
661 some extent, both autistic and neurotypical people are susceptible to sensory  
662 features of places. At the same time, even though these features can cause  
663 uncomfortable feelings to people with autism, preferences are important as  
664 well, and sometimes users are willing to overcome their aversions if they really  
665 like a place. See Mauro et al. (2020) for details about this.

## 666 8. Discussion

667 The experimental results allow us to positively answer our research ques-  
668 tions. Concerning RQ1, we found that a relevant amount of sensory infor-  
669 mation about places can be extracted from the reviews collected in location-

670 based services such as TripAdvisor, provided that they map the PoIs that  
671 the recommender system deals with. Especially for some features, such as  
672 **crowding** and **openness**, reviews offer rich information that can be reliably  
673 used to steer the suggestion of places to the individual user. Indeed, location-  
674 based services are particularly valuable because they represent a sustainable  
675 source of sensory data about PoIs, fed with a continuous, spontaneous re-  
676 viewing activity concerning places distributed all over the world.

677     Concerning RQ2, we found that sensory data extracted from TripAdvi-  
678 sor reviews is useful because it improves accuracy and ranking capability in  
679 recommendation algorithms that only use compatibility information about  
680 items, or which combine it with user preferences. Moreover, when merging  
681 this data with crowdsourced sensory information, the algorithms obtain bet-  
682 ter accuracy, ranking capability, and error minimization than when using a  
683 single data source. As all the results concern both users with autism and  
684 neurotypical ones, these findings show that consumer feedback is a precious  
685 type of information for the development of inclusive recommender systems.

686     These results have important practical implications. Regarding the spe-  
687 cific target of our work, our approach supports the development of compatibility-  
688 aware recommender systems that can serve several locations, instead of being  
689 constrained to restricted areas where sensory information has been specified.  
690 Our model can be applied to large geographical areas, or to areas spread  
691 all over the world, because the knowledge base of the recommender system  
692 can be fed in an automatic way through a continuous analysis of the con-  
693 sumer feedback collected by social media and location-based services. In  
694 turn, this might dramatically help people with autism because it would ex-

695 tend the availability of a technological support while they are on the move,  
696 thus minimizing the level of stress and improving their quality of life. On  
697 a different perspective, the applicability of our approach makes it adaptable  
698 to different targets. Even though we currently focus on autistic users, our  
699 approach can be useful to other fragile people, as well. In fact, the inte-  
700 gration of compatibility in the evaluation of the suitability of items to the  
701 user makes it possible to deal with different sources of incompatibility be-  
702 tween places and users, and thus with other types of disability. For instance,  
703 we might apply our approach to focus the recommendation algorithm not  
704 only on sensory aversions, but also on other specific user constraints and  
705 needs, such as trying to avoid architectural barriers for people with physi-  
706 cal impairments (OpenStreetMap and other similar platforms provide some  
707 information about wheelchair access to places).

## 708 **9. Limitations and future work**

709 The experiments we carried out show that our approach depends on the  
710 geographical coverage of the external data sources we exploit to retrieve  
711 sensory information about places. In this respect, we plan to extend our  
712 model in three ways. First, we will integrate in our feature extraction model  
713 further data sources, such Yelp and Google Maps, to retrieve sensory data  
714 about a larger number of places. Second, we will extend the analysis of  
715 reviews to infer feature values by exploiting the correlations among sensory  
716 features that we found by analyzing the Maps4All and TripAdvisor datasets.  
717 However, this inference is subject to uncertainty, which should be considered  
718 in the recommendation algorithms. Third, we plan to investigate the use of

719 generative models to address data sparsity.

720 Another limitation of our work is the fact that we recommend places  
721 by analyzing the user’s interests in the categories of places, but not in their  
722 features. We plan to acquire fine-grained data from geographical servers such  
723 as OpenStreetMap, and to extract features of places from consumer feedback,  
724 to manage fine-grained user preferences in the user profiles.

725 Currently, we are integrating the approach described in this paper into  
726 the PIUMA mobile guide (Cena et al., 2020, 2021) which suggests places to  
727 visit to people with autism. We then plan to test our recommender systems  
728 in the field, by carrying out a user study with people from the Adult Autism  
729 Center of Torino. So far, we could only perform offline experiments because  
730 the center was closed due to Covid-19 pandemic and thus we could not in-  
731 teract with its guests. The development of this app will make it possible  
732 to acquire precise evaluation data about PoIs and to know the identities of  
733 the people who have provided feedback about sensory features. This opens  
734 a research avenue towards the exploitation of information diffusion models  
735 in recommender systems, similar to what has been done in (Xiong et al.,  
736 2020b,a) for Matrix Factorization.

737 Our future work also includes a cooperation with psychologists to develop  
738 novel recommendation algorithms that are robust with respect to individual  
739 biases in the evaluation of sensory features. In fact, as the perception of  
740 places is subjective, the feature values extracted from consumer feedback, or  
741 explicitly crowdsourced, might be biased. Thus, the evaluation of compati-  
742 bility with a specific user might be affected by uncertainty.

## 743 10. Conclusions

744 Users with autism spectrum disorders are a particularly interesting tar-  
745 get of PoI recommender systems because of their specific needs regarding  
746 places. To suggest PoIs that they can like and serenely experience, both  
747 their preferences and aversions to sensory features must be considered. In  
748 fact, the compatibility of items with a user’s aversions can seriously affect  
749 her/his experience with places, causing negative feelings.

750 Given the difficulties in retrieving sensory data from geographic informa-  
751 tion servers, we proposed a model to extract this type of information from  
752 the consumer feedback collected by location-based services. We compared  
753 the performance of a set of recommender systems on sensory data about  
754 places gathered in a crowdsourced campaign, from TripAdvisor reviews, or  
755 from both data sources. By using consumer feedback, the systems obtained  
756 higher accuracy and ranking capability. By fusing the two data sources, they  
757 achieved even higher accuracy, ranking capability, and they improved rat-  
758 ing prediction. We also found that the algorithms that use compatibility in  
759 rating estimation outperform those that only rely on user preferences.

760 We conclude that the integration of user interests and sensory aversions  
761 is a promising approach to extend the target user groups of recommender  
762 systems. Concerning people with autism spectrum disorders, compatibility-  
763 aware recommender systems can reduce the level of stress perceived in moving  
764 within a city and increase autonomy. Notice that the extraction of sensory  
765 feature evaluations from consumer feedback can be used when the sensory  
766 data is scarce to improve the quality of the suggestions. Moreover, it can be  
767 used to increase the number of places that can be mapped in a city, and it

768 is more sustainable than a crowdsourced campaign.

## 769 **11. Acknowledgments**

770 This work is supported by the Fondazione Compagnia di San Paolo. We  
771 thank the colleagues of our Department for the support in the work and the  
772 Adult Autism Center of the City of Torino for the recruitment of the subjects  
773 who participated in our experiments. We also thank the anonymous reviewers  
774 of this paper for their thoughtful comments and suggestions.

## 775 **Appendix A. Detailed results using the 50 PoIs of set II.**

**Table A.8:** Top-N recommendation results on AUT dataset with N=5, using the information about the 50 PoIs of the II set. The lines of the table are ordered by MAP. The best value of each measure across all algorithms is printed in bold, the second best one is underlined. For each evaluation metric, “\*” denotes the statistical significance (t-test,  $p < 0.05$ ) of the difference between the best performing algorithm and the other ones on Maps4All. Similarly, “◊” denotes significance on TripAdvisor.

Maps4All							
Algorithm	Prec.	Recall	F1	MAP	MRR	MAE	RMSE
C-only <sub>Ave</sub>	0.5912	*0.5154	0.5270	*0.4142	0.7192	*1.3045	*1.6060
C-only <sub>Cos</sub>	0.6263	<b>0.6224</b>	<u>0.6001</u>	0.4877	0.7583	*1.3675	*1.6948
C-only <sub>Min</sub>	0.6065	*0.4999	0.5230	*0.4166	*0.7583	*1.3675	*1.6816
C-only <sub>RMSD</sub>	0.5850	*0.4970	0.5134	*0.3996	*0.7142	*1.2025	*1.4400
Ind <sub>Ave</sub>	0.6118	*0.5710	0.5736	0.4960	0.7667	0.9168	1.3659
Ind <sub>Cos</sub>	0.6290	<u>0.6207</u>	<b>0.6046</b>	<b>0.5384</b>	<b>0.8095</b>	0.9927	*1.4541
Ind <sub>Min</sub>	<b>0.6328</b>	0.5832	0.5910	<u>0.5125</u>	0.7825	<b>0.8691</b>	<b>1.3020</b>
Ind <sub>RMSD</sub>	0.5968	0.5525	0.5561	0.4787	*0.7537	<u>0.9018</u>	<u>1.3295</u>
MC <sub>Ave</sub>	0.6255	*0.5383	0.5575	0.4489	0.7792	*1.1902	*1.4861
MC <sub>Cos</sub>	0.5917	*0.5558	0.5459	*0.4336	*0.7217	*1.3534	*1.6236
MC <sub>Min</sub>	<u>0.6305</u>	*0.5057	*0.5344	*0.4352	<u>0.7950</u>	*1.4512	*1.7943
MC <sub>RMSD</sub>	0.6105	*0.5396	0.5477	*0.4429	0.7775	*1.1265	1.3607
Pref-only	0.6220	0.5912	0.5860	*0.5114	0.7858	0.9346	*1.4276
TripAdvisor							
C-only <sub>Ave</sub>	0.6512	◊0.6019	◊0.5978	0.4855	0.7692	◊1.2741	◊1.5587
C-only <sub>Cos</sub>	0.6423	<u>0.6418</u>	<u>0.6136</u>	<u>0.5185</u>	0.8003	◊1.2638	◊1.5513
C-only <sub>Min</sub>	0.6525	◊0.5380	◊0.5487	◊0.4497	0.7900	◊2.3017	◊2.6292
C-only <sub>RMSD</sub>	0.6453	◊0.5887	◊0.5881	◊0.4774	0.7775	◊1.3876	◊1.6562
Ind <sub>Ave</sub>	0.6380	0.6007	0.6009	0.5116	0.7800	<u>0.9685</u>	<b>1.3701</b>
Ind <sub>Cos</sub>	0.6113	◊0.5745	◊0.5704	0.4928	0.7783	◊1.0072	◊1.4244
Ind <sub>Min</sub>	0.6545	◊0.5680	0.5881	0.4971	0.7900	◊1.1948	◊1.6535
Ind <sub>RMSD</sub>	0.6380	0.6110	0.6050	0.5140	0.7800	0.9845	<u>◊1.3927</u>
MC <sub>Ave</sub>	<u>0.6577</u>	◊0.6169	0.6059	0.5055	0.8148	◊1.2010	◊1.4810
MC <sub>Cos</sub>	0.6533	<b>0.6666</b>	<b>0.6285</b>	<b>0.5306</b>	0.7978	◊1.1902	1.4237
MC <sub>Min</sub>	<b>0.6585</b>	◊0.5836	◊0.5768	0.4884	<b>0.8170</b>	◊2.3241	◊2.6586
MC <sub>RMSD</sub>	0.6473	◊0.5974	◊0.5900	0.4905	<u>0.8153</u>	◊1.3427	◊1.6144
Pref-only	0.6220	0.5912	0.5860	0.5114	0.7858	<b>0.9346</b>	1.4276

**Table A.9:** Top-N recommendation results on NEU dataset with N=5, using the 50 PoIs of the II set. We use the same notation as in Table A.8

Algorithm	Prec.	Recall	F1	MAP	MRR	MAE	RMSE
<b>Maps4All</b>							
C-only <sub>Ave</sub>	*0.5476	*0.4936	*0.4979	*0.3701	*0.7168	*1.2122	*1.4668
C-only <sub>Cos</sub>	0.5503	<b>0.5414</b>	0.5255	0.4000	0.7189	*1.4374	*1.7456
C-only <sub>Min</sub>	*0.5507	*0.4769	*0.4899	*0.3673	*0.7359	*1.1704	*1.4213
C-only <sub>RMSD</sub>	*0.5464	*0.4831	*0.4920	*0.3630	0.7215	*1.0908	<u>*1.3070</u>
Ind <sub>Ave</sub>	0.5740	0.5261	0.5262	0.4108	0.7555	1.1085	*1.4343
Ind <sub>Cos</sub>	0.5790	<u>0.5406</u>	<b>0.5349</b>	<b>0.4139</b>	0.7475	*1.1792	*1.5232
Ind <sub>Min</sub>	<u>0.5791</u>	0.5225	0.5250	<u>0.4120</u>	<b>0.7688</b>	1.0950	*1.4024
Ind <sub>RMSD</sub>	0.5817	0.5272	*0.5292	0.4101	0.7515	<u>1.0663</u>	*1.3796
MC <sub>Ave</sub>	0.5752	0.5154	0.5213	0.3995	0.7564	*1.1238	*1.3564
MC <sub>Cos</sub>	*0.5274	*0.5053	*0.4974	*0.3535	*0.6591	*1.2775	*1.5795
MC <sub>Min</sub>	0.5664	*0.4956	*0.5053	0.3890	<u>0.7583</u>	*1.1249	*1.4052
MC <sub>RMSD</sub>	0.5577	0.4809	*0.4953	*0.3746	0.7428	<b>1.0417</b>	<b>1.2447</b>
Pref-only	<b>0.5795</b>	0.5408	<u>0.5347</u>	0.4076	*0.7304	1.1416	*1.5270
<b>TripAdvisor</b>							
C-only <sub>Ave</sub>	0.6230	◊0.6016	◊0.5866	0.4621	0.7563	1.1163	1.3521
C-only <sub>Cos</sub>	<b>0.6310</b>	<b>0.6374</b>	<b>0.6063</b>	<b>0.4936</b>	<u>0.7847</u>	◊1.1398	◊1.4209
C-only <sub>Min</sub>	0.6110	◊0.5336	◊0.5315	◊0.4116	0.7314	◊2.0874	◊2.4154
C-only <sub>RMSD</sub>	0.6230	◊0.5989	◊0.5846	0.4569	0.7527	◊1.2508	◊1.5106
Ind <sub>Ave</sub>	◊0.6026	◊0.5585	◊0.5532	◊0.4412	0.7809	<u>1.0608</u>	◊1.3538
Ind <sub>Cos</sub>	◊0.6057	◊0.5695	◊0.5596	◊0.4499	<b>0.7878</b>	1.0708	◊1.3869
Ind <sub>Min</sub>	◊0.5854	◊0.5299	◊0.5286	◊0.4107	◊0.7491	◊1.3002	◊1.6550
Ind <sub>RMSD</sub>	◊0.6020	◊0.5581	◊0.5529	◊0.4429	0.7821	◊1.1085	◊1.4135
MC <sub>Ave</sub>	<u>0.6236</u>	◊0.6073	0.5891	0.4751	0.7801	1.0725	<u>1.3001</u>
MC <sub>Cos</sub>	◊0.6159	<u>0.6158</u>	◊0.5898	◊0.4786	0.7758	<b>1.0511</b>	<b>1.2935</b>
MC <sub>Min</sub>	0.6067	◊0.5555	◊0.5447	◊0.4259	0.7321	◊2.1211	◊2.4541
MC <sub>RMSD</sub>	0.6234	◊0.6031	0.5872	0.4736	0.7825	◊1.2202	◊1.4749
Pref-only	◊0.5795	◊0.5408	◊0.5347	◊0.4076	◊0.7304	1.1416	◊1.5270

776 **Appendix B. Detailed results using the 34 PoIs mapped in both**  
777 **Maps4All and TripAdvisor (MA $\cap$ TA).**

**Table B.10:** Results on AUT dataset for N=5, using the information about places provided either by Maps4All, or by TripAdvisor, on the 34 PoIs of set II that are mapped by both data sources ( $MA \cap TA$ ). We use the same notation as in Table A.8.

Maps4All							
Algorithm	Prec.	Recall	F1	MAP	MRR	MAE	RMSE
C-only <sub>Ave</sub>	0.6742	0.5705	0.5863	0.4933	0.7783	*1.2441	*1.5538
C-only <sub>Cos</sub>	0.6747	<b>0.6393</b>	<b>0.624</b>	0.5406	0.7775	*1.2518	*1.5839
C-only <sub>Min</sub>	0.6708	0.5303	0.5583	0.4578	0.7558	*1.4010	*1.6856
C-only <sub>RMSD</sub>	0.6727	*0.5503	0.5725	0.4698	0.7617	*1.1682	*1.3918
Ind <sub>Ave</sub>	0.6830	0.6255	0.6189	<b>0.5499</b>	0.7900	0.9339	*1.3682
Ind <sub>Cos</sub>	*0.6680	<u>0.6363</u>	<u>0.6189</u>	<u>0.5484</u>	0.7800	*1.0329	*1.4697
Ind <sub>Min</sub>	0.6855	0.6022	0.6101	0.5357	0.7883	<u>0.9015</u>	<u>1.3276</u>
Ind <sub>RMSD</sub>	0.6680	0.6155	0.6111	0.5385	0.7750	<b>0.8885</b>	<b>1.2681</b>
MC <sub>Ave</sub>	0.6887	0.5765	0.5960	0.5109	<b>0.8083</b>	*1.1540	*1.4572
MC <sub>Cos</sub>	0.6465	0.5920	0.5784	0.4982	0.7550	*1.2027	*1.4741
MC <sub>Min</sub>	<b>0.7133</b>	0.5453	0.5778	0.4838	<u>0.8083</u>	*1.5552	*1.8692
MC <sub>RMSD</sub>	<u>0.6968</u>	0.5882	0.6082	0.5100	0.8050	*1.1107	1.3481
Pref-only	*0.6857	0.5938	0.6005	0.5333	0.7967	*0.9484	*1.4583
TripAdvisor							
C-only <sub>Ave</sub>	◊0.6395	0.5742	0.5701	0.4857	◊0.7828	◊1.2034	1.4800
C-only <sub>Cos</sub>	◊0.6268	0.5828	0.5676	0.4816	0.7767	◊1.2602	◊1.5712
C-only <sub>Min</sub>	0.6528	◊0.4570	◊0.4730	◊0.4046	◊0.7275	◊2.0903	◊2.3653
C-only <sub>RMSD</sub>	0.6413	0.5820	0.5798	0.4919	0.7975	◊1.3099	◊1.5368
Ind <sub>Ave</sub>	0.6562	0.5897	0.5901	0.5353	0.7917	<b>0.9459</b>	<b>1.3692</b>
Ind <sub>Cos</sub>	0.6712	0.5922	0.5921	◊0.5231	0.7850	0.9781	1.4254
Ind <sub>Min</sub>	<b>0.6948</b>	0.5755	0.5939	<u>0.5357</u>	0.8067	◊1.1957	◊1.6454
Ind <sub>RMSD</sub>	0.6695	<b>0.6013</b>	<b>0.6041</b>	<b>0.5454</b>	0.8100	◊1.0091	<u>1.4196</u>
MC <sub>Ave</sub>	0.6652	0.5768	0.5827	◊0.4909	<u>0.8145</u>	◊1.1641	1.4396
MC <sub>Cos</sub>	◊0.6310	0.5750	0.5621	0.4843	0.7900	◊1.1871	1.4442
MC <sub>Min</sub>	0.6468	0.5452	◊0.5142	0.4540	◊0.7542	◊2.1382	◊2.4606
MC <sub>RMSD</sub>	0.6707	0.5710	0.5884	0.4964	<b>0.8183</b>	◊1.3206	◊1.5551
Pref-on	<u>0.6857</u>	<u>0.5938</u>	<u>0.6005</u>	0.5333	0.7967	<u>0.9484</u>	◊1.4583

**Table B.11:** Results on AUT dataset for N=5, focusing on the places of set  $MA \cap TA$ . The data about places provided by Maps4All and TripAdvisor is fused by applying Equation 6. For each evaluation metric, “•” denotes the statistical significance (t-test,  $p < 0.05$ ) of the difference between the best performing algorithm and the other ones.

Maps4All + TripAdvisor (M+T)							
Algorithm	Prec.	Recall	F1	MAP	MRR	MAE	RMSE
C-only <sub>Ave</sub>	•0.6670	0.6068	0.5993	•0.5034	•0.7600	•1.2185	•1.4951
C-only <sub>Cos</sub>	<u>0.7000</u>	<b>0.6427</b>	<b>0.6452</b>	<b>0.5767</b>	<u>0.8350</u>	•1.2144	•1.4993
C-only <sub>Min</sub>	•0.6217	•0.5258	•0.5392	•0.4528	•0.7417	•1.3864	•1.6779
C-only <sub>RMSD</sub>	0.6792	0.5930	0.5987	0.5158	0.7967	•1.1285	•1.3254
Ind <sub>Ave</sub>	0.6847	0.6163	0.6176	0.5447	•0.7917	<u>0.8985</u>	•1.3361
Ind <sub>Cos</sub>	0.6972	0.6038	0.6177	0.5487	•0.7950	•1.0227	•1.4484
Ind <sub>Min</sub>	0.6927	0.5997	0.6098	0.5375	0.7917	•0.9773	•1.3806
Ind <sub>RMSD</sub>	•0.6662	0.6047	0.5968	0.5192	•0.7733	<b>0.8694</b>	<b>1.2152</b>
MC <sub>Ave</sub>	0.6808	0.5983	0.6109	0.5387	0.8167	•1.0921	1.3754
MC <sub>Cos</sub>	0.6503	•0.5622	•0.5634	•0.4753	0.7958	•1.2220	•1.4940
MC <sub>Min</sub>	0.6895	0.5762	0.5897	0.4994	0.7792	•1.4909	•1.7999
MC <sub>RMSD</sub>	<b>0.7073</b>	<u>0.6373</u>	<u>0.6390</u>	<u>0.5731</u>	<b>0.8483</b>	•1.076	<u>1.2856</u>
Pref-only	0.6857	0.5938	0.6005	0.5333	•0.7967	•0.9484	•1.4583

**Table B.12:** Results on NEU dataset for N=5, using the information about places provided either by Maps4All, or by TripAdvisor, on the 34 POIs of set  $MA \cap TA$ . We use the same notation as in Table A.8.

Algorithm	Prec.	Recall	F1	MAP	MRR	MAE	RMSE
<b>Maps4All</b>							
C-only <sub>Ave</sub>	*0.5580	*0.5327	0.5186	0.4190	*0.7131	*1.1264	*1.3742
C-only <sub>Cos</sub>	0.5885	<b>0.6310</b>	<u>0.5825</u>	<u>0.4919</u>	0.7566	*1.2757	*1.5642
C-only <sub>Min</sub>	0.5809	*0.5221	0.5205	0.4163	0.7130	*1.1720	*1.4332
C-only <sub>RMSD</sub>	0.5642	*0.4985	*0.5059	*0.3941	*0.6973	1.0671	1.2868
Ind <sub>Ave</sub>	0.6090	0.5952	0.5717	0.4841	0.7576	<u>0.9804</u>	1.2989
Ind <sub>Cos</sub>	<b>0.6201</b>	<u>0.6215</u>	<b>0.5884</b>	<b>0.5058</b>	<b>0.7722</b>	*1.0363	*1.3663
Ind <sub>Min</sub>	0.6082	0.5809	*0.5638	*0.4717	0.7487	*1.0229	*1.3379
Ind <sub>RMSD</sub>	0.6109	0.5807	*0.5659	*0.4759	0.7534	<b>0.9746</b>	*1.2928
MC <sub>Ave</sub>	0.5812	0.5641	0.5449	0.4486	0.7422	1.0499	<u>1.2778</u>
MC <sub>Cos</sub>	*0.5544	*0.5847	0.5441	*0.4340	*0.6797	*1.1190	*1.3978
MC <sub>Min</sub>	0.5951	*0.5333	*0.5306	*0.4337	0.7389	*1.1520	*1.4491
MC <sub>RMSD</sub>	0.5711	*0.5217	0.5212	0.4217	*0.7281	1.0214	<b>1.2280</b>
Pref-only	<u>0.6139</u>	0.6046	*0.5765	*0.4902	<u>0.7577</u>	1.0012	*1.3733
<b>TripAdvisor</b>							
C-only <sub>Ave</sub>	0.5678	0.5831	0.5518	0.4435	◊0.6993	◊1.0753	◊1.2955
C-only <sub>Cos</sub>	0.5878	<b>0.6361</b>	<u>0.5844</u>	0.4877	◊0.7304	◊1.1639	◊1.4498
C-only <sub>Min</sub>	◊0.5042	◊0.3471	◊0.3509	◊0.2845	◊0.5743	◊1.9253	◊2.2629
C-only <sub>RMSD</sub>	0.5725	0.5686	0.5470	0.4317	◊0.7017	◊1.1739	◊1.4081
Ind <sub>Ave</sub>	0.6139	0.6091	0.5814	0.4954	<u>0.7642</u>	<b>0.9815</b>	<u>1.2781</u>
Ind <sub>Cos</sub>	<b>0.6226</b>	<u>0.6218</u>	<b>0.5920</b>	<b>0.5126</b>	<b>0.7852</b>	1.0187	◊1.3577
Ind <sub>Min</sub>	◊0.6015	◊0.5480	◊0.5356	◊0.4438	◊0.7296	◊1.0631	◊1.3953
Ind <sub>RMSD</sub>	<u>0.6177</u>	0.6070	0.5831	<u>0.4961</u>	0.7624	◊1.0093	◊1.3086
MC <sub>Ave</sub>	0.5952	0.6023	0.5718	0.4729	0.7401	◊1.0291	<b>1.2358</b>
MC <sub>Cos</sub>	◊0.5681	0.5754	0.5470	0.4546	0.7209	◊1.0673	◊1.3207
MC <sub>Min</sub>	◊0.4907	◊0.3607	◊0.3571	◊0.2908	◊0.5612	◊1.9627	◊2.3249
MC <sub>RMSD</sub>	0.5916	0.5731	0.5558	0.4530	◊0.7291	◊1.1336	◊1.3682
Pref-only	0.6139	0.6046	0.5765	0.4902	◊0.7577	<u>1.0012</u>	◊1.3733

**Table B.13:** Results on NEU dataset for N=5, focusing on the places of set  $MA \cap TA$ . The data about places provided by Maps4All and TripAdvisor is fused by applying Equation 6. We use the same notation as in Table B.11.

Algorithm	Prec.	Recall	F1	MAP	MRR	MAE	RMSE
<b>Maps4All + TripAdvisor (M+T)</b>							
C-only <sub>Ave</sub>	0.5968	0.5924	0.5665	0.4694	●0.7433	●1.0822	●1.3129
C-only <sub>Cos</sub>	●0.5882	<b>0.6289</b>	0.5819	<u>0.5112</u>	●0.7827	●1.2360	●1.5152
C-only <sub>Min</sub>	0.6029	0.5786	0.5635	●0.4546	●0.7202	●1.1196	●1.3694
C-only <sub>RMSD</sub>	0.6061	0.5870	0.5699	●0.4697	●0.7463	0.9951	<u>1.1946</u>
Ind <sub>Ave</sub>	<b>0.6260</b>	0.6136	0.5887	0.5047	●0.7717	0.9770	●1.2869
Ind <sub>Cos</sub>	0.6194	<u>0.6284</u>	<b>0.5933</b>	<b>0.5236</b>	<b>0.8017</b>	●1.0786	●1.3941
Ind <sub>Min</sub>	0.6189	0.5948	0.5761	0.4887	●0.7684	●1.0115	●1.3141
Ind <sub>RMSD</sub>	●0.6207	0.6027	0.5809	0.4960	●0.7718	<b>0.9589</b>	●1.2533
MC <sub>Ave</sub>	0.6125	0.6000	0.5810	0.5025	<u>0.7911</u>	1.0182	●1.2358
MC <sub>Cos</sub>	0.5724	●0.5575	0.5405	●0.4390	●0.7142	●1.1223	●1.3936
MC <sub>Min</sub>	0.6099	0.5860	0.5683	●0.4738	●0.7569	●1.1377	●1.4157
MC <sub>RMSD</sub>	<u>0.6241</u>	0.6088	<u>0.5903</u>	0.5009	0.7828	<u>0.9679</u>	<b>1.1615</b>
Pref-only	0.6139	0.6046	●0.5765	●0.4902	●0.7577	●1.0012	●1.3733

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