Is Salience Robust? A Heterogeneity Analysis of Survey Ratings

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Abstract

Differing weights for salience subdimensions (e.g. visual or structural salience) have been suggested since the early days of salience models in GIScience. Up until now, however, it remains unclear whether weights found in studies are robust across environments, objects and observers. In this study we examine the robustness of a survey-based salience model. Based on ratings of $N_o = 720$ objects by $N_p = 250$ different participants collected in-situ in two different European cities (Regensburg and Augsburg) we conduct a heterogeneity analysis taking into account environment and sense of direction stratified by gender. We find, first, empirical evidence that our model is invariant across environments, i.e. the strength of the relationships between the subdimensions of salience does not differ significantly. The structural model coefficients found can, hence, be used to calculate values for overall salience across different environments. Second, we provide empirical evidence that invariance of our measurement model is partly not given with respect to both, gender and sense of direction. These compositional invariance problems are a strong indicator for personal aspects playing an important role.

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1 Introduction

Models of salience have seen increased interest over the last two decades (see [39, 33, 9, 4, 8, 5, 37, 22, 34, 32, 18, 11, 30]). These models are important for several different reasons: they deepen the understanding of human perception and support the interpretation of spatial situations and subsequent decision making; they are applicable to provide route instructions enriched with salient objects for in- and outdoor environments, which is the preferred mode of route communication between humans (see e.g. [40, 43, 3, 26]). Finally, they may be used to design environments which are conducive to wayfinding and navigation.

Given their practical utility several different ways of estimating the salience of objects have been proposed over the years (see e.g. [33, 4, 37, 34, 41, 30]). There is, however, general agreement that salience is not inherent to objects but ascribed to them by an observer, where both, observer and observed, share the same environment (see [4]). Salience (and each of its proposed subdimensions, e.g. visual salience) itself is, in statistical terms, a latent variable, i.e. it cannot be directly observed, but must be measured using a combination of variables. Subdimensions may differ depending on the selected model of salience (see section 2), e.g. in the model by Sorrows and Hirtle [39] the four subdimensions visual, cognitive, structural salience and prototypicality were proposed. Using an extension of this salience model Kattenbeck [19] proposes a set of measured variables for each of five subdimensions and analyses the impact these have on each other and how these can be used to calculate the overall salience of objects.

Survey-based methods are particularly useful with respect to this aspect because they allow to collect data in-situ. This study uses the survey developed in [18] to present an analysis of its measurement invariance. To this end, we collect a dataset of salience ratings in Augsburg (Germany) and compare these ratings to those obtained in Regensburg, Germany (see [19]). The main goal of this paper is to assess measurement invariance with respect to environment, objects and observers of Kattenbeck's measurement model of salience and to analyze the observed heterogeneity taking environment and sense of direction (stratified by gender) into account. The personal aspects were chosen for two reasons. First, there is evidence that differences between genders regarding the preferred mode of orientation exist (see [6] for an overview). Second, subdimensions of state of the art salience models (see section 2) may be influenced by both, different levels (good vs. poor) and subdimensions of sense of direction (allocentric vs. egocentric vs. cardinal directions): for example, visual salience might be more important for those with poorer orientation skills because visual dimensions do not require any knowledge of the structure of the space persons are navigating in.

2 Related Work

The interest in diverging degrees of salience for different objects dates back to the 1960s [25, 1]. Subdimensions of salience were, however, not distinguished before the turn of the century. Sorrows and Hirtle [39] distinguish four subdimensions influencing salience:

1. visual salience, which describes visual characteristics of an object (e.g. salient color, outstanding height),
2. cognitive salience, which focuses on the meaning of a landmark (e.g. through cultural or historical importance),
3. structural salience, which is important because of its location in the structure of the space and
4. prototypicality, which describes how typical an object is with respect to a category [36].

These subdimensions are not mutually exclusive. In contrast, a combination of all subdimensions contributes to the overall salience ascribed to a single object. Many researchers use the classification by Sorrows and Hirtle [39] to develop their own models to assess the salience of objects. Raubal and Winter [33] define independent characteristics of landmark salience of objects based on visual attraction, semantic attraction and structural attraction. They do not consider prototypicality because extensive human subject testing would be required to derive useful results [33]. The aspect of prototypicality, however, plays an

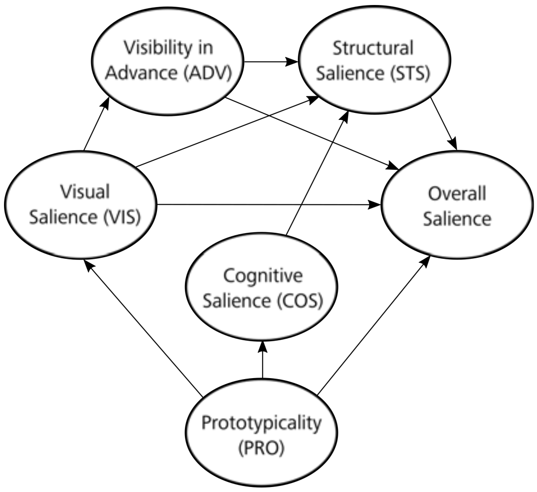

Figure 1 A graphical representation of the Structural Equation Model (i.e. its structural model part) presented in [19]. Table 4 provides the questions used as measured variables.

important role in the model presented in [8], where the usefulness of prototypes rather than particular object properties was used to determine cognitively salient landmarks.

Raubal and Winter's model [33] has been extended several times: Nothegger et al. [29] extend and test the model on façades of buildings. Their proof of concept based on real world data and human judgment shows that the model is a viable way to assess the salience of landmarks. Winter [42] extends [33] by adding *advance visibility* as important factor for landmark salience, i.e. a feature is more salient if it is identifiable earlier in a route than a feature that can only be spotted at the very last moment.

Klippel and Winter [23] complement landmark research with an approach to formalize structural salience. They describe objects as structurally salient if "their location is cognitively or linguistically easy to conceptualize in route directions" [23, p. 347]. In their work they propose taxonomic considerations of point-like objects with respect to their position along a route.

A final extension to the original model stresses the importance of the observer. Caduff and Timpf [4] provide a strong argument that the salience of landmarks is affected by the perspective of the observer, the surrounding environment and the objects contained therein. Salience is contingent on the current navigational context [4], i.e. an object's salience does not only depend on its individual attributes but also on its distinction with respect to attributes of objects nearby [33]. Salience is, consequently, not an inherent property of an object but is assigned to an object by the observer.

Based on these developments, Kattenbeck [20, p. 2] provides the following definition:

> Given a local environment an observer is in, (overall) salience (OVSAL) 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 of the object (visual salience - VIS),
> 2. the degree of prototypicality it shows (prototypicality - PRO),
> 3. how identifiable it is when approached (advance visibility - ADV),
> 4. the ease with which it may be integrated into a route description (structural salience - STS) and
> 5. the degree as to which it can evoke prior knowledge (cognitive salience - COS).

Overall salience seems to be highly dependent on personal subdimensions (see also [32, 11, 30, 38]), since VIS, PRO, COG and ADV depend on either perception or cognition of the observer and only STS and, to a certain extent, ADV and VIS are influenced by the physical environment. Taking the definition above as basis, Kattenbeck [18] reported data collection based on a survey presented there (see table 4). The predictive capability of these ratings was shown in [18, 19, 20] by means of PLS-based Structural Equation Models and suggests highly intertwined subdimensions of salience.

The goal of the present study is to follow up on these survey-based methods of salience measurement. This means, we collect an additional dataset applying the method described in [19] in order to assess whether the model derived from the results presented there (see figure 1) shows invariance across different environments and user groups. We, therefore, use the same statistical method as was used in [19], i.e. we apply PLS-based estimations (see section 4 for a short introduction on this method) of structural equation models to the new dataset collected in Augsburg. We do this in order to gain a better understanding of the model of salience, to determine if all necessary parameters have been included and to determine the robustness of the model.

3 Data Collection Method

In this study we analyze two different datasets of salience ratings by individuals collected while walking predetermined routes under guidance of an experimenter. For the first city, Regensburg, which is a town in Southern Germany, the first author of this paper collected data throughout his PhD [19]. As the goal of this study is the analysis of measurement invariance, it was most important for the current study to gain a second dataset by collecting the data for Augsburg in exactly the same manner as described there [19]. The data collection method and the resulting dataset are detailed below. This data will be accessible via Data in Brief `https://www.journals.elsevier.com/data-in-brief` by the end of 2018.

3.1 City 1: Regensburg, Germany

The Regensburg dataset is built from $N_{rR} = 55$ routes with $N_{oR} = 362$ objects (on average, 6 objects per route), which were rated by $N_{pR} = 112$ participants (68 females, age range: 18-65 years, $\overline{x}_{ageR}$=25.46 years). Experiments took 60 minutes on average (SD = 12 min, range: 38-113 min). The data was collected between November 2014 and February 2015 (see [19] for more details). The methods employed to find a sample of objects and conduct experiments were identical to those described for Augsburg below.

3.2 City 2: Augsburg, Germany

3.2.1 Selection of objects and routes

First, a sample of objects comparable to the one chosen for Regensburg had to be selected in Augsburg. In accordance to [19] it included salient as well as non-salient objects and, in addition, objects other than buildings (e.g. recycling bins, fountains or monuments) which can be referred to in route instructions. Therefore, geographical coordinates of 480 locations were generated randomly to gain a random sample of objects. The locations were inspected on-site. If an object or building was located at the coordinate, it was added to the sample. If neither a building nor any other object was located there the closest object in a randomly drawn direction was chosen. In case an object was not accessible (e.g. railways) they were excluded from the sample. Similarly, parked cars or other temporary objects were not added to the sample. This resulted in a sample size of $N_{oA} = 352$ objects for Augsburg. The sampled objects were randomly combined into routes, such that the time required for a single experiment was expected to be no more than 60 minutes. We aimed for an average of 6 objects per route. Taking these preconditions into account, $N_{rA} = 59$ routes were derived for Augsburg. The walking direction of each route was chosen randomly and each route was assigned randomly to participants. As in [19] we aimed at two independent ratings for each object.

3.2.2 Procedure

Data acquisition for Augsburg took place as part of course work for a seminar. Students taking the class were carefully instructed such that they were able to carry out experiments on their own. Participants were acquired via verbal announcements in university lectures or directly by student experimenters. Two restrictions applied: First, participants had not taken part in a prior experiment on pedestrian navigation. Second, special care was taken to ensure that there was no relationship between participants and student experimenters to avoid biases. A custom designed Android application facilitated the data collection in [19] and this application was reused for our study in Augsburg. The experiments were conducted between July 2017 and December 2017.

Each participant was guided on one of the routes by a student experimenter. Before walking the route, participants were asked to complete a demographic data questionnaire also comprising their personal interests. Participants completed, moreover, a German language self-report sense of direction survey [27]. On completion of these questionnaires, a picture of the first object to be rated was shown to the participants. Along the route, participants had to identify each of the objects on their own. Once the object had been identified they rated the object's salience by answering the questions presented in table 4. Having finished the survey, a picture of the upcoming object was displayed. Overall, $N_{pA} = 109$ (age range: 19-65 years, $\overline{x}_{ageA} = 25.97$ years, 38 females, 14% non-students) persons participated in Augsburg. The experiments took 51 min on average (SD = 13 min, range: 23-83 min). These values are comparable to those in Regensburg (see above). Unfortunately, due to issues with the mobile Internet connection the answers of 15 participants were lost. As a consequence, 90 objects were rated by only one person.

4 Statistical Analysis

Structural Equation Modeling is a multivariate statistical analysis technique that is used to analyze relationships between measured variables and latent constructs, i.e. between the five constructs describing salience and the measured variables to describe them (such as shape, age, length etc.). This section introduces PLS Path modeling as a statistical method and as an adequate means of assessing measurement invariance. This is an important property of a survey used to collect salience ratings: If given the survey measures the same construct across different environments, user groups etc. and weights do not need to be updated for different contexts.

4.1 PLS Path Modeling – A quick glance

In general, Structural Equation Models consist of two parts (see e.g. [12, p. 634f.]): The structural model part describes the relationships among latent variables (constructs), whereas the measurement model part establishes connections between each construct and the variables

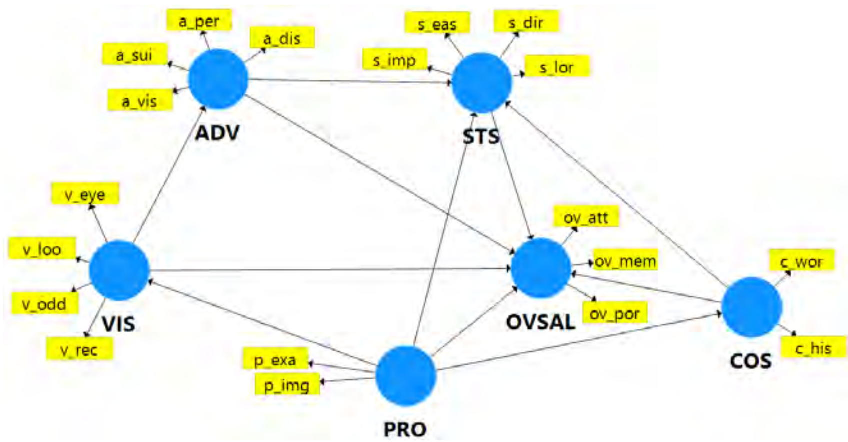

Figure 2 The model used for the analysis throughout this paper (see section 5.1 for the empirical reason to use reflective measurement for visual salience).

used to measure its value (see figure 2). Constructs with outgoing arrows only are referred to as exogenous, whereas those with incoming arrows are known as endogenous variables. A set of measured variables (depicted as rectangles) is used to assess the value of each of these latent variables, as they cannot be observed directly. Measured variables are related to latent variables in one of two measurement modes [10]. *Reflective measurement* (indicated by arrows pointing to measured variables) assumes that the unknown value of the latent variable causes the observed values of the measured variables. In contrast, *formative measurement* causes (arrow heads point to the construct) are thought of as causing the latent variable's value (see [2]).

Two methods to estimate structural equation models exist. The covariance-based approach aims to maximize similarity between the model's and the empirical covariance matrix. It is, hence, based on the assumption of multivariate normality of the data. The variance-based approach, which is called PLS Path Modeling [44, 45] is, in contrast, not based on any distributional assumptions. It focuses, similar to other approaches involving regression, on prediction, i.e. it maximizes the amount of variance explained in the endogenous construct(s) [13, p. 140]. This predictive focus is particularly valuable in case of the analysis reported here, where *overall salience* is the key target construct. When ratings of objects are collected in different environments it is particularly interesting to see, whether the impact that different latent variables have on each other is different. It is important to note that in traditional PLS Path Modeling (for a discussion of consistent PLS Path Modeling see [7]) error terms are not included on the latent variable level, i.e. latent variables are treated as composites regardless of the measurement model specification (see [15] for details).

The statistical analysis proposed here comprises two steps: First, the measurement invariance of the measurement model must be assessed. Second, the analysis of observed heterogeneity is performed taking city and sense of direction (the latter also stratified by gender) into account.

4.2 Assessing Measurement Model Invariance in PLS Path Modeling

Following the so-called MICOM-procedure suggested by Henseler et al. [16], measurement model invariance is tested based on three different criteria. Configural invariance is a necessary but insufficient condition for compositional invariance, which can be divided into partial and full measurement invariance, respectively. These three components are explained below.

4.2.1 Configural Invariance

Configural invariance can be achieved only in those cases where the same set of measured variables has been used for all groups and preprocessing steps and settings during the estimation process were identical (see [17, p. 142–143]). These preconditions were met in terms of data collection as the survey used to collect data comprised the same set of German language questions as presented in [19] (see table 4 for a translated version) and the measured variables were used to serve as proxies for the same set of latent variables. Moreover, SmartPLS software [35] was used for all comparisons. The weighting scheme (path), maximum number of iterations (300) and the stop criterion (10^{-10}) were kept equal across group comparisons. The configural invariance is thus given for all comparisons reported in this paper.

4.2.2 Compositional Invariance

Compositional variance can be divided into partial and full measurement invariance, both of which have an immediate effect on the type of comparisons which are feasible. Therefore, compositional invariance will be checked as a first step in each part of the analysis.

4.2.2.1 Partial Measurement Invariance

This criterion deals with latent variable score correlations (see [16] and [17, pp. 143–146]), which are assessed by means of a permutation test. First, the weights are found for each group. Second, latent variable scores are calculated for the whole dataset based on weights of each group separately. Pairwise correlations between the resulting latent variable scores are then established. Confidence intervals for correlations are found by permuting observations across groups and re-assessing the latent variable scores and correlations at least 1 000 times. This procedure provides statistical evidence whether the correlations of scores for the same composites differ significantly from one. Throughout the analysis presented below, 5,000 permutations were used in all cases.

4.2.2.2 Full Measurement Invariance

If both, configural invariance and partial measurement invariance are given, full measurement model invariance can be achieved. It is given if and only if "the confidence intervals of differences in mean values and logarithms of variances between the construct scores of the first and second group include zero" [16, p. 416]. It is important to note, however, that full measurement invariance will not be discussed throughout this analysis because we focus on structural relationships between the latent variables.

5 Results

We use the results presented in [19] to base our analysis on the structural model depicted in figure 1, including all formative causes for *visual salience* (see table 4).

The results are reported in the following order: We, first, assess differences between the two cities. Based on these results, we, second, analyze structural model differences based on the three subfactors (allocentric orientation, ego-centric orientation, orientation using cardinal directions) proposed in [27]. A third step of the analysis will reveal whether an interaction between gender and sense of direction yields group differences.

Table 1 Outer weights for both cities (standard PLS algorithm). Significant differences ($K = 5000$ permutations) are indicated by bold-faced column headers.

	age	area	intensity	tone	**condition**	height	length	location	**material**	motion	pattern	shape	signage	**size**	width
Augsburg	.073	−.018	.109	.256	.005	.085	−.058	.315	−.225	.094	.157	.267	.142	.017	.300
Regensburg	.240	.090	.266	.116	−.173	.010	−.010	.318	.017	.035	.097	.156	.194	.378	−.161

5.1 Comparing Two Cities

A permutation test revealed that compositional invariance was not given between the two cities: Correlations of cognitive salience (COS), prototypicality (PRO) and visual salience (VIS) differed significantly from one. With respect to COS ($cor = .947$, 90%-CI[.985]) the indicator c_eas turned out to have particularly adverse properties: Its outer loading in Augsburg is very small ($\lambda_{c2} = .105$). As a consequence, the indicator was removed from the model for the whole analysis, leaving COS as a 2 item construct. Furthermore, a closer look into VIS ($cor = .918$, 90%-CI[.940]) revealed significant differences in outer weights between both cities. While the Regensburg data suggests variable *size* to be most important (see [19]), this causal indicator is rendered insignificant for Augsburg. Table 1 shows the outer weights for both cities based on 5 000 permutations. Given these differences a redundancy analysis [14, p.121–122] was conducted to check whether formative measurement is statistically adequate for the Augsburg dataset. Based on the fact that the path coefficient did not meet the threshold of ($\beta = 0.80$) suggested in [14] we decided to use the reflective indicators to measure visual salience.

With respect to prototypicality, a very slight ($cor = .996$, 90%-CI[.997]), yet significant difference in correlations from one was found. As no theoretical insights justify the deletion of the construct (see [17] for this kind of advice), we decided to keep this construct but did not take direct or total effects of this latent variable into account. It is, however, reported for completeness reasons. As a consequence analyses reported in the remainder of this paper will be based on the model shown in figure 2.

A reassessment of compositional invariance with c_eas being removed and reflectively measured visual salience establishes partial compositional invariance. Thus, an analysis of structural relationships on pooled data is statistically feasible.

When Regensburg and Augsburg are compared, no significant differences are found for path coefficients nor total effects, i.e. the structural relationships are invariant across different environments of data acquisition. Pooled data from both cities can, thus, be used for the subsequent analyses reported in this paper.

5.2 Sense of direction

The pooled dataset was now used to compare good and poor orientation per one of the factors allocentric, egocentric or cardinal direction. The construct correlations in table 2 indicate that partial compositional invariance was established for all groups and differences in structural relationships can be assessed.

Based on the compositional invariance we uncovered the following significant differences, where groups of spatial abilities were found according to [28]. This means, good and poor groups were found based on raw values by age for the three subscales of sense of direction (allocentric, egocentric, cardinal directions) proposed in [27]. For example, a person aged 35 years having a raw score of 7 or less for factor cardinal direction strategy is assigned to the *poor* group, whereas persons with a raw score greater than 7 are assigned to the *good* group (see [28, pp. 805 and 809]).

Table 2 The mean correlations between bad and good groups based on 5 000 permutations. Neither of these correlations differs significantly from zero (the smallest p-value found across groups and latent variables was $p = .132$), i.e. partial measurement invariance is established between groups and structural relationships can be assessed. Please note: PRO is given for the sake of completeness, only, yet not taken into account (see section 5.1).

	ADV	COS	OVSAL	PRO	STS	VIS
allocentric	1.000	.999	1.000	.999	1.000	1.000
egocentric	1.000	.999	1.000	.999	1.000	1.000
cardinal	1.000	.999	1.000	.999	1.000	1.000

good allocentric vs. poor allocentric orientation The direct effect $ADV \rightarrow STS$ ($\beta_g = .718$, $\beta_b = .769$, 90%-CI $= [-.047; .047]$) differs significantly between both groups, suggesting that poorly allocentric oriented person's rely more on visibility in advance when judging structural salience than good allocentric oriented persons do.

good egocentric vs. poor egocentric orientation Both groups differ with respect to the direct effect visual salience has on overall salience ($\beta_g = .561$, $\beta_b = .643$, 90%-CI $= [-.072; .070]$), i.e. visual aspects turn out to be more important for persons with poor egocentric orientation.

good cardinal vs. poor cardinal The direct effect $VIS \rightarrow OVSAL$ ($\beta_g = .573$, $\beta_b = .655$, 90%-CI $= [-.073; .072]$) differs between both groups as well as $COS \rightarrow OVSAL$ ($\beta_g = .039$, $\beta_b = -.041$, 90%-CI $= [-.060; .059]$) does. These figures, again, indicate that visual aspects are more important to poorly cardinally oriented persons and that cognitive salience might have a negative impact for this group.

Taken together, these results indicate slight yet important differences between these groups. There is, however, evidence in psychology suggesting that gender may be an important factor with respect to orientation preferences (see [6] for a review).

5.3 Sense of Direction Stratified by Gender

We assessed the influence that gender has, first, between and, second, within groups. The between comparison is used to shed light on whether gender is a sufficient explanation for the SoD-related differences found, while the within part examines gender-related differences. The sense of direction groups were, again, found according to [28] (see above, section 5.2). Compositional invariance for both types of comparisons is presented in table 3. It reveals that compositional invariance is not given for several group comparisons across sense of direction factors.

5.3.1 Between sense of direction groups within gender

allocentric In contrast to the other factors, three out of four group comparisons show compositional invariance. Comparing well oriented females to poorly oriented males does not yield significant results and well oriented males do not differ from poorly oriented males. In contrast, well allocentric oriented females differ from poorly oriented females. Visibility in advance has a stronger direct effect on structural salience in the poor group ($ADV \rightarrow STS$ ($\beta_{gf} = .720$, $\beta_{pf} = .821$, 90%-CI $= [-.065; .065]$)); this turns out to be the case for the impact visual salience has on overall salience ($VIS \rightarrow OVSAL$ ($\beta_{gf} = .554$, $\beta_{pf} = .689$, 90%-CI $= [-.104; .135]$)).

Table 3 The construct correlations (4-digits, not rounded), where group comparisons showing compositional invariance are bold-faced. Correlations significantly ($\alpha = .1$ was applied to ensure conservative results) different from 1 are shown in italics. PRO is given for the sake of completeness, yet not taken into account (see section 5.1). The group sizes, i.e. the number of ratings in each group, are given in parentheses once per group for each factor. Level of SoD and gender are denoted as follows: *g-f* means *good oriented females*, *p-m* means *poor oriented males* etc.

Factor	level of SoD and gender	ADV	COS	OVSAL	PRO	STS	VIS
allocentric	g-f (389) vs. g-m (295)	*.9998*	9985	.9999	*.9991*	.9997	*.9998*
	p-f (200) vs. p-m (309)	.9996	.9987	.9999	.9981	.9997	.9998
	p-f vs. g-m	*.9997*	.9991	.9999	.9958	.9996	.9998
	g-f vs. p-m	.9997	.9982	.9999	.9994	.9998	.9998
	g-f vs. p-f	.9996	.9971	.9999	.9992	.9997	.9998
	g-m vs. p-m	.9997	.9993	.9999	.9972	.9997	.9998
egocentric	g-f(275) vs. g-m (167)	*.9996*	.9960	.9999	.9984	*.9997*	.9997
	p-f (314) vs. p-m (437)	.9997	.9992	.9999	.9990	.9998	.9999
	p-f vs. g-m	.9996	.9977	.9999	.9981	.9996	.9997
	g-f vs. p-m	.9997	.9989	.9999	.9990	.9998	*.9998*
	g-f vs. p-f	.9997	.9976	.9999	.9993	.9998	*.9998*
	g-m vs. p-m	.9997	.9990	.9999	.9938	.9996	*.9998*
cardinal	**g-f (247) vs. g-m (225)**	.9997	.9983	.9999	.9987	.9996	.9997
	p-f (342) vs. p-m (379)	.9997	.9988	.9999	.9988	.9998	.9998
	p-f vs. g-m	*.9996*	.9983	.9999	.9987	.9997	.9998
	g-f vs. p-m	.9997	.9987	.9999	.9988	.9998	.9998
	g-f vs. p-f	*.9996*	.9974	.9999	.9993	.9998	.9998
	g-m vs. p-m	*.9997*	.9982	.9999	.9987	.9996	.9997

egocentric Given the previous finding regarding the non-stratified egocentric group, the results of the compositional invariance when comparing males and females between both groups was unexpectedly not given for three out of four possible comparisons due to correlational differences in visual salience. Visual salience has a higher total effect on overall salience in poorly egocentric oriented females ($\beta_{gm} = .725$, $\beta_{pf} = .855$, 90%-CI $= [-.078; .079]$). Moreover, the direct ($\beta_{gm} = .064$, $\beta_{pf} = -.069$, 90%-CI $= [-.104; .103]$) and total ($\beta_{gm} = .071$, $\beta_{pf} = -.064$, 90%-CI $= [-.064; .065]$) effects of cognitive salience on overall salience are rendered significant. These are, however, in general very low.

cardinal Similar to the findings for the egocentric factor, only one group comparison is feasible out of four when orientation abilities based on cardinal directions are considered. The reason for this, however, is different: It is due to significant correlational differences found for construct visibility in advance. Based on this result, poorly visual salience has a higher impact on overall salience for poorly oriented males than is the case of good oriented females ($\beta_{gf} = .506$, $\beta_{pm} = .636$, 90%-CI $= [-.104; .104]$). Vice versa, advance visibility is more important for overalls salience in good cardinally oriented females than poorly oriented males (direct effect $ADV \rightarrow OVSAL$ ($\beta_{gf} = .196$, $\beta_{pm} = .072$, 90%-CI $= [-.120; .117]$ and the total effect $ADV \rightarrow OVSAL$ ($\beta_{gf} = .382$, $\beta_{pm} = .243$, 90%-CI $= [-.099; .096]$).

5.3.2 Within sense of direction groups but across gender

allocentric Poorly allocentric oriented females turn out to differ significantly from the male group with respect to two direct effects: Visibility in advance has a higher impact on structural salience for females ($\beta_{pf} = .821$, $\beta_{pm} = .726$, 90%-CI $= [-.064; .063]$). Furthermore, cognitive salience shows an adverse effect on structural salience in females ($\beta_{pf} = -.010$, $\beta_{pm} = .095$, 90%-CI $= [-.101; .102]$). This effect is very small, though. A group comparison by gender for the good group, however, is not feasible because compositional invariance is not given.

egocentric For poorly egocentric oriented females the direct effects $ADV \rightarrow STS$ ($\beta_{pf} = .766$, $\beta_{pm} = .693$, 90%-CI $= [-.057; .058]$), $COS \rightarrow OVSAL$ ($\beta_{pf} = -.069$, $\beta_{pm} = .009$, 90%-CI $= [-.070; .074]$), $COS \rightarrow STS$ ($\beta_{pf} = .029$, $\beta_{pm} = .147$, 90%-CI $= [-.082; .082]$), $VIS \rightarrow ADV$ ($\beta_{pf} = .639$, $\beta_{pm} = .705$, 90%-CI $= [-.064; .063]$) must be distinguished from poorly egocentric oriented males. These findings indicate that visual salience has a larger impact on advance visibility for males as well as cognitive has on structural salience. Similar to allocentric orientation visibility in advance shows a larger impact on structural salience for females than for males. Similar to allocentric orientation compositional invariance is not given for a good group comparison between gender.

cardinal Females showing a poor orientation based on cardinal directions differ from males with respect to the direct effect $VIS \rightarrow ADV$ ($\beta_{pf} = .645$, $\beta_{pm} = .710$, 90%-CI $= [-.061; .063]$): Visual salience has a higher impact on advance visibility for poorly oriented males than for females and vice versa for well-oriented females as compared to males ($\beta_{gf} = .684$, $\beta_{gm} = .586$, 90%-CI $= [-.096; .097]$).

6 Discussion

Our first goal is to assess measurement invariance; secondly, we are interested in differences between groups of environments and participants. As measurement invariance is a precondition of a heterogeneity analysis, we will discuss both aspects with respect to the different grouping variables.

6.1 Environment

The results suggest that the strength of the relationships (see figure 2) between the subdimensions of salience does not differ significantly. The coefficients found can, hence, be used to calculate values for overall salience across different environments. Having found no heterogeneity among different cities is, however, in contrast to those models stressing the importance of the environment (see e.g. [4, 11, 38]). Having said this, one must keep in mind that the data were collected in European cities of Roman descent with a similar layout, although the architectural differences between these two environments are substantial. These differences are reflected in the formative measurement model for visual salience (see section 5.1): In Regensburg the variable *size* has the strongest impact, but is rendered insignificant in Augsburg where *shape* is most important. This finding suggests that the differences between environments are most important at the level of individual formatively measured variables. The structural relationships based on reflective measurements, however, can be used to calculate overall salience scores across different environments and can, consequently, be used in mobile information systems.

6.2 Sense of direction and gender

Although measurement invariance was not established for a number of group comparisons with respect to these factors, we find evidence for the interaction between gender and orientation ability. The effect visual salience has on overall salience is particularly affected. The results suggest that a poorer orientation in females yields a larger importance of visual salience than is the case for good oriented women. This indicates the importance of personal cognitive factors. Individual aspect may also play an important role regarding the impact of cognitive salience. The coefficients found for cognitive salience are, although significant, very small. They show, moreover, a sign change in the poor allocentric oriented group, indicating an adverse effect of cognitive on structural salience in females. One has to keep in mind, though, that random measurement error may have an impact on these results because all but two indicators were removed for this construct, i.e. the lower bound for a suitable number of indicators according to reflective measurement theory is reached (see [21, pp. 178–179]).

We also find a gender-related effect in general. For example, we find evidence that visual cues have a larger impact on overall salience for females than males – despite their equal level of sense of direction. This finding may be related to the general difference in orientation strategies (see [6]): The preference for egocentric orientation in females may invoke visual cues more. This difference in strategies may also be important to explain the effect visual salience shows on visibility in advance (larger for females than males in the good cardinal group and vice versa for the poor cardinal group and the poor egocentric group) and visibility in advance has on structural salience (larger for females in both, the poor egocentric and poor allocentric group). These results are generally in line with those by Picucci et al. [31], who report on gender differences based on spatial confidence and orientation strategies

These findings with respect to sense of direction and gender stress the importance of personal factors in salience ratings. They reinforce the findings for indoor environments by Lawton et al. [24]: Individual and gender related differences seem to exist in outdoor environments, too. The importance of individual factors is fostered statistically by the generally large number of group comparisons which do not show partial measurement invariance. This statistical property indicates missing variables or constructs within the model which need to be studied in the future.

7 Conclusions and Future Work

The main goals of this paper are to assess invariance with respect to environment, objects and observers of Kattenbeck's measurement model of salience. Based on this, we analyze the observed heterogeneity, taking environment and sense of direction (stratified by gender) into account. We are, therefore, interested in assessing whether the measurement model may be re-used in different contexts, i.e. whether it provides a robust way of collecting salience ratings. The results indicate that the structural model is invariant across environment, i.e. the strength of the relationships between the subdimensions of salience does not differ significantly. The coefficients found can, hence, be used to calculate values for overall salience across different environments. We, moreover, provide empirical evidence that this is true with respect to both, gender and sense of direction. The degree of influence found for visual dimensions is, generally speaking, in line with what was to be expected: The impact of visual dimensions seems to be different for women and men. Mobile information systems should, thus, take these differences into account, when calculating route instructions. The compositional invariance problems (configural invariance is given for all comparisons reported) occurring throughout the analysis of personal factors can be regarded as an indicator for the importance of personal factors beyond gender and sense of direction. Taken together, our results indicate that more studies on salience, especially on the impact of personal characteristics, are needed and models have to be adapted so that they can incorporate personal factors.

With respect to future work a next step will be to assess whether the found, often slight, differences have an impact on wayfinding performance in real world scenarios. This will also be examined with respect to the different salience yielded by different models, e.g. by a comparison of wayfinding performance when salience values are based on the Raubal and Winter model [33] vs. the survey-based ratings used in the current study. Furthermore, the need to empirically measure personal preferences has become obvious and will be examined in a future workshop. Thirdly, it will be interesting to learn more about differences in weights subdimensions of salience show on each other and on overall salience, when, e.g. urban and non-urban environments are compared or different languages and/or Non-European urban settings are contrasted.

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A Appendix: Variables and Questions

Table 4 Table 4 was taken literally from [18, p. 10]: "A description of constructs (LV) and measured variables (MV) used in this study. Column *ToM* indicates the type of measurement employed for the MV, where *R* denotes *reflective* and *F* means *formative* measurement, respectively. Please note: All questions were translated from German to English." Please note: We used the German language questions presented in [19] to conduct experiments in Augsburg.

LV	Description	MV	Phrasing	ToM
Salience [OVSAL]	"The overall salience of geographic features is defined as a three-valued vector, whereby the components capture perceptual, cognitive, and contextual aspects of geographic objects" [4, p. 264].	ov_att	To what extent does this object draw your attention?	R
		ov_por	How suitable is this object to be used as a point of reference?	R
		ov_mem	How memorable is this object?	R
Proto-typicality [PRO]	"[...] that is, how typically they represent a category" [39, p. 43]	p_exa	To what extent is this object suitable as an example of objects belonging to the category you named?	R
		p_img	To what extent does this object represent your impression of such objects?	R
		p_sim	How often do you encounter similar objects?	R
Visual Salience [VIS]	"the features of contrast with surroundings, prominence of spatial location, and visual characteristics that make the landmark particularly memorable" [39, p. 45].	v_loo	To what extent does the appearance of this object draw your attention?	R
		v_odd	How unusual is the appearance of this object?	R
		v_eye	How eye-catching is this object?	R
		v_rec	How recognizable is this object?	R
			Please find below several visual attributes. For each of these please indicate the extent to which the named visual attribute contributes to an object's salience given its surroundings.	
		v_cin	intensity of color	F
		v_mot	motion (e.g. flashing, flow)	F
		v_col	tone	F
		v_loc	location (e.g. raised, very close to street)	F
		v_siz	size	F
		v_sha	shape	F
		v_con	condition (e.g. new, dirty, etc.)	F
		v_sig	signs attached	F
		v_hei	height	F
		v_wid	width	F
		v_len	length	F
		v_are	area	F
		v_pat	pattern	F
		v_mat	material (as far as identifiable)	F
		v_age	To what extent is this object salient as a result of how old it looks?	F
Structural Salience [STS]	"Objects are called structurally salient if their location is cognitively or linguistically easy to conceptualize in route directions" [23, p. 347].	s_eas	How easy is it for you to refer to this object in a route description?	R
		s_lor	How easy is it to describe this object's location as part of the current route?	R
		s_imp	To what extent is this object located at an important location within the current route?	R
		s_dir	To what extent may this object be suitable to determine whether this is the appropriate route or a change in course is required?	R
Advance Visibility [ADV]	The degree as to which an object at a potential decision point may be seen from the direction it is approached at (cf. [42]).	a_dis	To what extent can one easily refer to this object from afar?	R
		a_vis	Given the current route, to what extent were you able to see this object from a distance?	R
		a_per	To what extent is this object generally perceptible from afar?	R
		a_sui	In the context of the current route to what extent is this object suitable to explain the route?	R
Cognitive Salience [COS]	"[...t]he processing of information is based on prior knowledge, while intentions and strategies of the observer are in control of the allocation of attention. In our framework, we will use the term Cognitive Salience to refer to the endogenous factors that influence salience" [4, p. 255]	c_per	To what extent do you have personal memories concerned with this object?	R
		c_his	To what extent does this object's appearance suggest it to be historic?	R
		c_wor	To what extent do you regard this object to be worthy of preservation?	R
		c_cus	To what extent is the current use of the object obvious?	R
		c_pus	To what extent is the former use of the object obvious?	R
		c_eas	How easy is it for you to label this object?	R