Empirical Evidence for Concepts of Spatial Information as Cognitive Means for Interpreting and Using Maps

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Abstract

Due to the increasing prevalence and relevance of geo-spatial data in the age of data science, Geographic Information Systems are enjoying wider interdisciplinary adoption by communities outside of GIScience. However, properly interpreting and analysing geo-spatial information is not a trivial task due to knowledge barriers. There is a need for a trans-disciplinary framework for sharing specialized geographical knowledge and expertise to overcome these barriers. The *core concepts of spatial information* were proposed as such a conceptual framework. These concepts, such as *object* and *field*, were proposed as cognitive lenses that can simplify understanding of and guide the processing of spatial information. However, there is a distinct lack of empirical evidence for the existence of such concepts in the human mind or whether such concepts can be indeed useful. In this study, we have explored for such empirical evidence using behavioral experiments with human participants. The experiment adopted a contrast model to investigate whether the participants can semantically distinguish between the *object* and *field* core concepts visualized as maps. The statistically significant positive results offer evidence supporting the existence of the two concepts or cognitive concepts closely resembling them. This gives credibility to the core concepts of spatial information as tools for sharing, teaching, or even automating the process of geographical information processing.

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Supplementary Material
Dataset: `https://github.com/quangis/Core-Concept-Study---Contrasting-Maps`
Dataset (Dataset backup at DataverseNL): `https://doi.org/10.34894/IOGWDP`
Dataset (Dataset backup at DANS EASY): `https://doi.org/10.17026/dans-xg5-cw67`

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1 Introduction

Going beyond manipulating map layouts and data formats, concepts of spatial information enable us to effectively handle maps by accounting for a map's semantics. This, in turn, allows us to decide on analytic methods, answer questions, and make decisions with maps. For example, we can use a map of height contour lines to assess the slope and aspect of the terrain in order to assess the potential for solar energy. Yet, the way that maps represent these concepts is rather indirect. Despite what one might think, maps do not wear their content on their sleeves. In the solar energy example, the contour map may be encoded as vector polygons and might be visualized in terms of graded colors, just like a choropleth map. Yet, in contrast to a choropleth map, human map interpreters need to conceive of the contour lines not as boundaries of objects, but rather as boundaries of height intervals. Thus, the polygon map really represents a spatial height field broken down into intervals, and not a collection of objects. This *conceptualization* of the map's information content does not follow from the way it is encoded, and thus requires a skilled human interpreter.

Since the concepts represented by maps are usually not (fully) explicit in a map, empirical investigation is needed to find out which conceptual distinctions are used and which role they play in map interpretation and map usage. Spatial concepts have been found to play a role early in the development of young children [5, 8, 9]. One example is the concept of (relative) location, which is a primary concept in spatial cognition and orientation [22, 10] and is also underlying spatial reference systems. Yet for interpreting maps, further concepts are required. Research in human cognition found that space is only one out of four main systems of core knowledge acquired early in life, including also objects, actions and numbers [27]. Naive Geography set out to study cognitive models of the common-sense geographic world, including topology, metrics, as well as discrete and continuous spatial entities [6]. However, potential concepts underlying Geography abound [10], and it remained unclear which ones should be regarded as essential for geographic information. More recently, the *core concepts of spatial information* were suggested as a concise model of different conceptualizations of the environment in this context [20], forming a basis for trans-disciplinary spatial thinking[2]. They include *objects* (e.g. buildings or administrative units), *fields* (e.g. temperature), *events* (e.g. earthquakes), and *networks* (e.g. commuter flows). Related concepts of measurement (such as extensive and intensive amounts and measurement levels) have been suggested earlier in theories about Geographic Information Systems (GIS) [3], and were recently used together with core concepts to describe spatial data models on a conceptual level (e.g. [25]) to automate the answering of geographic questions and the synthesis of workflows [19].

Although this provides a kind of indirect evidence for the importance of concepts in handling spatial information, there is still a lack of primary *empirical evidence* for such concepts as cognitive tools for interpreting and using maps[3]. Hence, it is still unclear which concepts precisely should serve as a transdisciplinary framework [20] for sharing geographic

[2] Concepts are regarded as trans-disciplinary because the underlying (GIS) methods are used across many disciplines, just like in Statistics. For a justification of core concepts in this respect, cf. [20].

[3] The fact that a concept is part of documented knowledge does not yet mean it is used effectively. Cognitive research is required to determine this [27].

knowledge. Furthermore, it is also unclear whether information systems that utilize such concepts (e.g. [26, 21]) reflect distinctions that mirror human cognition. Therefore, the goal of this study is to collect such evidence. Our main research question is:

Are there mental skills that allow users to distinguish maps on a conceptual level that, at least partially, corresponds to the core concepts of spatial information?

Knowing the definition of concepts does not imply the ability to effectively use them for spatial analysis. For example, human users may still have difficulty differentiating between the field and object interpretations despite knowing the conceptual difference. This leads to the sub-question *R1* below. Next, the visual perception of maps can influence the interpretation of spatial data. Spatial datasets representing the same phenomenon may still invoke different interpretations due to differences in symbology or geometry (e.g. point vs lines). Sub-question *R2* should account for this possible visual interference in our study. Finally, the ability to distinguish concepts and to effectively use them for interpreting maps may be an acquired skill that develops with the level of experience. This concern leads to sub-question *R3*.

- RQ1: *To what extent can users effectively distinguish maps that are attributed to different core concepts?*
- RQ2: *To what extent is the ability to distinguish conceptually different maps dependent on visual geometric properties?*
- RQ3: *To what extent is the ability to distinguish conceptually different maps dependent on a user's level of expertise?*

2 Related work

To better understand geographic information (GI) and its applications, authors have suggested conceptual frameworks to categorize GI-tools and operations [11, 12, 1, 2], syntactic data types [11, 12] and representation models [20, 21, 25, 13, 18]. Kuhn's core concepts of spatial information [20, 21] are an example of the last group and the focus of this study. The core concepts were used in the development of web-based ontologies [25], for pedagogical purposes [7, 17] and for automatic question-answering [30]. Multiple scholars, among them Kuhn himself, argue for the usefulness of the core concepts for the transdisciplinary communication and teaching of GI-knowledge. However, only Ishikawa [17] so far used the core concepts for the evaluation of empirical data.

Table 1 Semantically distinct dataset types based on the core content concept *object* and *field* and geometry combinations. The terms in brackets are abbreviations.

	Point	Line	Non-tessellated polygon	Tessellated polygon		
Object	Point object (PO)	Line object (LO)	Region object (RO)	Lattice (LA)	Lattice (LA)	Square lattice (SL)
Field	Point measure (PM)	Line measure (LM)	Region patch (RP)	Contour (CO)	Coverage (COV)	Raster field (RF)
Group	PO-PM	LO-LM	RO-RP	LA-CO	LA-COV	SL-RF

In the latest iteration [21], the core concepts framework includes five content concepts (*location*, *field*, *object*, *network*, and *event*) and two quality concepts (*granularity* and *accuracy*). The quality concepts are of less relevance to this study and, therefore, ignored. *Location* denotes the relation of some spatial phenomenon with its space or 'grounds'. A *Field* measures time-varying spatial phenomena "*...that have a scalar or vector attribute everywhere in a space of interest, for example, air temperatures on the Earth's surface*" [20, p. 2272]. *Objects* describe spatially bounded individuals with identity and spatial and thematic properties that vary in time. *Events* have temporal boundaries (e.g. an earthquake). Finally, a *network* is a binary relation between objects, such as a road network or import/export trade flows.

The content concepts are generally not mutually exclusive because they are dependent on each other and the interpretation of a map therefore can be ambiguous. For example, *location* is an orthogonal concept used to represent the spatial aspect of every other core concept. It is also a relational concept often defined relative to *object*. *Network* is a relation between pairs of *objects* [24], while *event* is a temporal phenomenon in which *objects* or *fields* can participate. This naturally leads to variations in the interpretation of a given map. Furthermore, in which way the important concepts of amount and measurement relate to core concepts is still an open question [28]. However, one and the same represented phenomenon is usually not interpreted both as *object* and *field* at the same time. That is, the interpretation of an entity as *object* usually excludes parallel interpretation of the same as *field*. As mentioned later, this independence is important and makes *object* and *field* the main focus of our study.

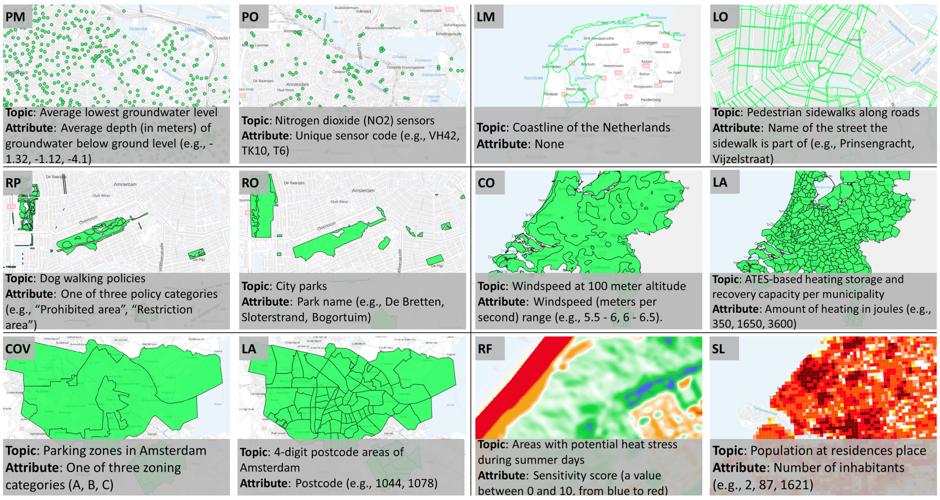

Figure 1 Examples for each dataset type listed in Table 1. The letters in the top-left corners are the abbreviations for the dataset types.

In a map, a given concept can be represented by different types of geometries: points, lines, and polygons (vector) or tessellated squares (raster). When polygon datasets are *tessellated*, they are covering the entire extent of the dataset without any gaps. Furthermore, different conceptualizations of the same geometry express different spatial semantics [25]. In Table 1, we suggested a way to capture the resulting diversity of dataset interpretations based on the combinations of geometries and the *object* and *field* concepts. Different semantic interpretations of the same geometry type are summarized into groups (see table columns). Example maps for these dataset types are shown in Fig. 1. Points and lines can represent fields (e.g. pointwise temperature measurements; contour lines) as well as objects (intersections; roads). We furthermore distinguish tessellated datasets that represent objects, called *lattices* (e.g. administrative units), from ones representing fields. An example of the latter is *contour polygon maps* which depict a strictly ordered value gradient of a field [14]. Following [25], we also gave *coverages* (e.g. landcover data) and *patches* (non-tessellated regions of homogeneous landuse) a field interpretation. This allowed us to distinguish landcover maps that are self-similar and thus can be dissected arbitrarily for spatial analysis from objects with spatial unity[4]. Raster datasets predominantly represent fields. However, we consider a square lattice as a particular form of object tessellation where each polygon is squarely shaped and measures some amount, e.g., of population.

3 Methodology

3.1 Theoretical framework

As discussed earlier, the core concepts can be used to interpret questions, datasets, and analytical tools. This study focuses on dataset interpretation as the simplest form of the three. Spatial datasets can be visualized as maps, which are easier to interpret even for participants who do not have formal GIS training. This choice makes the experiment accessible to a wide range of participants with varying GIS experiences. Furthermore, the scope of the experiment is focused on *object* and *field* core concepts only. The two content concepts are often mutually exclusive, limiting the possibility of concurrent interpretation of the same map. They are also the most prevalent core concepts occurring in spatial datasets. Hence, these two concepts are most likely to result in observable effects during the experiment.

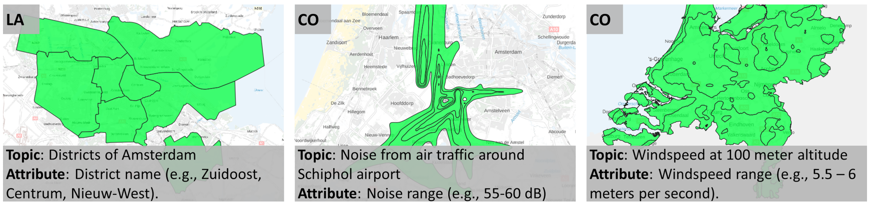

Figure 2 An example triplet of maps (LA-CO). The left-most map is city districts as tessellated objects. The other two maps visualize noise and wind-speed fields as contour maps.

As an experiment framework, we adopt a contrast model for exploring semantic similarity [15]. The basic experiment setup is to display to a participant a set of three maps (see Fig. 2). Two maps (the contrast maps) represent the same concept while the remaining map (the odd map) represents a different concept in our interpretation. For example, three maps can visualize two object datasets and one field dataset, or vice versa. Each map is accompanied by a short description of the topic and the attribute of the dataset. The participants are asked to compare the three maps and identify the one that is semantically at odds with the two others. We hypothesize that (1) participants need to rely on some form of spatial cognitive concepts to identify the odd dataset, and (2) these cognitive concepts correspond, to some degree, to our distinction of *field* and *object* core concepts.

Since core concepts are, as explained above, largely agnostic to the geometry types, participants should be able to differentiate between object and field equally well for all geometry types. In our experiment, a triplet contrasts the types from the same column of Table 1 but not the types across the columns. For example, a point object dataset is contrasted against point measure datasets only and not against any other dataset types. Similarly, a square lattice is contrasted against a raster field due to geometrical similarities when visualized as maps. This restriction limits geometric differences that may interfere

[4] A more nuanced alternative would be to interpret coverage regions and patches as particular *amount objects*, and distinguish them from objects with unity. However, since the amount concept is still under development, we remained with the simpler interpretation here. For the purpose of this paper, the relevant conceptual distinctions can still be drawn.

with the interpretation of semantic differences. Overall, Table 1 lists six possible contrasts of field and object, further referred to as contrast groups. The last row lists the names of the contrast groups. Each contrast group has two possible combinations for a triplet (two objects and one field or vice versa) resulting in 12 possible triplets in total.

3.2 Dataset compilation and annotation

Three sources provided geo-spatial datasets. *PDOK* (`https://www.pdok.nl/datasets`) is an open platform for accessing the geodata of the Dutch government. *Nationaal Georegister* (`https://nationaalgeoregister.nl`) is the data portal of the Dutch National Geo-registry. *Maps Amsterdam* (`https://maps.amsterdam.nl/open_geodat`) is the open geodata portal of Amsterdam municipality. These sources follow the same regulations for sharing open data thereby ensuring the comparable quality of datasets. All collected datasets were manually annotated by the authors of this study. This preliminary annotation involved assigning to each dataset one of the types from Table 1. The preliminary annotations were then finalized by discussing and resolving any annotation disagreements between the annotators. The main source of disagreement was the datasets with multiple attributes corresponding to different core concepts. In such cases, only one attribute was picked as being representative of the dataset. Subsequently, the selected attribute was included in the description of the corresponding map (see Fig. 1 and Fig. 2 for example descriptions). From the collected pool, we selected 36 datasets to be used in our experiment. Except for *Lattice*, three distinct datasets were selected for each dataset type. Six distinct datasets were selected for *Lattice* since it is contrasted against two other *field* types.

3.3 Survey design

We have used two online survey platforms to collect responses, Google Surveys (`https://surveys.google.com`) and Qualtrics (`https://www.qualtrics.com`). Google Surveys was used to survey random participants from the general public, while Qualtrics was used to survey a controlled selection of participants who work or study in Geography and GIScience domains. Each survey mainly consisted of a set of questions. In each question, a participant had to select an odd map when presented with a distinct triplet of maps.

Table 2 Combining Region Object (RO) and Region Patch (RP) datasets into distinct triplets.

Question Id	Odd dataset	Contrast dataset 1	Contrast dataset 2
Q13	RO1	RP1	RP2
Q14	RO2	RP2	RP3
Q15	RO3	RP3	RP1
Q16	RP1	RO2	RO1
Q17	RP2	RO3	RO2
Q18	RP3	RO1	RO3

The questions were generated with the 36 annotated datasets. Each contrast group has six datasets (three for *field* and *object* each), which were used to generate six questions each with a unique triplet combination. As an example, Table 2 demonstrates how the questions were generated for the RO-RP group. Three rules were used to assign the datasets to the triplets. First, each dataset was used as the odd one in one triplet only. Second, each dataset was used as a contrasting dataset in exactly two triplets. Third, the same combination of two contrasting datasets occurred in one triplet only. These three rules ensure that all six datasets occur equally often in different roles while preventing the repetition of the same combination. This design ensures that no bias based on presentation frequency is introduced to participants. This design is used to generated the questions for the other contrast groups.

As discussed earlier (Fig. 2), the datasets were visualized as maps in the questions. The visual style was homogeneous across all maps except for *Raster Field* and *Square Lattice*. The polygon datasets were visualized with the same green shading and black border. The line datasets were visualized with lines of the same green color and width. Similarly, the point datasets were depicted with circles of the same size, green shading color, and black border color. *Raster Field* and *Square Lattice* datasets were visualized with color gradients that did not repeat between the datasets.

3.3.1 Design for the survey on Google Surveys

The free version of Google Surveys allows 10 questions per survey. Hence, we used only one contrast group in the survey. The survey started with a single-choice question: "*Categorize your expertise with Geographic Information Systems (GIS)*". The options were "*Laymen: never used GIS*", "*Beginner: can use basic GIS functions*", "*Trained: formally trained by a GIS course*", and "*Expert: used GIS for 5 years or more*". Except for Laymen, the three expertise categories were reused from an existing validated questionnaire on GIS [31]. Next, the survey presented the six questions from the RO-RP contrast group. The order of these questions was randomized for the survey but not per participant (not supported by the platform). Each of the six questions was accompanied with the instruction text: "*Which one of the three spatial datasets is more different from the two others in terms of spatial analyses that can be done on it.*" The final 8th question asked if participants were familiar with the core concepts of spatial information. Google Surveys was arranged to collect responses from 100 people. In total, 1205 random people from the United States were screened for the survey. 1055 participants reported as being Laymen and were screened out. Of the remaining 150 participants, 101 participants completed the survey. Another 12 participants responded as being familiar with the core concepts and were also filtered out. The responses from the remaining 89 participants (further referred to as the *general* cohort) were analyzed. The focus on non-laymen participants increases the chances of finding a positive effect and maximizes the information gain in this uncharted territory. In case of absence of a positive effect, we can safely assume that a laymen group will also not perform well.

3.3.2 Design for the survey on Qualtrics

The survey on Qualtrics started with informed consent, an agreement to which was necessary for further progression. The consent was followed by questions about the age, gender, and GIS expertise level of the participants. The expertise question used the same four options as in Google Surveys. Next, instruction on how to answer the contrast questions was shown to the participants. Finally, the participants were shown 18 questions from three randomly selected contrasts groups. The order of the 18 questions and the order of three maps within each question were also randomized per participant. We targeted two cohorts of participants differing in level of GIS expertise. The first cohort, the *student* cohort, included 61 students who were either Bachelor students in a Geo-Information minor program or attending our Applied Data Science MSc course focusing on spatial data analysis. As part of their study, the students were taught the core concepts. We selected the students who were not yet introduced to the core concepts. The second cohort, the *skilled* cohort, included participants who were manually evaluated by the investigators to have sufficient skills in Geography and GIScience. These participants had to have a completed Master's degree in a relevant domain and actively practice in either academia or industry. Of the 40 invited participants, 18 participants completed the survey in the *skilled* cohort.

4 Results

4.1 Comparing responses in the RO-RP contrast group

Due to randomization, 29 and 9 participants from the *student* and *skilled* cohorts respectively answered the six questions from the RO-RP contrast group. These responses were compared with the responses from the *general* cohort with the 89 participants.

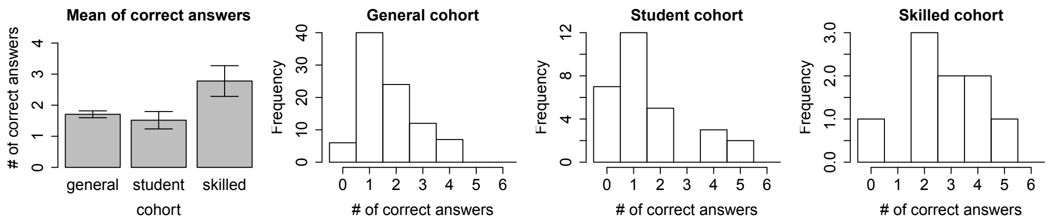

Figure 3 The left-most graph depicts means with standard errors of correct questions answered by the participants in each cohort. The remaining three graphs depict distributions of participants in three cohort according to the number of correct responses.

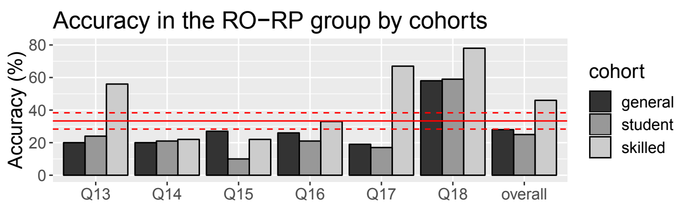

Figure 4 Accuracy for RO-RP individual questions and overall accuracy for the three cohorts. The solid red line depict expected accuracy based on a random choice. The dashed red lines depict 5% thresholds around the random choice probability.

The mean accuracies and the three accuracy distributions in Fig. 3 suggest the general and student cohorts have similar performances and the skilled cohort shows a better performance. The three distributions were analyzed for identicality with a Kruskal Wallis Test. The test is an alternative to one-way ANOVA for cases with non-normal distributions and uneven sample sizes. The test indicates a significant difference between the three distributions: $H(2) = 8.25, p = .02$. We did a follow-up pairwise comparison of the distributions with the Dunn's test with the Holm–Bonferroni correction for multiple testing. As suspected, the general and student cohorts are not significantly different ($p = 0.15$, *adjusted* $p = 0.46$). The skilled cohort is significantly more accurate than the student cohort ($p < 0.01$, *adjusted* $p = 0.01$). The skilled cohort is not significantly different from the general cohort with the Holm–Bonferroni correction (*adjusted* $p = 0.07$) but is significantly more accurate without the adjustment ($p = 0.02$). Therefore, we suspect there may have been a significant difference between the two cohorts if the sample size for the skilled cohort was bigger.

Table 3 *p-value* from two-sided exact binomial tests of accuracies in Fig. 4 for significant difference from the expected probability of 0.33 from random choice. The *correct* rows list the numbers of correct responses. The colored cells indicate significant or near significant p-values.

		Q13	Q14	Q15	Q16	Q17	Q18
general ($N = 89$)	correct	18	18	24	23	17	52
	p-value	0.01	0.01	0.26	0.18	0.01	< 0.01
student ($N = 29$)	correct	7	6	3	6	5	17
	p-value	0.43	0.17	0.01	0.17	0.08	0.01
skilled ($N = 9$)	correct	5	2	2	3	6	7
	p-value	0.17	0.73	0.73	1	0.07	0.01

We have calculated overall accuracies from the pooled responses of all participants for all questions and applied exact binomial tests against the success rate of 33% from the random choice strategy. The results are 28% ($N = 534$, $p = 0.03$), 25% ($N = 174$, $p = 0.03$), and 46% ($N = 54$, $p = 0.04$) for the *general*, *student*, and *skilled* cohorts respectively. The significant results indicate that the participants use specific strategies instead of random guesses. However, both *general* and *student* cohorts use ineffective strategies with their performance being below the chance threshold, and only the *skilled* cohort uses strategies that are more effective than random guessing. Finally, Fig. 4 depicts accuracies for individual questions and by cohorts. Table 3 lists the results of exact binomial tests of these accuracies against the chance probabilities. For the *general* and *student* cohorts, the accuracies are either below or at the chance level except for question Q18. The accuracies are exceptionally and significantly high for Q18 (RO-RP) in all three cohorts. We explore potential explanations for these results in the Discussion section.

4.2 Comparing performance across the six contrast groups

Out of 18 questions, on average, 8.9 ($SD = 2.6$) and 10.9 ($SD = 2.7$) questions are answered correctly in the *student* and *skilled* cohorts respectively (Fig. 5). These constitute 49% and 61% success rates respectively, which are considerably higher than the 33% success rate expected with the random choice strategy. The Kruskal Wallis test indicates that the *skilled* cohort is significantly more accurate than the *student* cohort ($H(1) = 8.79, p < .01$). A follow-up test is not necessary since there are only two cohorts.

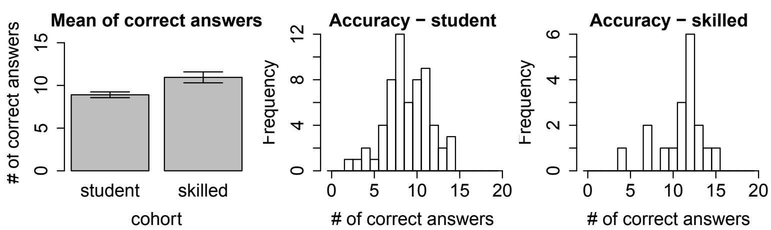

Figure 5 The left-most graph depicts means with standard errors of correct questions answered by the participants in each cohort. The remaining two graphs depict distributions of participants in the *student* and *skilled* cohorts according to the number of correct responses.

Next, we have calculated the averages of participants' accuracies for each contrast group. The results are shown in Fig. 6. Interestingly, compared to the RO-RP contrast group, the participants performed considerably better in the five other contrast groups. According to the results of the two-sided exact binomial tests (Table 4) both cohorts demonstrate above chance accuracies in these five contrast groups. The only exception is M=43% ($SE = 10.4\%$) average accuracy of the *skilled* cohort in the SL-RF group. However, considering the magnitude of the standard error, we suspect the test would have been significant with a bigger sample size for the *skilled* cohort.

The overall results suggest that participants can distinguish well between the maps depicting *object* and *field* across most data representations. Tessellated polygon and line representations achieve higher accuracies across both student and skilled cohorts, whereas PM-PO and RO-RP were mastered significantly better by skilled users. However, it is also interesting that overall, participants' performance in the RO-RP contrast group is significantly different than in the other contrast groups. A probable explanation for this result is discussed in the next section.

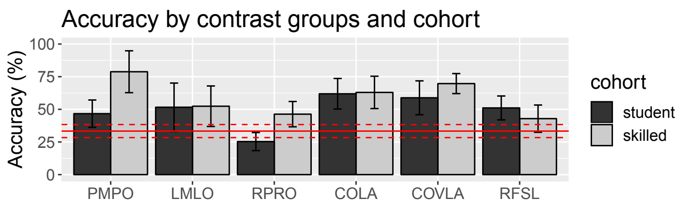

Figure 6 Mean accuracies for the six contrast groups calculated separately for the *student* and *skilled* cohorts. The mean is calculated from the proportions of the correct answers per a participant. The interval bars depict standard error intervals.

Table 4 *p-value* from two-sided exact binomial tests of accuracies in Fig. 6 for significant difference from the expected probability of 0.33 from the random choice strategy. The rows *correct/total* list correct and total responses respectively.

		PO-PM	LO-LM	RO-RP	LA-CO	LA-COV	SL-RF
student	correct/total	84/180	96/186	44/174	104/168	120/204	95/186
	p-value	0	0	0.03	0	0	0
skilled	correct/total	52/66	22/42	25/54	34/54	46/66	18/42
	p-value	0	0.01	0.04	0	0	0.19

5 Discussion

The responses in the RO-RP contrast group suggest two distinct dominant strategies used by the participants. The basic strategy is to select the option that is the most visually contrasting from the two other maps. For example, the correct option in Q18 (Fig. 7) is also the most visually contrasting map, which results in the majority of correct responses in all three cohorts (Fig. 4). The participants in the general and student cohorts seem to prefer this strategy in most questions. However, this visual strategy fails to consider semantics leading to mostly incorrect responses and low accuracy (Fig. 4) for these two cohorts. The existence of this strategy also explains why the two cohorts perform worse than if they simply would have guessed. For example, Fig. 7 depicts how this visual strategy leads the general and student cohorts into incorrect responses in questions Q17 and Q15. For Q17, 54% and 69% of all responses selected the middle map in the general and student cohorts respectively. Similarly, the visually distinct right map in Q14 is selected in 58% and 69% of all responses.

The second more advanced strategy is to compare the maps based on the attribute descriptions. More specifically, the participants try to distinguish between the maps with categorical and non-categorical attributes. Only the skilled cohort seems to efficiently employ this strategy, which explains why its response pattern diverges from the other two cohorts' patterns. This strategy is also more likely to lead to correct responses, which explains the higher accuracy of the skilled cohort (Fig. 4). For example, in question Q17 (Fig. 7), only the correct option mentions categories in its attribute description, thus, resulting in a correct response. In question Q14, however, the skilled participants fail to identify that the right dataset is also categorical since the same place name can be associated with multiple polygons and does not identify a distinct object on a map. Therefore, the strategy leads to the incorrect map that explicitly mentions category, which accounts for 56% of all responses.

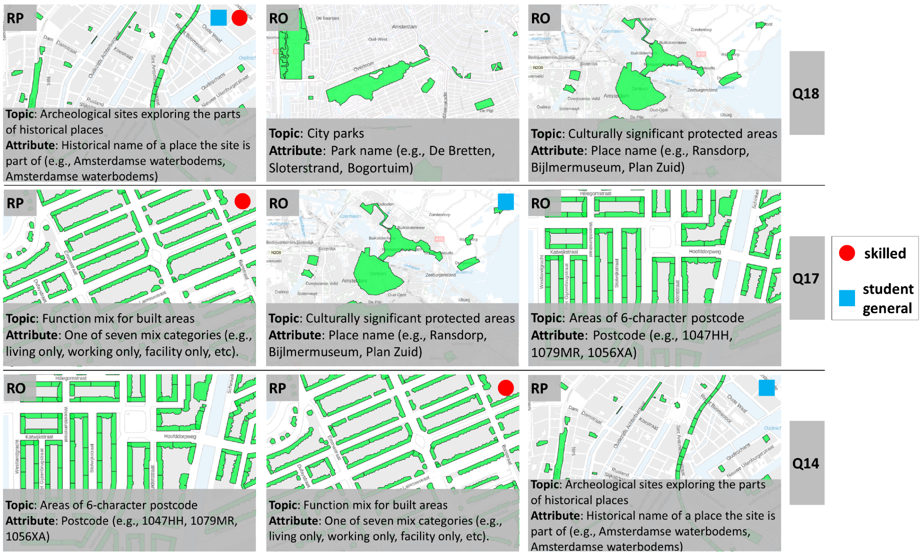

Figure 7 The questions Q18, Q17, and Q14 from the the RO-RP contrast group. In each question, the left-most map is the odd one (the correct option). The blue rectangles and the red circles in the top-right corners mark the most frequently selected options among the student/general and skilled cohorts respectively.

The two strategies together explain the most frequent responses by cohorts in each question of the RO-RP contrast group. Visual contrast-based strategy is commonly observed in many decision-making and visual search tasks [23]. The strategy often relies on the well-known bottom-up visual pop-out effect [29] where an object with an odd color (e.g. a red dot among blue dots), shape, or orientation automatically stands out and attracts priority attention. The low-effort bottom-up (automatic) nature of the pop-out effect makes the visual strategy more preferred to the less trained participants in the general and student cohorts. The second strategy of comparing attributes requires a more thoughtful approach and, more importantly, recognition that attributes play an important role in the conceptual interpretation of the datasets [27, 25]. Such a strategy requires an ability to distinguish between categorized and named datasets, which is not easy but can be improved with experience. The more experienced skilled cohort is more willing to apply the second strategy. Such experience-based transition from a simple bottom-up visual strategy to a top-down mental strategy is documented in other tasks [4, 16]. Hence, we can reasonably assume that such a transition is also happening from the basic to the advanced strategies.

Fig. 6 shows that the student cohort is more accurate in the five other contrast groups than in the RO-RP contrast group. These five contrast groups are geometrically represented by points, lines, and tessellations. Unlike the RO-RP maps, the maps within these group are visually more homogeneous, giving less room to apply the basic visual strategy. Hence, we assume that the student cohort is incentivised to use the advanced strategy that is more likely to lead to the correct responses and overall higher accuracies than in the RO-RP group. This implies that the participants in the student cohort know the advanced strategy but prefer to use the basic strategy when possible. This preference likely stems from the fact the advanced strategy requires more effort that can be minimized with training and more experience. Nevertheless, there is also unexplained variance in performance between the contrast groups suggesting other decision making factors that should be investigated further.

6 Conclusion

In most of the contrast groups, the student and skilled cohorts demonstrated significantly high accuracies (Fig. 6) thereby supporting the thesis that people can effectively distinguish maps with different concept-based interpretations (Research Question 1). An exception is the RO-RP contrast group where the general and student cohorts showed lower accuracies than would have been achieved with the naive guessing strategy. The pattern of responses suggests that a visual presentation of geometric shapes significantly interferes with a participant's ability to conceptually interpret the maps (Research Question 2). However, it should be noted that this interference can be an artifact of the experimental design based on the contrasting three maps, and requires further investigation. Finally, the skilled cohort consistently demonstrated better performance than the general and student cohorts suggesting that experience plays an important role (Research Question 3). However, higher experience seem to result in better utilization of the existing concepts necessary for interpretation of the maps rather than the development of new concepts. This result suggests that even people untrained with spatial data may have certain conceptual notions similar to the core concepts of spatial information. Overall, the study provides evidence supporting the existence of mental analytical skills that are of comparable use for distinguishing maps in terms of concepts of spatial information. The future studies should focus on replicating the current findings and verifying whether they can be generalized to laymen population. We should further explore if the core concept distinction applies to other aspects of geo-analytics such as analytical tools and questions.

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