TESTING A MODEL OF DESTINATION IMAGE FORMATION:

Application of Bayesian Relational Modeling and fsQCA

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Abstract

Individuals' destination images are constantly updated through their exposure to various stimuli sent from diverse information sources[1] widely accessible in the modern society. Such dynamics of destination image formation[2] is better explained with the iterative process of a concept learning framework integrated into the destination image models. DDIF implies that individuals having been exposed to similar stimuli in the iterative image formation process have a higher likelihood of developing a similar mental representation[3]. Accordingly, this study employs an innovative methodological framework to extract patterns of MR of destinations held by groups of individuals (segments) and to compare segment-specific patterns of MR with their relations to willingness to visit[4] and to ISs. The results demonstrate that what segments associate with a destination relates to their W2V, and segments having rich and positive associations with a destination accessed a wider range of ISs to learn about the destination.

Keywords: destination image formation, mental representation, concept learning, segmentation, fsQCA, nonparametric Bayesian relational modelling

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[1] Information Sources: ISs
[2] Dynamics of Destination Image Formation: DDIF
[3] Mental Representation: MR
[4] Willingness to Visit: W2V

1. Introduction

Tourists' decision-making and destination choice process is closely connected to their familiarity with a destination (Baloglu, 2000; Campbell & Keller, 2003; Gartner, 1989), socio-psychological motivations to visit a destination (Jang & Liping, 2002; Prayag, Disegna, Cohen, & Yan, 2015), knowledge about product attributes formed and stored in a consumer's memory structure (Alba & Marmorstein, 1987; Scott, Schewl, & Frederick, 1978; Woodside & Clokey, 1974), and image of a destination (Baloglu & McCleary, 1999; Beerli & Martín, 2004; Echtner & Ritchie, 1991; Kock, Josiassen, & Assaf, 2016; Mazanec & Strasser, 2007; Woodside & Lysonski, 1989). However, recent studies have pointed out a scarcity of studies regarding the image held by non-visitors (Cherifi, Smith, Maitland, & Stevenson, 2014), the relations between tourists' prior knowledge and their risk perceptions (Sharifpour, Walters, Ritchie, & Winter, 2014), and the dynamics of image formation before, during and after visiting a destination (Martín-Santana, Beerli-Palacio, & Nazzareno, 2017; McCartney, Butler, & Bennett, 2008).

These recent trends in studies are evidence that tourism marketers are, in the modern society, challenged to comprehend how consumers who are potential tourism customers perceive and learn about a destination through the diverse information sources (ISs) widely accessible with the development of information technologies (Govers, Go, & Kumar, 2007). In such an environment, individuals' destination images are constantly updated through their exposure to both positive and negative stimuli sent from various ISs. This implies that understanding the dynamic formation process of both positive and negative destination images held by diverse types of individuals is crucial for tourism marketers to develop an effective communication strategy. Accordingly, the present study sheds light on this dynamic formation process of destination images held and shared by groups of individuals.

Our study consists of three empirical analyses. The uniqueness of the first analysis is the employment of a nonparametric Bayesian relational model known as the infinite relational model (IRM) (Kemp, Tenenbaum, Griffiths, Yamada, & Ueda, 2006; c.f. Glückstad et al., 2013; Miller, Jordan, & Griffiths, 2009; Mørup, Madsen, Dogonowski, Siebner, & Hansen, 2010; Schmidt & Mørup 2013; Xu, Tresp, Yu, & Kriegel, 2006) that was initially developed to analyse mental representations (Kemp, Tenenbaum, Niyogi, & Griffiths, 2010) and concept learning (Tenenbaum, Kemp, Griffiths, & Goodman, 2011). In the tourism literature, the destination image has often been referred to as a mental representation (MR) (Baloglu & McCleary, 1999; Gunn, 1972; Kock et al., 2016). Unlike previous studies in the tourism literature referring to the destination image as a static MR (Rosch, 1975, cited in Kock et al., 2016), the current study assumes that individuals' destination image is iteratively updated in individuals' minds in the form of a system of concepts (Murphy, 2002; Tenenbaum et al., 2011). Based on this principle, the first analysis investigates how individuals' MRs are structured in the form of groups of attributes associated with three specific destinations.

The study further analyses how patterns of association with the three specific destinations held by individuals are shared among a group of individuals (segment) and distinguished across segments. The assumption behind the first analysis is that individuals' MRs are diverse because their prior knowledge about and their willingness to visit the three destinations are different. However, depending on their access to certain ISs about, familiarity with, and preferences for the destinations, some might share specific MR patterns distinguished from the other segments and from the other destinations. Accordingly, the second analysis investigates how patterns of MRs held by the segments and their willingness to visit are related for the three respective destinations. The second investigation employs a fuzzy set qualitative comparative analysis (fsQCA) (Ragin, 1997, 2000, 2008; Thiem & Duşa, 2013a, 2013b) examining relations between conditions (groups of attributes members of a segment associated with a destination) and outcome (degrees of willingness to visit the destination expressed by the segment). This way, the fsQCA enables us to conduct a between-segment analysis comparing relations between various conditions and the outcome.

Finally, the study also assumes that individuals' MRs are developed and updated through their access to various ISs. Therefore, the third analysis addresses how groups of individuals who hold distinctive MRs of the three destinations have accessed ISs to learn about the respective destinations.

2. Theoretical Background

2.1. Destination image and mental representation (MR)

As the existing review of destination image literature (Josiassen, Assaf, Woo, & Kock, 2016) points out, the term 'destination image' has been defined in various ways in previous studies. Tourism scholars refer to destination image as a MR of a destination (Gunn, 1972; Kock et al., 2016), defining it as "an attitudinal construct consisting of an individual's MR of knowledge (beliefs), feelings, and global impression about an object or destination" (Baloglu & McCleary, 1999, p. 870), and study individuals' perceived attributes of a destination (Echtner & Ritchie, 1993; Gartner, 1989, 1993; Mazanec & Strasser, 2007). The existing tourism literature, however, ambiguously uses the term 'mental representation': in cognitive science and philosophy of the mind it is defined as "a basic concept of the Computational Theory of Mind, according to which cognitive states and processes are constituted by the occurrence, transformation and storage (in the mind/brain) of information-bearing structures (representations) of one kind or another (Pitt, 2018, introduction)" and concepts that is "a kind of mental glue, then, in that they tie our past experiences to our present interactions with the world and because the concepts themselves are connected to our knowledge structures (Murphy, 2002, p. 1)." The recent concept learning literature (Murphy & Medin, 1985; Wisniewski & Medin, 1994) proposing the knowledge theory has integrated two classic theoretical views: i) the prototype theory (Rosch, 1973, 1975); and ii) the exemplar theory (Ashby & Maddox, 2005; Medin & Schaffer, 1978). An important point in knowledge theory is that "concepts are influenced by what we already know, but a new concept can also affect a change in our general knowledge" (Murphy, 2002, p. 60). Considering this, MRs of destinations—i.e. destination images—are dynamically updated in individuals' minds, which is inherently aligned with the recent studies reporting that destination images are formed at different levels depending on individuals' prior experiences with a destination (Cherifi et al., 2014; Govers et al., 2007; Martín-Santana et al., 2017; Sharifpour et al., 2014). Accordingly, the current study considers the destination image as a MR of a destination based on the cognitive scientific definition, and defines it as a structured form of objects (destinations) and their semantic properties (attributes) constantly updated and restructured based on individuals' exposure to new stimuli.

2.2. Formation of destination image

Previous studies have suggested that image formation is influenced by personal factors such as values, motivations, personality and socio-demographic characteristics (Baloglu & McCleary, 1999; Beerli & Martín, 2004), and stimulus factors such as primary experience of a previous visit (Phelps, 1986), intensity of visit (Beerli & Martín, 2004), and type and number of ISs (Baloglu &

McCleary, 1999). As individuals' familiarity and destination images are closely connected (Scott et al., 1978), previous studies reported that individuals form destination images at different levels depending on their knowledge acquired through various ISs (Baloglu, 2001; Baloglu & McCleary, 1999; Beerli & Martín, 2004; Gartner, 1989; Phelps 1986). Gartner (1989) classifies these ISs into three categories: induced ISs, delivered via conventional advertising in the mass media and the destination's promotional activities; autonomous ISs, such as mass media broadcasting news, documentaries, etc.; and organic ISs, delivered via friends and families. However, the content of ISs has radically changed in contemporary society due to the emergence of information technologies (Govers et al., 2007). Therefore, the type and intensity of exposure to various ISs must influence individuals' image formation in different situations. Recent studies have addressed and compared different stages of destination images—i.e. non-, pre- and post-visit phases (Cherifi et al., 2014; Jani & Hwang, 2011; Martín-Santana et al., 2017).

From the view of well-established concept learning theories (Kemp et al., 2006, 2010; Murphy, 2002; Murphy & Medin, 1985; Tenenbaum et al., 2011), such dynamics of the MR formation process can be conceptualised as an iterative process. These cognitive theories imply that, when individuals are exposed to a stimulus sent from primary or secondary ISs, they undertake inductive reasoning based on their prior knowledge about a destination (a specific place/country). This means that, although the same stimulus is sent to a target audience, that audience's MR of the destination is elastically updated and revised based on the unique MR stored in the audience's mind. Figure 1 conceptualises this dynamic destination image formation (DDIF), integrating the cognitive scientific theories into the existing destination image formation models (Baloglu & McCleary, 1999; Beerli & Martín, 2004).

(Insert Figure 1 here)

In Figure 1, DDIF considers individuals' destination image as an iterative process of concept learning—i.e. the MR is updated and grows over time (Murphy, 2002; Tenenbaum et al., 2011). Specifically, when a person updates his/her MR triggered by a given stimulus, the updated MR eventually becomes his/her prior knowledge. Such prior knowledge will then be used for the next inductive reasoning, when hs/she encounters a new stimulus. In DDIF, while the stimulus factors are integrated into the iterative MR formation process, personal factors are most likely located outside the iterative process and therefore indirectly influence the inductive reasoning and the reformation of the MR. During the process of inductive reasoning about a destination, he/she may also undertake reasoning relevant to his/her positive or negative valence induced from the given stimuli combined with his/her prior knowledge about a destination. Finally, the behavioural intention most likely relates to the latest MR updated by the given stimulus. DDIF implies that multiple individuals who are iteratively exposed to similar stimuli (similar intensity and type) have a higher likelihood of associating similar attributes and so are likely to develop a similar MR. Moreover, the types of attribute (e.g. cognitive and affective attributes with either positive or negative context) they associate may be connected with their behavioural intention.

Based on these assumptions, the current study applies DDIF to interpret the results of the three explorative analyses respectively addressing the three questions:

i) How patterns of associations with the three specific destinations held by individuals are shared among a group of individuals (segment) and distinguished across segments;

ii) How patterns of MRs held by the segments and their willingness to visit are related for the three respective destinations; and

iii) How groups of individuals who have developed distinctive MRs of the three destinations have accessed information sources to learn about the respective destinations.

3. Methodological Background

3.1. Data structure and analysis of MRs

Scholars in cognitive science often structure MR data in the form of a matrix consisting of a list of attributes and a list of objects (de Deyne et al., 2008; see also Kemp et al., 2006, Figures 3, p.5 and 6, p.8; Tenenbaum et al., 2011, Figure 2, P. 1282). The existing marketing and tourism literature also expresses knowledge about products in the form of a list of attributes formed and stored in a consumer’s memory structure (Dolnicar & Huybers, 2010; Echtner & Ritchie 1993; Gartner, 1989; Mazanec & Strasser, 2007; Scott et al., 1978; Woodside & Clokey, 1974). The literature review by Echtner and Ritchie (1991) reports that the main stream of the tourism literature has investigated a relatively small number of attributes (e.g. 10–20), measured by Likert scales, and has mainly focused on the static structure of the destination image and its overall relationship with behaviours (Baloglu & McCleary, 1999; Govers et al., 2007). However, some recent works (Dolnicar & Huybers, 2010; Glückstad, Kock, Josiassen, & Assaf, 2017; Mazanec & Strasser, 2007) have attempted to conduct a perception-based analysis (Mazanec & Strasser, 2007) using larger sets of perceived attributes in a binary data format, and to extract sub-groups of individuals who share homogeneous patterns of perceived attributes. For example, Mazanec and Strasser (2007) employed latent class analysis (LCA) to partition 817 people based on 21 binary image attributes. However, Dolnicar, Kaiser, Lazarevski, and Leisch (2012) argue that, in contrast to the LCA that has a limitation of handling larger numbers of attributes, a bi-clustering technique is suitable to extract homogeneous segments that are sufficiently heterogeneous for small sample sizes by accommodating a large number of descriptor variables. They demonstrated simultaneous co-clustering of 1,003 respondents and 44 variables representing vacation activities.

Unlike these techniques, the current study employs the IRM (Kemp et al., 2006) based on the Bayesian principle, which was initially developed for the purpose of investigating individuals' MRs (Kemp et al., 2010). The IRM was chosen as a method not only because of the technical aspect of the advanced bi-clustering function enabling us to handle sparse data, but also because of the theoretical aspect of MR analysis. Tenenbaum et al. (2011, p. 1280) state: "Abstract knowledge is encoded in a probabilistic generative model, a kind of mental model that describes the causal processes in the world giving rise to the learner's observations." Extending such an IRM framework, Glückstad et al. (2013) investigated, in parallel, 34 matrices representing 34 Japanese students' MRs consisting of a list of 19 clothing items labelled in English (objects) and a list of 74 attributes. In the tourism discipline, Glückstad et al. (2017) investigated the MR of the European destination expressed by five individuals in the form of five matrices consisting of 23 European countries as objects and 71 attributes. These previous works indicate that the IRM is suitable for designing flexible and complex data analysis (i.e. parallel bi-clustering) and complements the limitations of the existing methods (e.g. Dolnicar et al., 2012) employed in the previous tourism and marketing literature. Accordingly, the current study employs an extended version of the IRM (Glückstad et al., 2013, 2017) to analyze 70 perceived attributes of 512 individuals about the three destinations in parallel.

3.2. Between-segment analysis

Whereas Baloglu and McCleary (1999) and Govers et al. (2007) pointed out that the majority of works in the destination image literature shed light on the static structure of the destination image and its overall relationship with behaviours (Assaker, Vinzi, & O'Connor, 2011; Baloglu, 2000; Josiassen & Assaf, 2013; Kock et al., 2016; Pike 2002; Prayag & Ryan, 2012; Woodside & Lysonski, 1989), the attribute-based segmentation approach has the potential to analyse dynamic aspects of destination image formation. Specifically, the between-segment analysis of segment-specific MR patterns, exposure to ISs and behaviour intention of the respective segments enables us to estimate levels of the iterative process of image formation each segment has gone through. Accordingly, the current study employs the fsQCA (Ragin, 1997, 2000, 2008; Thiem and Duşa, 2013a, 2013b) to conduct the between-segment analysis.

In the tourism research discipline, the fsQCA has been applied among others for testing the configurational perspective of cultural influence on tourist behaviours (Hsu, Woodside, and Marshall, 2013); cultural values on tipping prevalence (Ferguson, Megehee, and Woodside, 2017); and country collectors' motives and behaviours (Woodside, Li, and Muniz, 2014). The fsQCA is a case-based approach (Woodside, 2018) enabling analysis of the asymmetric relationships between condition(s) combining independent variables and an outcome (a dependent variable). While the widely applied regression analysis typically reports a level of symmetric relationship between independent variables and a dependent variable according to a degree that cases are found along the main diagonal between X (conditions) and Y (outcome), the fsQCA focuses on how the respective cases are positioned along the XY diagonal (Woodside, 2018, p. 9). The current study considers segments as cases and employs the fsQCA to analyse case-specific relations between sets of attributes extracted from the IRM as conditions and either positive or negative willingness to visit as an outcome.

3.3. Survey design

The current study analyzes the MR of the three selected destinations, two of them (France and Germany) potentially being grouped as one category and one (Turkey) being relatively remote and distinguished from the other two destinations. The study assumes that the patterns of MR will indicate whether sub-groups of individuals associate with, for example, Paris and/or the French Alps when they are asked to specify what they associate with France as a destination. Therefore, the study considered country as an appropriate abstract level of concept (destination) which subsumes several specific local units (e.g. Paris, French Alps). The selected destinations have some variance in terms of their visibility among various media and ISs. While all these destinations are known as tourist destinations, they had, at the time of the survey implementation between December 2016 and April 2017, intense media coverage due to terror-related incidents in their respective destinations, which might have influenced individuals' perception of these destinations. The quantitative data (n=521) were collected via a Qualtrics-based survey platform integrated with Amazon's MTurk registered in the US. US-registered respondents were chosen as subjects of the investigation because of their remote distance from the destinations (i.e. long haul travels to Europe) and the country's high internet and social media penetration (e.g. Chaffery, 2019).

The questionnaire consisted of three sections. For each of the three destinations, respondents were asked to complete the following:

i) One multi-choice question about ISs accessed to learn about a destination. The multi-choice option includes 12 items consisting of secondary sources such as mass media broadcasting news, TV programmes/documentaries about the place, films or books where the place appears in the story, travel guides/travel magazines, friends and family, etc., covering the induced, organic and autonomous ISs (Gartner, 1993, cited in Beerli & Martín, 2004), along with the recently emerged social media (Govers et al., 2007), primary sources indicating the intensity of the visit (Beerli & Martín, 2004), and other sources contributing to develop individuals' prior knowledge (i.e. part of school education).

ii) Two multi-choice questions including in total 70 generic destination attributes selected from Beerli and Martín (2004, p. 659) that classify the listed attributes into natural resources (e.g. tourist leisure and recreation sites), general infrastructure (e.g. cultural institutions, social environment) and tourist infrastructure (e.g. accommodation, etc.). Some attributes were added to distinguish valences of the descriptive attributes (e.g. "low crime rate" and "high crime rate" instead of "crime rate").

iii) Four questions on willingness to visit the destination, based on Kock et al. (2016), using a seven-point Likert scale.

In addition, respondents' educational background and gender were included as demographic information.

4. Step-One Analysis

4.1. Summary of the IRM framework applied

The IRM framework's underlying principle can be recognized as a family of mixture models widely employed in segmentation studies such as (Ter Hofstede, Steenkamp, & Wedel, 1999; Wedel & Kamakura, 2000). As explained in Kemp et al. (2006), the uniqueness of the IRM is its capacity for flexible data analysis as compared to other bi-clustering models (e.g. Anderson, Wasserman, & Faust 1992; Wasserman and Anderson 1987; Dolnicar et al. 2012). For example, the simultaneous partitioning of observations and variables is statistically supported by data sources about various contexts such as multiple destinations. Furthermore, the Bayesian inference mechanism employed to extract homogeneous segments that are sufficiently heterogeneous for small sample sizes (n=521) can accommodate a large number of descriptor variables (70 destination attributes). Moreover, the IRM automatically identifies the optimal number of clusters for both observations and variables, even in the case of small sample sizes, of which the final results are represented by posterior probability distributions of latent classes and supported by the Bayesian statistics. The further details of the algorithm and the computational program is available in Data in Brief (Glückstad, Schmidt, & Mørup, under review/in print).

4.2. Results of the IRM analysis

The IRM algorithm was run ten times with 10,000 iterations each to assure the quality of the extracted clusters. Among these, the fifth run that partitioned 521 people into 16 segments and 70 generic attributes partitioned into 23 feature clusters was selected for further analysis, as it resulted in the highest likelihood solution. The procedure, results of further performance validations and demographics of the extracted segments are elaborated in Glückstad et al. (under review/in print).

(Insert Table 1 here)

(Insert Figure 2 here)

Table 1 gives an overview of the labels representing the attributes of the respective feature clusters (F1–F23). In Figure 2a, the densities of the blue dots are observable in the respective intersections between a segment (a group of individuals) and a feature cluster (a group of generic destination attributes).

For example, “Segment 1 (S1)” and “F3 (big city)” intersect with higher density for Germany and France than for Turkey. On the other hand, the intersection between S1 and F4 (developing) for Turkey has a relatively high density. Figure 2b also depicts average scores of one of the willingness to visit (W2V) scales using a seven-level Likert computed for S1–S16. Here, S1, S2 and S10 have a greater W2V France than W2V Germany, while their W2V Turkey is low. On the other hand, S8’s W2V Germany is higher than that of France, while the W2V Turkey is also low. S4’s W2V Germany and France is equally high, but the W2V Turkey is low. In contrast, S3, S5, S6, S7 and S9 all have a relatively high W2V Turkey, France and Germany.

4.3. Sub-conclusion

The results of the step-one analysis addressing the first research question demonstrate that the IRM extracted segments according to shared distinctive patterns of association differentiated across the respective destinations, and thereby demonstrated that the shared patterns of attributes individuals associate with the three selected destinations differ across the segments. A manual inspection of the extracted segments showed different levels of average W2V the three destinations expressed by the respective segments. The step-two analysis conducts a systematic inspection of relations between specific conditions (attribute groups associated with the destinations) and W2V the three destinations.

5. Step-Two Analysis

5.1. Qualitative analysis of the segments employing the fsQCA[5]

The study employed the QCA package available in R (Thiem & Duşa, 2013b) to conduct the fsQCA where combinations of F1–F23 are defined as condition(s) X_m, and one of the variables measuring W2V ("It is likely that I would choose [destination] as my tourist destination") as an outcome Y_m, where $m = 1, \ldots 10$ represent the extracted segments S1-S10[6] as cases. To conduct the fsQCA, case-specific calibrated scores of X_m and Y_m were computed based on a procedure described in Data in Brief (Glückstad et al., under review/in print).

(Insert Figure 3 here)

Figure 3 gives an overview of the case-specific calibrated scores for the mono-conditions (individual F1–F23) and the outcome (W2V, as well as negated W2V, calculated as: w2v=1-W2V) for Germany, France and Turkey. At the bottom part of the respective columns for F1–F23, Figure 3 also includes the four types of score: Necessity-Consistency (Nec.Cons.), Necessity-Coverage (Nec.Cov.), Negated-Consistency (Cons.Neg), and Negated-Coverage (Cov.Neg.). Nec.Cons.= $\sum \min(X_{m,} Y_m) / \sum Y_m$, and evaluates the degree to which the respective cases (S1–S10) are members of both a condition X_m and an outcome Y_m in relation to their overall membership in Y_m (Thiem & Duşa, 2013b, p. 63). A high score in Nec.Cons. indicates that "the evidence is consistent with the hypothesis that X_m is necessary for Y_m" (Thiem & Duşa, 2013a, p. 90). Provided that the inclusion condition is satisfied, Nec.Cov.= $\sum \min(X_{m,} Y_m) / \sum X_m$, and assesses "the frequency with which the outcome Y_m occurs relative to X_m" (Thiem & Duşa, 2013a, p. 90). Setting a criterion of a condition that explains the outcome as Nec.Cons. > 0.7, and Nec.Cov. > 0.7, Figure 3 highlighted F3, F12, F15,

[5] Datasets and R codes are accessible in Data in Brief (Glückstad et al. under review/in print)
[6] Since S11–S16 consist of fewer than five members, only S1–S10 are included in the analysis.

F16, F20 and F21 as conditions that explain the positive W2V Germany, and F3, F9, F14, F15, F16 and F21 as conditions for a positive W2V France. The selected feature clusters clearly indicate that general and affective attributes represented by, for example, F3 (big city), F15 (scenery), F16 (attractive) and F21 (interesting) are common for both Germany and France, while F12 (local-hood) and F20 (friendly) are specific conditions for Germany, and F9 (gorgeous) and F14 (hedonistic) apply in particular to France.

(Insert Figure 4 here)

Another uniqueness of the fsQCA method is the ability to develop configurational models inductively by testing all possible combinations of conditions (including negative conditions) that have effect on an outcome without a deductive pre-selection of the combinations. Figure 4 offers an overview of the models selected by the sufficiency analysis (Thiem & Duşa, 2013a, 2013b) for the outcomes explaining positive W2V Germany and France in the form of Venn diagrams. Identified models are:[7][8] F3*f9 (BIG_CITY*gorgeous); F3*f7*f11*F16 (BIG_CITY*local_nature*spiritual*ATTRACTIVE); F3*f7*F16*f23 (BIG_CITY*local_nature*ATTRACTIVE*risk_of_terror); and F3*f8*F16*f23 (BIG_CITY*adventure*ATTRACTIVE*risk_of_terror), according to the cut-off criteria, Suf.Cons > 0.96 and Suf.Cov. > 0.75, for Germany; and F3*f5 (BIG_CITY*crowded); F3*f17 (BIG_CITY*exotic); F3*f20 (BIG_CITY*friendly); f5*F15 (crowded*SCENERY); and F9*F21*f23 (GORGEOUS*INTERESTING*risk_of_terror), according to the cut-off criteria Suf.Cons > 0.98 and Suf.Cov. > 0.63, for France. The Venn diagrams display that three (S4, S8, S9) out of four (S4, S7, S8, S9) segments belong to positive W2V Germany and all four models.

[7] "*" indicates "and".

[8] Low case: "negated".

On the other hand, two (S1, S5) out of six (S1, S4, S5, S6, S7, S9) segments belong to positive W2V France and all four models.

(Insert Figure 5 here)

Figure 5 further depicts relationships between the negated W2V (w2v = 1-W2V) as the outcome and configurational models selected based on the cut-off levels: Nec.Cons > 0.85 and Nec.Cov. > 0.65 for France; Nec.Cons > 0.96 and Nec.Cov. > 0.9 for Turkey; and w2v > 0.5 for the w2v. Figure 5 depicts that f3*F23 (big_city*RISK_OF_TERROR); f6*F23 (developed*RISK_OF_TERROR); f15*F22 (scenery*LANGUAGE_BARRIERS); and f15*F23 (scenery*RISK_OF_TERROR) are the models sufficiently explaining w2v France indicated by S8. For Turkey, F11 (SPIRITUAL), F19 (POLITICAL_INSTABILITY), F22 (LANGUAGE_BARRIERS) and F23 (RISK_OF_TERROR) sufficiently explain w2v for S1, S4, S8, S9 and S10.

5.2. Sub-conclusion

The fsQCA addressed the second research question and complemented the interpretation of the IRM analysis. Specifically, the analysis of necessity identified mono-conditions that influence positive W2V Germany and France respectively (Figure 3). Secondly, the analysis of sufficiency inductively identified distinctive configurational models to explain the positive W2V Germany and France and the negative W2V (w2v) France and Turkey (Figures 4 and 5).

(Insert Table 3 here)

Table 3 summarises the results of the fsQCA and characterises S1–S10 systematically—i.e. the left column indicates demographic characteristics (gender proportion, educational level); the next lists the W2V level (average of the Likert scores) for the three destinations. The last two columns list the configurational models characterising the W2V levels of the respective segments (S1–S10). Here, S1, S2, S4, S5, S8, S9 and S10 are the segments whose outcomes for one or more of the destinations are explained by some of the configurational models identified. Remarkably, S1, S5 and S8's W2V Germany and France are not consistent—i.e. S8 is a male-dominated segment with positive W2V Germany associating with all the models consisting of positive attributes, such as F3 (BIG_CITY) or F16 (ATTRACTIVE_TOWN), while S8 has negative W2V France by specifically associating with F23 (RISK_OF_TERROR) and F22 (LANGUAGE_BARRIERS). In contrast, both S1 and S5's W2V are positive towards France, but non-positive towards Germany. In particular, S1's non-positive W2V Germany is specifically explained by F3*f9 (BIG_CITY*gorgeous). A possible implication is that S1, which is female-dominated, might be a segment that seeks gorgeous and hedonistic attributes, which France generally satisfies, but not Germany. The analysis explicitly identified segments that favour one of the two neighbouring destinations (Germany and France) associated with specific groups of attributes. Accordingly, the third procedure further inspects how S1 and S8, who have developed distinctive MR for the three destinations, have accessed ISs to learn about the respective destinations

6. Step-Three Analysis

6.1. A summary of the analytical method

The third-step analysis employs another IRM-based algorithm, a so-called multinomial IRM (mIRM) in Mørup, Glückstad, Herlau, and Schmidt (2014), that counts how many members in a segment selected both a specific attribute and an IS for all possible combinations, and identifies groups of attributes and groups of ISs sharing a higher count. This way, the analysis investigates which ISs have influenced the eventual MR formation of the destinations. Further details about the analytical method and the computational program are given in Data in Brief (Glückstad et al., under review/in print).

6.2. Results and discussion of the third procedure

(Insert Figure 6 here)

(Insert Figure 7 here)

(Insert Figure 8 here)

Figure 6 depict the output of the mIRM analysis for S1 (n=100), which is the female-dominant segment with positive W2V France, non-positive W2V Germany, and negative W2V (w2v) Turkey. The yellowish colour in the plots indicates the strength of links calculated between an attribute and an IS, defined as strength = (number of members who selected both an attribute and an IS) / (number of members in a segment). Subsequently, the mIRM partitioned attributes and ISs simultaneously according to the strength of the links between all combinations of the 70 attributes and the 12 ISs. The three plots indicate that a wider range of attribute groups and IS groups established stronger links for France compared to those for Germany and for Turkey. Figure 7 further visualise average strengths of the intersections linking an attribute group and an IS group (avr.strength > 0.3) for the three destinations. The graphs clearly demonstrate that S1's links between positive attribute groups (e.g. fashionable, luxurious and shopping) and autonomous/organic IS groups (e.g. TV programmes and documentaries/social media) are strong for France. On the other hand, for Turkey, links are established between a negative attribute group and an autonomous IS group. Furthermore, links between IS groups and attribute groups for Germany are substantially weaker than the links for France.

Similarly, Figure 8 visualises links between attribute groups and IS groups for S8 (n=27), which is the segment with a positive W2V Germany and a negative W2V (w2v) France and Turkey. The graphs depict that links between a group of attributes including negative contexts (e.g. overcrowding, risk of terror) and autonomous IS groups are strong for France, while links between attribute groups (e.g. HQL: high quality of life, beautiful landscape) and autonomous but also primary sources (i.e. actual visit) that might have influenced the formation of affective associations (e.g. enjoyable) are strong for Germany. S8 also associated Turkey with both positive (e.g. friendly people) and negative (e.g. risk of terror attacks, unpleasant) attributes linked with organic ISs.

The above results of S1 and S8 clearly indicate that individuals' associations with the destinations and the ISs (primary and secondary, autonomous/organic) they have accessed to learn about them are closely related, and the strengths and types of the links are also related to their willingness to visit the respective destinations.

7. Discussions and Conclusions

This study conducted explorative analyses of the dynamic destination image formation process integrating the cognitive scientific definition of MR (Murphy 2002; Murphy & Medin, 1985; Tenenbaum et al., 2011), conceptualised as DDIF in Figure 1. The DDIF implies that individuals who have been exposed to similar stimuli in the iterative image formation process may have a higher likelihood of associating similar groups of attributes. Thus, they likely develop a similar MR. Assuming this, the first-step study extracted groups of people who shared similar MRs of the three destinations at the time of the survey implementation. The study further assumed that types of attribute (i.e. cognitive and affective attributes with either positive or negative contexts) that the members of the respective segments associate are connected with their positive or negative W2V. The summary of the second-step analysis shown in Table 2 clearly indicated that the segments with a distinct W2V (either positive or negative) across the three destinations were better characterised by the configurational models (sets of positive or negative attributes) in contrast to those segments whose levels of W2V were moderate. Finally, DDIF also assumes that the stimulus factors are integrated into the iterative image formation process, and positive or negative valences are induced from the given stimuli combined with prior knowledge about the destination during the process of inductive reasoning about the destination.

The third-step analysis examining S1 and S8 attempted to explain this scenario. Especially for both S1 and S8, general attributes such as cultural heritage were common for both Germany and France, linked with autonomous IS such as school, books, TV programmes, etc. These abstract images are general prototype images of European countries, covering both Germany and France, and have most likely been acquired at an earlier stage of the image formation process. The results of the third-step analysis presented in section 6.2 may be interpreted such that S1's exposure to positive stimuli about France has been broader than those about Germany and Turkey, so that S1 went through several iterative processes to develop the positive and concrete MR of France in comparison to the other destinations. Eventually, the positive image was connected with a positive W2V, which is consistent with other existing literature, such as Kock et al. (2016). However, an interesting question is whether a positive image of a destination triggers consumers' W2V the destination (e.g. Kock et al., 2016) or whether consumers seek to be exposed to positive stimuli because they have higher W2V or preference for the destination. This 'chicken and egg' question may be better addressed by DDIF, where the latest perceived image of the destination can be used iteratively as prior knowledge about the destination for the next iteration phase of the image formation process. In such a model, positive W2V also stimulates consumers to access additional ISs and updates the latest destination image iteratively.

Another noteworthy point shown in Figure 8 is that the attribute "risk of terror" was included among both positive and negative attributes for France and linked with the group of autonomous ISs (Gartner, 1993): news and articles, TV programmes and documentaries, and movies and books. This raises another interesting question: whether the classification proposed by Gartner (1993) is sufficient to explain the important nature of some of the ISs included in the autonomous sources. For example, ISs such as movies and books that contain narratives and are repetitively retrieved for the long term may have higher effects in terms of the receiver's memory retention. Therefore, they may better contribute to the iterative process of positive image formation (shopping, gastronomy, nightlife, cultural heritage, HQL, etc.). On the other hand, ISs such as news and articles about terror attacks may be temporary information retrieved intensively only at the time of incident. Hence, the image saturation effect (Jeong & Holland, 2012) might be expected. The current study applying DDIF has raised awareness of such effects in relation to memory retention and the saturation of MRs, which might be an important research topic in destination image research in the future. One potential research setting in the future would be to investigate patterns of MRs in the same person in different iterative stages controlled by different types of stimuli and content, as also addressed in previous literature (e.g. Cherifi et al., 2014; Jani & Hwang, 2011 Martín-Santana et al., 2017). In this respect, the IRM framework employed in the current research is a useful tool that enables researchers to design a multi-dimensional bi-clustering model suitable for various forms of MR research, which the conventional bi-clustering (e.g. Dolnicar et al., 2012) and LCA approaches are not capable of. By integrating the cognitive scientific MR theories and cognitive modelling methods, the stimuli factors defined by Gartner (1993) may potentially be advanced through a classification based on, for example, expected effects of memory retention and saturation, and may better explain the iterative image formation process of DDIF.

A major limitation of the current research is that the survey conducted did not contain variables related to personal factors and demographic variables. Some characteristics of the segments identified in the explorative analysis would have been supported by rich demographic information. As personal factors such as values and motivations may be the determinants of positive or negative valences, the integration of personal factors and socio-demographic variables is crucial in future research.

From the managerial viewpoint, as communication is an inferential process (Sperber & Wilson, 1986), understanding of an audience's MR is a first step to develop a resonating communication strategy that may positively affect the memory retention of the targeted audience. By advancing the current research in the direction mentioned here, cognitive scientific MR (i.e. DDIF process) research would further help marketers to identify effective message and information channels that create longer memory retention effects of their promotion for a specific target audience.

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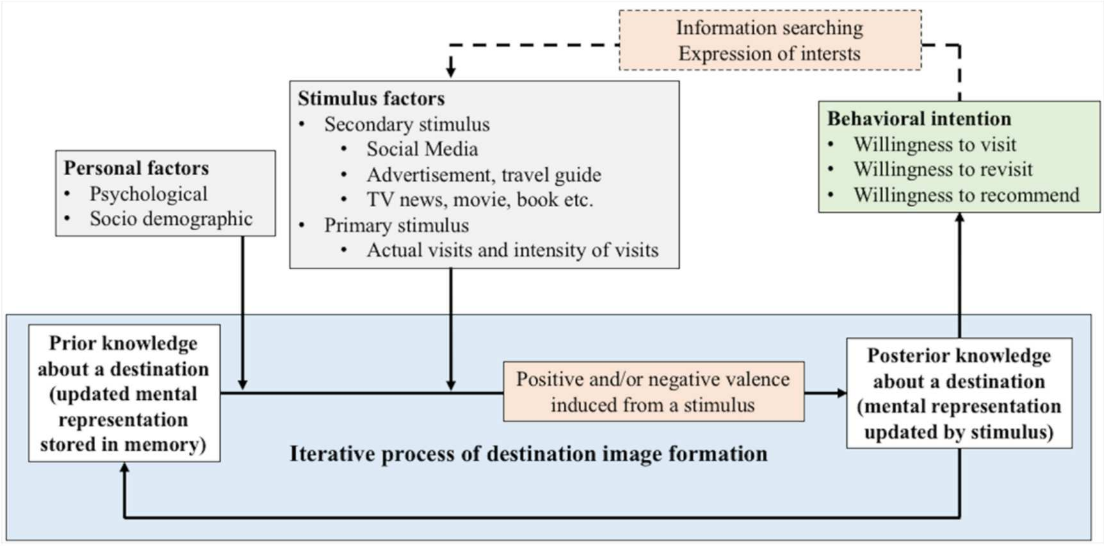


Figure 1: Dynamic Image Formation of Destination

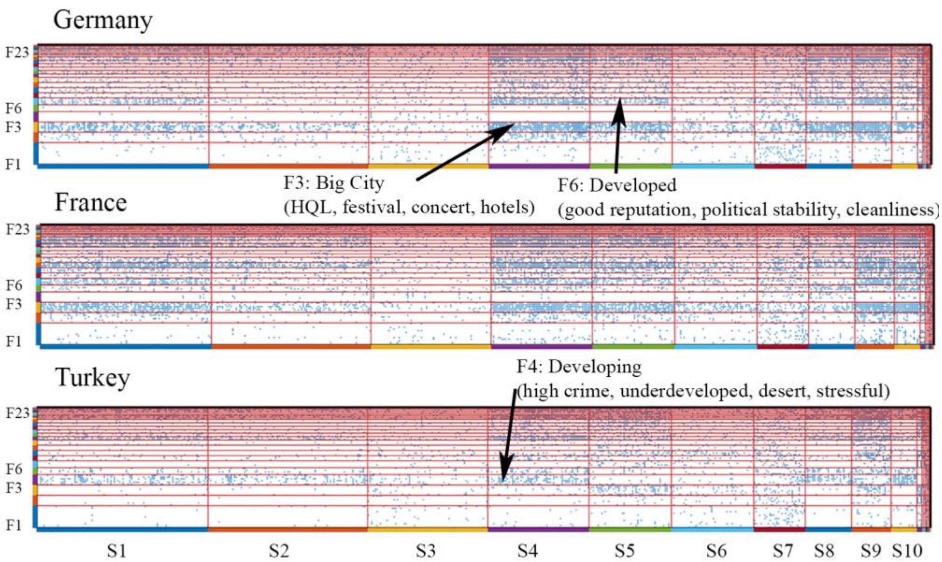


Figure 2a: Segment specific association patterns with the three destinations

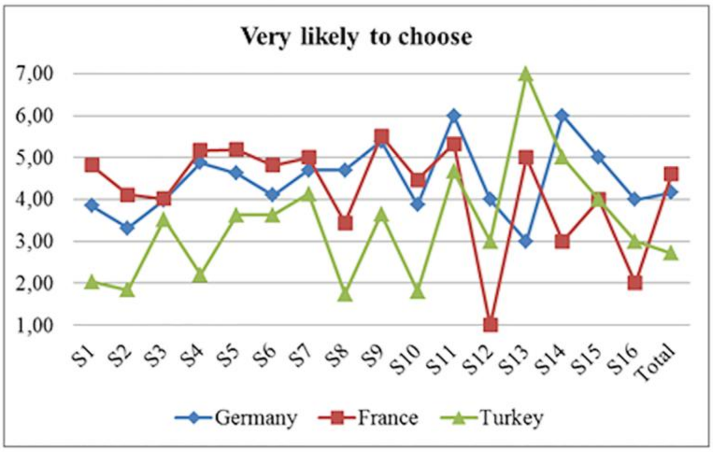


Figure 2b: Segment specific willingness to visit the three destinations

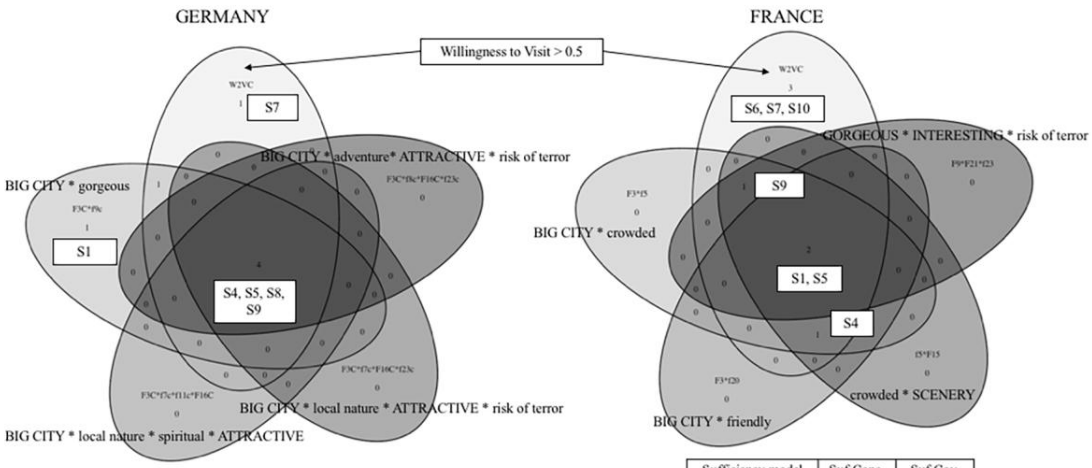
Figure 2: Patterns of mental representations held by the segments (2a) and their average scores of willingness to visit the destinations (2b)

Germany	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13	F14	F15	F16	F17	F18	F19	F20	F21	F22	F23	W2V	w2v	N
S1	0.00	0.01	**0.51**	0.00	0.00	0.42	0.05	0.08	0.01	0.09	0.00	0.39	0.00	0.09	0.33	0.48	0.00	**0.88**	0.00	0.35	**0.98**	**0.52**	0.02	0.35	0.56	100
S2	0.00	0.00	0.22	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.01	0.19	0.00	0.06	0.23	0.27	0.00	**0.76**	0.01	0.15	0.48	**0.51**	0.09	0.07	**0.78**	93
S3	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.04	0.01	0.00	0.00	0.02	0.00	0.06	0.00	0.10	0.00	0.24	0.06	0.00	0.20	0.20	0.04	0.33	0.58	70
S4	0.00	0.29	**0.90**	0.00	0.00	**0.77**	0.25	0.22	0.30	0.34	0.09	**0.69**	0.00	0.45	**0.62**	**0.96**	0.00	**1.00**	0.00	**0.79**	**1.00**	**0.64**	0.15	**0.90**	0.27	59
S5	0.00	0.15	**0.65**	0.00	0.00	0.46	0.02	0.25	0.15	0.19	0.16	0.30	0.00	0.35	0.46	**0.71**	0.00	**0.84**	0.00	**0.55**	**0.91**	0.24	0.05	**0.72**	0.40	48
S6	0.00	0.00	0.24	0.00	0.00	0.12	0.00	0.11	0.04	0.00	0.00	0.15	0.00	0.02	0.09	0.27	0.00	**0.88**	0.00	0.15	0.35	0.12	0.00	0.44	0.52	48
S7	0.12	0.20	0.31	0.10	0.06	0.27	0.05	0.17	0.21	0.04	0.04	0.31	0.06	0.17	0.35	0.31	0.44	0.42	0.11	0.35	0.40	0.26	0.04	**0.77**	0.38	30
S8	0.00	0.24	**0.88**	0.00	0.00	**0.65**	0.20	0.21	0.30	0.36	0.22	**0.82**	0.00	0.36	**0.60**	**0.95**	0.00	**1.00**	0.00	**0.55**	**0.86**	0.44	0.35	**0.88**	0.29	27
S9	0.00	**0.55**	**1.00**	0.00	0.00	**0.99**	0.38	0.41	0.39	0.36	0.01	**0.86**	0.06	**0.52**	**0.89**	**1.00**	0.08	**0.98**	0.00	**0.92**	**0.98**	0.32	0.12	**0.98**	0.09	23
S10	0.00	0.00	**0.61**	0.00	0.22	0.25	0.11	0.30	0.48	0.11	0.36	**0.56**	0.08	0.31	**0.51**	0.48	0.10	**0.89**	0.02	0.39	**0.89**	**0.82**	0.31	0.59	0.46	15
Nec. Cons.	0.02	0.25	0.83	0.02	0.05	0.68	0.19	0.32	0.33	0.26	0.16	0.73	0.04	0.42	0.72	0.84	0.11	0.93	0.04	0.73	0.90	0.60	0.21			
Nec. Cov.	1.00	1.00	0.88	1.00	1.00	0.97	1.00	1.00	1.00	1.00	1.00	0.97	1.00	1.00	1.00	0.86	1.00	0.67	1.00	0.98	0.72	0.84	1.00			
Cons.Neg.	0.03	0.22	0.65	0.02	0.07	0.49	0.18	0.34	0.35	0.25	0.21	0.57	0.05	0.40	0.58	0.68	0.13	0.92	0.05	0.56	0.80	0.68	0.25			
Cov. Neg.	1.00	0.67	0.53	1.00	1.00	0.54	0.73	0.82	0.81	0.73	1.00	0.58	1.00	0.72	0.62	0.53	0.90	0.50	1.00	0.58	0.49	0.73	0.92			

France	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13	F14	F15	F16	F17	F18	F19	F20	F21	F22	F23	W2V	w2v	N
S1	0.00	0.05	**0.69**	0.00	0.05	**0.60**	0.04	0.24	**0.82**	0.36	0.05	0.11	0.00	**0.86**	**0.68**	**0.87**	0.10	**1.00**	0.00	0.25	**0.95**	**0.52**	0.30	**0.68**	0.32	100
S2	0.00	0.00	0.25	0.00	0.00	0.09	0.00	0.04	**0.54**	0.14	0.00	0.01	0.00	**0.60**	0.25	0.49	0.09	**1.00**	0.02	0.04	0.46	0.39	0.46	0.45	0.55	93
S3	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.06	0.00	0.00	0.00	0.00	0.14	0.00	0.02	0.06	0.26	0.06	0.06	0.11	0.09	0.15	0.45	0.55	70
S4	0.00	0.19	**0.92**	0.00	0.24	**0.70**	0.14	0.29	**0.94**	**0.52**	0.08	0.49	0.00	**1.00**	**0.80**	**1.00**	0.35	**1.00**	0.00	0.25	**1.00**	**0.71**	**0.61**	**0.79**	0.21	59
S5	0.00	0.11	**0.75**	0.00	0.01	0.49	0.09	0.39	**0.80**	0.35	0.15	0.06	0.00	**0.86**	**0.71**	**0.97**	0.31	**0.92**	0.00	0.32	**0.88**	0.31	0.17	**0.76**	0.24	48
S6	0.00	0.00	0.38	0.00	0.02	0.19	0.00	0.22	0.26	0.00	0.01	0.00	0.00	**0.58**	0.34	0.38	0.08	**0.52**	0.00	0.26	0.38	0.24	0.15	**0.76**	0.24	48
S7	0.08	0.12	0.26	0.02	0.19	0.30	0.06	0.31	0.41	0.27	0.14	0.04	0.08	0.45	0.25	0.35	0.26	0.35	0.00	0.34	0.34	0.08	0.11	**0.75**	0.25	30
S8	0.00	0.00	0.29	0.10	0.46	0.15	0.00	0.00	**0.55**	0.38	0.10	0.21	0.00	**0.81**	0.22	0.34	0.24	**1.00**	0.14	0.00	**0.70**	**0.56**	**0.74**	0.25	**0.75**	27
S9	0.08	0.48	**0.99**	0.00	0.27	**0.91**	0.41	**0.71**	**0.84**	**0.74**	0.20	**0.59**	0.06	**0.86**	**1.00**	**1.00**	**0.58**	**1.00**	0.02	**0.66**	**0.98**	**0.55**	0.40	**0.85**	0.15	23
S10	0.10	0.20	**1.00**	0.00	**0.62**	**0.70**	0.26	**0.88**	**0.94**	**0.51**	0.31	0.24	0.15	**1.00**	**1.00**	**1.00**	**0.61**	**1.00**	0.00	**0.61**	**1.00**	**0.90**	**0.76**	0.54	0.46	15
Nec. Cons.	0.04	0.18	0.76	0.02	0.25	0.62	0.16	0.44	0.80	0.50	0.17	0.28	0.05	0.87	0.74	0.81	0.42	0.87	0.04	0.43	0.82	0.59	0.50			
Nec. Cov.	1.00	1.00	0.86	1.00	0.84	0.95	1.00	0.89	0.82	0.96	1.00	1.00	1.00	0.77	0.88	0.79	0.97	0.68	1.00	0.98	0.76	0.85	0.81			
Cons.Neg.	0.07	0.22	0.65	0.03	0.42	0.55	0.20	0.49	0.81	0.58	0.27	0.28	0.08	0.89	0.63	0.73	0.51	0.92	0.07	0.51	0.84	0.74	0.78			
Cov. Neg.	1.00	0.71	0.44	1.00	0.83	0.50	0.74	0.59	0.49	0.66	0.95	0.59	1.00	0.46	0.45	0.42	0.70	0.43	1.00	0.68	0.46	0.63	0.75			

Turkey	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13	F14	F15	F16	F17	F18	F19	F20	F21	F22	F23	W2V	w2v	N
S1	0.00	0.00	0.00	0.25	0.00	0.00	0.00	0.00	0.00	0.00	**0.60**	0.17	0.09	0.00	0.00	0.00	0.29	**0.51**	**0.80**	0.00	**0.51**	**0.68**	**0.75**	0.00	**1.00**	100
S2	0.00	0.00	0.00	0.19	0.00	0.00	0.00	0.00	0.00	0.00	0.44	0.08	0.00	0.00	0.00	0.00	0.09	0.44	0.44	0.00	0.20	0.46	**0.68**	0.00	**1.00**	93
S3	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.12	0.00	0.00	0.00	0.01	0.00	0.06	0.10	0.01	0.00	0.06	0.01	0.05	0.34	**0.66**	70
S4	0.00	0.00	0.00	0.35	0.25	0.00	0.17	0.06	0.00	0.04	**0.90**	0.42	0.26	0.25	0.35	0.12	**0.75**	**0.77**	**0.98**	0.08	**0.70**	**0.91**	**0.92**	0.00	**1.00**	59
S5	0.00	0.00	0.38	0.00	0.01	0.10	0.02	0.30	0.06	0.02	0.42	0.26	0.34	0.30	0.49	**0.59**	**0.56**	**0.75**	0.17	**0.62**	**0.89**	0.38	0.41	0.31	**0.69**	48
S6	0.00	0.00	0.09	0.00	0.00	0.00	0.00	0.22	0.00	0.00	0.06	0.02	0.00	0.00	0.14	0.12	0.00	0.35	0.00	0.17	0.15	0.16	0.00	0.31	**0.69**	48
S7	0.09	0.10	0.11	0.12	0.12	0.12	0.10	0.25	0.05	0.10	0.11	0.16	0.12	0.34	0.26	0.21	0.30	0.19	0.26	0.16	0.22	0.30	0.26	0.46	0.54	30
S8	0.00	0.00	0.00	0.41	0.24	0.00	0.04	0.00	0.00	0.00	**0.74**	0.32	0.08	0.04	0.06	0.00	0.44	**0.65**	**0.95**	0.05	0.41	**0.65**	**0.76**	0.00	**1.00**	27
S9	0.00	0.01	0.30	0.19	0.34	0.02	0.39	0.40	0.16	0.41	**1.00**	**0.52**	**0.58**	0.41	**0.77**	**0.86**	**0.92**	**0.98**	**0.66**	**0.68**	**1.00**	**0.77**	**0.73**	0.25	**0.75**	23
S10	0.00	0.00	0.00	**0.68**	0.27	0.00	0.00	0.04	0.01	0.00	**0.64**	0.22	0.09	0.00	0.08	0.00	0.39	**0.61**	**0.69**	0.10	0.31	**0.90**	**0.66**	0.00	**1.00**	15
Nec. Cons.	0.05	0.07	0.46	0.19	0.23	0.14	0.22	0.61	0.16	0.22	0.51	0.41	0.41	0.53	0.58	0.53	0.55	0.70	0.41	0.53	0.59	0.62	0.52			
Nec. Cov.	1.00	1.00	0.86	0.15	0.31	1.00	0.51	0.80	0.96	0.65	0.17	0.32	0.44	0.66	0.45	0.47	0.24	0.22	0.14	0.48	0.22	0.20	0.17			
Cons.Neg.	0.01	0.01	0.11	0.26	0.15	0.03	0.09	0.15	0.03	0.07	0.57	0.26	0.19	0.16	0.26	0.22	0.44	0.61	0.60	0.22	0.48	0.62	0.63			
Cov. Neg.	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.95	1.00	1.00	1.00	0.99	0.94	0.96	0.95	1.00	1.00	0.90	1.00	1.00			

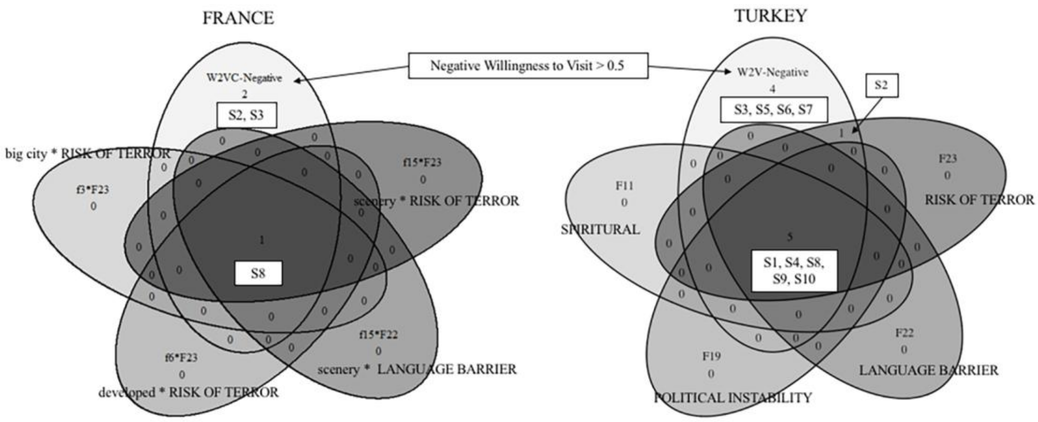
Figure 3: An overview of the segment-specific calibrated scores
Calibration scores > 0.5, Nec.Cons. > 0.7 and Nec.Cov. >0.7 are highlighted.



Sufficiency model	Suf.Cons.	Suf.Con
F3*f9	0.973	0.767
F3*f7*f11*F16	0.96	0.769
F3*f7*F16*f23	0.975	0.758
F3*f8*F16*f23	0.968	0.753

Sufficiency model	Suf.Cons.	Suf.Cov.
F3*f5	0.989	0.707
F3*f17	0.988	0.632
F3*f20	0.988	0.634
f5*F15	1	0.688
F9*F21*f23	0.981	0.642

Figure 4: Venn diagrams of selected configuration models (positive willingness to visit)



Sufficiency Model (Negative)	Suf.Cons.	Suf.Cov.
f3*F23	1	0.575
f6*F23	0.968	0.72
f15*F22	0.977	0.57
f15*F23	1	0.613

Sufficiency Model (Negative)	Suf.Cons.	Suf.Cov.
F11	0.95	0.574
F19	1	0.595
F22	0.996	0.624
F23	1	0.627
f12*F18	0.989	0.552

Figure 5: Venn diagrams of selected configuration models (negative willingness to visit)

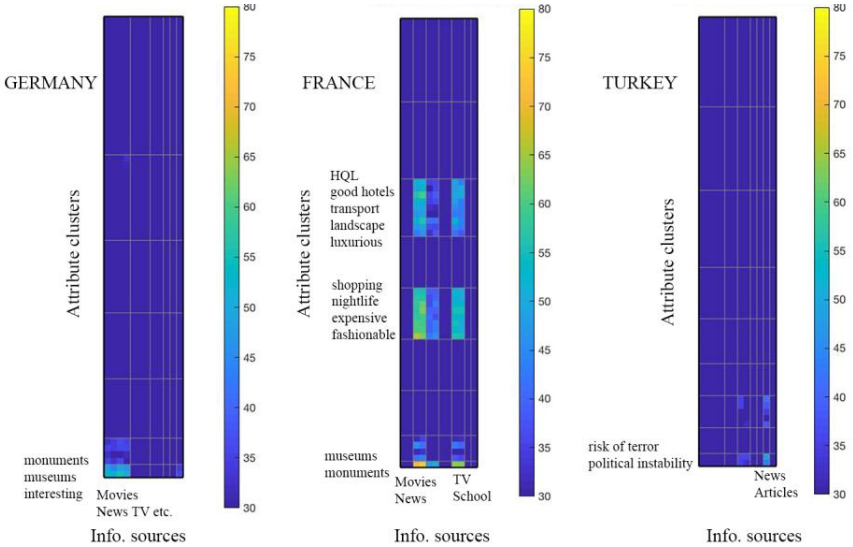


Figure 6: Strength of intersections between a group of information sources and a group of attributes (Segment 1)
Strength = (number of members who selected both an attribute and an IS) / (number of members in a segment)

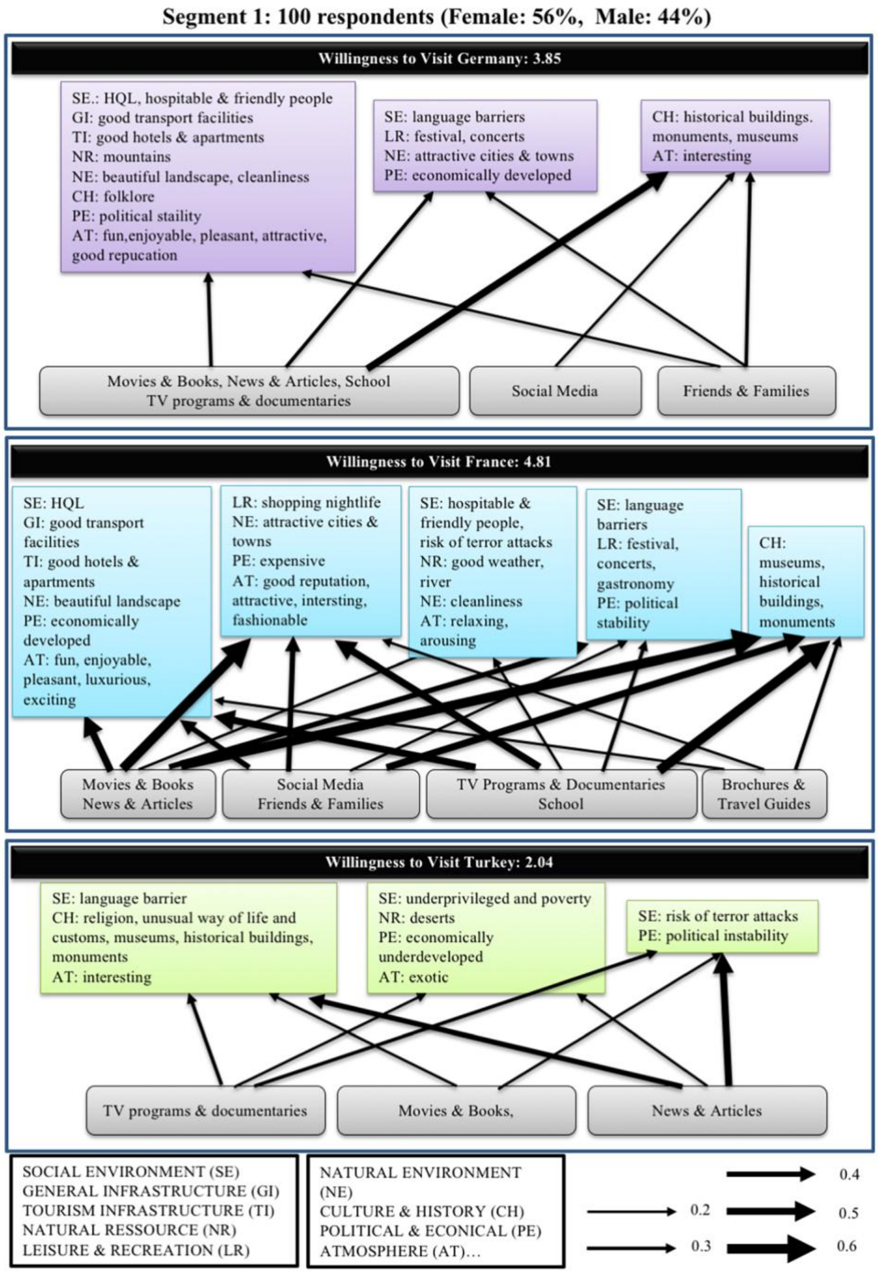


Figure 7: Links between information sources and associated attributes (Segment 1)

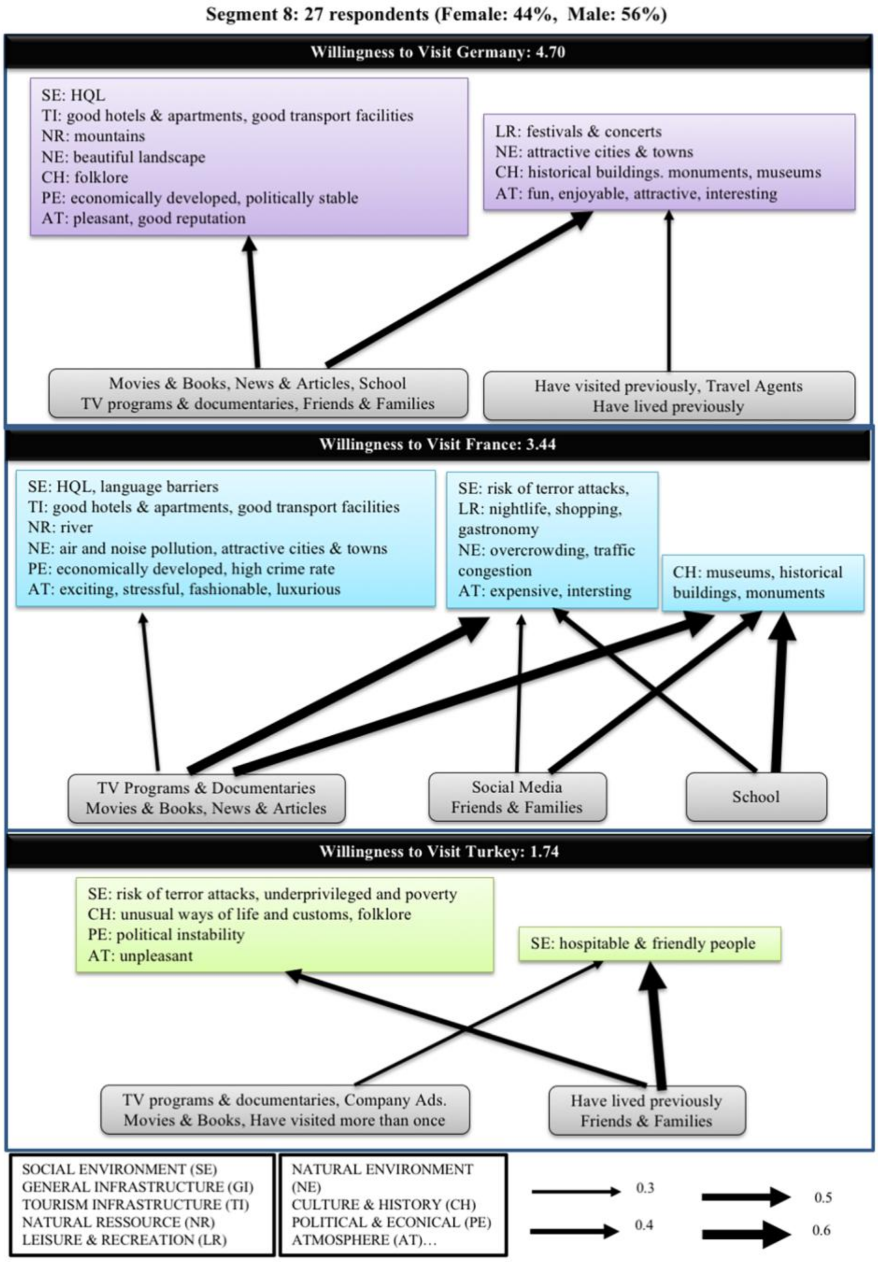


Figure 8: Links between information sources and associated attributes (Segment 8)

Table 1: List of feature clusters

Feature clusters	Attributes
F1 (mixture)	scuba diving, rocky beaches, fishing, casinos, theme parks, zoos, golf, water parks, protected nature reserves, hunting, bad weather, sleepy, boring
F2 (peaceful)	skiing, lakes, ease of communication, low crime rate, offers personal safety, family-oriented destination
F3 (big city)	festival, concerts, high quality of life, good infrastructure of hotels and apartments, economically developed, fun and enjoyable, pleasant
F4 (developing)	deserts, economically underdeveloped, high crime rate, underprivileged and poverty, stressful, unpleasant
F5 (crowded)	sandy beaches, overcrowding, traffic congestion, air and noise pollution
F6 (developed)	well-developed transport facilities, political stability, cleanliness, place with good reputation
F7 (local nature)	Trekking, variety of flora and fauna, handicraft
F8 (adventure)	adventure activities, good weather, relaxing
F9 (gorgeous)	Expensive, fashionable, luxurious
F10 (culinary)	gastronomy, river, arousing
F11 (spiritual)	religion, unusual ways of life and customs
F12 (local hood)	folklore, mountains
F13 (mysterious)	inexpensive, mystic
F14 (hedonistic)	shopping, night life
F15 (scenery)	exciting, wealth and beauty of landscape
F16 (attractive)	attractive, attractiveness of the cities and towns
F17 (exotic)	exotic
F18 (cultural)	museums, historical buildings, monuments
F19 (political instability)	political unstability
F20 (friendly)	hospitable and friendly people
F21 (interesting)	interesting
F22 (language barriers)	language barriers
F23 (risk of terror)	risk of terrorist attacks

Table 2: Characteristics of S1-S10

		Y: outcome*	X: conditions
Gender Edu.	**W2V General profiles**	**Calibrated W2V** Negated W2V (w2v)	Configurational models explaining the corresponding Y: outcome.
S1 Female Higher	Germany: moderate France: high Turkey: low	***W2V Germany (low)*** **W2V France (high)** w2v Turkey (high)	*F3*f9 (big city AND negated gorgeous) for W2V Germany* All positive models for W2V France All negative models for w2v Turkey
S2 Female Middle	Germany-moderate France-mid-high Turkey-low	 w2v France (high) w2v Turkey (high)	Not appeared in the VennDiagram Without any associated models for w2v France F23 (risk of terror) w2v Turkey
S3 Male Middle	Germany: mid-high France: mid-high Turkey: mid-high	 w2v France (high) w2v Turkey (high)	Not appeared in the VennDiagram Without any associated models for w2v France Without any associated models for w2v Turkey
S4 Female High	Germany: high France: high Turkey: very low	**W2V Germany (high)** **W2V France (high)** w2v Turkey (high)	All models for W2V Germany "f5*F15 (negated crowded AND scenery)", "F3*f20 (big city AND negated friendly)", "F3*f5 (big city AND negated crowded)"for W2V France All models for w2v Turkey
S5 Male Higher	Germany: mid-high France: high Turkey: moderate	***W2V Germany (low)*** **W2V France (high)** w2v Turkey (high)	*All models for W2V Germany* All models for W2V France Without any associated models for w2v Turkey
S6 Female High	Germany: moderate France: mid-high Turkey: moderate	 **W2V France (high)** w2v Turkey (high)	Not appeared in the VennDiagram Without any associated models for W2V France Without any associated models for w2v Turkey
S7 Male Middle	Germany: mid-high France: mid-high Turkey: moderate	**W2V Germany (high)** **W2V France (high)** w2v Turkey (high)	Without any associated models for W2V Germany Without any associated models for W2V France Without any associated models for w2v Turkey
S8 Male Higher	Germany: high France: moderate Turkey: very low	**W2V Germany (high)** *w2v France (high)* w2v Turkey (high)	All models for W2V Germany *All models for w2v France* All models for w2v Turkey
S9 Female High	Germany: high France: high Turkey: mid-low	**W2V Germany (high)** **W2V France (high)** w2v Turkey (high)	All models for W2V Germany "F3*f5 (big city AND negated crowded)", "F9*F21*f23 (gorgeous AND interesting AND negated risk of terror)" "f5*F15 (negated crowded AND scenery)" for W2V France All models for w2v Turkey
S10 Female Lower	Germany: moderate France: moderate Turkey: very low	 w2v Turkey (high)	Not appeared in the VennDiagram Not appeared in the VennDiagram All models for w2v Turkey

* W2V (highlighted with bold) and w2v respectively refer to positive and negative willingness to visit a destination. "high" and "low" refer that W2V/w2v above and below the crossover-point (0.5), respectively. The segments highlighted with italic texts refer that their W2V to Germany and France are not consistent (one of them are negative, or not positive enough)