Is Familiarity Reflected in the Spatial Knowledge Revealed by Sketch Maps?

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Abstract

Despite the frequent use of sketch maps in assessing environmental knowledge, it remains unclear how and to what degree familiarity impacts sketch map content. In the present study, we assess whether different levels of familiarity relate to differences in the content and spatial accuracy of environmental knowledge depicted in sketch maps drawn for the purpose of route instructions. To this end, we conduct a real-world wayfinding study with 91 participants, all of whom have to walk along a pre-defined route of approximately 2.3 km length. Prior to the walk, we collect self-report familiarity ratings from participants for both a set of 15 landmarks and a set of areas we define as hexagons along the route. Once participants finished walking the route, they were asked to sketch a map of the route, specifically a sketch that would enable a person who had never walked the route to follow it. We found that participants unfamiliar with the areas along the route sketched fewer features than familiar people did. Contrary to our expectations, however, we found that landmarks were sketched or not regardless of participants' level of familiarity with the landmarks. We were also surprised that the level of familiarity was not correlated to the accuracy of the sketched order of features along the route, of the position of sketched features in relation to the route, nor to the metric locational accuracy of feature placement on the sketches. These results lead us to conclude that different aspects of feature salience influence whether the features are included on sketch maps, independent of familiarity. They also point to the influence of task context on the content of sketch maps, again independent of familiarity. We propose further studies to more fully explore these ideas.

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1 Introduction

Research on the role of familiarity in environmental cognition has gained attention in a variety of research domains over the last several decades. Researchers have conceptualized and measured familiarity in a variety of ways, ranging from length of residency in an area (see e.g. [28, 21]) or the amount of time people have been exposed to an environment (see e.g. [18, 44]) to self-reports of one's subjective sense of familiarity with particular landmarks, paths, or places (see e.g. [15, 7]). In some cases, evidence of familiarity has been sought in performance on tests of spatial knowledge, such as the accuracy and completeness of locational knowledge for features and areas (see e.g. [42, 48]). A widely used tool to assess spatial knowledge of environments has been the sketch map (see [20], [39]). This is based on two premises: (1) familiarity and spatial knowledge are related – more familiar people know more and more accurately than less familiar people, and a given person knows more and more accurately about familiar environments than unfamiliar; and (2) sketch maps are valid and reliable ways to assess the completeness and accuracy of spatial knowledge of environments. In the present study, we explore whether different levels of familiarity relate to differences in the content and spatial accuracy of environmental knowledge depicted in sketch maps when participants are asked to draw such a map for the purpose of giving route instructions to a third person. Self-reports of familiarity are collected for areas within a campus route walked by participants and for particular landmarks along the route. We do find differences in the spatial knowledge depicted in sketch maps as a function of familiarity, although not in a simple linear fashion. For example, in some cases, landmarks reported to be familiar are not included on sketch maps, while much less familiar landmarks are included. These results lead us to conclude that different types of feature salience (visual, semantic, or structural, see [36]) and different task contexts influence what people choose to include on their sketch maps. We propose further studies to more fully explore the role of familiarity in spatial knowledge recall as a function of salience and different instructional contexts, as revealed by sketch maps.

2 Related work

We review studies in which sketch map content and/or qualitative or quantitative spatial accuracy is related to familiarity. Generally speaking, the studies reviewed can be divided into two main groups based on the way these studies assess familiarity: The first consists of studies which use frequency or time of exposure to assess familiarity. The second includes studies which base their familiarity assessment on self-report ratings (sometimes in combination with other measures). Regardless the type of familiarity measurement, however, we see a variety of measures used to evaluate the sketch maps, ranging from feature counts to topological accuracy.

2.1 Studies using frequency or time of exposure to an environment as a measure of familiarity

Using a large sample size ($N = 271$), Horan [6] compared sketch maps of an university library drawn by upper-division students with those sketched by first-semester students, distinguishing students completely unfamiliar with the campus to those with some level of familiarity. Horan thus based the conceptualization of familiarity on the frequency of exposure to an environment, finding that first-semester students drew fewer features than did upper-division students. Chen and colleagues [2] used a small sample of only five participants, rank ordering their familiarity in terms of frequency of exposure. They found that the number of details included on sketch maps increased with increasing familiarity. Haq and colleagues[3] had participants ($N = 128$) acquire familiarity with an indoor environment through an initial free-exploration phase followed by directed search tasks. They found that completeness and topological configuration accuracy increased as the number of solved wayfinding tasks increased, i.e., with increasing familiarity, from the authors' conceptual point of view. Studying $N = 14$ participants, Molmer [26] exposed participants either to a real-world environment or a virtual-reality representation of it. Subsequently, he used sketch maps to assess familiarity and found that exposure to the real-world environment yielded sketch maps which resembled the spatial layout better. Imani et al. [9] distinguished binary levels of familiarity (not at all vs. completely) in terms of frequency of exposure (first-time visitors vs. residents of an area). They found that sketch maps by familiar people were more detailed and accurate ($N = 50$ participants). The authors do not detail, however, how they operationalize accuracy. Using a virtual environment, Kelsey [14] investigated the impact of global vs. local landmarks on wayfinding performance and spatial knowledge acquisition ($N = 60$ participants). Kelsey used the amount of time a person had spent in the virtual environment as a measure of familiarity. Kelsey's findings suggest that global landmarks located in the periphery are recalled better than other landmark types are. Looking at landmark type and location separately, Kelsey provides evidence that recall rates for global landmarks are higher, with distinctions between types of landmarks becoming less significant as familiarity grow. Additionally, peripheral landmarks are recalled more frequently than internal ones across all familiarity levels (see [14, p. 136]).

2.2 Studies using subjective self-report measures of familiarity

Kitchin [15] compared 13 different tests to assess configurational knowledge in sketch maps ($N = 279$ participants). He used subjective self-report measures of familiarity, with 7 levels of familiarity. Kitchin found that familiarity was strongly related to increased configurational knowledge, especially when tasks were spatially cued by location. Merriman and colleagues [25] studied the relation between spatial memory and environmental familiarity for younger and older adults. Familiarity with two urban routes was measured on a 7-point self-report scale. Participants ($N = 71$) learned the locations of novel objects the researchers placed along the routes in virtual renderings. On a variety of spatial knowledge tasks, younger adults mostly outperformed older adults, but especially the latter were relatively better in familiar environments. Zhang [49] used both subjective self-report assessment of familiarity with different areas of a college campus and an ordinal assessment of how many years a person had been on campus ($N = 126$). Zhang's analyses suggested a consistent effect for both measures of familiarity: As familiarity increased, the number of features included on sketch maps and their topological accuracy increased. Assessing familiarity by means of self-report (5 levels), Harrell and colleagues [4] studied how sketch maps differ when participants ($N = 360$) were asked to imagine drawing the maps to give directions to hypothetical visitors with different levels of familiarity. Male participants considered visitor characteristics, including familiarity, more in drawing their maps, providing more complete maps for some visitors than others. Participants more familiar with the campus did not draw very different maps than those less familiar, although they did include more labeled buildings. Muffato and Meneghetti [27] studied, among other aspects, the impact of self-reported landmark familiarity (7-point scale) on sketch mapping, shortest-route finding, and pointing accuracy ($N = 92$). With respect to sketch mapping, they did not find a significant effect of landmark familiarity on the accuracy of locating landmarks on the maps.

Finally, Li and co-authors [19] assessed the influence of familiarity and landmark salience on sketch mapping, with $N = 50$ participants[2]. Participants were guided along two different routes and then sketched a map for themselves so they would be able to follow the routes one month later. Results indicated that across sketch maps for both routes, more familiar people sketched more landmarks with a higher structural salience.

In contrast to all of these studies, we use a task context for sketch mapping, which deals with the explanation of a route to a third person. Our research question centers around the completeness, qualitative spatial accuracy, and absolute spatial accuracy of sketch maps as a function of familiarity if a sketch map is drawn for the purpose of explaining a route of considerable length to someone else. As a consequence, our study is not about what one knows so much as what one knows that they choose to include in route instructions.

3 Methods and Available Data

3.1 Participants

We recruited participants through advertisements in classes and publicly on campus. They were offered a compensation of USD 40. Overall, 91 successfully finished the study; occasionally, graduate students and staff members participated, but most of the participants were undergraduate students. Of the participants, 4 did not complete the sketch mapping task as they had to leave for other appointments. Moreover, recording of demographic data failed for one person due to a technical malfunction. The remaining 86 participants were, on average, $M = 22.2$ years old ($MD = 21$, $SD = 5.9$) and had been on campus for an average of $M = 7.7$ quarters ($MD = 6$, $SD = 9.6$). Overall, we collected sketch maps from 54 female, 28 male, and 4 non-binary participants.

3.2 Procedure

The sketch maps and further data we collected (see below) were part of a larger data collection effort, which had an online (demographics, individual differences, environmental familiarity – described below) and an in-situ part. The online part was carried out at least four days prior to the in-situ part. The in-situ part involved a wayfinding task across the campus of UC Santa Barbara, approximately 2.3 km in length (see Figure 2). Wearing sensors to track their eye and body movements, all participants were required to walk the same, predefined route of approximately 2.3 km in length (divided into four legs) by following a campus map with the route marked out. Participants were allowed to look at the map as much as they wanted. After arriving at the destination of leg 4, they were given up to five minutes to sketch a map of the entire route, starting from the beginning of leg 1 to the destination of leg 4 (we did not interrupt participants if they did not sketch in this order). Our instructions specifically told participants to imagine explaining the exact route to a person who had never walked this particular route before (the degree of familiarity of the sketch map receiver with the campus in general was not stated explicitly). We asked participants to include any information they deemed helpful for this imagined person to follow the route. The whole study was approved by the HSC of UC Santa Barbara (approval code: 60-23-0056).

[2] While the authors claim to assess familiarity according to Raubal and Winter [36] and Nothegger, Raubal, and Winter [29], it remains unclear from their text whether they considered the local environment of the landmarks or not.

This is an excerpt of the verbatim instructions:

> "As you have now reached your final destination, I would like you to sketch a map of the route you have taken through the environment. When you sketch the route, imagine you will need to explain the exact route to a person who has never walked this particular route before.…You should include any information[3] on the map that would help others to follow the route."

3.3 Measures recorded

During the online data phase, we collected a variety of measures, including the following specifically relevant to the current paper:

Familiarity data for hexagons along the route. The whole route was broken into 13 equally-sized hexagons (see Figure 2), which were part of a hexagonal tessellation of the UC Santa Barbara campus calculated for an online study conducted earlier. Hexagons were used over squares and equilateral triangles as the complete, non-overlapping tessellation with minimum perimeter length (the *honeycomb conjecture*). The hexagons were presented as an overlay of a basemap derived from OpenStreetMap, showing campus roads, campus buildings, parking lots, sports greens or the like, the campus lagoon, and the coast line. Participants rated their familiarity with each of these cells on a 7-point scale (1: *unfamiliar*, 7: *very familiar*). Figure 1 is a bar chart showing the frequencies of familiarity ratings for all hexagons.

Familiarity data for 15 building landmarks. In addition, each participant rated their familiarity with 15 building landmarks located along the route that we named (1 per hexagon plus two additional buildings for which the boundary of a hexagon cut through a building) using the same 7-point scale. The location was presented on the basemap described above in conjuction with a popup, showing a picture of the landmark and its name. The order in which landmarks were presented was randomized per participant.

Individual differences. We collected self-report sense-of-direction (SOD) using the Santa Barbara Sense-of-Direction scale [5]. This self-report instrument asks participants to rate themselves on 15, 7-point Likert items, with mean scores ranging from 1.0 (poorest) to 7.0 (best). In fact, our participants self-reported a mean SOD of $M = 4.4$, ($MD = 4.4$, $SD = 0.9$).

A variety of measures were collected during the in-situ part. The relevant data for this paper were the sketch maps provided by participants. Participants sketched their maps on a legal size (35.56 cm × 21.59 cm) sheet of paper after they arrived at their final destination (see above). Three landmarks, which are major anchor points for any person knowing the campus (Storke Tower, Bus Loop [North Hall], Henley Gate), were placed on this sheet to provide scale and locational anchor. In addition, the coastline was shown, and a scale and an arrow pointing north were given. A rectangular frame was placed on the sheet to indicate the drawing area.

[3] In fact, only three participants chose to also include written route instructions on the sketch map.

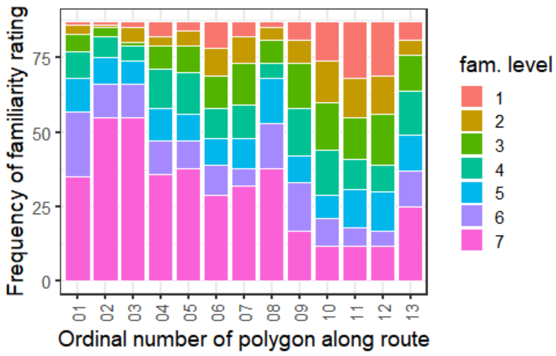


Figure 1 Frequency counts of familiarity ratings per hexagon (participants w/ sketchmaps).

4 Analysis

Prior to doing the analyses described below[4], all sketch maps were scanned and georeferenced in ArcGIS Pro. It was easy to georeference because of the three reference landmarks we provided to participants on their sketch map sheet. A campus map published by UC Santa Barbara[5] through an ArcGIS Map Server was used as a basemap. We analyzed the presence or absence of landmark features, two ordinal measures of landmark placement accuracy (correctness of linear order and correctness of positioning in relation to the route), and a distance measure of locational error for landmarks (calculated as the straight-line distance between the position of the sketched landmark and its actual location).

Overall, participants sketched a total of $N_{sket} = 1526$ features. Of these, $N_{ident} = 1442$ were identifiable: We counted features that participants labeled comprehensibly, and if unlabeled features ($N_{unl} = 276$) or incomprehensibly labeled features ($N_{inc} = 20$) could be identified independently by two raters based on their shape and location ($N_{agr} = 212$), we counted those too. If ambiguous, we excluded features shown on the maps ($N_{excl} = 84$). This resulted in a set of 87 distinct and identifiable features, of which 45 were buildings and 42 were non-buildings. These included point-like ($N = 3$, e.g., the location of a crosswalk), line-like ($N = 17$, e.g., bike paths), and polygonal features ($N = 67$, e.g., buildings or plazas). Of the 87 distinct features, 75 were located within 50 m of the test route. Out of the 87 distinct features, 28 were only sketched by a single participant (23 different participants). After coding features was complete, we standardized feature labels for all participants by using the names indicated on the official campus map.

Based on this, we assessed the following aspects, which are based (with exception of locational error) on suggestions by [38]:

Sketch map completeness. We assessed this by counting the number of features drawn by a participant. The average number of features sketched per participant (including those which were not identifiable) equaled $M = 18.2$ ($MD = 17.5$, $SD = 7.2$, $MIN = 3$, $MAX = 37$). For analyses at the hexagon level, we used ground-truth data to assess in which hexagon a feature was located. Figure 3b provides an example: The shared

[4] The analysis was done using a combination of GNU R (v 4.2.2)[35] and its packages tidyverse (v 1.3.2)[47], ggplot2 (v 3.4.1) [46], sf (v 1.0.15) [32, 31], sp (v 1.6.0) [1, 33], correlation (v 0.8.4) [23, 22] and Python (v 3.8.3)[43] and its pandas (v 1.0.5) package [30, 45].

[5] `https://tiles.arcgis.com/tiles/4TXrdeWh0RyCqPgB/arcgis/rest/services/UCSB_DFSS_BASEMAP_20211119/MapServer`, last accessed on Jan 14th, 2024

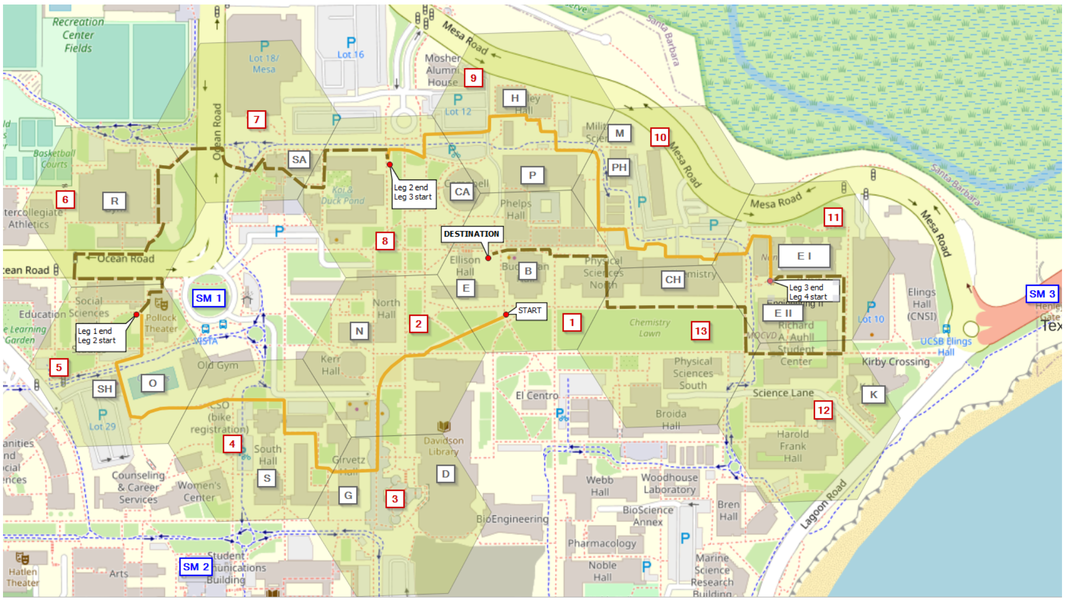


Figure 2 This figure shows the individual parts of the route in orange and brown and the hexagons for which we collected area ratings in green (labeled using red rectangles in the order of sequence they occur along the route). The figure has labels (grey rectangles) for the 15 building landmarks, for which we collected familiarity ratings (E: Ellison Hall, B: Buchanan Hall, N: North Hall, D: Davidson Library, G: Girvetz Hall, S: South Hall, O: Old Gym Pool, SH: Old A.S. Bike Shop, R: Robertson Gymnasium, SA: SAAS Building, CA: Campbell Hall, H: Henley Hall, P: Phelps Hall, M: Military Science, PH: Physical Sciences, CH: Chemistry Building, E I: Engineering Science, E II: Engineering II, K: Kohn Hall). In addition to that, the location of the three landmarks, which were included as point features on the sketch map sheet, are shown in blue rectangles (SM 1: Bus Loop [North Hall], SM 2: Storke Tower, SM 3: Henley Gate). Figure created using QGIS [34]; basemap (loaded via the QuickMapServices Plugin provided by QGIS): © OpenStreetMap contributors, CC-BY-SA.

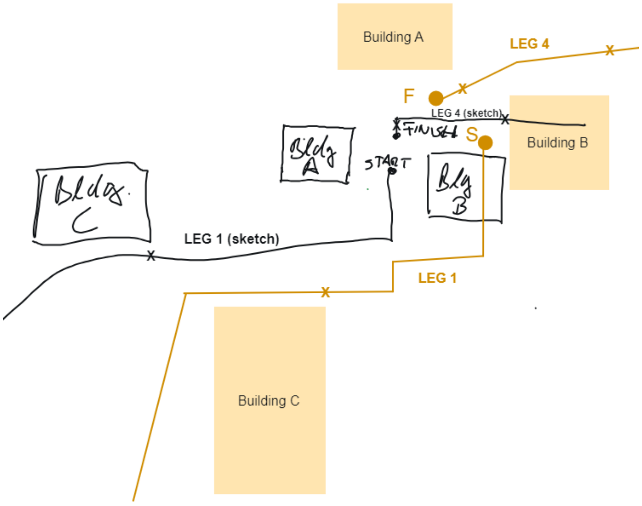
boundary of the hexagons 85 and 101 divides a building footprint; consequently, we include these in the count for each of these hexagons when it is sketched. Similarly, for analyses at the route-leg level, a feature could be part of more than one leg (which is, e.g., true for Phelps Hall, located along legs 3 and 4).

Linear order. We based the assessment of the correctness of linear order on the Levenshtein distance [17], a measure of the similarity of two strings or sequences of symbols (in this case, the order of landmarks as drawn and the actual order). To this end (see Equation 1), we (1) assigned a unique character to each of the sketched features; (2) built a participant string, e.g., per leg, and a ground-truth string based on these character representations, and calculated the Levenshtein distance, standardized by string length; and (3) subtracted the standardized Levenshtein distance from 1.0 in order to ensure that participants who were better at ordering the sketched features had higher values.

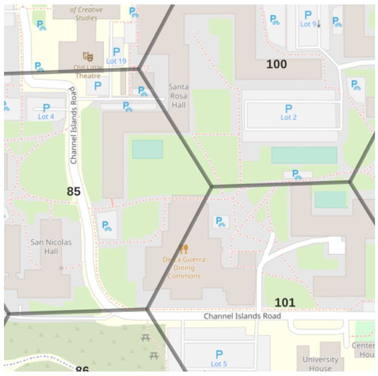
$$lin\_ord\_meas = 1 - \frac{dist(string(p), string(gt))}{len(string)} \tag{1}$$

Position. We quantified the position of sketched features relative to their actual position on the route at the moment the participant had reached them for the first time along their walk[6]. We did this on a per route-leg basis. At each point of first encountering

[6] This approach is in contrast to the method suggested in [38], where the authors do the positional



(a) Schematic depiction of sketched features and route (given in black) vs actual features on the basemap and the route course participants were required to walk as indicated on the basemap (both given in orange; the actual basemap is not shown for the sake of clarity). The positions marked in black and orange, respectively, represent the locations at which the position of the feature in relation to the sketched (black) or actual course of the route (orange) was assessed. For example, on leg 1, Building B is located left of the sketched route as it is in the real-world; Building C, however, is actually located to the left, whereas it is depicted to the right of leg 1 on the sketch map.



(b) Schematic example in which the footprint of a building is located within two hexagons labeled 85 and 1011, respectively. If this building was sketched, we would use it in each of the hexagons 85 and 101 when assessing measures on the hexagon-level. Figure created using QGIS [34]; basemap (loaded via the QuickMapServices Plugin provided by QGIS): © OpenStreetMap contributors, CC-BY-SA.

Figure 3 Figure (a) explains how the position along route was determined; Figure (b) explains how hexagon-level assessments were done if a feature polygon was located within more than one hexagons.

a feature along a leg (i.e., when it is reached), a given feature can be coded as either left, right, or in front of the route moving forward (at the start of legs, behind was also possible). Figure 3a provides an example: The sketched features are given in black, and the ground-truth features are given in orange at their actual location on the basemap (basemap not shown for clarity).

Locational error. We quantified error in the recalled locations of features by determining the centroids of each polygonal feature on the sketch maps and in actuality. If participants simply labeled a feature without drawing a polygon, we used the centroid of the verbal label. All coordinates of the $N = 1089$ centroids were reprojected to EPSG:2770 prior to calculating straight-line distances in meters between the drawn centroids and the actual centroids as a measure of locational error. Figure 4 provides an overview of the distribution of the calculated locational errors. The distribution is right-skewed ($Min = 2$ m, $Max = 890$ m, $M = 172$ m, $Median = 154$ m, $SD = 108$ m, $MAD = 111$ m, $IQR = 152$ m, $x_{.25} = 90$ m, $x_{.75} = 242$ m) with a long tail, as one would expect for a distance error measure.

assessment based on route segments. However, participants in our study made very heavy use of junction-merge (see [24]), which rendered this approach hardly feasible.

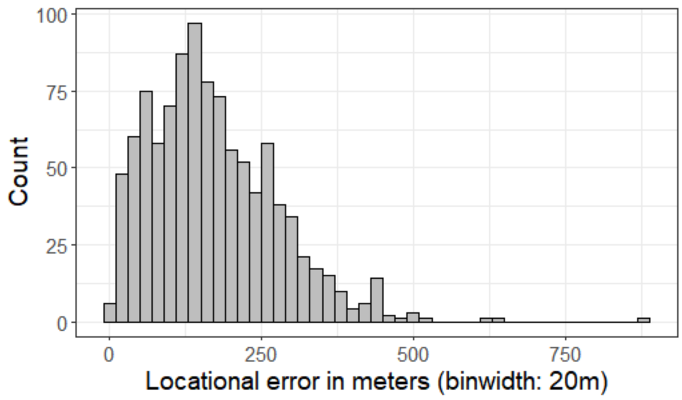


Figure 4 A histogram of the locational errors in meters between sketched and actual feature positions for all sketched non-line-like features, for all participants.

5 Results and Discussion

In order to answer our research question (see Section 2), we present results of our analyses with respect to (1) how often a feature was sketched depending on its familiarity (we expect that more familiar landmarks are sketched more frequently); (2) the number of features sketched within a hexagon as a function of the familiarity with this hexagon (higher familiarity, more features sketched); (3) locational errors of sketched features depending on feature, area, leg, or route familiarity (lower error in case of higher familiarity); (4) the correctness of the linear order of features in relation to spatial familiarity (higher familiarity yields more correct results); and (5), the correctness of the position along the route (higher familiarity yields more correct results). We expect to see a positive impact of environmental familiarity, i.e., familiar features being sketched more frequently.

5.1 Sketching frequency and landmark familiarity

Instead of looking at all features sketched, we assess in this section the sketching frequency of the 15 landmarks for which we collected familiarity ratings from all participants. Figure 5 provides bar charts of the frequency with which each of these landmarks was sketched by participants. One immediate impression is that frequencies with which landmarks were sketched do not necessarily correspond to their reported familiarity level. We calculated Fisher's Exact test for each of the landmarks (significance level of $\alpha = 0.05$ corrected according to Holm[41]) to compare frequencies with which a landmark was sketched across familiarity levels. We achieve a significant result exclusively for the SAAS Building (two-sided $p = 0.0003$*). This raises several questions: (1) Why are certain very familiar landmarks sketched while others equally familiar are not, (2) why are certain landmarks sketched regardless their familiarity level, and (3) why are some objects not sketched at all?

One potential explanation, which is related to all three of these questions, is that sketched and unsketched landmarks differ in their structural, visual, and semantic salience. As mentioned above (see Section 2), Li and colleagues assessed the salience of features [19] for each feature apparently separately. Empirical evidence and theoretical reasoning (see [12]) suggests that salience is not inherent to an object but ascribed to it based on the local surroundings in which it is embedded (see the model by Raubal and Winter [36] and Nothegger, Winter and Raubal [29]) and the context stimulated by the particular task being performed. We discuss this further below.

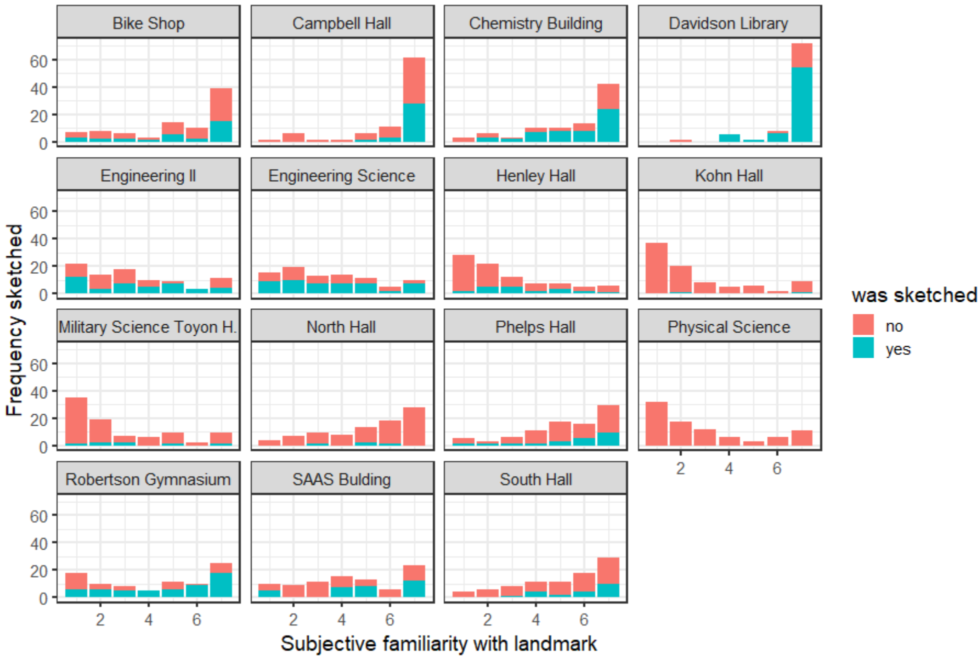


Figure 5 Overview of the frequencies with which a certain landmark was sketched per level of familiarity rating. The height of each bar represents the frequency with which a certain familiarity level rating was given for a particular landmark. The sum of frequencies in each subgraph equals the number of participants, $N = 86$.

5.1.1 Non-sketched familiar buildings

The majority of participants were unfamiliar with Kohn Hall, Military Science, and Physical Sciences; and, in line with expectations, participants did not sketch these landmarks. In contrast, North Hall, Phelps Hall, and South Hall were all quite familiar to participants. Nevertheless, participants did not sketch these. A likely explanation in case of North Hall is the fact that it is located in the vicinity of Davidson Library, which is one of the most visually, semantically, and structurally salient landmarks on campus. The adjacency of South Hall and Girvetz Hall can provide an explanation why South Hall was infrequently sketched: $N = 52$ of all participants included Girvetz Hall in their sketches, as this is a structurally salient building when following the test route (participants had to walk through its passage way and cross its courtyard).

Phelps Hall, however, is a large building and participants pass by it on leg 3 (north face) and leg 4 (south face). They are, moreover, facing towards it during the sketch map task. An explanation why many people might have chosen not to sketch Phelps Hall may be its lack of structural salience compared to two adjacent buildings. Considering the fact that $N = 69$ participants have chosen to either sketch Ellison Hall or Buchanan Hall, the data suggest that participants found these buildings, which are located adjacent to Phelps Hall, more structurally salient: much of the sensor calibration was done in front of them, the outfitting was done inside Ellison Hall, and the task started and ended between these two buildings.

5.1.2 Familiar buildings – sketched or not sketched

The Old A.S. Bike Shop, Chemistry Building, Davidson Library, and Campbell Hall were all very frequently rated as familiar. However, in the cases of the Old A.S. Bike Shop and Campbell Hall, more people who were very familiar with them did not sketch them than those who were very familiar and did sketch them. For the Old A.S. Bike Shop, the fact that it is located adjacent to the Old Gym Pool might be an explanation, as the Old Gym Pool was drawn very frequently (by 51 participants), as participants are walking almost 270 degrees around it. For Campbell Hall, one reason may be that the course of the route "turned away" from Campbell Hall before actually reaching it (despite the fact that it is located only 38 m away from this junction). For Chemistry Building and Davidson Library, those who were very familiar and sketched them were more common than those who were very familiar but did not sketch them. An obvious reason for Davidson Library is, as mentioned above, its visual, semantic, and structural salience. A likely explanation for sketching the Chemistry Building is that approximately 1/6 of each of legs 3 and 4 was located alongside this building, which is 109 m wide.

5.1.3 Buildings sketched sometimes and sometimes not – irrespective of their familiarity ratings

Engineering II and Engineering Science, Robertson Gymnasium, and the SAAS Building all show a similar pattern: These buildings were sometimes sketched and sometimes not, whatever their level of familiarity. A reason why participants unfamiliar with Robertson Gymnasium still sketched it might be that approximately half of the 2nd route leg (the route was divided into 4 legs) was next to this building. Engineering II and Engineering Science were both located at the end of leg 3 and, hence, leg 4 started between these two. They are very large buildings and participants walked along these features at the beginning of leg 4 and through Engineering II during the further course of the route. Finally, the SAAS Building might have been included because the route course was particularly difficult for many participants in the vicinity of this building, which, again, points towards the importance of structural salience.

5.1.4 Summary

Taken together, these results suggest that it is important to consider the local environmental context to explain what participants will sketch when asked to do the sketch for the purpose of route explanation. Clearly, this may be true in various ways: While relative salience values could be calculated using the formulae by [36] based on a set of features located within a certain distance, as suggested by [29], one could also use human-subject ratings to assess the salience of a feature within a particular spatial environment (as suggested by [11, 13]). Whatever the method used to obtain relative salience values, further studies are needed in order to disentangle the relationship between familiarity and multiple dimensions of the salience of buildings and other features. Our results suggest that visual (see, e.g., Davidson Library vs. North Hall), structural (see, e.g., Girvetz Hall vs. South Hall, or Robertson Gymnasium), and semantic salience (Davidson Library vs. North Hall) all have the potential to "overwrite" the influence of familiarity.

In addition, experimental designs also need to assess the degree to which the relationships between salience and familiarity are mediated by the actual sketch-mapping task: Despite the fact that our task description asked for route-like sketch maps, there were structurally salient landmarks with which participants were familiar yet frequently did not sketch (e.g.,

Table 1 Assessment whether different levels of familiarity (columns fam_l_1 and fam_l_2) yield differences with respect to the average number of features sketched (columns avg_grp_1 and avg_grp_2). The alternative hypothesis was for all tests that hexagons with a smaller rating have less features sketched. Based on an adjusted significance level according to Holm, only the differences between level 1 and levels 5, 6, 7 are significant at the corrected $\alpha = 0.05$ level as indicated by an asterisk.

fam_l_1	fam_l_2	N_grp_1	avg_grp_1	N_grp_2	avg_grp_2	p_value	Corr. Sign. Lev.
1	6	38	1.03	53	1.96	0.0005*	0.0024
1	5	38	1.03	55	1.85	0.001*	0.0025
1	7	38	1.03	73	1.66	0.0013*	0.0026
2	6	41	1.23	53	1.96	0.005	0.0028
1	4	38	1.03	56	1.68	0.0057	0.0029
2	5	41	1.23	55	1.85	0.007	0.0031
3	6	51	1.36	53	1.96	0.0081	0.0033
2	7	41	1.23	73	1.66	0.0106	0.0036
3	5	51	1.36	55	1.85	0.0144	0.0038
2	4	41	1.23	56	1.68	0.0278	0.0042
3	7	51	1.36	73	1.66	0.029	0.0045
3	4	51	1.36	56	1.68	0.0656	0.005
1	3	38	1.03	51	1.36	0.0906	0.0056
4	6	56	1.68	53	1.96	0.1594	0.0063
4	5	56	1.68	55	1.85	0.2635	0.0071
1	2	38	1.03	41	1.23	0.2772	0.0083
2	3	41	1.23	51	1.36	0.2922	0.01
5	6	55	1.85	53	1.96	0.3601	0.0125
4	7	56	1.68	73	1.66	0.445	0.0167
5	7	55	1.85	73	1.66	0.7395	0.025
6	7	53	1.96	73	1.66	0.8176	0.05

Campbell Hall). In our study, the instructions to sketch a map for an unfamiliar person to follow led participants to consider particular aspects of salience over other aspects when deciding what to sketch.

5.2 Differences in number of features sketched per hexagon

We assessed whether different familiarity ratings for hexagons yielded a different number of sketched features within a hexagon; we assumed that lower levels of familiarity would result in a smaller number of features sketched. Considering all sketched features for this analysis, we found that the number of distinct features drawn per hexagon ranged between $[3; 13]$. As a Bartlett test of homogeneity of variances indicated no significant heteroskedasticity between groups ($K^2 = 8.31$, $p = 0.216$), we calculated a one-way ANOVA as an omnibus test ($F_{6,360} = 3.82$, $p = 0.001052^{**}$). Based on this significant result, we did pairwise Mann-Whitney-U tests in order to compare different familiarity levels. In order to account for Type I error inflation, we adjusted the significance level $\alpha = 0.05$ according to Holm. Table 1 indicates that there are significant differences between familiarity rating levels 1 and 7, 1 and 6, 1 and 5.

This result suggests that it is possible to distinguish at least whether people are quite familiar (ratings 5–7) or unfamiliar with an area based on the average number of features sketched within the area. This finding is in line with Harrell et al. [4], who provided evidence that more familiar people include more labeled buildings. Further research is needed to better understand the impacts of the specific spatial environment. Two questions that arise in this respect are: (1) Is this effect specific to building features, i.e., would a different environment with more but smaller or fewer buildings yield similar results? and (2) Are there spatial environments which would allow us to distinguish more levels of familiarity (e.g. level 1 vs. 3 vs. 5 vs. 7) by looking at the number of features sketched?

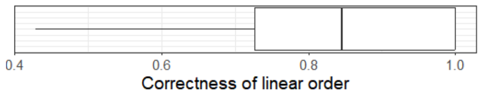


Figure 6 A boxplot of the correctness scores of linear order based on the Levenshtein distance across participants. A score of 1 represents a completely correct linear order.

5.3 Locational errors of sketched features

We use straight-line distances to assess the locational error of all non-line-like features. We base our correlational analysis on the means of familiarity ratings and locational errors in order to investigate the general trend. In line with prior evidence (see, e.g., [10]), we see a modest but significant negative correlation between the self-report SOD of participants and mean locational error ($r = -0.287 \mid p = 0.011 \mid 95\%CI[-0.487; -0.059]$). However, we do not find a significant correlation between mean locational error and mean familiarity rating at the participant level, the leg level, or the hexagon level, regardless of whether we tested within or across genders. While there is a significant difference ($W = 303701$, $p = 0.03$*) between female ($Median = 153$ m) and male ($Median = 170$ m) participants in our dataset with respect to overall locational error, it is contrary to prior evidence (see [8, p. 12]) as the error is larger for males. When focusing exclusively on the set of 15 landmarks for which we collected familiarity ratings, we again found no significant correlation regardless at the landmark, participant, or leg level. Both of these findings are in line with Muffato's and Meneghetti's findings [27], who did not find a correlation between familiarity with landmarks and the locational accuracy of sketched features.

5.4 Linear order of features

We based our analysis of participants' ordinal accuracy of feature placement along the route on all features which they sketched; included cases must have at least 2 features. For example, when assessing correlations at the hexagonal level, a participant who sketches only 1 feature in a particular hexagon was excluded from the analysis of this particular hexagon.

As described above, we based our analysis on a standardized version of the Levenshtein distance. As prior evidence and theoretical reasoning suggests that participants who are more familiar have a more accurate configurational spatial knowledge (see, e.g., Kitchin [15] or Zhang [49]), we expected a positive correlation between level of familiarity and degree of correctness of linear order. However, we did not find these significant correlations, whether at the level of the participant or at any of the leg levels. At the hexagon level, however, we did find a significant (corrected according to Holm) Spearman correlation ($\rho = 0.352$, $p = 0.0028$*) exclusively for the second hexagon along the route. This is the hexagon in which Davidson Library and the The Arbor Quad are located and both of these are highly salient landmarks on UC Santa Barbara campus.

In general, the fact that the linear order values achieved by participants are frequently close to the maximum of 1.0 (see Figure 6) suggests either that experiencing the environment during the study washed out any potential impact of prior familiarity, or that order recall has a ceiling effect such that it is too easy to reveal effects of familiarity.

5.5 Position in relation to the route

Finally, we assessed the relationship between familiarity with hexagons and the correctness of positioning features left, right, behind, or in-front when approached for the first time along a leg of the route. To do this, we calculated the fraction of correctly placed features out of all features drawn, per hexagon. For per-leg and per-participant assessments, we used the mean of this fraction. Based on similar reasoning as for linear order of features (see above), we expected a significant positive correlation between familiarity and the correctness of feature position. But we did not find significant Spearman correlations for any of these comparisons.

6 Conclusion

We used self-report familiarity with landmarks and areas in conjunction with sketch maps collected after a wayfinding task in order to assess how different levels of familiarity impact sketch map content and accuracy when participants are asked to draw the sketch map for the purpose of explaining the route to someone. We assessed this relationship with respect to completeness, locational error, and two qualitative spatial accuracy measures (correctness of linear order and correctness of positioning in relation to the route, respectively). In line with our expectations, our results suggested an impact of familiarity on the number of features sketched. However, even though this relationship held, we found that some familiar landmarks were not included while some unfamiliar landmarks were. In addition to that, not finding relations of familiarity with locational error or qualitative spatial accuracy clearly contradicted our expectations. Hence, our results indicate that further research is needed in order to fully understand the role of familiarity with respect to spatial knowledge as depicted on sketch maps drawn for the purpose of route explanation. To this end, we propose research on the following three topics in order to come closer to this understanding. All three topics have in common that the impact of sketch mapping instructions (see [16]) on sketch-map content needs to be carefully taken into account.

Disentangling the relationship of direct experience and familiarity. As we do not find correlations between spatial familiarity and correctness of linear order/position of sketched features along the route, we propose to study whether different setups for the wayfinding task yield different results. For example, is the familiarity effect also washed out if participants follow an in-person guide along a route instead of looking at a map like our participants did? Similarly, the impact of certain environments should be studied: For example, do we see an effect of familiarity in environments having less built features and more natural features? What about environments with a higher density of buildings than a university campus? Another important aspect is the relationship between structural salience of features and both of the qualitative spatial accuracy measures we used. For example, despite the fact that people are quite good at ordering landmarks along the route, are more structurally salient features included in areas which impose challenges to wayfinders?

Locational error and familiarity. Based on our data, we do not see a correlation between familiarity levels and locational error. Several questions arise from this result. How do task descriptions for sketch mapping tasks impact this particular measure? The instructions we gave participants were based on an imagined person having to walk a particular route. So, would we see a different result regarding locational error for different familiarity levels if sketch maps were imagined to serve different purposes? Is the impact of familiarity on locational error masked by the number of basemap features given on the sketch mapping sheet? In our case, the only context given were three anchor points, depicted as point-like features and the coastline, represented as line-like feature; such a map makes it easier for well-oriented people to sketch a route accurately (which is supported by the negative correlation between self-report SOD and locational error in our dataset). However, due to our experimental design, even well-oriented participants had different levels of familiarity with areas along the route. Therefore, would different levels of detail on the basemap yield differences between familiarity ratings, which are not masked by SOD?

Sketch map completeness: Salience vs. (feature) familiarity. When assessing sketching frequency, we saw that there was no simple relationship between familiarity with a landmark and whether it was sketched or not. We also saw that participants sketched less features in areas with which they were not familiar at all (familiarity rating of 1), compared to those with which they were familiar (levels 5, 6, or 7). Are there spatial environments which would allow us to distinguish more levels of familiarity (e.g. level 1 vs. 3 vs. 5 vs. 7) by looking at the number of features sketched? Prior evidence (see Sloan et al. [40]) suggests that basemap size has an impact on the number of features sketched (with larger maps resulting in more features sketched). The sketching area on the sheets in our study was close to legal size paper (35.56 cm $\times$ 21.59 cm). In addition to that, the sheets indicated a scale of the map by displaying a ruler indicating a distance of 0-500 ft in 100 ft steps to participants. So, would larger sizes allow us to distinguish more familiarity levels based on sketched feature frequency? Put another way, how much can the sheet size be shrunk before familiar and unfamiliar people can no longer be distinguished from each other? How would sketches differ if a different scale was used? How does the spatial environment relate to all of this? With respect to differences in the number of features sketched at each familiarity level, salience may also play an important role. Do unfamiliar people include more salient features and if so, is this true for all aspects or sub-dimensions of salience to the same degree?

With respect to the finding that feature familiarity does not predict whether a feature is sketched, further studies are needed to understand the role of feature salience, in particular as salience is known to be an important aspect in route explanation (see, e.g., [37, 50]). Which aspects or sub-dimensions of feature salience are important to determining whether features are sketched? What impact does the task description have when it comes to the importance of salience sub-dimension; for example, does the importance of structural salience as discussed in our results hold across different task descriptions? What role does the spatial environment play in this relationship, i.e., are there environments in which salience does not mask familiarity?

It seems advisable to tackle all of the research problems mentioned here by a combination of immersive virtual-reality studies and in-situ studies. Studies in virtual environments will allow us to systematically assess the impact of different salience dimensions on familiarity, e.g., by systematically changing façade colors of buildings in order to modify visual salience. However, studies in real environments are important in order to maximize ecological validity, particularly for this research problem.

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