IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 8 May 2023, accepted 7 June 2023, date of publication 12 June 2023, date of current version 23 June 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3285258

RESEARCH ARTICLE

How Personality Traits can be Used to Shape Itinerary Factors in Recommender Systems for Young Travellers

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This work involved human subjects or animals in its research. Approval of all ethical and experimental procedures and protocols was granted by the Comitato di Bioetica d'Ateneo (Bio Ethics Committee), University of Turin under Application No. 0631 962.

ABSTRACT Planning an itinerary is a complex activity, which includes the choice of a few places to see, coupled with information on timing, transferring methods and related activities. Intelligent tools such as recommender systems have been used in order to support these activities. While decisions regarding the type of trip to undertake are strongly influenced by tourists' personalities, currently only a few recommenders exploit information about this aspect. Our aim is to provide itinerary recommender system designers with some guidance on the integration of knowledge on personality traits and itinerary factors in a recommender. To do so, first we modeled the most important aspects of an itinerary, starting from the state-of-the-art literature on recommender systems for tourism. We identified thirteen factors, from the variety (in type and topic) of Points-of-Interest (POIs) to the expected duration of transfer times, grouped into three broader dimensions (POIs, time and choice modality). Then, we carried out a survey-based study on Generation Z (namely, the generation of people born between 1996/1997 and 2012) to investigate if the Big Five personality traits can affect the user's decision-making process when planning an itinerary, and, in particular if they are related to user preferences for the itinerary factors in our model. Finally, we used our findings to define some guidelines for the design of advanced itinerary recommender systems.

INDEX TERMS Itinerary, personality-traits, decision-making, user study, recommender systems, correlation analysis, simple regression, canonical correlation analysis.

I. INTRODUCTION

In organizing a journey, tourists usually spend some time in the complex activity of planning an itinerary, which is a route composed of one or more points of interest (POIs), coupled with basic information on timing, transferring methods and related activities and attractions [1], [2]. The time spent on the planned activity can be positively or negatively affected by some itinerary factors [3], such as the type of travel planned. People tend to spend more time planning trips that are expensive or involve particularly far and hard-to-reach destinations. On the contrary, the quantity of time spent planning a trip usually decreases if the person has already a certain familiarity with the destination or if the planning activity is entrusted to a travel agent [4], [5], [6]. Other user-related variables influencing itinerary planning are the traveller's age, income, motivations, educational level [7], and the word of mouth, i.e. the opinions of other users [8], [9].

Thus, itinerary planning represents a complex decision-making process which involves many different factors besides people's preferences and interests [10], especially for the

The associate editor coordinating the review of this manuscript and approving it for publication was Huiyan Zhang.

younger generations [11]. For example, when tourists plan trips to new cities, given their interest (*"I like Baroque Churches."*) they have to choose: *what to see*, and in particular, the type of attractions to see according to their interests (*"I'd like to visit Baroque Churches."*); how similar the attractions should be (*"Would I like to see only one type of attraction, e.g., only churches, or heterogeneous types, so also museums, shops, parks, squares?"*); whether to see as many things as possible (*"I'd like to see ALL the Baroque Churches in the city."*) or fewer things but in more detail (*"I'd like to visit very well the two most important Baroque Churches in the city."*). In making their decisions, tourists also have to take into account different aspects related to *time*, e.g., the total time they can devote to the trip, the time needed to visit each attraction, the opening times of each attraction, the time needed to move from one attraction to another, how to distribute time during the entire trip, if they want to carve out some free time for other activities, which are the peak visiting hours for each attraction. The tourist can apply different *choice modalities*, e.g., some people prefer to carefully plan the trip before departure, while others prefer not to plan and instead to follow the inspiration of the moment during the trip ([12], [13], [14]). Some people prefer to plan their trips autonomously, while others prefer to be guided by the people they consider experts ([9], [15]).

In order to support people in the decision-making process, intelligent tools such as Recommender Systems (RSs) [16] have been used. RSs *"produce individualized recommendations as output or have the effect of guiding the user in a personalized way to interesting or useful objects in a large space of possible options"* [17]. Recommendations are usually related to simple low-risk decision-making processes, such as products to buy, music to listen to, or movies to watch. However, these systems can also be exploited to make more complex high-risk decisions, related to e.g., health, money, time management, and itinerary planning red [18]. In this context, in order to provide effective support, a recommender system should act similarly to the *way* people make decisions: i.e., it should manage a large amount of information about places and users, as well as take into account the different aspects that impact the decision-making processes. Instead, many early works on itinerary recommendation [19], [20], [21] are only based on the *orienteering problem* [22], where the main objective is to recommend an itinerary that maximizes a global profit/reward and can be completed within a specific budget. Other works used *attraction popularity* [23], [24], [25]. In recent years, more researchers have incorporated *user interests and/or specific preferences* to personalize such itinerary recommendations [26], [27], [28], [29].

Relevant work has shown that tourists' decisions regarding the experiences they choose to live and the type of trip they decide to undertake are strongly influenced by their personality [30], [31]. Personality also has an impact on user perception of tourism-related information sources [32], travel behavioural patterns [33], [34], [35] and preferred locations and activities [30], [36], [37], [38]. However, only a few studies consider psychological traits in the user profile and in the recommendation process [39], [40], [41].

Starting from these considerations, our aim is to provide travel recommender system designers with guidance on the integration of personality traits in an itinerary recommender. The main idea is that they can mediate user preferences for several aspects of an itinerary. To do so, we first created a model of an itinerary. We identified its most relevant dimensions by analysing the state-of-the-art of itinerary recommender systems and literature on the psychology of tourism. Further, we investigated if specific psychological traits can affect users' decision-making process when choosing an itinerary. More specifically, we refer to the five personality traits included in the Big Five Model: openness to experience, conscientiousness, extraversion, agreeableness and neuroticism [42], which is probably the most popular personality model nowadays. We carried out a survey-based correlational study to understand if the Big Five traits can be used to predict user preferences with respect to some itinerary dimensions (such as type and topic variety, duration of transfer times or availability of free time), or with respect to the choice of methodology (planning or not, source of the advice). We decided to focus on young adults (19-24 years), the so-called Z generation.[1] This is the first generation which was exposed to the Internet from early childhood, hence the people from this generation are accustomed to the use of technology and social media, which do affect their behaviour to a certain extent. They have been referred to as "digital natives". This category of young adults is an interesting target in the tourism domain for the following reasons:

- they are skilled technology users, hence many are capable of making informed decision when planning their travel or organizing visits to the sites that interest them
- for many of them traveling is an integral part of their lives
- they have access to services which make them autonomous in their travel organization and planning
- their behaviour, planning and motives are strongly influenced by social media
- they are highly concerned about safety and privacy
- they are willing to collaborate with others, at the same time respecting the private space of the others
- they are invested into well being of others and of our planet.

Finally, we used the findings of this study to define the guidelines which could be used to support the design of itinerary recommender systems that consider itinerary dimensions and users' traits.

[1]The term Generation Z (or Centennials, Digitarians, Gen Z, iGen, Plurals, Post-Millennials, Zoomers) refers to the generation of people born between 1996/1997 and 2012, generally children of Generation X (1965-1980) and the last Baby Boomers (1946-1964). This generation was preceded by the Millennials.

Thus, our paper provides multiple contributions:

- firstly, we defined a model of the most important itinerary dimensions;
- secondly, we identified statistical correlations between personality traits (represented according to the Big Five model) and itinerary dimensions;
- thirdly, we provided a set of guidelines which suggest how such correlations can be used to inspire the design of itinerary recommender systems.

The paper is structured as follows. In Section II, we provide the state-of-the-art on the psychology of tourism and itinerary recommenders. Section III presents our itinerary model. Section IV describes our user study, followed by the statistical data analysis in Section V. The main findings are presented and discussed in Section V-E. Section VI provides some guidelines for the design of itinerary recommender systems. Section VIII concludes the paper.

II. STATE OF THE ART

The expression "Psychology of tourism" has been coined in recent years to account for a tendency to move from understanding tourist activity as merely and purely economic activity to considering other aspects as well, such as psychological and social ones. Psychology also studies the processes travellers follow to make their own decisions and many factors, including personality traits, which can influence the decision-making process [43]. In this section, we start by providing a brief overview of the Big Five model of personality and how it has been used in tourism and in the domain of itinerary recommender systems.

A. THE BIG FIVE MODEL OF PERSONALITY

In psychology, trait theory is based on the idea that personality can be described according to traits, i.e., habitual patterns of behaviour, thought, and emotion. While they differ across individuals, traits are relatively stable over time and situations [44]. Trait theories have suggested a variable number of traits: for example, Cattell [45] identified 16 personality factors, whereas Eysenck limited himself to only three [46]. The so-called Big Five is a five-factor model which has received wide attention as a comprehensive model of personality traits. The five factors, each of which represents a range between two extremes, are the following [42]:

1) **Openness to experience**. This trait is related to the imagination, audacity, originality and breadth of interest which can be observed not only in ideas and values, but also in other areas, such as fantasy, feelings and actions. Although open individuals are often deemed (and see themselves) as relatively more intelligent, openness and intelligence are separate aspects of individual differences.
2) **Conscientiousness**. This trait can be intended as either the fact of being governed by one's own conscience, or as carefulness and thoroughness. Individuals who are high in conscientiousness can be best described as *directed*, a concept which includes scrupulousness, dutifulness and pro-activity.
3) **Extraversion**. This factor can be identified with lively sociability and enjoying the company of other people (although the opposite is not necessarily true). An extrovert can usually be described as "sociable, fun-loving, affectionate, friendly and talkative" [42].
4) **Agreeableness**. This factor is related to trust, affection, and prosocial behaviors. While individuals high in agreeableness are more cooperative, those who are best described by the opposite pole, antagonism, "always seem to set themselves against others" [42]. On the other hand, high agreeableness may degenerate into dependence and fawning.
5) **Neuroticism**. According to most theorists, this trait apparently includes negative effects such as anxiety, depression, anger and embarrassment. In addition, it can be characterized by the disturbed thoughts and behaviours that can accompany emotional distress. This trait is also often named after its positive extreme, i.e., *emotional stability* [47]. We will use the second term in our study since it can be seen as a positive personal trait and fits better into our considerations.

B. BIG FIVE AND TOURISM

Several studies have shown different trends in people's attitudes in relation to a greater presence of one or the other trait.

Tan and Tang [32] focused on information search behaviour in Taiwan, investigating how the Big Five personality traits affect the user perception of different tourist information sources and feedback channels. Relevant correlations were found mainly for openness to experience, conscientiousness, extraversion and neuroticism.

Jani [33] analyzed data coming from a survey administered to Korean domestic tourists and discovered statistically significant associations between the Big Five factors and the twelve travel personalities of Mitsche et al. [48], i.e., *cultural creature*, *city slicker*, *sight seeker*, *family guy*, *beach bum*, *avid athlete*, *shopping shark*, *all rounder*, *trail trekker*, *history buff*, *boater* and *gamer*.

Neidhardt et al. [34] combined the Big Five personality traits with the seventeen tourist roles of Gibson and Yiannakis [49] developing the Seven-Factor Model which describes independent travel behavioural patterns. In the authors' work, the travel profile of users is identified by asking them to choose a set of pictures which determine the scores associated to each factor.

Tran et al. [36] used canonical regression analyses to study the correlation between the Big Five personality traits and the five dimensions described by Pizam and Sussmannn [50] which represent different tourist behaviour characteristics. Results also indicate what type of tourist activities and attractions may be associated to each personality trait: for example, extroversion is positively associated with social interactions, openness with adventure and novelty, while conscientiousness with knowledge about the destination.

In their recent work, **Akhrani and Najib** [37] put forward a subdivision of travel styles based on the Big Five personality traits, investigating the correlation between the latter and the individual preferences for soft-adventure travels (i.e., travels characterized by low levels of risk, definite results, careful planning, and safe, controlled environments) or riskier journeys. They found that the preference for soft adventures positively correlates to conscientiousness, agreeableness and extraversion, but does not correlate to neuroticism or openness to experience (which can be instead associated to a preference for high-risk activities, according to [51]).

Alves et al. [30] proposed a model to relate the Big Five personality dimensions with individual's preferences for tourist attractions. To this aim, the authors extracted eleven categories representing factors that characterize attractions and investigated what personality traits were relevant to predict user's preferences. Among other things, they found a negative relation between conscientiousness and a preference for adventure, indicating that less conscientious people tend to enjoy risky activities.

Table 1 presents the specific goals, the models involved and the method used for each study.

Our study is different from such state-of-the-art studies since we focused on the relation of personality traits with specific dimensions of an itinerary.

C. PERSONALITY-BASED RECOMMENDATION

As mentioned in the Introduction (Section I), only a few recommender systems consider the Big Five model in the creation of a personalized recommender. The most relevant for the tourism domain are the following ones.

Bachrach et al. [52] developed a crowdsourced tourism recommender system which uses the Big Five personality traits to build user profiles and predict how individuals would rate single attractions.

Braunhofer et al. [53] developed a context-aware mobile recommender system for POIs in which user preferences are learned by using the information on the individual's personality.

Ishanka and Yukawa [39] proposed a travel recommender system which exploits information on emotion and personality to model user profiles. Behaviour data, collected on Twitter, are used by the system to determine the individual's Big Five personality traits and each user is assigned a personality category depending on the most relevant trait.

Jeong et al. [40] designed a travel recommender system which employs Deep Learning to suggest tourist attractions based on the user's personality type (extrovert or introvert).

Atas et al. [41] studied the process of determination of preferences and how they are influenced by various psychological factors such as personality traits.

Our work is positioned in this context since we aim at helping in the design of itinerary recommender systems which consider the Big Five dimensions in their recommendations.

III. ITINERARY MODEL

To reach our goal, we first modeled the notion of "itinerary". A tourist itinerary is a reference for the tourist to follow during the journey, such as Points-of-Interest (POIs), hotels, time taken between two POIs, meal plans, activities, etc. [54]. Thus, "planning an itinerary involves substantial effort in choosing POIs, deciding in which order to visit them, and accounting for the time it takes to visit each POI and transit between them" [55]. Wikipedia defines it as "a schedule of events relating to planned travel, generally including destinations to be visited at specified times and means of transportation to move between those destinations." Thus, from those definitions we can see an itinerary as composed of three main elements:

- P. **Places**, and in particular a set of POIs
- T. **Time** devoted to an itinerary
- C. **Choice** made by a person on how to combine places and time

A. POINTS-OF-INTEREST (POIs)

Regarding the first aspect of the itinerary, we adopted a bottom-up approach and analysed state-of-the-art itinerary recommenders to see which POIs-related itinerary factors they considered. We noticed that usually the popularity of the POIs is the most important aspect considered by recommender systems [56], [57], [58], [59], [60], [61], [62], [63], [64], [65]. Also the preferences of the users for the categories of the place are often exploited to generate recommendations [56], [57], [58], [59], [60], [61], [62], [63], [64], [65]. Being already well-covered in the literature, these factors can be given for granted. Therefore, we do not further explore them in our itinerary model, we rather focus on other aspects not used so far that we deemed relevant, i.e.:

P1. POIs similarity
- Uniformity among the attractions (UNI)
- Variety (VAR)

P2. POIs extent
- Breadth (BRE) which indicates if the person wants to see as many things as possible or a few chosen ones in more depth
- Depth (DEP) indicating the amount of time devoted to each attraction.

B. TIME

As seen from the definition above, and supported by the literature on recommenders for tourism [4], [66], [67], time is one of the relevant aspects of an itinerary. We analysed again the state-of-the-art of itinerary recommenders to see which time-related itinerary dimensions they considered and we reported them in Table 2.

Among them, we chose to include in our model the following objective factors:

TABLE 1. Big five in tourism studies.

Study	Purpose	Theory and models used	Method used
[32]	Investigate how Big Five influence the perceived usefulness of different pre-trip and on site information sources and post-trip feedback channels	Big Five	Hierarchical regression analyses
[33]	Explore the relationship between Big Five and travel personality	Big Five; 12 travel personalities [48]	ANOVA tests
[34]	Develop a model to be used in RSs to elicit user preferences for tourism products and holiday behavioral patterns	Big Five; 17 tourist roles [49]; Seven-Factor Model (developed)	Factor analysis with varimax rotation
[36]	Explore the influence of personality traits on recreation types in order to maximize revenues in tourism and hospitality domain	Big Five; Pizam and Sussmann's 5 behavioral dimensions [50]	Canonical regression analyses
[30]	Develop a model to relate Big Five with preferences for tourist attractions to be used in RSs	Big Five	Exploratory Factor Analysis with Varimax rotation and Keiser normalization
[37]	Investigate the influence of Big Five on the individual interest in soft-adventure travels	Big Five	Multiple regression analysis

TABLE 2. Time-based Itinerary dimensions from state-of-the-art itinerary recommenders (RS).

Study	Total Available Time	Travel Time	Visiting Time	Opening Time	Best Visiting Time	Dist. btw. POIs
[56]	x	x	x			
[57]	x	x	x			
[58]			x		x	
[59]			x			
[60]	x					
[61]	x	x	x			x
[62]	x	x	x	x		x
[63]	x	x		x		
[64]	x	x	x		x	
[65]						x
[68]		x	x			x

T1. Total available time (TOT)
T2. Travel time (TRA)
T3. Efficient time allocation (EFF) (which combines the distance among POIs, opening times and the best visiting times).

Moreover, we added two additional features, more related to user's individual preferences, that we deemed relevant to increase user satisfaction:

S1. Willingness to carve out free time during the trip (FRE)
S2. Willingness to avoid busy hours (BUS).

C. CHOICE MODALITY

In our definition of an itinerary, the third dimension is related to the decision-making process, as pointed out by the literature on tourism [10], [69], [70], [71], [72], [73], [74]. A person can apply different choice modalities, in particular in relation to the organisation of the itinerary. To this aim, some people prefer to carefully plan the trip prior to the departure, while others prefer not to plan and instead to follow the inspiration of the moment during the trip [12], [13]. Other dimensions concern how people make their final decisions: if they prefer to choose autonomously by themselves, or if they prefer to be guided by experts [15], [75].

The following are the factors related to the choice modality we consider in our itinerary model:

C1. Organisation method:
   - Careful planning (PLA), i.e. deciding all the things to do before the trip
   - Unpremeditated choices (UNP), i.e. basing the decisions on the spur of the moment, making on the fly decisions during the trip.

C2. Source, i.e., the *agent* who plays the main role in the decision making process
   - Autonomous planning (AUT), in which the travelers prefer to make their own choices in autonomy
   - Expert advice (EXP), in which the travelers prefer to follow experts' advice.

Table 3 reports our final itinerary model.

IV. USER STUDY

Aiming at identifying meaningful correlations between Big-Five personality traits and relevant aspects of travel itineraries identified in Section III, we carried out an online survey where participants were asked to complete a personality test and to assess the importance of such factors in their itinerary planning.

A. HYPOTHESES

Based on the standard descriptions of the Big Five traits and relevant literature which discusses the impact of personality in the tourism domain, we formulated the following hypotheses:

- **H1**: Each personality trait influences positively or negatively user preferences for certain itinerary factors.
- **H2**: For each itinerary factor, there are certain personality traits which influence it the most, in a positive or a negative way.

B. MEASURES AND MATERIAL

1) MEASURES

Personality traits were collected using a translated and validated version of the TIPI (Ten Item Personality

TABLE 3. Itinerary model.

Dimensions	Sub-dimensions	Factors
POIs	Similarity	Uniformity (UNI) Variety (VAR)
	Extent	Breadth (BRE) Depth (DEP)
TIME	Objective	Minimum travel time (TRA) Efficient allocation (EFF) Total time (TOT)
	Subjective	Free time (FRE) Busy hours avoidance (BUS)
CHOICE MODALITY	Organisation	Careful planning (PLA) Unpremeditated choices (UNP))
	Source	Autonomous planning (AUT) Expert recommendations (EXP)

TABLE 4. Dimensions, factors, questions (the exact introductory statement to all questions was: "When you choose what to visit, you make sure to…").

Dimensions	Factors	Questions
POIs	Uniformity (UNI)	[...] guarantee type and/or topic uniformity in POIs
	Variety (VAR)	[...] guarantee type and/or topic variety in POIs
	Breadth (BRE)	[...] visit as many POIs as possible, so as to have a good overview of the place you are visiting
	Depth (DEP)	[...] allow enough time to carefully visit the chosen POIs
Time	Minimum travel time (TRA)	[...] minimize travel time between POIs
	Efficient allocation (EFF)	[...] efficiently allocate visits to the available days
	Total time (TOT)	[...] not exceed your total available time
	Free time (FRE)	[...] include some free time to relax
	Busy hours avoidance (BUS)	[...] avoid crowded places and times
Choice modality	Careful planning (PLA)	[...] carefully plan an itinerary you will follow scrupulously
	Unpremeditated choices (UNP)	[...] avoid overplanning, so as to be able to make spur-of-the-moment decisions
	Autonomy in planning (AUT)	[...] personally plan your itinerary
	Expert recommendations (EXP)	[...] follow recommendations from experts and trusted sources (e.g., travel agencies, travel bloggers, travel guides, ...

Measure) [76], a 10-item measure of the Big Five dimensions, originally developed by [47]. In the TIPI, each item consists of a pair of adjectives which refer to a certain Big Five dimension: for example, "Extraverted, enthusiastic" (Extraversion) or "Calm, emotionally stable" (Emotional stability). Respondents were asked to assess the extent to which each pair applies to them, using a 7-point Likert scale which ranges from "Disagree strongly" to "Agree strongly".

As for relevant aspects of itinerary planning, respondents were asked to assess the thirteen different factors, related to the dimensions discussed in Section III. Factors and their corresponding dimensions: i) POIs - similarity and extent, ii) time - objective and subjective aspects, iii) choice modality - organisation and source, are reported in Table 4, together with the questions used in our survey. For each factor, participants were asked to assess its importance in itinerary planning decisions, using a series of 5-point Likert scales which ranged from "Absolutely no" to "Absolutely yes", including also "I don't know" option.

2) MATERIAL

The survey was carried out as an online questionnaire, for ease of distribution and data collection purposes [77].

C. PARTICIPANTS

We administered the survey to 101 Italian people belonging to the z Generation (18-24 years old). After removing the observations with missing values we obtained a data set with 87 observations. The participants were recruited through the availability sampling strategy.[2] The participants are frequent computer and Web application users, who, due to their familiarity with technology, could represent a good target for recommender systems usage. The sample is balanced gender-wise. The sample size, although not particularly large, is enough to obtain statistically significant results and is in line with other studies in the same area (see, e.g., [79]).

V. STATISTICAL DATA ANALYSIS

In this section, we report the statistical results pertinent to our study. First of all, we present basic descriptive statistics for both personality traits and itinerary features in Section V-A. Next, we provide the correlation analysis tables and their initial interpretation in Section V-B, followed by the study of linear regression models in Section V-C. Finally,

[2]Availability sampling is a sampling of convenience, based on subjects available to the researcher. Even though random sampling is the best way to obtain a representative sample, these strategies require a great deal of time and money. Therefore, much research in psychology is based on samples obtained through non-random selection [78].

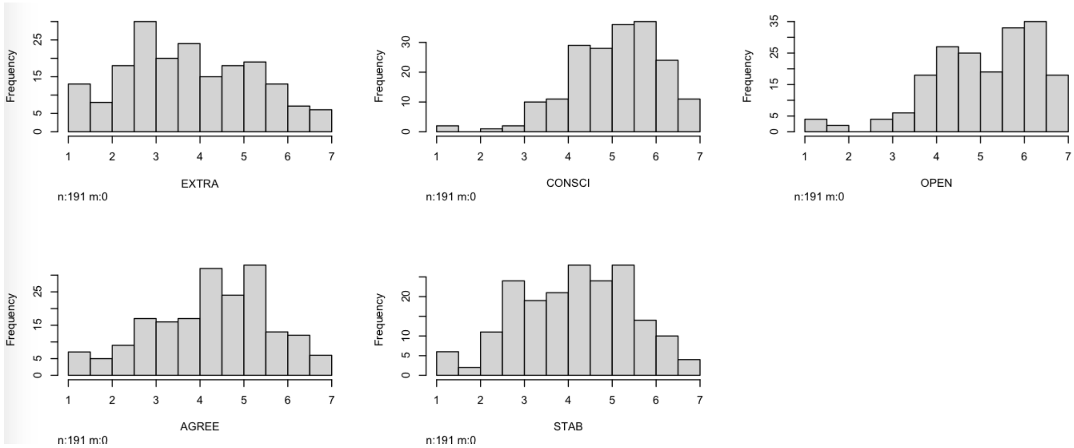

FIGURE 1. Histogram for Big Five personality traits.

TABLE 5. Summary of abbreviations for personality traits and itinerary features.

Abbreviation	Full name
EXTRA	Extraversion
CONSCI	Conscientiousness
OPEN	Openness
AGREE	Agreeableness
STAB	Stability
UNI	Uniformity
VAR	Variety
BRE	Breadth
DEP	Depth
TRA	Minimum travel time
EFF	Efficient allocation
TOT	Total time
FRE	Free time
BUS	Busy hours avoidance
PLA	Careful planning
UNP	Unpremeditated choices
AUT	Autonomy in planning
EXP	Expert recommendations

in Section V-D we performed the Canonical Correlation Analysis (CCA) to obtain further insights into our findings. We conclude by discussing our hypotheses in Section V-E in the light of the obtained results.

For the sake of conciseness, in this section we will use abbreviations to refer to both personality traits and itinerary features. All such abbreviations are reported in Table 5, together with their corresponding full names.

A. DESCRIPTIVE STATISTICS

We divided our data set into two parts. The first part considers the Big Five personality traits (*personality*) and the second part considers the itinerary factors (*itinerary*).

The summary descriptive statistics and standard deviation for the Big Five personality traits are reported in Table 6. The histograms showing the distribution of the users' responses regarding Big Five personality traits are provided in Figure 1.

The personality traits can take values from 1 to 7. From Table 6, we can observe that the trait with the highest mean

TABLE 6. Summary statistics and st. dev. for Big Five personality traits.

	EXTRA	CONSCI	OPEN	AGREE	STAB
Minimum	1.00	1.00	1.00	1.00	1.00
1st quartile	2.50	4.50	4.50	4.00	3.00
Median	3.50	5.50	5.00	5.00	4.00
Mean	3.79	5.31	4.98	4.61	4.10
3rd quartile	5.00	6.00	6.00	5.50	5.00
Maximun	7.00	7.00	7.00	7.00	6.50
St. dev	1.45	1.07	1.24	1.40	1.31

(indicating the most important personality trait to keep in mind) and also with the lowest standard deviation value (which indicates the least variability among observations) is CONSCI ($mean = 5.31$, $sd = 1.07$), followed by OPEN ($mean = 4.97$, $sd = 1.24$). On the other hand, EXTRA has the lowest mean and at the same time the highest standard deviation ($mean = 3.79$; $sd = 1.45$), which indicates that this is the the least important trait in the analysis with the most variability among observations. The median values of 5.5, 5 and 5 for CONSCI, OPEN and AGREE indicate that half of the interviewed people consider themselves being highly conscientious, open to new experiences and agreeable with others.

The summary descriptive statistics and standard deviation for the itinerary factors are reported in Table 7. The histograms showing the distribution of the users' responses regarding itinerary factors are provided in Figure 2.

The itinerary factors can take values from 1 to 5. We can see from Table 7 that 7 out of 13 factors received an average rating of 4 or more, EFF being considered the most important aspect on average with the lowest variability among responses ($mean = 4.75$, $sd = 0.61$). Other factors which were considered especially relevant are TOT ($mean = 4.67$, $sd = 0.73$), VAR ($mean = 4.4$, $sd = 0.88$) and TRA ($mean = 4.28$, $sd = 1.04$), which suggests that our participants deem it important to efficiently allocate visits to the available days, include different POIs in their itineraries, and use their time in the best possible way. The median values of 5 for VAR, TRA, EFF and TOT confirm this statement.

TABLE 7. Summary statistics and st. dev. for the itinerary factors.

	UNI	VAR	BRE	DEP	TRA	EFF	TOT	FRE	BUS	PLA	UNP	AUT	EXP
Minimum	1.00	1.00	2.00	2.00	1.00	1.00	1.00	0.00	1.00	1.00	1.00	2.00	1.00
1st quartile	1.00	4.00	4.00	4.00	4.00	5.00	5.00	3.00	3.00	2.00	2.00	4.00	3.00
Median	2.00	5.00	4.00	4.00	5.00	5.00	5.00	4.00	4.00	4.00	3.00	4.00	4.00
Mean	2.25	4.40	4.22	4.09	4.28	4.75	4.67	3.97	3.89	3.36	2.87	4.22	3.55
3rd quartile	3.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	4.00	4.00	5.00	4.50
Maximun	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00
St. dev	1.14	0.88	0.87	0.84	1.04	0.61	0.73	1.22	1.21	1.28	1.35	0.81	1.24

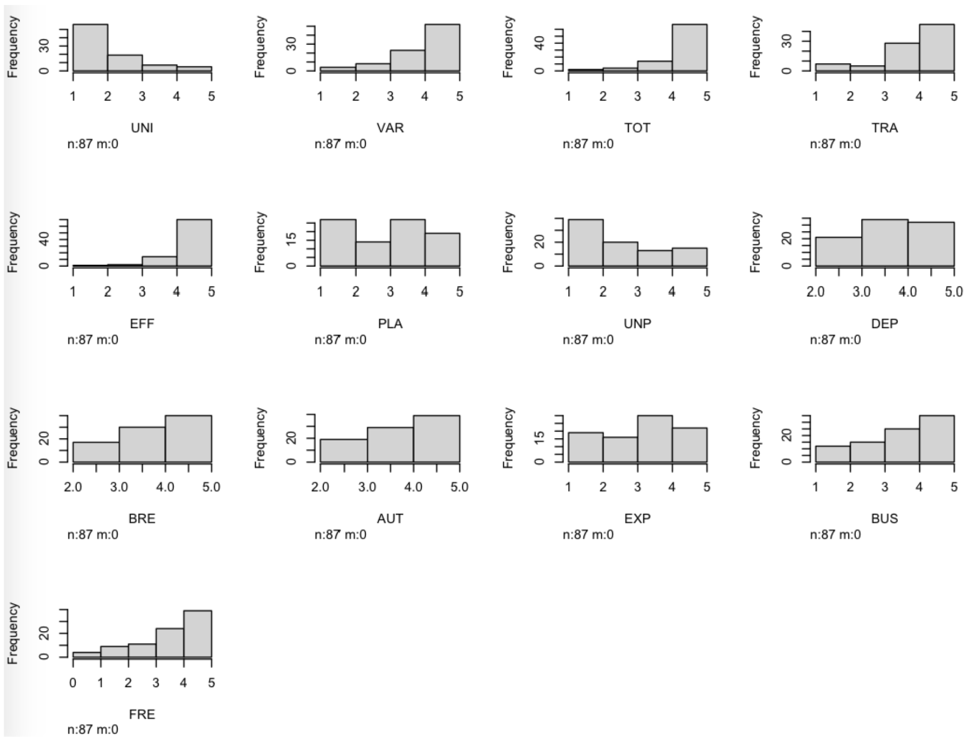

FIGURE 2. Histogram for the itinerary factors.

While the large number of positive responses might be due to an agreement bias, it is particularly interesting to focus on a few dimensions which raised less enthusiasm, i.e., UNI ($mean = 2.25$, $sd = 1.14$) and UNP ($mean = 2.87$, $sd = 1.35$). These results suggest that participants in our evaluation, in general, do not make any special effort to carve out opportunities to make unpremeditated choices, or to guarantee POI uniformity in their planned itineraries.

B. CORRELATION ANALYSIS

To identify possible relations between personality traits and itinerary-related factors, we used the Pearson correlation coefficient which describes the strength of the linear correlation, if any, between two variables. Pearson correlation coefficient ranges from -1 (perfect negative association) to +1 (perfect positive association), with a value of 0 indicating that there is no association between the two variables. We will consider the values between $0 \leq r < 0.25$ weak positive, $0.25 \leq r < 0.75$ moderate positive and $0.75 \leq r < 1$ strong positive correlation. Analogous intervals apply to negative values.

The correlation matrix for the Big Five personality traits and itinerary factors is presented in Figure 3.

The correlation matrix can be interpreted in two ways. One way is to observe for each personality trait, which itinerary factors are positively or negatively influenced by that specific trait (the first table read vertically). On the other hand we can try to find out for each itinerary factor which personality traits influence it the most, in a positive or a negative way (the second table read horizontally). The positive influence is emphasised with green and blue and the negative with red and orange.

We can observe that EXTRA is positively correlated with UNP and EXP and negatively with TRA and PLA. This can be interpreted as extravert people being willing to make unpremeditated choices and act on the spur of the moment, while also taking expert advice into account. They do not seem to be very interested in optimizing their time and put too much effort into planning.

CONSCI is positively correlated with PLA, TOT and EFF, while being negatively correlated with UNP. This means that people who consider themselves conscientious will put effort

	EXTRA	CONSCI	OPEN	AGREE	STAB
UNI	-0.15	0.05	0.17	0.07	0.04
VAR	0.14	0.20	0.22	0.03	0.17
BRE	0.05	0.23	0.01	0.17	-0.06
DEP	0.01	0.14	0.20	0.08	0.00
TRA	-0.21	0.24	0.10	0.21	0.01
EFF	0.08	0.33	0.39	0.36	0.00
TOT	0.04	0.44	0.08	0.33	0.03
FRE	0.09	0.20	0.13	0.24	0.06
BUS	-0.03	0.15	0.19	0.17	-0.03
PLA	-0.20	0.31	-0.15	0.12	-0.19
UNP	0.21	-0.15	0.25	0.08	0.27
AUT	-0.03	0.24	0.07	0.15	-0.20
EXP	0.27	-0.06	0.35	-0.01	0.09

	EXTRA	CONSCI	OPEN	AGREE	STAB
UNI	-0.15	0.05	0.17	0.07	0.04
VAR	0.14	0.20	0.22	0.03	0.17
BRE	0.05	0.23	0.01	0.17	-0.06
DEP	0.01	0.14	0.20	0.08	0.00
TRA	-0.21	0.24	0.10	0.21	0.01
EFF	0.08	0.33	0.39	0.36	0.00
TOT	0.04	0.44	0.08	0.33	0.03
FRE	0.09	0.20	0.13	0.24	0.06
BUS	-0.03	0.15	0.19	0.17	-0.03
PLA	-0.20	0.31	-0.15	0.12	-0.19
UNP	0.21	-0.15	0.25	0.08	0.27
AUT	-0.03	0.24	0.07	0.15	-0.20
EXP	0.27	-0.06	0.35	-0.01	0.09

FIGURE 3. Correlation matrix.

into planning and optimizing their time and efficiency, while not making many spontaneous decisions. Positive correlation also exists with BRE, TRA, AUT, but it is lower than the correlation with PLA, TOT and EFF.

OPEN is positively correlated with EFF and EXP and negatively only with PLA. We might conclude that people with open character are open to expert advice and try to use their time efficiently, but are not very interested in detailed planning of their trip. Positive correlation also exists with UNP but it is lower than the correlation with EFF and EXP.

AGREE is positively correlated with EFF and TOT which indicates that people who show cooperative and prosocial behaviour are mostly interested in optimizing their time usage. There are no negative correlations for AGREE. Positive correlation also exists with FRE but it is lower than the correlation with EFF and TOT.

Finally, STAB is positively correlated with UNP, which might be interpreted as people being at easy with themselves and hence, willing to act spontaneously. STAB is negatively correlated with PLA and AUT, which means that these people might also be fine with not planning too much and doing things autonomously.

The correlation matrix is a preliminary tool which helped us observe the most evident correlation values. We explored the influence of Big Five personality traits to itinerary factors further by building linear regression models for each of the itinerary factors. The same result could be obtained by applying the Multivariate Regression Analysis (MRA). Hence, we will discuss the second table in Section 3 after performing linear regression analysis.

C. LINEAR REGRESSION MODELS

Given the differences between the various personality traits we did expect that each itinerary factor would be influenced by different personality traits and that not all of the personality traits would be significant in predicting a certain itinerary factor. With the help of regression analysis, we managed to pinpoint two factors in most cases which are statistically significant for deciding which itinerary factors to use.

TABLE 8. Linear Regression model for EFF. Standard errors in parentheses. Signif. codes: * p<0.05, ** p<0.01, *** p<0.001.

	Coef.Estimate	p-value
Intercept	2.600 (0.361)	2.55e-10 ***
CONSCI	0.125 (0.054)	0.024 *
OPEN	0.180 (0.045)	0.000 ***
AGREE	0.128 (0.041)	0.003 **
Multiple R-squared	0.320	
Adjusted R-squared	0.295	
F(3, 83)	13.01	
p-value (F)	4.791e-07	

Linear regression models can be used to model the relationship between an output (dependant) variable y and one or more input (independent) variables $x_1, \ldots, x_n$. The linear regression model for the sample is given by

$$\hat{y} = \beta_0 + \beta_1 x_1 + \ldots + \beta_n x_n + \varepsilon$$

and the coefficients $\beta_0, \beta_1, \ldots, \beta_n$ are estimated from the data, most commonly using the least squares approach, but other ways could be used as well.

Since we have 13 itinerary factors we built 13 linear models in which we use personality traits as independent variables. We will present in detail the two most important linear models and summarize the results for the remaining ones.

1) LINEAR REGRESSION MODEL FOR EFF

We observed from the correlation matrix that EFF is moderately positively correlated with CONSCI, OPEN and AGREE. Hence we built a linear regression model using these three personality traits as input variables to be able to predict EFF. The model is the following:

$$EFF = b_0^E + b_1^E \cdot CONSCI + b_2^E \cdot OPEN + b_3^E \cdot AGREE$$

where $b_0^E, b_1^E, b_2^E, b_3^E$ are the estimates of the coefficients for the Linear Regression model.

The results of the Linear Regression algorithm are given in Table 8.

The first column of the table reports the estimates of the linear regression coefficients $b_0^E, b_1^E, b_2^E, b_3^E$, with the

TABLE 9. Linear Regression model for TOT. Standard errors in parentheses. Signif. codes: * p<0.05, ** p<0.01, *** p<0.001.

	Coef.Estimate	p-value
Intercept	2.780 (0.374)	7.83e-11 ***
CONSCI	0.254 (0.067)	0.000 ***
AGREE	0.117 (0.051)	0.0256 *
Multiple R-squared	0.240	
Adjusted R-squared	0.222	
F(2, 84)	13.29	
p-value (F)	9.657e-06	

corresponding standard errors in the parenthesis. The second column reports the p-values for each coefficient. We can see that all the coefficients are statistically significant at 5% significance level. The highest p-value corresponds to the coefficient for CONSCI (indicating its least significance), whereas all the others are significant also at 1% significance level.

This model indicates that there is statistically significant positive correlation between EFF and CONSCI, OPEN and AGREE. For one unit increase in CONSCI (respectively OPEN and AGREE) there will be 0.125 unit increase in the mean of EFF (respectively 0.180 and 0.128). The highest coefficient (different from intercept) is b_2^E which means that OPEN influences the most the output variable EFF. Even when other predictors are equal to zero, the coefficient $b_0^E = 2.600$ is significant, which indicates that EFF is important regardless of personality traits.

The Multiple R-squared index is 0.32 which means that this model explains 32% of the variability of the initial data set. The value of adjusted R-squared index equal to 0.295 is relatively similar, but it also takes the number of predictors into account. Finally, the high p-value which corresponds to the value of F-statistics indicates that the complete model would be better in explaining the variability of the model, although the coefficients would not be statistically significant.

2) LINEAR REGRESSION MODEL FOR TOT

We saw from the correlation matrix that TOT is moderately positively correlated with CONSCI and AGREE. Hence we built a linear regression model using these two personality traits as input variables to be able to predict TOT. The model is the following:

$$TRA = b_0^T + b_1^T \cdot CONSCI + b_2^T \cdot AGREE$$

where b_0^T, b_1^T, b_2^T are the estimates of the coefficients for the Linear Regression model.

The results of the Linear Regression algorithm are given in Table 9.

The first column of the table reports the estimates of the linear regression coefficients b_0^T, b_1^T, b_2^T, with the corresponding standard errors in the parenthesis. The second column reports the p-values for each coefficient. We can see that all the coefficients are statistically significant at 5% significance level. The highest p-value corresponds to the coefficient for CONSCI (indicating its least significance), whereas all the others are significant also at 1% significance level.

TABLE 10. Significant correlations for POIs. Signif. codes: . p<0.1, * p<0.05, ** p<0.01, *** p<0.001.

Itin. Fact.	UNI	VAR	BRE	DEP
posit. corr.	OPEN *	CONSCI . OPEN .	CONSCI *	OPEN .
negat. corr.	EXTRA *			

This model indicates that there is statistically significant positive correlation between TOT and CONSCI and AGREE. For one unit increase in CONSCI (respectively AGREE) there will be 0.254 unit increase in the mean of TOT (respectively 0.117). The highest coefficient (different from intercept) is b_1^T which means that CONSCI influences the most the output variable TOT. Even when other predictors are equal to zero, the coefficient $b_0^T = 2.780$ and is significant, which indicates that TOT is important regardless of personality traits.

The Multiple R-squared index is 0.24 which means that this model explains 24% of the variability of the initial data set. Also in this case, the adjusted R-squared index is similar, and it takes into account the number of predictors. Finally, the high p-value which corresponds to the value of F-statistics indicates that the complete model would be better in explaining the variability of the model, although the coefficients would not be statistically significant.

In Tables 10, 11 and 12 we summarize the statistically significant personality traits for each of the itinerary factors.[3]

We can conclude that:

1) UNI is positively correlated with OPEN and negatively with EXTRA. This indicates that people open to new experiences will still be interested in uniformly spread activities, whereas extravert people would seek different experiences.
2) VAR is positively correlated with CONSCI and OPEN, but the coefficients are not very significant which indicates not a strong dependence of VAR on these personality traits.
3) BRE has a significant positive correlation with CONSCI which means that conscientious people care about seeing as many different places as possible.
4) DEP has a positive correlation with OPEN but also in this case the influence is not very strong.
5) TOT is positively correlated with CONSCI and AGREE, CONSCI being very significant. This means that people who are conscientious and careful are very aware of the total time they have at their disposal and the time they would need to complete the activity. Agreeable people maybe a bit less, but still this trait is important for TOT.

[3]For the sake of completeness, in Tables Tables 10, 11 and 12 we report all correlations having p<0.1. However, in the discussion that follows, we only consider as significant correlations having p<0.05.

TABLE 11. Significant correlations for Time. Signif. codes: . p<0.1, * p<0.05, ** p<0.01, *** p<0.001.

Itin. Fact.	TOT	TRA	EFF	FRE	BUS
posit. corr.	CONSCI *** AGREE *	CONSCI *	CONSCI * OPEN *** AGREE **	AGREE *	OPEN .
negat. corr.		EXTRA *			

TABLE 12. Significant correlations for Choice modality. Signif. codes: . p<0.1, * p<0.05, ** p<0.01, *** p<0.001.

Itin. Fact.	PLA	UNP	AUT	EXP
posit. corr.	CONSCI **	OPEN . STAB *	CONSCI *	OPEN ***
negat. corr.	EXTRA .		STAB .	

6) TRA is positively correlated with CONSCI and negatively with EXTRA. AGREE proved not to be the significant personality trait for TRA. This can be interpreted as conscientious people being concerned about total travelling time, whereas extravert people care less about this factor.
7) EFF is positively correlated with CONSCI, OPEN and AGREE. All of these factors influence the importance of efficient planning, especially OPEN. Which means that even the people who are open to new experiences deem it important to use their time efficiently.
8) FRE is positively correlated with AGREE, which means that agreeable people care about the efficient use of their time, despite their agreeable nature.
9) BUS is positively correlated with OPEN, but the correlation is not very significant.
10) PLA has very significant positive correlation with CONSCI and not strongly significant negative correlation with EXTRA. This means that conscientious people will carefully plan their itinerary, whereas extravert people will tend to do the opposite.
11) UNP has not very significant positive correlation with OPEN, but it has significant positive correlation with STAB. This means that stable people could opt for unpremeditated choices when planning their itineraries.
12) AUT has a significant positive correlation with CONSCI which means that conscientious people would take the situation in their hands and likely organize their journey autonomously (without the help of a travel agent). It also has a not very significant negative correlation with STAB.
13) EXP is highly positively correlated with OPEN which means that open people will be open to the advice from experts.

It is evident that CONSCI, OPEN and AGREE are the factors which are positively correlated with all of the itinerary factors, whereas EXTRA has a negative correlation with some of the itinerary factors. STAB behaves in different ways depending on the itinerary factor, but it has significant correlation with only a few itinerary factors.

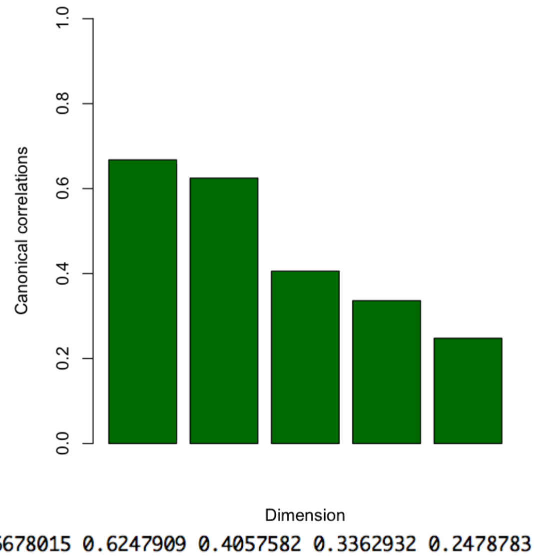

FIGURE 4. Correlations between canonical variables.

D. CANONICAL CORRELATION ANALYSIS (CCA)

Canonical Correlation Analysis (CCA) is a multivariate statistics technique used to study correlations between two data sets.

First, *canonical variables* are defined as linear combinations of the variables in each of the data sets. As a next step, pairs of canonical variables (one from each data set) are built by choosing the canonical variables that have the *largest possible correlation*. These pairs are called *dimensions*. The maximum number of dimensions is equal to the number of variables in the smaller data set. The correlation between canonical variables is called *canonical correlation*. In this setting, the goal of CCA is to discover which original variables are represented by each of the canonical variables.

As specified before, we split our data set into two parts: personality traits and itinerary factors. We then fitted the model and obtained a list of all the coefficients which relate the original variables with canonical variables. We omit here the output of the model and present only the bar plot which illustrates the correlations for each pair of canonical variables (see Figure 4). We can see that the first two dimensions have very strong correlations, hence we will use them for the remaining analysis.

Table 13 also helps us decide how many dimensions are significant in describing our data set. We can see that all five dimensions together are statistically significant ($p - value = 0.00038$), as well as the dimensions from 2 to 5 ($p - value = 0.047$). But dimensions 3, 4 and 5 alone are not statistically

TABLE 13. Wilk's Test: Wilks' Lambda, using F-approximation (Rao's F).

	stat	approx	df1	df2	p.value
1 to 5	0.2348687	1.8214229	65	330.0249	0.0003765745
2 to 5	0.4239191	1.4125342	48	271.6860	0.0473552618
3 to 5	0.6953640	0.8347305	33	209.8831	0.7260221938
4 to 5	0.8324121	0.6915682	20	144.0000	0.8296832675
5 to 5	0.9385563	0.5310032	9	73.0000	0.8474183374

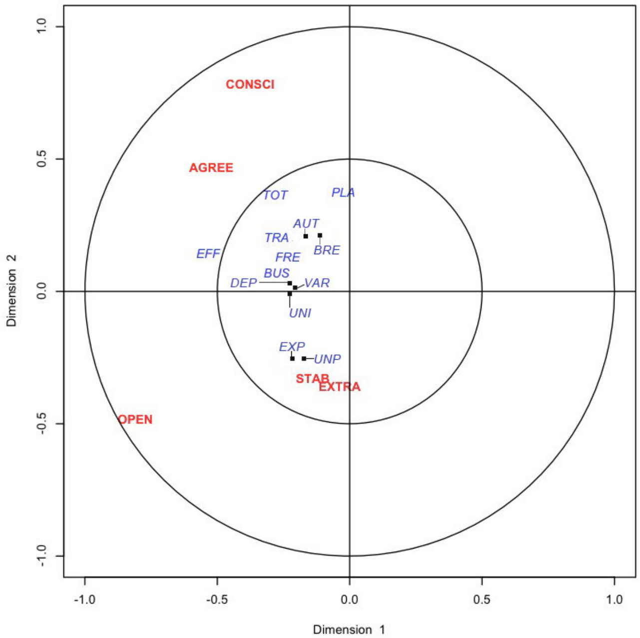

FIGURE 5. Plotting the variables.

significant. The same is true for the dimensions 4 and 5 and the dimension 5 alone. Which means that we can relay on only the first two dimensions.

Finally, Figure 5 uses the first two dimensions as axes and illustrates the directions of each of the original variables in this new coordinate system. The proximity of the items on the graph shows the relationships between the variables of the two sets of variables.

We can see that CONSCI and AGREE have a similar influence on itinerary factors, as well as STAB and EXTRA. OPEN seems to have a bit different behaviour from the other personality traits. EFF, TOT and PLA seem to be dominant itinerary factors, followed by EXP and UNP.

E. DISCUSSION

Our analysis shows that some of the itinerary factors we identified were assessed similarly by all participants, irrespective of their personality. On the positive side, efficiently allocating visits (EFF), taking into account the total available time (TOT), guaranteeing POIs variety (VAR) and minimizing travel time between POIs (TRA) were all considered very important factors. On the negative side, guaranteeing type and/or topic uniformity in POIs (UNI) and avoiding to overplan (UNP) were generally disregarded. Hence, an itinerary recommender system which is unaware of its users' personalities can safely focus on the first four factors and not provide any support for itinerary uniformity and unpremeditated choices.

Regarding our hypothesis H1, we found that all personality traits exert some influence on user preferences for itinerary factors. However, their effect differs in terms of strength, significance and kind of impact, whether positive or negative. At least one personality trait among conscientiousness (CONSCI), openness to experience (OPEN) and agreeableness (AGREE) was always found to have a positive impact on user preferences, considering all itinerary factors. Interestingly, our results regarding conscientiousness seem to be in line with those from [30], [36], and [37]. In fact, these authors all reported a correlation between conscientiousness and soft, less risky adventures, which appears to be coherent with conscientious individuals' preferences for compliance with time constraints (TOT, TRA), efficient time management (EFF) and careful planning (PLA). On the other hand, extraversion (EXTRA) and stability (STAB) have a negative correlation with some of the itinerary factors. In particular, we found that extraversion is negatively correlated to careful planning (PLA). This result can be explained by the fact that psychological literature sometimes describes extraversion in terms of surgency [80], i.e., a personality factor characterized by quickness, cleverness, responsiveness and spontaneity, and which can therefore be associated to unpremeditated decisions.

Regarding our hypothesis H2, our linear regression models show that all itinerary factors are correlated to at least one personality trait, although in a few cases (i.e., VAR, DEP, BUS) the coefficients are only significant at 10% level, thus indicating that there is no strong dependence on personality. In all other cases, at least one personality trait significantly affects user preferences, with correlation coefficients being significant at least at 5% level, some being significant even at 0.1% level. Efficient allocation of visits to the available days (EFF) and compliance with constraints on the total available time (TOT) seem to depend on personality traits in a particularly meaningful way, with the coefficients for at least two personality traits being statistically significant at least at 5% level.

VI. DESIGN GUIDELINES

The findings from our study can be used to support the design of itinerary recommender systems being able to consider user personality traits. This implies that the recommender system needs to be able to calculate the user personality traits, for example, by providing a standard questionnaire for the Big-five assessment at the beginning of the interaction. We present some design guidelines that suggest how to exploit information on user personality in an itinerary recommender system (See Tables 14 - 24). Notice that the label *Principle* takes into account the results of our study.

Since every user has a score for each personality trait which can be considered a probability value on the

TABLE 14. Design guidelines for uniformity/variability.

Problem	When generating personalized itinerary recommendations, a decision must be made regarding the uniformity/variety trade-off.
Use when	Your itinerary recommender system has the ability to control the type/category of POIs which are recommended, building either thematic (uniform) itineraries, or suggesting more varied options.
Principle	• Uniformity is positively correlated to openness • Uniformity is negatively correlated with extraversion • Uniformity is scarcely appreciated in general • Variety is highly appreciated in general • There is no strong correlation between variety and personality traits
Solution	Adjust the level of uniformity/variety in a recommended itinerary based on users' personality, following these guidelines: • Open users: Thematic itineraries can be recommended, as well as more varied ones. • Extrovert users: Always generate itineraries which include POIs belonging to different categories, types and topics. • Other users: Avoid generating itineraries where all the POIs are similar, prefer variety over uniformity if possible.
Why	Most users appreciate type/topic variety in recommended POIs, while they are less enthusiastic about the idea of thematic, uniform itineraries. Thus, varied itineraries are suitable for everyone. Extraverted users strongly dislike uniform itineraries, so these should not be recommended. On the other hand, thematic itineraries might still be appealing to open users.

TABLE 15. Design guidelines for breadth/depth.

Problem	When generating personalized itinerary recommendations, a decision must be made regarding the breadth/depth trade-off.
Use when	Your itinerary recommender system has the ability to adjust the time allowed to visit each POI, so as to either maximize the number of visited POIs, or grant abundant time to carefully visit a few POIs.
Principle	• Breadth is positively correlated to conscientiousness • The correlation between depth and personality traits is not very significant. • User preferences for breadth/depth are very heterogeneous in general
Solution	• Conscientious users: Consider slightly shorter-than-average visiting times for each POI, so as to be able to pack a few more POIs in their recommended itineraries. • Other users: Consider average visiting times when determining the time to be granted for each POI. • All users: Allow users to adjust visiting times, either globally or for single POIs, and, consequently, the number of POIs to be visited.
Why	In general, users all have different preferences about the ideal amount of time to spend for each POI, which are only partially related to personality traits. Conscientious users are expected to appreciate the possibility to visit more POIs and get a good overview of the beauty spots of the place they are visiting. For other users, average visiting times can be used as a baseline to build itineraries which are neither too tight nor too loose. The possibility to manually adjust visiting times is very useful for all users, since each of them may have very specific preferences.

TABLE 16. Design guidelines for travelling times.

Problem	When generating personalized itinerary recommendations, it must be decided to what extent travelling time between POIs should be minimized.
Use when	Your recommender system has the ability to take into account and optimize the travelling time between POIs when creating itineraries to be suggested.
Principle	• Conscientiousness is positively correlated to minimum travel time • Extraversion in negatively correlated to minimum travel time
Solution	• Conscientious users: try to keep the travelling time between POIs in the itinerary as short as possible. • Extravert users: travel time minimization can be overlooked as a factor to generate the itinerary.
Why	Not all users are particularly interested in minimizing the travel time between POIs. Only conscientious people seem to attach significant importance to this factor and may appreciate itineraries that save them time when moving. Reducing the travelling time for this type of people may also help them to visit a higher number of POIs. On the contrary, giving much importance to travel time minimization is useless when recommending itineraries to extravert users, since they are not concerned about it.

TABLE 17. Design guidelines for efficiency.

Problem	When generating personalized itinerary recommendations, it must be decided whether the efficient allocation of visits to the available days should be maximized.
Use when	Your itinerary recommender system has the ability to optimize the efficient allocation of visits to the available days.
Principle	• Conscientiousness, openness and agreeableness are significantly positively correlated to the efficient allocation of visits
Solution	Decide on the optimization of the efficient allocation of visits based on users' personality, following these guidelines: • Conscientious, open, agreeable users: the efficient allocation of visits should be maximized. • All other users: efficiency in the allocation of visits is not a priority.
Why	Different users have different opinions and needs as far as the optimization of the efficient allocation of visits is concerned, and such preferences partially depend on user's personality. Itineraries where the efficient allocation of visits is not maximized might be perceived as poorly organized by conscientious, open, and agreeable users, while efficiency maximization is unnecessary for users with different personalities.

TABLE 18. **Design guidelines for total time.**

Problem	When generating personalized itinerary recommendations, it must be decided whether the itinerary time schedule can be flexible, exceeding the total available time specified by the user, if needed.
Use when	The starting and the ending time of your recommender system itineraries can be scheduled according to user preferences.
Principle	• Conscientiousness and agreeableness are positively correlated to total time
Solution	• Conscientious and agreeable users: avoid planning activities that exceed the user's total available time for the itinerary.
Why	Agreeable users, and conscientious people even more, may feel uncomfortable when the itinerary is not planned taking into account the total time they want to devote to visits. Therefore, when generating an itinerary to be suggested, designers should avoid including activities that make it exceed the user's total available time. It would be better to allocate some extra time for each activity, so that planned visits can still take place in case of unforeseen events (e.g., delays in the travelling time between POIs), without forcing users to change the extent of their available time.

TABLE 19. **Design guidelines for free time.**

Problem	When generating personalized itinerary recommendations, a decision must be made on the possible inclusion of free time slots.
Use when	Your itinerary recommender system has the ability to either include a few free time slots in the suggested itinerary, or to fill all the available time with recommended POIs.
Principle	• Agreeableness is positively correlated to the inclusion of free time slots • Free time opportunities are highly appreciated in general
Solution	• Agreeable users: Always generate itineraries which include a few free time slots. • Other users: include free time opportunities if possible.
Why	Most users appreciate having a little free time for themselves, so a few free time slots should be included in recommended itineraries whenever possible. Agreeable users, in particular, would not appreciate itineraries which take up all the available time, leaving no room for relaxing, shopping, social activities or unplanned activities.

TABLE 20. **Design guidelines for busy hours avoidance.**

Problem	When generating personalized itinerary recommendations, it must be decided whether busy hours should be avoided or not.
Use when	Your itinerary recommender system has the ability to take into account predictions on busy hours when scheduling visits to different POIs.
Principle	• There is only a correlation with very low significance between preference for busy hours avoidance and personality traits • The possibility to avoid crowded places and times is generally appreciated
Solution	Avoid scheduling visits in busy hours whenever possible. However, this criterion can be dropped when in conflict with other criteria, such as the inclusion of highly appreciated POIs, efficient visits allocation, or compliance with the total available time.
Why	Most users are happy to avoid crowded places and times, and this preference holds irrespective of user's personality. However, user preference for busy hours avoidance is not particularly strong on average, meaning that users might be willing to compromise on this aspect if the satisfaction of other, more important requirements is at stake.

TABLE 21. **Design guidelines for careful planning.**

Problem	When generating personalized itinerary recommendations, the correct level of detail in planning must be determined.
Use when	Your itinerary recommender system has the ability to adapt the level of detail in itinerary planning.
Principle	• Conscientiousness is positively correlated to careful planning • User preferences for careful planning are very heterogeneous in general
Solution	Adapt the level of detail in planning based on users' personality, following these guidelines: • Conscientious users: maximum possible level of detail • Other users: average level of detail • All users: allow users to adjust the level of detail in recommended itineraries.
Why	In general,different users have different opinions and needs as far as the level of detail they deem desirable when planning a travel itinerary, and such preferences only partially depend on user's personality. Conscientious users are expected to find loosely planned itineraries not useful, so a high level of detail is recommended. For the other users, an average level of detail can be used as a baseline. The possibility to manually adjust the level of detail should be provided to all users, since each of them may have very specific preferences.

strength of the association between the two, in case of conflicts between the guidelines, the one associated with the strongest trait prevails. Alternatively, it is possible to consider a combination of the strength of the guideline, which comes from the significance and strength of the trait-factor relationship, and the strength of the association between the person and the personality trait, as in the previous option.

VII. ETHICAL ISSUES

In planning the user study we complied with literature guidelines on controlled experiments[4] [81].

As described in Section IV, before starting the test, participants had to read the informed consent form describing

[4]https://www.tech.cam.ac.uk/research-ethics/school-technology-research-ethics-guidance/controlled-experiments

TABLE 22. Design guidelines for unpremeditated choices.

Problem	When generating personalized itinerary recommendations, it must be decided whether all the POIs to visit must be determined in advance.
Use when	Your itinerary recommender system has the ability to generate alternatives for a certain time slot and/or to provide real-time suggestions about possible POIs to include in a pre-planned itinerary.
Principle	• Emotional stability is negatively correlated to unpremeditated choices • In general, users do not care much about being able to make spur-of-the-moment decisions
Solution	• Emotionally unstable users: Alternative options can be provided for a certain time slot, and a few POIs can be recommended in real time, for example based on users' location, special offers, etc. • Other users: Avoid generating itineraries where some slots are undefined. Avoid recommending POIs last minute.
Why	Most users are not interested in making spur-of-the-moment decisions, which is probably why they are using an itinerary recommender system in the first place. Thus, it is advisable to provide well defined suggestions for all the available time slots. On the contrary, people who are emotionally unstable seem to appreciate the possibility to choose what to do off the cuff, and might therefore appreciate to be suggested alternatives or to receive real time recommendations.

TABLE 23. Design guidelines for planning autonomy.

Problem	When generating personalized itinerary recommendations, it must be decided whether to let users partially plan their itineraries.
Use when	Users have the possibility to explicitly express preferences on the itineraries to be generated by your recommender system and/or to modify the itineraries.
Principle	• Autonomy in planning is positively correlated to conscientiousness • The interest in planning autonomy is not very strong for all the other users
Solution	• Conscientious users: give them the possibility to express their preferences on some aspects of the itineraries and use this information to personalize the recommended solutions. • All users: allow them to express their preferences on some aspects of the itineraries before generating solutions.
Why	User preferences for autonomy in planning can be quite heterogeneous, so the recommender system should ask all the users for some details on the desired itinerary. Since conscientious people particularly like to personally plan their itineraries, the recommendations for such users should always consider their explicit preferences as important factors to generate or modify the proposed itineraries.

TABLE 24. Design guidelines for expert recommendations.

Problem	When generating personalized itinerary recommendations, it must be decided whether (partial) solutions from experts and trusted external sources should be included.
Use when	Your itinerary recommender system has access to contents generated by external sources, can recommend them or use them as building blocks for its itinerary recommendations.
Principle	• Openness is very strongly positively correlated to a preference for advice from experts • User preferences for advice from experts are very heterogeneous in general
Solution	• Open users: Be sure to include suggestions from experts in the recommended itineraries. • Other users: Include a few suggestions from experts if possible. Alternatively, provide a button to retrieve recommendations from experts only if desired.
Why	Users have heterogeneous, although generally positive, opinions about recommendations from experts. In particular, open users highly appreciate such recommendations, which should therefore be included among the system standard recommendations and presented prominently. For other users, it is enough to allow them to access expert recommendations if they wish.

the nature of the tasks to be performed and their rights and confirm that they had read and understood their rights by filling in the form. By using informed consent, we notified participants about (i) the right to stop participating in the experiment at any time, without giving a reason; (ii) the right to obtain further information about the purpose, and the outcomes of the research; (iii) the right to have their data anonymized. Every participant was given the same instructions by the researcher assisting the experiment.

During the user study, we did not collect participants' names, nor any data that could be used to identify them: we worked with anonymous codes (U1, ..., Un) that the researcher attributed to users immediately before they started the test.

VIII. CONCLUSION

In comparison with traditional recommender systems widely used in e-commerce, designing effective recommender systems for the tourism domain requires great efforts, because the variables that affect travelers' choices in deciding the details of their itinerary are numerous. With this work, we aim at supporting designers of recommender systems being able to suggest itineraries considering also user's personality traits. To do so, first, we modelled an itinerary, identifying the most important dimensions in the state-of-the-art of recommender systems and tourist literature. Then, we investigated if specific personality traits could affect users' decision-making process when choosing an itinerary, carrying out a survey-based study to understand if the Big Five traits can be used to predict user preferences with regard to several itinerary dimensions or to choose a methodology. Finally, we used the findings of this study to define some design guidelines in order to support the design of itinerary recommender systems that consider both different itinerary dimensions and user's personality traits.

The main limitations of our work are the following. First, we focus only on a specific target, the Z generation. While the Z generation represents a suitable target for a tourist recommender system, we cannot generalize our findings to a population with different features, even if we can surmise that relationships between personality traits and itinerary factors maintain their validity irrespective of other user features.

Second, we focused on a comprehensive personality model, which aims at modeling personality through five broad dimensions. While this approach has its advantages, the study of specific personality traits, although less common in the recommender systems area, has already provided interesting results. For example, *mindset* was found to influence users' behaviour [82], as well as their satisfaction with recommender systems [83] and willingness to accept recommendations [84]. Similarly, *need for cognition* has proved to have an impact on users' acceptance of recommendations [85] and explanations [79]. *Locus of control*, which concerns, among other things, decision-making processes and the use of information [86], has been found to predict users' patterns of concordance with recommendations [87] and, similarly to *self-efficacy* [88], could be linked to factors in the "choice modality" dimension. Thus, as future work, we plan to replicate the study with a wider sample, including specific traits which can have an impact on recommendation acceptance and users' behaviour within the recommender system.

Finally, as an additional step, we are planning to use our results as a basis to formulate heuristics which can be used directly in recommender systems to implement personality-based recommendations, for example in order to prune alternatives in itinerary construction. To this aim, we are aware that a general bottleneck is to gather user personality traits by the recommender system. Therefore, we aim at finding novel engaging ways to collect such individual features, without bothering the user too much. New methods proposed in recent studies include, for example, asking the individual to select some pictures [34], [89], [90], inviting the user to play a game [91], [92], predicting personality traits from static facial images [93], [94], [95] or exploiting social media data [96], [97], [98], [99].

CONTRIBUTION

All the authors contributed equally to the work.

REFERENCES

[1] S. Rani, K. N. Kholidah, and S. N. Huda, "A development of travel itinerary planning application using traveling salesman problem and K-means clustering approach," in *Proc. 7th Int. Conf. Softw. Comput. Appl.*, New York, NY, USA, Feb. 2018, pp. 327–331.

[2] A. Eletxigerra, J. M. Barrutia, and C. Echebarria, "Tourist expertise and pre-travel value co-creation: Task-related processes and beyond," *Tourism Manage. Perspect.*, vol. 37, Jan. 2021, Art. no. 100772.

[3] A. Rahman, G. I. Crouch, and J. H. Laing, "Tourists' temporal booking decisions: A study of the effect of contextual framing," *Tourism Manage.*, vol. 65, pp. 55–68, Apr. 2018.

[4] A. Zalatan, "The determinants of planning time in vacation travel," *Tourism Manage.*, vol. 17, no. 2, pp. 123–131, Mar. 1996.

[5] S. Talwar, A. Dhir, P. Kaur, and M. Mäntymäki, "Why do people purchase from online travel agencies (OTAs)? A consumption values perspective," *Int. J. Hospitality Manage.*, vol. 88, Jul. 2020, Art. no. 102534.

[6] C. Backhaus, T. Heussler, and V. Croce, "Planning horizon in international travel decision-making: The role of individual and cultural determinants," *J. Travel Res.*, vol. 62, no. 2, pp. 432–447, Feb. 2023.

[7] I. Gallego, M. R. González-Rodríguez, and X. Font, "International air travel attitude and travel planning lead times across 45 countries in response to the COVID-19 pandemic," *Tourism Manage. Perspect.*, vol. 44, Oct. 2022, Art. no. 101037.

[8] S. Doosti, M. R. Jalilvand, A. Asadi, J. K. Pool, and P. M. Adl, "Analyzing the influence of electronic word of mouth on visit intention: The mediating role of tourists' attitude and city image," *Int. J. Tourism Cities*, vol. 2, no. 2, pp. 137–148, May 2016.

[9] R.-A. Pop, Z. Săplăcan, D.-C. Dabija, and M.-A. Alt, "The impact of social media influencers on travel decisions: The role of trust in consumer decision journey," *Current Issues Tourism*, vol. 25, no. 5, pp. 823–843, Mar. 2022.

[10] L. P. Pearce, *The Sage Handbook of Tourism Management*. London, U.K.: Sage Publications, 2018, pp. 102–117.

[11] C. K. Dimitriou and E. AbouElgheit, "Understanding generation Z's travel social decision-making," *Tourism hospitality Manage.*, vol. 25, no. 2, pp. 311–334, 2019.

[12] Y.-H. Hwang and D. R. Fesenmaier, "Unplanned tourist attraction visits by travellers," *Tourism Geographies*, vol. 13, no. 3, pp. 398–416, Aug. 2011.

[13] G. Richards, "Tourism attraction systems: Exploring cultural behavior," *Ann. Tourism Res.*, vol. 29, no. 4, pp. 1048–1064, 2002.

[14] F. Dai, D. Wang, and K. Kirillova, "Travel inspiration in tourist decision making," *Tourism Manage.*, vol. 90, Jun. 2022, Art. no. 104484.

[15] M. Fernndez-Herrero, R. M. Hernndez-Maestro, and S. Gonzlez-Benito, "Antecedents of tourist trip planning autonomy: The moderating effects of a global economic crisis," *Tourism Econ.*, vol. 2021, Jan. 2021, Art. no. 1354816620981523.

[16] F. Ricci, L. Rokach, and B. Shapira, *Recommender Systems Handbook*, 3rd ed. New York, NY, USA: Springer, 2022.

[17] R. Burke, "Hybrid recommender systems: Survey and experiments," *User Model. User-Adapted Interact.*, vol. 12, no. 4, pp. 331–370, Nov. 2002.

[18] A. Jameson, M. C. Willemsen, A. Felfernig, M. D. Gemmis, P. Lops, G. Semeraro, and L. Chen, "Human decision making and recommender systems," in *Recommender Systems Handbook*. Cham, Switzerland: Springer, 2015, pp. 611–648.

[19] M. De Choudhury, M. Feldman, S. Amer-Yahia, N. Golbandi, R. Lempel, and C. Yu, "Automatic construction of travel itineraries using social breadcrumbs," in *Proc. 21st ACM Conf. Hypertext hypermedia*, Jun. 2010, pp. 35–44.

[20] H.-P. Hsieh, C.-T. Li, and S.-D. Lin, "TripRec: Recommending trip routes from large scale check-in data," in *Proc. 21st Int. Conf. World Wide Web*, Apr. 2012, pp. 529–530.

[21] X. Li, "Multi-day and multi-stay travel planning using geo-tagged photos," in *Proc. 2nd ACM SIGSPATIAL Int. Workshop Crowdsourced Volunteered Geograp. Inf.*, Nov. 2013, pp. 1–8.

[22] P. Vansteenwegen, W. Souffriau, and D. V. Oudheusden, "The orienteering problem: A survey," *Eur. J. Oper. Res.*, vol. 209, no. 1, pp. 1–10, Feb. 2011.

[23] P. Varakantham and A. Kumar, "Optimization approaches for solving chance constrained stochastic orienteering problems," in *Proc. Int. Conf. Algorithmic Decis. Theory*. Cham, Switzerland: Springer, 2013, pp. 387–398.

[24] A. Gunawan, Z. Yuan, and H. C. Lau, "A mathematical model and metaheuristics for time dependent orienteering problem," in *Proc. 10th Int. Conf. Pract. Theory Automated Timetabling*, York, U.K., Aug. 2014, pp. 202–217.

[25] Y. Sun, H. Fan, M. Bakillah, and A. Zipf, "Road-based travel recommendation using geo-tagged images," *Comput., Environ. Urban Syst.*, vol. 53, pp. 110–122, Sep. 2015.

[26] K. H. Lim, J. Chan, C. Leckie, and S. Karunasekera, "Towards next generation touring: Personalized group tours," in *Proc. Int. Conf. Automated Planning Scheduling*, vol. 26, 2016, pp. 1–16.

[27] I. Garcia, L. Sebastia, and E. Onaindia, "On the design of individual and group recommender systems for tourism," *Expert Syst. Appl.*, vol. 38, no. 6, pp. 7683–7692, Jun. 2011.

[28] S. Halder, K. H. Lim, J. Chan, and X. Zhang, "Efficient itinerary recommendation via personalized POI selection and pruning," *Knowl. Inf. Syst.*, vol. 64, no. 4, pp. 963–993, Apr. 2022.

[29] H. Papadakis, C. Panagiotakis, P. Fragopoulou, G. Chalkiadakis, E. Streviniotis, I.-P. Ziogas, M. Koutsmanis, and P. Bariamis, "Visit planner: A personalized mobile trip design application based on a hybrid recommendation model," Res. Square, Tech. Rep., 2023, doi: 10.21203/rs.3.rs-2731618/v1.
[30] P. Alves, P. Saraiva, J. Carneiro, P. Campos, H. Martins, P. Novais, and G. Marreiros, "Modeling tourists' personality in recommender systems: How does personality influence preferences for tourist attractions?" in *Proc. 28th ACM Conf. User Modeling, Adaptation Personalization*, Jul. 2020, pp. 4–13.
[31] A. Tešin, S. Kovačić, and S. Obradović, "The experience I will remember: The role of tourist personality, motivation, and destination personality," *J. Vacation Marketing*, vol. 2023, Jan. 2023, Art. no. 13567667231164768.
[32] W.-K. Tan and C.-Y. Tang, "Does personality predict tourism information search and feedback behaviour?" *Current Issues Tourism*, vol. 16, no. 4, pp. 388–406, May 2013.
[33] D. Jani, "Relating travel personality to big five factors of personality," *Tourism, Int. Interdiscipl. J.*, vol. 62, pp. 347–359, Jan. 2014.
[34] J. Neidhardt, L. Seyfang, R. Schuster, and H. Werthner, "A picture-based approach to recommender systems," *Inf. Technol. Tourism*, vol. 15, no. 1, pp. 49–69, Mar. 2015.
[35] N. Sreen, A. Tandon, F. Jabeen, S. Srivastava, and A. Dhir, "The interplay of personality traits and motivation in leisure travel decision-making during the pandemic," *Tourism Manage. Perspect.*, vol. 46, Mar. 2023, Art. no. 101095.
[36] X. Tran, L. B. Nguyen, and C. M. Nguyen, "Effects of the big five personality traits on recreation types—The case of Vietnam tourism," Univ. Massachusetts, Amherst, MA, USA, Tech. Rep., 2015. [Online]. Available: https://scholarworks.umass.edu/cgi/viewcontent.cgi?article=1043&context=ttra
[37] L. A. Akhrani and A. Najib, "Tell me who you are and I will tell you where to go: Examining the role of big five personality in soft-adventure traveling type," *GeoJournal Tourism Geosites*, vol. 32, no. 4, pp. 1299–1303, Dec. 2020.
[38] A. Agarwal, "Gauging the role of personality in risk perception during a health crisis and its impact on tourist consumption behaviour," *J. Sustainability Resilience*, vol. 3, no. 1, p. 1, 2023.
[39] U. P. Ishanka and T. Yukawa, "User emotion and personality in context-aware travel destination recommendation," in *Proc. 5th Int. Conf. Adv. Inform., Concept Theory Appl. (ICAICTA)*, Aug. 2018, pp. 13–18.
[40] C. S. Jeong, J. Y. Lee, and K. D. Jung, "Adaptive recommendation system for tourism by personality type using deep learning," *Int. J. Internet, Broadcast. Commun.*, vol. 12, no. 1, pp. 55–60, Feb. 2020.
[41] M. Atas, A. Felfernig, S. Polat-Erdeniz, A. Popescu, T. N. T. Tran, and M. Uta, "Towards psychology-aware preference construction in recommender systems: Overview and research issues," *J. Intell. Inf. Syst.*, vol. 57, no. 3, pp. 467–489, Dec. 2021.
[42] R. Robert McCrae and T. Paul Costa, "Validation of the five-factor model of personality across instruments and observers," *J. Personality Social Psychol.*, vol. 52, no. 1, pp. 81–90, 1987.
[43] G. F. Ross, *The Psychology of Tourism*. New York, NY, USA: Hospitality Press, 1994.
[44] S. Kassin, *Psychology*. London, U.K.: Pearson, 2004.
[45] R. B. Cattell, *Personality and Motivation Structure and Measurement*. New York, NY, USA: World Book, 1957.
[46] H. J. Eysenck and S. B. G. Eysenck, *Manual for the Eysenck Personality Inventory*. San Diego, CA, USA: Educational and Industrial Testing Service, 1968.
[47] S. D. Gosling, P. J. Rentfrow, and W. B. Swann, "A very brief measure of the big-five personality domains," *J. Res. Personality*, vol. 37, no. 6, pp. 504–528, Dec. 2003.
[48] N. Mitsche, U. Gretzel, Y.-H. Hwang, and R. Daniel Fesenmaier, "Travel personality testing for destination recommendation systems," in *Destination Recommendation Systems: Behavioural Foundations and Applications*. CABI Digital Library, 2006.
[49] H. Gibson and A. Yiannakis, "Tourist roles: Needs and the lifecourse," *Ann. Tourism Res.*, vol. 29, no. 2, pp. 358–383, 2002.
[50] A. Pizam and S. Sussmann, "Does nationality affect tourist behavior?" *Ann. Tourism Res.*, vol. 22, no. 4, pp. 901–917, Jan. 1995.
[51] G. Breivik, "Personality, sensation seeking and risk taking among Everest climbers," *Int. J. sport Psychol.*, vol. 27, pp. 308–320, Jan. 1997.
[52] Y. Bachrach, S. Ceppi, I. A. Kash, P. Key, F. Radlinski, E. Porat, M. Armstrong, and V. Sharma, "Building a personalized tourist attraction recommender system using crowdsourcing," in *Proc. 2014 Int. Conf. Auto. Agents Multi-Agent Syst.*, 2014, pp. 1631–1632.
[53] M. Braunhofer, M. Elahi, and F. Ricci, "Usability assessment of a context-aware and personality-based mobile recommender system," in *Proc. Int. Conf. Electron. Commerce Web Technol.*, 2014, pp. 77–88.
[54] M. Oppermann, "A model of travel itineraries," *J. Travel Res.*, vol. 33, no. 4, pp. 57–61, Apr. 1995.
[55] S. Basu Roy, G. Das, S. Amer-Yahia, and C. Yu, "Interactive itinerary planning," in *Proc. IEEE 27th Int. Conf. Data Eng.*, Apr. 2011, pp. 15–26.
[56] K. Taylor, K. H. Lim, and J. Chan, "Travel itinerary recommendations with must-see points-of-interest," in *Proc. Companion Web Conf. Web Conf.*, 2018, pp. 1198–1205.
[57] M. Tenemaza, S. Lujan-Mora, A. De Antonio, and J. Ramirez, "Improving itinerary recommendations for tourists through metaheuristic algorithms: An optimization proposal," *IEEE Access*, vol. 8, pp. 79003–79023, 2020.
[58] K. H. Lim, J. Chan, S. Karunasekera, and C. Leckie, "Personalized itinerary recommendation with queuing time awareness," in *Proc. 40th Int. ACM SIGIR Conf. Res. Develop. Inf. Retr.*, Aug. 2017, pp. 325–334.
[59] I. Refanidis, C. Emmanouilidis, I. Sakellariou, A. Alexiadis, R. A. Koutsiamanis, K. Agnantis, A. Tasidou, F. Kokkoras, and P. S. Efraimidis, "MYVISITPLANNER GR: Personalized itinerary planning system for tourism," in *Proc. Hellenic Conf. Artif. Intell.* Cham, Switzerland: Springer, 2014, pp. 615–629.
[60] L. Chen, L. Zhang, S. Cao, Z. Wu, and J. Cao, "Personalized itinerary recommendation: Deep and collaborative learning with textual information," *Expert Syst. Appl.*, vol. 144, Apr. 2020, Art. no. 113070.
[61] H. Yoon, Y. Zheng, X. Xie, and W. Woo, "Smart itinerary recommendation based on user-generated GPS trajectories," in *Proc. Int. Conf. Ubiquitous Intell. Comput.* Cham, Switzerland: Springer, 2010, pp. 19–34.
[62] A. Fogli, A. Micarelli, and G. Sansonetti, "Enhancing itinerary recommendation with linked open data," in *Proc. Int. Conf. Hum.-Comput. Interact.* Cham, Switzerland: Springer, 2018, pp. 32–39.
[63] G. Cai, K. Lee, and I. Lee, "Itinerary recommender system with semantic trajectory pattern mining from geo-tagged photos," *Expert Syst. Appl.*, vol. 94, pp. 32–40, Mar. 2018.
[64] M. De Choudhury, M. Feldman, S. Amer-Yahia, N. Golbandi, R. Lempel, and C. Yu, "Constructing travel itineraries from tagged geo-temporal breadcrumbs," in *Proc. 19th Int. Conf. World Wide Web*, Apr. 2010, pp. 1083–1084.
[65] P. D. Bitonto, F. D. Tria, M. Laterza, T. Roselli, V. Rossano, and F. Tangorra, "Automated generation of itineraries in recommender systems for tourism," in *Proc. 10th Int. Conf. Current Trends Web Eng.* Berlin, Germany: Springer, 2010, pp. 498–508.
[66] P. L. Pearce, "Tourists' perception of time: Directions for design," *Ann. Tourism Res.*, vol. 83, Jul. 2020, Art. no. 102932.
[67] L. Botti, N. Peypoch, and B. Solonandrasana, "Time and tourism attraction," *Tourism Manage.*, vol. 29, no. 3, pp. 594–596, Jun. 2008.
[68] H. Ding, L. Ke, and Z. Geng, "Route planning in a new tourist recommender system: A fireworks algorithm based approach," in *Proc. IEEE Congr. Evol. Comput. (CEC)*, Nov. 2016, pp. 4022–4028.
[69] S. Nuraeni, A. P. Arru, and S. Novani, "Understanding consumer decision-making in tourism sector: Conjoint analysis," *Proc. Social Behav. Sci.*, vol. 169, pp. 312–317, Jan. 2015.
[70] P. L. Pearce, "Fundamentals of tourist motivation," in *Tourism Research: Critiques and Challenges*. London, U.K.: Routledge and Kegan Paul, 1993, pp. 113–134.
[71] H. Bansal and H. A. Eiselt, "Exploratory research of tourist motivations and planning," *Tourism Manage.*, vol. 25, no. 3, pp. 387–396, Jun. 2004.
[72] C. M. Nichols and D. J. Snepenger, "Family decision making and tourism behavior and attitudes," *J. Travel Res.*, vol. 26, no. 4, pp. 2–6, Apr. 1988.
[73] K. Hyde, "Independent traveler decision-making," *Adv. Culture, Tourism Hospitality Res.*, vol. 2, pp. 151–143, Jul. 2008.
[74] G. Lyons, "The role of information in decision-making with regard to travel," *IEE Proc.-Intell. Transp. Syst.*, vol. 153, no. 3, pp. 199–212, Sep. 2006.
[75] H. M. Lefcourt," *Locus of Control*. New York, NY, USA: Academic, 1991.
[76] C. Chiorri, F. Bracco, T. Piccinno, C. Modafferi, and V. Battini, "Psychometric properties of a revised version of the ten item personality inventory," *Eur. J. Psychol. Assessment*, vol. 31, no. 2, pp. 109–119, May 2015.
[77] C. Courage and K. Baxter, *Understanding Your Users: A Practical Guide to User Requirements Methods, Tools, and Techniques*, 1st ed. San Francisco, CA, USA: Morgan Kaufmann, 2005.
[78] A. R. Singleton and C. B. Straits, *Approaches to Social Research*. Oxford, U.K.: Oxford Univ. Press, 2005.

[79] M. Millecamp, N. N. Htun, C. Conati, and K. Verbert, "To explain or not to explain: The effects of personal characteristics when explaining music recommendations," in *Proc. 24th Int. Conf. Intell. User Interface*, New York, NY, USA, Mar. 2019, pp. 397–407.

[80] R. N. Lussier and C. F. Achua, *Leadership: Theory, Application, Skill Development*. Mason, OH, USA: Thomson/South-Wester, 2004.

[81] E. Roger Kirk, *Experimental Design: Procedures for the Behavioral Sciences*. Newbury Park, CA, USA: Sage,, 2013.

[82] N. J. M. Reijmer, "Improving energy saving decisions by matching recommender type with domain knowledge and mindset," Ph.D. thesis, Dept. Ind. Eng. Innov. Sci., Eindhoven Univ. Technol., Eindhoven, The Netherlands, 2011.

[83] D. Y. Kim and H. Im, "Good or better; the effect of comparative mindset with recommended products on product evaluation and purchase decision," in *Proc. Int. Textile Apparel Assoc. Annu. Conf.*, vol. 75, 2018, p. 3.

[84] M. Aljukhadar and S. Senecal, "The effect of consumer-activated mindset and product involvement on the compliance with recommender system advice," *SAGE Open*, vol. 11, no. 3, 2021, Art. no. 21582440211031550.

[85] S. T. Tong, E. F. Corriero, G. Robert Matheny, and T. Jeffrey Hancock, "Online daters' willingness to use recommender technology for mate selection decisions," in *Proc. IntRS@RecSys*, 2018, pp. 1–10.

[86] O. Olaronke and O. Sunday, "Influence of locus of control, work motivation and information use on decision-making of managers in the aviation industry in Nigeria," *Int. J. Appl. Sci.*, vol. 4, no. 10, pp. 56–70, 2015.

[87] N. N. Sharan and D. M. Romano, "The effects of personality and locus of control on trust in humans versus artificial intelligence," *Heliyon*, vol. 6, no. 8, Aug. 2020, Art. no. e04572.

[88] A. Bandura, *Social Foundations of Thought and Action: A Social Cognitive Theory*. Upper Saddle River, NJ, USA: Prentice-Hall, 1986.

[89] Z. Halim and A. Zouq, "On identification of big-five personality traits through choice of images in a real-world setting," *Multimedia Tools Appl.*, vol. 80, no. 24, pp. 33377–33408, Oct. 2021.

[90] A. Hilliard, E. Kazim, T. Bitsakis, and F. Leutner, "Measuring personality through images: Validating a forced-choice image-based assessment of the big five personality traits," *J. Intell.*, vol. 10, no. 1, p. 12, Feb. 2022.

[91] P. Haizel, G. Vernanda, K. A. Wawolangi, and N. Hanafiah, "Personality assessment video game based on the five-factor model," *Proc. Comput. Sci.*, vol. 179, pp. 566–573, Jan. 2021.

[92] D. B. Palhano, L. dos S. Machado, and A. A. F. de Almeida, "Paki Mirabolandia: A serious game to identify player personality," in *Proc. IEEE 8th Int. Conf. Serious Games Appl. Health (SeGAH)*, Aug. 2020, pp. 1–5.

[93] A. Kachur, E. Osin, and D. Davydov, "Assessing the big five personality traits using real-life static facial images," *Sci. Rep.*, vol. 2020, pp. 1–10, Oct. 2020.

[94] J. Xu, W. Tian, G. Lv, S. Liu, and Y. Fan, "Prediction of the big five personality traits using static facial images of college students with different academic backgrounds," *IEEE Access*, vol. 9, pp. 76822–76832, 2021.

[95] M. A. Moreno-Armendáriz, C. A. Duchanoy Martínez, H. Calvo, and M. Moreno-Sotelo, "Estimation of personality traits from portrait pictures using the five-factor model," *IEEE Access*, vol. 8, pp. 201649–201665, 2020.

[96] D. Azucar, D. Marengo, and M. Settanni, "Predicting the big 5 personality traits from digital footprints on social media: A meta-analysis," *Personality Individual Differences*, vol. 124, pp. 150–159, Apr. 2018.

[97] S. BaÅaran and H. O. Ejimogu, "A neural network approach for predicting personality from Facebook data," *SAGE Open*, vol. 11, no. 3, 2021, Art. no. 21582440211032156.

[98] H. Christian, D. Suhartono, A. Chowanda, and K. Z. Zamli, "Text based personality prediction from multiple social media data sources using pre-trained language model and model averaging," *J. Big Data*, vol. 8, no. 1, pp. 1–20, Dec. 2021.

[99] R. P. Pratama and W. Maharani, "Predicting big five personality traits based on Twitter user U sing random forest method," in *Proc. Int. Conf. Data Sci. Appl. (ICoDSA)*, Oct. 2021, pp. 110–117.

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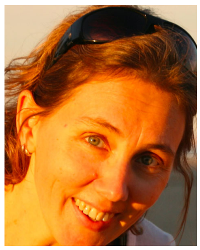

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Open Access funding provided by 'Università degli Studi di Torino' within the CRUI CARE Agreement