How Subdimensions of Salience Influence Each Other. Comparing Models Based on Empirical Data*

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Abstract

Theories about salience of landmarks in GIScience have been evolving for about 15 years. This paper empirically analyses hypotheses about the way different subdimensions (visual, structural, and cognitive aspects, as well as prototypicality and visibility in advance) of salience have an impact on each other. The analysis is based on empirical data acquired by means of an in-situ survey (360 objects, 112 participants). It consists of two parts: First, a theory-based structural model is assessed using variance-based Structural Equation Modeling. The results achieved are, second, corroborated by a data-driven approach, i.e. a tree-augmented naïve Bayesian network is learned. This network is used as a structural model input for further analyses. The results clearly indicate that the subdimensions of salience influence each other.

1998 ACM Subject Classification G.3 Multivariate Statistics

Keywords and phrases Salience models, consistent PLS-SEM Analysis, Bayesian Networks

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1 Introduction

Human navigation is an intrinsically complex task, involving a diverse range of spatial cues, computational mechanisms and spatial representations (cf. [41]). Despite its complexity, humans are able to successfully find their way on a day-to-day basis. The importance of landmarks for human navigation is undoubted across disciplines. Prototypical systems using landmarks have revealed their usefulness in supporting human wayfinding of pedestrians and drivers, alike (cf. [32, p. 83]). Theories about the landmarkness of objects, i.e. about the salience of (geographical) objects have been developed for the last 15 years (cf. Section 2). However, lack of empirically validated models of *salience* was identified to be a major weakness in current research on estimation of salience (cf. [32]). Accordingly, the goal of this paper is to add to state-of-the-art theories by proposing hypotheses about the way subdimensions of salience, i.e. *visual salience*, *cognitive salience*, *structural salience*, *visibility in advance*, and *prototypicality*, are intertwined. It focuses, thereby, on pedestrian navigation scenarios. Using a dataset based on an in-situ study (cf. [24]) the analysis of the predictive capabilities of the model proposed here, in turn, comprises two steps. First, the degree of influence different subdimensions of salience show on each other is assessed using consistent Partial Least Squares Structural Equation Modeling (PLSc). Afterwards, the results of this theoretical model are compared to those based on a prior Bayesian Network analysis (cf. Section 5.2.2) in order to further backup theoretical claims empirically.

* Parts of this paper were taken from an unpublished doctoral thesis (cf. [25]).

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2 Related Work – Theories about Salience

While the earliest empirical attempt to gain an insight into the factors which contribute to a building's *salience* date back to [1], *salience* as a concept had been formalized around the turn of the century. Five papers, published between 1999 and 2005 build the nucleus of the work done. In [36] Sorrows and Hirtle distinguish three dimensions contributing to salience: visual, structural and cognitive aspects (encompassing, among others, prototypicality, thereby drawing heavily on [34]). However, they do not develop a formal model to capture these. Raubal and colleagues (cf. [31]) introduce a formal model providing measures for each of the three constructs. However, Raubal et al. refer solely to the façades of buildings. Nothegger et al. (cf. [29]) show that the model introduced in [31] is useful for distinguishing between different buildings. Winter (cf. [39]) adds the notion of visibility in advance as contributing to a landmark's *salience*, i.e. he clearly stresses the importance of the particular route. Finally, Klippel and Winter (cf. [26]) give a very detailed account of structural salience, and, in doing so, change the meaning proposed in [31]: 'Objects are called structurally salient if their location is cognitively or linguistically easy to conceptualize in route directions' [26, p. 347].

This initial work was refined by two publications (cf. [5, 6]). The key idea of this refinement is the fact that no object is salient eo ipso. [6] stresses the importance of context by focusing on the interaction between observer, observed, and surroundings. Based on this understanding Caduff proposes a Bayesian network for computing salience values which is largely based on visual attention research (cf. [5]). He distinguishes between

perceptual salience which reflects exogenous allocation of attention

cognitive salience which mirrors endogenous allocation of attention

contextual salience which acknowledges the current navigational context

Based on these definitions Caduff introduces several auxiliary components, e.g. degree of recognition, idiosyncratic relevance, scene context, and combines these to a Bayesian Network. It is noteworthy, though, that – in opposition to the current study – no relationships among perceptual, cognitive or contextual salience as high-level components were hypothesized.

Based on these studies, the following operational definition of *salience* can be derived.

▶ **Definition 1** (Salience). Given a local environment an observer is in, *salience* is the degree to which an object, persistent enough to be used in route instructions, draws the average pedestrian observer's attention. This degree is evoked by

1. visual features the objects has (*visual salience*),
2. the degree of prototypicality it shows (*prototypicality*),
3. how identifiable it is when approached (*visibility in advance*),
4. the ease with which it may be integrated into a route description (*structural salience*) and
5. the degree as to which it can evoke prior knowledge about the object (*cognitive salience*).

According to [24] several items for each of these dimensions were included in the survey they used for data acquisition. Therefore, instead of repeating the full list of questions, which can be found in [24], Table 1 is used to give an impression of the questions asked.

3 A theory-driven Structural Model

Based on these theoretical explanations it is important to note that none of the studies mentioned hypotheses causal relationships between the different subdimensions of *salience*. Contrastingly, the theoretical model proposed (cf. Figure 1) is based on several hypotheses about the way the subdimensions influence each other. Given these hypotheses, *prototypicality* is the only exogenous latent variable.

Table 1 The number of survey questions per construct. The wording of questions can be found in [24].

Construct	n	Example
Overall Sal.	3	To what extent does this object draw your attention?
Visual Sal.	15	intensity of color / tone / size
Cognitive Sal.	6	To what extent does this object's appearance suggest it to be historic?
Structural Sal.	4	How easy is it for you to refer to this object in a route description?
Visibility in Adv.	4	To what extent can one easily refer to this object from afar?
Prototypicality	3	To what extent does this object represent your impression of such objects?

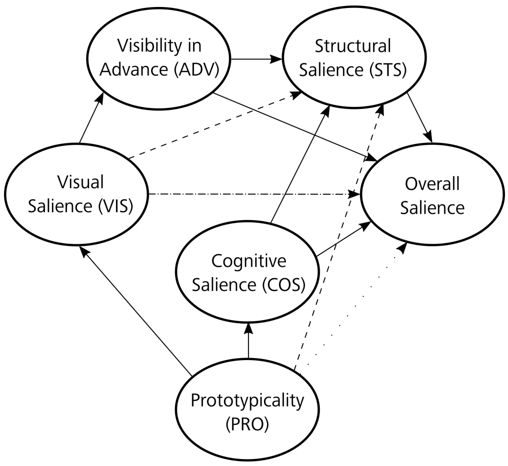

Figure 1 The structural relationships of the theoretical model. The dotted line $PRO \rightarrow Overall$ reflects the full mediation via VIS. The paths $VIS \rightarrow STS$ and $PRO \rightarrow STS$ are added in order not to inflate unexplained variance. Finally, the path $VIS \rightarrow Overall$ was dashed and dotted in order to indicate that a partial mediation of this effect is hypothesized. The figure was drawn using Inkscape [38].

H_1–H_5. Each of the subdimensions contributes positively to *overall salience*.
H_6. The greater an object's *visual salience*, the easier it is to see from advance.
H_7. The greater an object's *visibility in advance*, the more suitable it is to be included in route instructions.
H_8. The greater an object's *prototypicality* ,the larger its *cognitive salience* is.
H_9. The greater an object's *cognitive salience*, the easier it is to be integrated in route instructions.
H_{10}. The effect *prototypicality* has on *overall salience*, is mediated by *visual salience*.

These hypotheses reflect a proposed three-path mediated effect[1] for *visual salience*: Visual aspects become salient at a very early stage of human perception and are consistent across individuals (cf. [20, 5]). Hence, they determine whether or not, as well as to what extent other subdimensions are affected by it. The positive impact *visual salience* has on *overall*

[1] It is important to note that a number of assumptions regarding correctness apply to three-path mediated models, cf. [37, p. 265] for details.

salience is modeled to be partially mediated by *visibility in advance*, which in turn has a positive influence on *structural salience*, which is positively related to *overall salience*, too. A rationale to propose a positive influence of *visibility in advance* on *structural salience* can be based on the understanding of *visibility in advance*. Basically, objects that 'are identifiable early on along a route are more useful than those that can only be spotted at the very last moment' [33, p. 142]. [4] found strong evidence that salient objects in unknown environments must be first and foremost recognizable, a property that relies mostly on the visual features in a given context. Additionally, [27] reports on the strong influence *visual salience* has on object recognition (imagine, e.g. a blue colored house in a neighborhood, where all other houses are painted white). Furthermore, the hypotheses presented indicate a multiple mediation for *prototypicality*. On the one hand, it is mediated by *visual salience*, which is reasonable based on the fact that mental images of objects may well guide our visual attention on the pre-attentive level (cf. [43]). On the other hand, *prototypicality* is supposed to have a positive influence on *cognitive salience* because prototypical objects may eventually be conceptualized more easily. This presumably has, in turn, a positive effect on the value the object has for use in route instructions, i.e. on *structural salience*. As it is common not to model direct paths in mediator analysis [45, pp. 204–205], it must be stressed that this is done purposefully in the hypotheses H_1 to H_5. Based on prior empirical evidence full mediation cannot be assumed. It is important to note, moreover, that these hypotheses are motivated by the aim of establishing a causal chain, which is a major difference to existing models. [31] propose different weights for visual, semantic and structural attraction based on its significance. This means, they do not account for any kind of impact that measures may have on one another. Similarly, the Bayesian network presented in [5] does not include any connections between high-level components such as *visual salience* or *cognitive salience*.

4 Method

As Structural Equation Modeling in general and PLSc in particular are currently not widespread in GIScience research, some general remarks on this method are appropriate. In opposition to that, Bayesian networks (BNs) are much more common and, therefore, only few remarks regarding the algorithm applied to learn the structure of the latent variables network and the steps used to combine BNs and PLSc approaches are given. This section ends with a short description of the in-situ, survey-based data acquisition method according to [24].

4.1 A Rational to use Structural Equation Models

All current models of *salience* share one important aspect: *Salience* is always viewed as having multiple subdimensions. The hypotheses presented (cf. Section 3) lead to a model including multiple relationships between multiple constructs. As a consequence, a statistical method is needed which allows for the use of all available information concurrently. In contrast to factor analysis, multiple regression or MANOVA approaches, Structural Equation Modeling (SEM) has these capabilities. The relations between several latent variables in a so-called structural model can be assessed simultaneously accompanied by the measurement models proposed for each of these constructs (cf. [16]). This means, in contrast to exploratory factor analysis, where no measurement model specification is required at all [17, p. 641], SEM analysis requires a specification of dependencies according to theory. Using latent, i.e. not directly measured, variables to build a model is particularly sensible as the use of multiple indicators to measure a single variable reduces measurement error [17, p. 635]. While covariance-

(commonly referred to as LISREL, cf. [23]) and variance-based methods (commonly referred to as PLS Path Modeling, cf. [42]) to assess models exist, the variance-based approach, i.e. PLS Path Modeling, is used here. There are two reasons for this decision: First, PLS Path Modeling allows for formative measurement and *visual salience* was modeled to be measured formatively[2]. Second, PLS Path Modeling is particularly suitable to assess the degree of influence each subdimension has in terms of predicting both, each other and *overall salience*, thereby virtually making no assumptions about the distribution of the data (cf. [7]). In accordance with recent methodological advancements (cf. [12, 13]) – and, therefore, in contrast to [24], where non-consistent PLS Path Modeling was used – PLS Path Modeling in its consistent version (PLSc) using ADANCO (cf. [8]) is applied. PLSc comprises four steps (cf. [12] for a detailed account):

1. Run the PLS-SEM algorithm, which is alternating the estimation of the measurement model and the structural model estimation until convergency.
2. Calculate ρ_A for all reflective latent variables (i.e. set $\rho_A = 1$ for those modeled formatively).
3. Correct the correlations of latent variables obtained in step one to find consistent correlations.
4. (Re-)Estimate path coefficients using the correlations found in step 3.

4.2 Why combine Bayesian Networks and consistent PLS-SEM – and how

As mentioned above (cf. Section 4.1) the structural model part in SEM must generally be specified prior to a PLSc analysis. It allows hypotheses to be tested with respect to the way latent variables influence each other. However, as these hypotheses are based on theoretical considerations solely it is interesting to investigate whether data driven methods yield similar results. BNs are particularly useful in this context. Their network structure can either be predefined or derived from input data (cf. e.g. [22]). The latter case is particularly useful to establish an empirically based structural model. Following the method of combination suggested in [44], PLSc and BN analyses are linked based on a two-step procedure.

1. Learn a network structure between latent variables from data using Tree-Augmented Naïve Bayes as a search algorithm in WEKA [14].
2. Use the network structure as input for a subsequent PLS-SEM analysis using ADANCO [8].

While WEKA implements several different search algorithms (e.g. K2, C4.2, Naïve Bayes) tree-augmented naïve Bayes (TAN) is particularly suitable for the current research questions. [15] provides evidence that TAN is capable to achieve stable results for correlated attributes while yielding a directed acyclic graph with a singular top level node. It, therefore, allows for an increase in network structure complexity (cf. [44, p. 136]). At the same time, [22] stress that, compared to Naïve Bayes, common measures of classification analyses are significantly increased if TAN is applied (cf. [44, p. 136]).

Found differences or commonalities between the theoretical and the empirical model yield insights into the degree and the way subdimensions of *overall salience* influence each other.

[2] While the ongoing discussion about formative measurement in general (cf. e.g. [2]) cannot be detailed here, a major difference to reflective measurement shall be given: Formative causes must not be mutually interchangeable (cf. [21, p. 203]). From my point of view, the dimensions found to be important to *visual salience* in earlier studies (cf. [24] for a comprehensive list) are not interchangeable, but all of them contribute to *visual salience*. Hence, this subdimension was modeled formatively

4.3 Data acquisition

The data used in this paper are user ratings of a a large-scale, in-situ, survey-based study. The 361 objects to be rated were selected based on randomly chosen geographic coordinates, yielding a variety of objects, two thirds of which comprise buildings and the remaining third a large variety of other urban objects, fences, post boxes and benches among them. Each participant was guided by the first author on one of 55 different routes (routes may have had overlapping segments) which the chosen objects were randomly assigned to. The trials took 60 min on average and routes showed a mean length of 1.5 km. Participants rated 7 objects by answering 41 German language questions (see [24] for the comprehensive list and Table 1 for examples) on a five-point Likert scale for each object. Participants were required to spot the object presented to them using a photo shown on a 7 inch tablet themselves. Two ratings per object were collected and all calculations were done on the average of both ratings for each variable in order to counterbalance potential bias due to personal preferences. More details about this data can be found in [25].

5 Results

For the sake of readability of tables three letter acronyms for each of the (sub-)dimensions of *salience* are used throughout this section: ADV ::= *visibility in advance*, COS ::= *cognitive salience*, PRO ::= *prototypicality*, $OVSAL$ ::= *overall salience*, STS ::= *structural salience*, VIS ::= *visual salience*. First, a short glance on PLSc measurement model results is provided. Second, the theoretical structural model is assessed. Third, the estimation results of a structural model resulting from a prior BN analysis are presented.

5.1 Measurement Model Results

As the focus of this paper is on ways subdimensions of *salience* influence each other only a short report about the measurement model results is given. It is necessary, though, as [24] reports results based on PLS instead of PLSc. Formative measurement model results, however, are not affected by this shift in estimation methods. Therefore, *visual salience* is not discussed below. Table 2 presents standard measures for the reflectively measured[3] latent variables. The figures indicate well-fitting measurement models except for *cognitive salience*. For this subdimension common thresholds are neither met for Cronbach's α ($\alpha < .0.6$, cf. [17, p. 92]) nor for rho_A ($rho_A < 0.7$, cf. [18, p. 12]) nor for AVE ($AVE < 0.5$, cf. [17, p. 688], i.e. the latent variable explains, on average, less than 50% of the variance present in its measured variables). The figures indicate that *cognitive salience* was revealed to be a latent variable with a meaning, difficult for people to grasp. The HTMT-values[4] (cf. [19]) suggest a good discriminant validity of the reflective latent variables (cf. Table 3).

All HTMT-values achieved are significantly lower than one at a significance level of $\alpha = 0.01$. However, despite the significant difference to one, the HTMT-values for ADV and $OVSAL$, for ADV and STS and for STS and $OVSAL$ are large. This suggests that these

[3] Measured variables are considered as effect indicators, i.e. they 'share [...] [a] common cause' [10, p. 12] in case of reflective measurement, which is, therefore, often referred to as *common factor model*.

[4] The HTMT is defined in [19, p. 121] 'as the average of the heterotrait-heteromethod correlations (i.e., the correlations of indicators across constructs measuring different phenomena), relative to the average of the monotrait-heteromethod correlations (i.e., the correlations of indicators within the same construct). Since there are two monotrait-heteromethod submatrices, we take the geometric mean of their average correlations'.

Table 2 Cronbach's α, Dijkstra-Henseler's ρ_A and Average Variance Extracted (AVE) for each of the reflectively measured latent variables.

Method	OVSAL	PRO	COS	STS	ADV
Cronbach's α	0.922	0.849	0.589	0.890	0.900
Dijkstra-Henseler ρ_A	0.923	0.875	0.622	0.900	0.916
AVE	0.800	0.753	0.341	0.700	0.684

Table 3 The bootstrapping results for HTMT-values of reflective constructs. *** indicates $p < 0.001$. A significant result means that the HTMT-value is significantly smaller than one.

	COS	PRO	OVSAL	STS
ADV	0.547***	0.373***	0.815***	0.881***
COS		0.293***	0.694***	0.566***
PRO			0.394***	0.346***
OVSAL				0.831***

constructs are interrelated – a fact further examined by means of the mediation analysis reported below. Overall, the measurement models show a good fit and the items, consequently, provide a sound basis for further structural model analyses. In particular the items derived for *overall salience* show desirable properties, which is important, as all other items are used to measure this particular value.

5.2 Structural Model Results

A two step approach is taken in providing structural model results: First, PLSc figures for the theoretical model are presented. Second, a structural model using TAN involving the subdimensions of *salience*, is learned and assessed based on PLSc.

5.2.1 Theory-based Structural Model

Table 4 presents figures about the size of direct, indirect and total effects constructs have on each other according to the theoretical model (cf. Figure 1).

The figures show:

1. that visual dimensions have the largest effect on *overall salience* and that this effect is only partially mediated via ADV and STS, because both, the direct and indirect effect *visual salience* has on *overall salience* are significant;
2. that *visual salience* has a very large effect on *visibility in advance*, which in turn has a very large effect on *structural salience* while the direct effect $VIS \rightarrow STS$ is rendered insignificant, i.e. the more salient the visual features of an object are, the easier it can be recognized from afar and the easier it is to be referred to in route instructions;
3. *prototypicality* has a significant but small effect on *overall salience*, whereas its effect on *cognitive salience* is medium sized;
4. *cognitive salience* does not substantially add to capturing *overall salience*.

The adjusted R^2-values of endogenous constructs ($R^2(OVSAL) = 0.92$, $R^2(STS) = 0.82$, $R^2(ADV) = 0.56$, $R^2(COS) = 0.13$) reveal, that the subdimensions have a very high predictive relevance for *overall salience*. On the other hand, they further support the influence visual attributes and *visibility in advance* have on ease of reference in route instructions. Finally, the small amount of variance explained in *cognitive salience* shows that the degree of prototypicality is not enough to explain as to why an object is seen as historical etc., although prototypicality has a medium sized effect on this construct.

Table 4 Direct, indirect and total effects of the theoretical model. *** indicates $p < 0.001$, ** indicates $p < 0.01$ and * means $p < 0.05$ ($K = 5000$ resamples).

Effect	Direct	Indirect	Total	Cohen's f^2	Hypotheses
ADV → STS	0.773***	n/a	0.773***	1.410	H_7 holds
VIS → ADV	0.750***	n/a	0.750***	1.278	H_8 holds
STS → OVSAL	0.234**	n/a	0.234**	0.123	H_3 holds
PRO → VIS	0.094**	n/a	0.094**	0.025	H_{10} holds partially
VIS → OVSAL	0.634***	0.220***	0.854***	1.527	H_1 holds
ADV → OVSAL	0.090n.s.	0.181**	0.271***	0.018	H_4 holds
PRO → COS	0.368***	n/a	0.368***	0.157	H_8 holds
COS → OVSAL	0.060n.s.	0.027n.s.	0.087n.s.	0.018	H_2 holds not
VIS → STS	0.075n.s.	0.579***	0.654***	0.010	
COS → STS	0.116n.s.	n/a	0.116n.s.	0.031	H_9 holds not
PRO → OVSAL	0.040n.s.	0.110**	0.150***	0.017	H_5 holds
PRO → STS	−0.006n.s.	0.104**	0.097*	0.000	

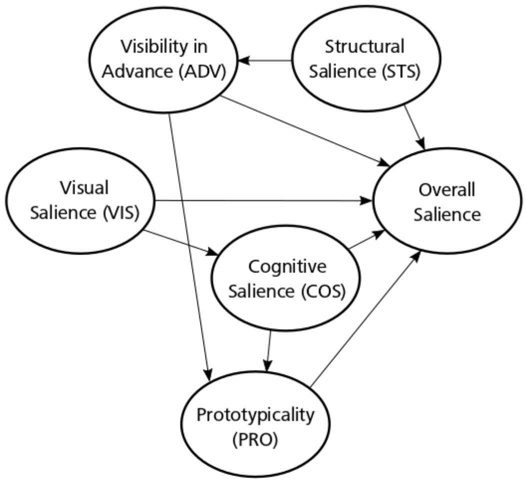

Figure 2 The structural model resulting from a Bayesian Network analysis using TAN as search algorithm.

Overall, the results stress the model's plausibility. However, as stressed by Hair et al. (cf. [17, p. 647]), there are always at least two models, which demonstrate an equally good fit in SEM analyses.

5.2.2 Bayes Net based Structural Model

In order to cross-check the results achieved so far a structural model is divised based on a BN analysis using TAN as a search algorithm. With this goal in mind a multiple regression analysis to calculate the *visual salience* for each of the objects was applied first. This method is reasonable due to the fact that formative measurement was used for *visual salience*. Second, values for all remaining subdimensions were calculated as means of all items associated with a particular dimension – which is in line with the common understanding of reflective measurement as all items reflect the latent variable and their mean provides a most suitable proxy, consequently (cf. e.g. [11]). The structural model resulting from the TAN search based on these figures is shown in Figure 2 while the numerical results are given in Table 5.

Only two direct effects on *overall salience* are rendered significant in this case. *Visual salience* shows a significant, large direct effect on *overall salience* and *structural salience* has

Table 5 Direct, indirect and total effects of the structural model derived by means of a Bayesian Network analysis using TAN as search algorithm. Cohen's f^2 values refer to the direct effects. *** indicates $p < 0.001$, ** indicates $p < 0.01$, * means $p < 0.05$ ($K = 5000$ resamples).

Effect	Direct	Indirect	Total	Cohen's f^2
VIS → OVSAL	0.644***	0.033n.s.	0.677***	1.580
COS → OVSAL	0.036n.s.	0.009n.s.	0.045n.s.	0.007
PRO → OVSAL	0.047n.s.	n/a	0.046n.s.	0.022
ADV → OVSAL	0.090n.s.	0.013n.s.	0.102n.s.	0.017
STS → OVSAL	0.242**	0.092n.s.	0.334***	0.131
COS → PRO	0.183*	n/a	0.183*	0.026
VIS → COS	0.732***	n/a	0.732***	1.152
ADV → PRO	0.267***	n/a	0.267*	0.056
STS → ADV	0.899***	n/a	0.899***	4.210
VIS → PRO	n/a	0.134*	0.134*	n/a
STS → PRO	n/a	0.240***	0.240**	n/a

a medium sized effect. This construct has a very large impact on *visibility in advance*, too. Furthermore, this model reveals a strong impact *visual salience* has on *cognitive salience*. In terms of variance explained ($R^2(OVSAL) = 0.92$, $R^2(COS) = 0.53$, $R^2(PRO) = 0.16$, $R^2(ADV) = 0.81$) the TAN-based model can explain an equal amount of variance in *overall salience* as compared to the theoretical model. *Visual salience* accounts for half of the variance present in *cognitive salience* which stresses its importance.

6 Discussion

From the beginning of *salience* theory, weights for the different subdimensions have been incorporated (cf. [31]). However, studies trying to estimate weights are rarely found nor do they simultaneously take all subdimensions into account. This shortcoming is overcome by the current analysis based on an in-situ dataset (as compared to online studies like [40] or those conducted in virtual reality environments such as [35]). Although the evidence-based structural model and the theoretical model presented show major differences, the total effect of *visual salience* is large in both cases. This finding is in line with other studies in the broader field of research on *salience*. For example, [9] study the importance of *visual salience* for the strategies used to orient oneself in a real-world spatial environment using different kinds of maps. They provide evidence for the high distractive impact visually salient objects have on the orientation of map viewers. Furthermore, the influence *structural salience* and *visibility in advance* have on each other is similar to earlier findings, where objects located at intersections and their resulting *structural salience* have drawn particular interest in recent years. For example, [35, p. 146] finds that participants prefer those 'landmarks that were located in the direction of turn' in case of cross-intersections. However, whether *structural salience* affects *visibility in advance* or vice versa is not evident from the statistical results of both models.

In general, the results provide sound empirical evidence that the subdimensions of *overall salience* are not equally important and highly intertwined. This is in clear contrast to the assumptions of independence made in [5]. Similarly, the results of the analysis presented are in contrast to the findings in [24], where a model with acceptable predictive capabilities is presented in which subdimensions are independent. This shows, first, the importance to assess different models based on the same data. Second, the differences may stem from the fact that non-consistent PLS-SEM was used then which is now outdated. As the models presented here are capable to explain a larger proportion of the variance present in *overall salience*, they are to be preferred. A major difference between models found here, however, is the direct effect *visual salience* has on *cognitive salience* in case of the BN-based model. This effect is particularly reasonable, though: Visual aspects are rendered salient in an early stages of perception (cf. Section 3) whereas *cognitive salience* needs conscious cognitive processing. However, the impact visual dimensions have on *overall salience* is not mediated through *cognitive salience*.

Given these statistical results presented important subdimensions other than those proposed in common theories may be missing. One candidate dimension is *emotional salience*, which has recently gained importance particularly in psychological research. [28, p. 13:1] show that '[e]motional salience can override visual salience and can determine attention allocation in complex scenes.'. By means of a lab-based VR study [3] find evidence wayfinding performance is enhanced by those landmarks with which negative emotions are associated, whereas positive emotions foster route learning. Another dimension worth investigating is *familiarity*. [30] reveal *visual salience*, *structural salience* and *semantic salience* to have an impact on all participants, but those who are familiar with the study area prefer objects which have a meaning for them. *Familiarity*, however, may be hard to distinguish from *emotional salience* or may at least have an impact on it. Imagine the object to be rated is a person's school house. This object is certainly familiar to her/him, but it is also likely to evoke emotional affect due to this familiarity. Further analysis of the dimensions of *emotional salience*, however, is necessary to substantiate this claim.

7 What Do Found Differences Mean – Conclusion and Future Work

This study uses state-of-the-art theories about *salience* to investigate the way commonly accepted subdimensions of *salience* influence each other. In doing so, the nature of the study is, at the same time, both theoretical and empirical in nature. It proposes hypotheses about causal relationships between *overall salience*, *visual salience*, *visibility in advance*, *prototypicality*, *structural salience*, and *cognitive salience*. Then, survey-based ratings of 361 different objects collected in-situ (cf. [24]) are used to assess the predictive capabilities of the model. The structural relationships between the subdimensions are double checked by combining Baysian networks and consistent PLS-SEM. Using TAN as a search algorithm, an empirically based structural model is created by means of a Bayes Network analysis and estimated using consistent PLS-SEM. The results of both, the theoretical and the data-driven model, are not contradictory in terms of effect size and amount of variance explained. Indeed, an important effect of visual dimensions is found, which is in line with results of earlier studies. However, some differences with respect to paths and their causal direction are found. As a consequence, future work will be guided along three lines of research. First, we are currently working on data acquisition in a city environment different to the one described in [24] in order to further evaluate the stability of sizes and directions of effects. Second, lab-based, controlled studies are planned in order to further investigate the direction of influence between *structural salience* and *visibility in advance* dimensions. Third, several experiments will be divised to find ways of capturing *emotional salience* (and other personal factors) and to understand its impact.

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