Dissertation Abstract: Empirically Measuring Salience of Objects for Use in Pedestrian Navigation

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1 Motivating Research on Salience Measurement

¹Humans usually refer to landmarks when they give route directions to pedestrians. To date, however, the use of salient objects is not widespread in mobile pedestrian navigation systems (PNSs) (cf. [2, p. 84]). This is in contradiction to the expectations users of these systems have (cf. [3]). From a long-range perspective it is desirable to guide users of PNSs based on objects drawing an observer's attention, as a consequence. However, the amount of data needed to fulfill this goal is vast. Motivating users to engage in estimating the *salience* of landmarks, i.e. using a crowd-sourced like approach, seems a promising way to address this problem (cf. [2]).

Currently, attempts to empirically sound, survey-based in-situ measurement of the *salience* of objects do not exist. The knowledge on landmark identification, however, has generally been growing for years. Theories about the *salience* of objects were established (cf. e.g. [4, 5]) and several empirical, small-scale in-situ studies (cf. e.g. [6, 7]) were published reporting on important dimensions revealed.

What is still missing (cf. [2, 8]) is a large scale experiment, bridging theories and empirical evidence. It is of benefit to empirically reveal which of the known dimensions are most important and how the different sub-dimensions of *salience* relate to each other because this kind of knowledge can foster the development of theories about the *salience* of landmarks as well as its empirical measurement. The thesis abstracted here has three aims, consequently:

1. To provide a critical overview of prior empirical and theoretical work regarding *salience*.
2. To derive a measurement model for each of the proposed subdimensions of *salience*.
3. To analyze two different structural models for *overall salience* based on data of a large scale in-situ experiment. This analysis includes the assessment
 - (a) whether subgroups of visual dimensions can be derived and to determine how their importance differs.
 - (b) whether the influence of visual aspects is mediated by other latent variables.

2 Understanding what Salience Means

Based on a thorough review of the literature in the fields of Information Science, Computer Vision and GIScience an operational definition of *salience* was derived: given a local environment an observer is in, *salience* is the degree to which an object, persistent enough to be used in route

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¹ Parts of this work have been extracted from the author's unpublished doctoral thesis [1].

Table 1 The number (column *k*) of variables used to measure the constructs accompanied by a sample question

Construct	k	Example
Overall	3	To what extent does this object draw your attention?
Visual	15	Intensity, tone, size, location
Cognitive	6	To what extent is the current use of the object obvious?
Structural	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?

Translations of questions were first published in [10]

instructions, draws the average 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*).

This definition reflects two important points, which were also stressed by [9]. First, *salience* is not inherent to an object but assigned to it by an observer. Second, the local environment both, observer and observed, are located in is highly influential for *salience* judgments.

This definition yields, moreover, two consequences in terms of experimental setup. Regarding a sample of objects, buildings and non-buildings must be included because any geographical object can become salient (given that it is persistent enough to be used in route instructions). With respect to the empirical method taken, the object's local surroundings must be visible to the observer. These facts lead to the decision to conduct an in-situ experiment during which participants are required to walk a route and rate randomly chosen objects on this route using a survey.

3 In-Situ Study Design

Data was collected by means of a large scale in-situ study conducted in the city district of Regensburg, a town located in Southern Germany. In accordance with general rules of survey design, each latent variable was measured using several items (cf. Table 1), which were derived from existing literature. It is important to note that *visual salience* is modeled to be measured formatively, whereas all other constructs are modeled reflectively. The mixture of measurement models has major

consequences on the data analysis method chosen (cf. Sect. 4). A suitable sample size of $n = 360$ objects was calculated apriori in order to achieve a desirable level of statistical power. These were randomly chosen based on their geographical coordinates, leading to the inclusion of 120 non-buildings. Tuples of objects were built yielding 55 different routes. Each participant was guided on a randomly assigned route by the author. On average, $n_{obj} = 7$ objects were located on each route and participants were required to rate each of these objects by means of a survey comprising 46 questions in German. A route covered an average distance of $\overline{dist} = 1.5$ km and a trial took $\bar{x} = 60$ min. Overall, $N = 112$ ($M = 25.46$ years, range: 18–65 years) persons participated and 68 of them were females. Thereby, two ratings provided by two different participants were collected for each object.

4 Subdimensions Strongly Influence each Other: Findings

Structural equation modeling (SEM) was used in order to be able to assess both, the relationship of latent variables as well as the influence of measured variables. Any structural

Fig. 1 Model I (first published in [10]) is based on extensive assumptions of independence of subdimensions of *salience*

Fig. 2 Model II hypothesizes different types of mediating effects subdimensions have on each other

Table 2 PLS-SEM results for model II

Effect	PLS-SEM path coeff.
ADV → STS	0.841***
VIS → ADV	0.703***
STS → OVSAL	0.371**
PRO → VIS	0.007
VIS → OVSAL	0.199***
ADV → OVSAL	0.213
PRO → COS	0.317***
COS → OVSAL	0.211**
VIS → STS	−0.022
COS → STS	0.123*
PRO → OVSAL	0.049
PRO → STS	0.004

*** indicates $p < 0.001$, ** indicates $p < 0.01$ and * means $p < 0.05$ ($K = 5000$ bootstrap resamples)

equation model consists of two parts. The structural model part shows the relationships between constructs whereas the measurement model part describes the way latent variables are measured (cf. Table 1). Two different structural models were estimated. Model I (cf. Fig. 1) hypothesizes on independent subdimensions, i.e. each contributes to *overall salience* exclusively. Model II (cf. Fig. 2), in contrast, makes extensive use of hypotheses about mediational effects. The proposed models were analyzed using partial least squares structural equation modeling (PLS-SEM).

Table 3 Predictive accuracy and predictive relevance of those latent variables with a structural relationship to *structural salience* based on consistent PLS-SEM estimations

	$R^2(STS)$	$Q^2(STS)$	f^2	q^2
Complete	0.821	0.501	NA	NA
w/a VIS	0.823	0.501	−0.011	0.000
w/a ADV	0.505	0.313	1.765	0.377
w/a PRO	0.821	0.502	0.000	−0.002
w/a COS	0.809	0.497	0.067	0.008

The figures stress the major impact *visibility in advance* has

In contrast to covariance based assessment this method is particularly suitable to examine the degree of influence variables have in terms of predicting values: multiple OLS regressions based on construct values are calculated in order to maximize the amount of explained variance in the endogenous variables. Far-reaching methodological advancements have been made to this data analysis method during late 2015 leading to so-called consistent PLS-SEM (cf. [11]). I give a thorough overview of the progress made accompanied by a discussion of its effect on my results in my thesis (cf. [1, pp. 155–173]). The results reported below are based on consistent PLS-SEM figures.

In general, measurement model results show good fit for *overall salience*, *structural salience*, and *visibility in advance*. Furthermore, two out of three indicators yielded significant outer loadings in case of *prototypicality*. *Cognitive salience*, however, turned out to be a construct, whose meaning is very hard to grasp. Only two out of six indicators showed high and significant outer loadings.

By means of a convergent validity analysis formative measurement of *visual salience* was shown to be adequate. Size was the most important cause of all causal-formative indicators. Furthermore, participants tend to subsume area, height, length and width as size. In general, aspects of geometry were more important than color was. Colour intensity was highly important but tone was rendered non-significant. While surprising on first sight, these results are in line with earlier, qualitative findings (cf. e.g. [12]). Different lighting conditions, however, may yield different results (cf. e.g. [13] who revealed colour to be most important during nighttime conditions).

According to consistent PLS-SEM results model I does not hold. In contrast, model II (cf. Table 2) results show highly intertwined subdimensions of *overall salience*.

Visual salience has a strong impact on *visibility in advance*. In turn, this latent variable is very important for *structural salience*, both in terms of predictive

Table 4 Predictive accuracy and predictive relevance of those latent variables with a structural relationship to *overall salience* based on consistent PLS-SEM estimations

	$R^2(OVSAL)$	$Q^2(OVSAL)$	f^2	q^2
Complete	0.813	0.619	NA	NA
w/a VIS	0.801	0.587	0.064	0.084
w/a ADV	0.806	0.607	0.037	0.031
w/a STS	0.791	0.593	0.118	0.068
w/a PRO	0.811	0.617	0.011	0.005
w/a COS	0.788	0.610	0.134	0.024

The figures reveal the major impact *visual* and *structural salience* have

accuracy and predictive relevance (cf. Table 3): Almost 82% of all variance present in *structural salience* can be explained by *visibility in advance* as the effect *cognitive salience* has on it is negligibly small. Although its direct effect is only second largest visual aspects are most important to *overall salience*, i.e. *visual salience* has a highly significant direct (0.199***) as well as indirect effect (0.361***). This importance of *visual salience* is generally in line with earlier findings (cf. e.g. [14]), although visual cues may not be most important in all cases (cf. e.g. [15]). In general, the size of effects on *overall salience* is rather small (cf. Table 4). While all subdimensions show medium sized f^2 values *prototypicality* is of very small importance with respect to the model's predictive capabilities and explains only a very small amount of variance which is present in *cognitive salience*, too. Finally, the predictive relevance of the subdimensions is rather low, stressing that subdimensions have a small but important effect.

5 Conclusions and Future Work

In general, the findings reported are particularly useful to enhance existing models. The low effect sizes are a strong indicator that some subdimensions of *salience* are missing. *Emotional salience* and *familiarity* are two candidate dimensions but, at the same time, may be very hard to measure reliably across individuals. From a practical point of view the results achieved lead to an empirically sound way of measuring *salience* by means of a survey. The findings are, therefore, applicable to Volunteered Geographic Information (VGI, cf. [16]) scenarios. Acquisition of *salience* ratings using a crowd-sourced approach will enhance the availability of data on a scalable basis. These data can be used to describe routes to users of PNSs based on salient objects instead of distances.

The results achieved are of interest for future studies with respect to different environments and participants.

The importance of the geometry of objects is particularly interesting due to the possibility to use official data sources in order to enlarge available databases of salient objects: Geometrical dimensions, at least of buildings, can often be derived from land surveying data (cf. e.g. [17]). As this doctoral work reports on experiments in one particular outdoor environment, reassessing the original model in other cities is worthwhile. Any such analysis would shed light on the question of whether the weights found are generic. As eyesight tends to degrade when people get older, different age groups may have different preferences for *visual salience* and/or its causes. Finally, men and women may differ in their estimation of different subdimensions of *overall salience* (cf. [18] who find different impressions of *structural salience*).

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