Icon Design for Landmark Importance in Mobile Maps

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ABSTRACT
Markers denoting the location of landmarks and search results in mobile apps are used extensively in many applications. The presence of large volumes of markers clutters the information space, making it hard for users to visually differentiate between highly important or recommended locations, or to browse the depicted locations in order to identify suitable choices. In this paper, we present the results of a participatory design process to improve the utility of marker icons in a tourist application. We explore three alternative designs derived from this process by implementing and testing a mobile application that recommends venues based on their popularity (check-in count) in a well-known social network (FourSquare). Our lab experiments highlight aesthetic, utility and performance issues in marker design that affect the usability of mobile map applications.

CSS Concepts
• Human-centered computing ~ Empirical studies in ubiquitous and mobile computing • Human-centered computing ~ Information visualization • Human-centered computing ~ Geographic visualization

Keywords
Mobile maps, Marker icons, Marker scaling, Generative Markers

1. INTRODUCTION
of the primary goals of visitors in a city is to discover and explore venues and landmarks that characterize the area, following recommendations from experts, locals and other tourists that have previously visited the same area. Although official guides and curated advice (e.g. guidebooks) are often available for many urban destinations, word-of-mouth information is highly influential for tourists, particularly because sources such as guidebooks are often biased, static and possibly out of date [12]. Word-of-mouth information is not restricted to that which is orally communicated (e.g. discussion between tourists and locals or tourists and friends who may have previously visited), but extends to written comments and discussions in online fora, blogs or social networks [11]. Although on-line information is often curated by the management of venues, the majority of comments are genuine and arise from other visitors. As such, it is perceived as a trustworthy and reliable source [11]. Word-of-mouth information is not restricted to verbal communication. Other items of information are implicit indicators of a location's popularity and importance. Such information might be the number of people who have performed particular actions relating to a location via social networks, indicating a visit or a subjective appraisal of its importance (e.g. "checking in", posting a picture, "liking", rating or leaving a tip/comment for others). Such information is easy to retrieve via the various APIs that modern social networks provide and can be used to estimate the general importance of locations. In some cases, there is evidence that such information is a more impartial indicator of venue popularity compared to the analysis of written feedback, as users tend to share negative experiences more often than positive ones [3]. A further advantage of this type of information is its dynamic nature – quantitative metrics such as the number of check-ins at a location exhibit different growth patterns depending on the popularity and seasonality of locations, hence allowing for up-to-date and contextualized recommendations. However, with the growing popularity of social networks, the number of locations that can be visualised by mining the relevant APIs has grown exponentially. For example, the popular FourSquare network claims to have over 65 million locations in its database as of December 2015 [14]. Trying thus to depict locations in any urban area via a mobile app creates a very significant problem due to the small size of the information space (mobile screen) and large volume of markers that have to be displayed. The end result is visual clutter, which makes it difficult for users to locate and view information about important locations. This issue is mitigated by two predominant strategies: Marker clustering (i.e. aggregating multiple proximal markers into a single visual representation, often accompanied by a count and colourisation to depict density) and marker limitation (maintaining a consistent marker visual style but limiting the visualised markers to just a few recommended locations). The latter approach though still suffers from a major issue, which is the differentiation of importance between the limited number of markers displayed on the user's screen (i.e. all markers look the same, so the user is not offered clues on where to begin their search). In this paper, we aim to address this issue by exploring alternative marker designs that convey location importance as a core visual element.

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2. RELATED WORK
A significant issue with markers on digital maps, particularly affecting mobile maps due to the small screen limitation, is the presence of high volumes of markers in the map view. Several approaches for limiting the clutter on maps have been proposed, most of which focus on the heavy context-aware filtering of visualised POIs, in order to reduce the displayed volume. A visual approach is to cluster markers and representing these with an aggregate marker symbol. A further approach is to use heatmaps,

to depict the density of markers in an area. Tiled heatmaps are a more simplified alternative to traditional heatmaps, using a "tiled" approach instead of a dynamic ellipsoidal visualization like standard heatmaps. Finally, another alternative is choropleth maps, which are akin to tiled heatmaps but differ in that the "regions" are typically polygonal pre-defined shapes (e.g. political land boundaries). These approaches are reviewed in [10] and all relate to solving the problem of marker density, as opposed to marker importance. Literature on the design of individual marker icons is extremely limited. Elias & Paelke [7] highlight a lack of literature in POI marker design in mentioning, having found an extremely small body of literature in this area. Their work examined a variety of landmark marker design approaches that adopt various levels of abstraction (from photos to iconology and words) and propose design guidelines for marker visualisation, in which icons, symbols and words for depicting landmark types is found to be the best approach. The use of photographs of landmarks is recommended as appropriate for representing visual aspect, a finding supported by Hile et al. [9] and also Delikostidis et al. [6].

Heidmann states that the fundamental aims of visualizing spatial data points are to allow a user to locate, read, classify, group and compare [8]. The aforementioned visualisation approaches however miss out entirely the comparison element. To help with this dimension, it has previously been shown that a range of visual marker variables [1] can be used to aid users in differentiating but also ranking locations (e.g. marker colour and size [2]). Perhaps the first researcher to have examined the relationship between understanding a marker's importance and its graphical elements was Chittaro [4], who introduced the concept of dynamically drawn POI markers that incorporate contextual information on the represented POI, in terms of the degree in which POIs fulfill filtering criteria. This was accomplished by drawing a green bar on the side of each icon in a 2D mobile map, whose height represented the degree in which a POI matched filtering criteria. We are not aware of any other significant literature in this area, with the exception of a recent paper by Meier [13], who proposed the concept of "generative markers", combining a clustering depiction varied by with colour, size and iconographic elements. Meier did not actually test his proposed designs, but conducted evaluations of various other clustering methods, including single markers that varied in size and colour (to depict density). The results of these evaluations highlight that users commonly relate visual variable manipulation of markers as pertinent to ranking (e.g. restaurant rankings from a social media platform). He also concluded that size is a good visual variable for identifying the maximum (although this is applied to the number of markers clustered into a single one).

These findings raise the question on whether a process whereby the automatic manipulation of marker visual variables (size and colour) can have an impact on the ability of mobile spatial app users to quickly assess and compare the importance of locations on a mobile map. This question forms the motivation behind our work. The next sections describe our investigation in designing such markers and their evaluation.

3. APPROPRIATING VISUAL VARIABLES IN MARKER DESIGN

We began our design effort with several preliminary focus groups, aimed at introducing participants to our goal and to determine attitudes and directions for appropriating visual variables such as size and colour in markers, in order to convey location importance in mobile maps.

3.1 Criteria for Selecting a Location

Our first focus group aimed at assessing the importance of social network information as a proxy for location importance. We held two sessions with twelve participants (6 female) aged between 25-35 years old, split in two equal size groups. They participated in a semi-structured discussion concerning criteria for selecting a location, ways of finding local information and using mobile apps as an aid for tourism. Our participants were asked to brainstorm for criteria for selecting locations and then collectively rank these for locations local to their hometowns and for locations in an unfamiliar city. They mentioned that for local places, the primary criterion for them was their current mood and whether a location matches that. The second most important was whether a location had been previously visited by friends (hence recommended). Venue popularity ranked third, followed by other criteria such as services offered at the location, price or distance. For places in unfamiliar cities, venue popularity emerged as the most important criterion, while the rest followed in the same order as for local places. Participants strongly viewed popularity as reliable indicator of the "must-do" locations while visiting.

We also asked participants to express where they might obtain reliable information for "must-do" locations. They indicated that locals (e.g. taxi drivers, receptionists, waiters) are the most reliable sources. Half of them stated they might look up information on the web prior to the visit, while the rest would attempt to look up information using their mobiles while there. Apps such as TripAdvisor were mentioned as rich sources, but with low reliability as the information comes mostly from other tourists rather than locals. In contrast, when we asked them about their views on information such as check-ins, they viewed this favourably since they perceived that a large percentage would also be generated by locals and not only tourists. They also agreed with the statement that they personally would only check in to locations that would make them "proud to be seen in". Our participants expressed some concern about fake check-ins (i.e. users stating being at a location while really being somewhere else) but also check-ins motivated by local businesses (e.g. by offering a discount). However they felt that fake check-ins were not a common occurrence. With regard to motivated check-ins, participants stated a clear awareness that this resulted to advertising a venue to their friends, so they would not do it for venues they didn't feel were worth it, or they would do it in order to take advantage of an offer at a location, limiting the visibility of their check-in through privacy settings.

Finally we asked our participants to explore the idea of a tourism app that would expose information from social networks to users. They stated that they would appreciate being able to visualize venue popularity as indicated by check-ins, using ranked lists but also being able to see this ranking on maps, so as to assess the spatial relationship amongst venues and their current location. Map semiology should be such that would allow them to distinguish location categories using marker colour and importance using marker size.

3.2 Participatory Design of Location Markers

Our preliminary focus groups provided confirmation that location importance is a critical element in mobile spatial apps, as well as a few hints on how marker styles variables could be manipulated to afford richer understanding of the user's surroundings. With these results in mind, we conducted a participatory design session with a further 5 users (2 female) aged 28-32. Each participant was asked to individually imagine and draw a low-fidelity set of sketches on paper, depicting the core elements of a mobile application showing locations and their importance to tourists. We then shared all designs between participants and asked them to freely comment on each. Our first participant came up with a design that presents venues in a ranked list. A map is shown only when a user selects a venue from the list, for the purposes of navigation. Other participants negatively commented on this approach, particularly because a user had to first select a venue category and then a location, making it impossible to see the spatial relationship between the chosen location and others. Our second participant adopted a map-based approach where venues from all categories were shown on the map, each marker depicting popularity using a different colour. She provided the ability to filter categories through a drop-down menu. This approach was highly rated by other participants, who noted however that a legend would be required in order to remind them the relationship between colour and popularity. Our third participant also adopted a map as the main information space, using colour to denote venue category in markers and a clustering of "dots" to show the number of check-ins at a location. Hence, a location was represented by a multitude of densely clustered markers ("dots") resulting in a visualization that resembles a cross between markers and tile heatmaps. Other participants liked this idea but were unsure how this would work in terms of "tapping" on a marker to view more information.

Figure 1. Prototype designs by participants 2-5 (clockwise from top left)

Our fourth user adopted a generative approach, where marker visual elements were modified according to venue popularity. In his example, "coffee shops" were depicted by a coffee cup icon. The cup was depicted as being more "full" at popular locations, while being "empty" at locations that were not popular. This was received as an imaginative and creative approach by others, however there was uncertainty in how this would be used in other categories (e.g. food). Finally, our fifth participant adopted a map based approach where markers were depicted as "stacks of Lego bricks", with popularity shown by the number of "bricks" in a marker. Colour was used to differentiate between categories of venues. This generative approach is more abstract than that of Participant 4 and was received as the best overall design.

The results of our exercise provided some good insights relating to marker design. Overall we participants felt that colour is best used to help differentiate between venue categories. Abstract representations with clear additional graphical elements (e.g. liquid level in coffee cup, number of "bricks") are good ways of helping users assess importance. A combination of additional graphical elements that result in enlarged marker size to highlight important locations also offers the added advantage that it makes for easier "tapping" targets.

3.3 Prototype Design

Based on the review of literature, the outcomes of our preliminary focus groups and also the participatory design sessions, we developed a mobile app on Android, using three alternative marker designs, all of which are based on the concept of using colour to depict location category and size to depict location importance. For this purpose, we use three 2-D marker designs, inspired by elements of urban landscapes. Our designs were made to accommodate not just the results from our exploratory participatory design, but the aesthetic and functional recommendations of literature as follows:

Trees: Nature-inspired graphics to show the accumulation of events via *continuous* scaling [5], **Pins**: Abstract graphics to show the accumulation of events via *continuous* scaling [2] and; **Buildings**: Generative graphics to show the accumulation of events by adding *discrete* graphical elements (i.e. floors) [13] (Fig.2)

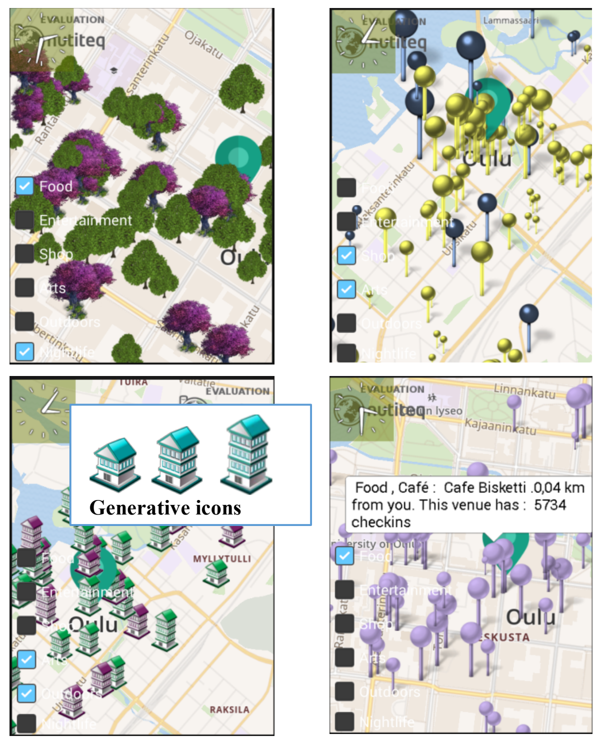

Figure 2. Map UI showing our marker styles

Our first marker type is a "pin", with a slim body and rounded head. This type of abstract marker is reminiscent of lamp-posts, a ubiquitous item of urban furniture, but also of actual pins that are often placed on real paper maps. Pins are scaled relevant to location importance. The second type is an abstract building. This marker type has more "floors" added to it, as venue importance increases. Finally, the third type is trees, in which case the foliage colour (and shape) depict venue category and the marker size is scaled in relation to venue importance. Graphical depictions inspired by nature have been used in a number of projects in the past to depict the accumulation of events (e.g. in [5], physical activity events and their intensity are shown as flowers which increase in height). An important distinction between the marker types is that while pins and trees are scaled on a continuous level, buildings have floors added at specific interval thresholds only. This is necessary for logical consistency, as it would not make sense in this case to partially add a floor to the marker icon, from a user perspective.

Our application allows users to show one or more categories of locations on the map by applying filters depicted as checkboxes on the left of the screen. Tapping on a marker brings up an pop-up balloon with some details of the venue (category, name, distance and popularity). A further tap on the balloon takes the user to a location detail screen, showing photos of the venue. For the purposes of our experiment, this screen also displays a "back" and "final choice" button, as will be explained later. Our prototype fetches venue information from the FourSquare API, based on a pre-compiled list of discovered venues described in [x]. For our implementation, we used the Nutiteq 3D maps library for Android, as it permits the dynamic scaling of markers. The application code is available as an open-source project at *[url blinded for review]*.

4. EVALUATION

4.1 Experiment setup

To assess the impact of our designed landmark icons, we performed a lab-based evaluation with 18 participants (8 female), aged (28-36). All participants performed a series of tasks on a Sony Experia E smartphone to ensure the screen space available to them was equal. Our experiment took place in Greece. As such we wanted to use a geographical location that represented a location that none of our participants had ever visited. We chose the city of Oulu in Finland, as in a previous experiment we had collected a large dataset from FourSquare covering this location (>2000 POIs) and it was also a location that none of the participants knew.

The participants performed four tasks using each icon design, using a different order of tasks and icon designs to avoid any learning effects. The tasks were performed using a choice of 16 scenarios in random order, which were constructed using combinations of the following features: (F1) Search range (nearby venues only, or the whole city), (F2) Venue category (selecting one from Food, Outdoors, Nightlife, Arts) and, (F3) Venue popularity (selecting the most or least popular). Each scenario set contained two scenarios for each value of F1, one scenario for each value of F2, three scenarios of F3-popular and one scenario of F1-unpopular. An example of a task set constructed with these constraints follows:

S1. Based on your current location, you would like to find a nearby beautiful outdoor location to spend some time. Which one would you choose?

S2. It's after dark and you and your friends want to have fun at a nearby bar. Which one would you choose?

S3. You are at your hotel and want to find a good place to eat, anywhere in town. Which one would you choose?

S4. You are your hotel and it's your last day in the city. You'd like to visit an art venue that's interesting and worth visiting. Which place would you NOT choose under any circumstances?

For each task, we recorded the overall completion time, number of icons clicked, number of detail screens opened and time in each screen, the check-ins for the clicked icons and the check-ins for the participants' final choice. Following each task set with each icon design, we asked our participants to complete a NASA-TLX questionnaire. At the end of the experiments, we asked participants to respond to five subjective questions using Likert scales.

Our results are presented excluding the data from one participant who appeared to be largely distracted during the experiment, and hence we excluded him from the analysis. Statistical tests shown below (t-tests and Wilcoxon signed rank tests) are made according to the distribution of variables, which was examined using Shapiro-Wilk normality tests.

4.2 Performance measures

4.2.1 Task completion times

Overall participants took longer with the tree icon representation (m=116.97s, sd=54.25s). Pairwise comparisons with t-tests reveal that this difference compared to time taken with the pin icons (m=81.21s, sd=33.04s) is statistically significant ($t(17)=3.719$, $p<0.01$). Comparing time with the tree icons to the time taken with the building icons, which exhibited the shortest time (m=71.36s, sd=21.33s) is also statistically significant ($t(17)=3.949$, $p<0.01$). A comparison between the time taken with the pin and building icons was not found to be statistically significant ($t(17)=1.804$, $p=0.09$). As such the two best performing designs are pins and buildings.

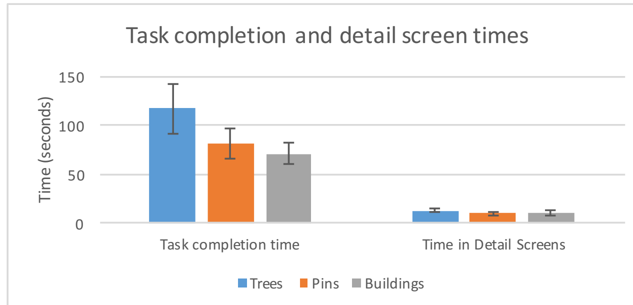

Figure 3. Time data during task completion

We also examined the time taken examining detail screens (which is included in the overall time taken to complete the task), in order to examine how much of the task completion time was spent on the map screen compared to examining venue detail screens. We note here that the time taken examining the detail screens is very low compared to the overall task time. On average, participants took the most time examining detail screens with the tree icon representation (m=13.39s, sd=5.34s). This was followed by the time in the building icon representation (m=10.70s, sd=5.40s), with the difference being statistically significant ($t(17)=2.442$, $p<0.05$). The lowest time in details screens was taken with the pin representation (m=9.88s, sd=4.33s). The difference with the tree icon representation is again statistically significant ($t(17)=2.884$, $p<0.05$). The difference between time in detail screens with the pin and building representation is not statistically significant ($t(17)=-1.035$, $p=0.316$). Again we find the best two performing designs to be pins and buildings.

4.2.2 Interaction with the User Interface

Less interaction with the UI is a key goal in mobile application design, as a user should be able to process the presented information visually and without needing to access further options available in the UI. As we noted a difference in the time taken examining detail screens, we wanted to see whether this arises from a difference in the number of detail screens viewed. On average participants opened more detail screens while using the tree icons (m=4.31, sd=1.42). This was followed by the number of screens opened while using building icons (m=4.11, sd=1.29) but the difference is not statistically significant ($t(17)=0.373$, $p=0.714$). The smallest number of detail screens was opened while using the pin icons (m=3.37, sd=1.55) and this difference is statistically significant to those while using tree icons ($t(17)=2.825$, $p<0.05$) but not while using building icons ($t(17)=-1.472$, $p=0.160$), which explains the time differences described in the previous sections. The best performing designs are again pins and buildings.

Further to this, we examined the number of icons clicked in each map visualization (bringing up the pop-up info balloon for each landmark), to see if the time differences in completing tasks can be explained by this. Participants clicked on more landmark icons in each task using the tree representation (m=5.74, sd=2.39). This was followed by the pin icons (m=5.01, sd=1.96), but the difference is not statistically significant (Z=01.613, p=0.107). The least icon clicks were made with building icons (m=4.25, sd=1.73), which exhibit a statistically significant difference to the tree icons (Z=-2.467, p<0.05), but not pin icons (t(17)=1.607, p=0.128). As such we can conclude that the time taken to complete tasks was a direct result of the number of clicks on icons and time taken in detail screens, resulting in worse performance using the tree icons, and comparable best performance using building and pin icons.

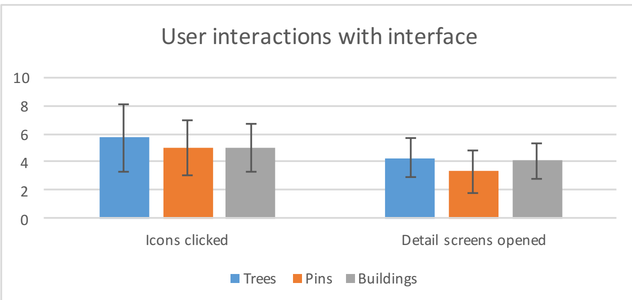

Figure 4. Number of interactions with the UI during tasks

4.2.3 Task success

Given the above, one final issue to investigate was to examine the extent to which icon representations helped participants spot the best candidate landmarks for their selection and to differentiate between popular venues and unpopular ones. For this, we looked at the cases where the task required a popular place to be found and those where the task required the opposite.

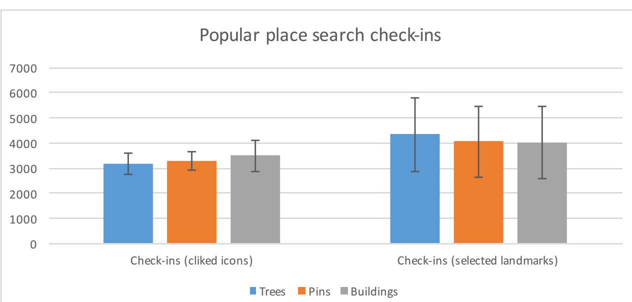

Figure 5. Average check-ins at clicked icons and selected landmarks (searching for a "busy" place)

Where the participants looked for popular venues, on average the venues they examined showed the most check-ins with the building icons (m=3492.49, sd=1321.56). This was followed by the pin icon representation (m=3297.04, sd=821.43) but the difference between the two was not statistically significant (Z=-0.893, p=0.372). The tree icon representation showed the least average check-ins on clicked icons (m=3173.50, sd=878.95), but again this difference was not statistically significantly different to either pins (Z=-0.682, p=0.496) or buildings (t(17)=-0.989, p=0.382). When examining the participants' final choice for each task, we found that when using tree icons, participants selected the venues with the most check-ins (m=4390.94, sd=3135.46). This was followed by pin representation (m=4049.67, sd=3090.34) but the difference between the two was not statistically significantly different (Z=-0.682, p=0.496). The least check-ins at selected venues were found with the building representation (m=4027.11, sd=3098.69), but there were no statistically significant differences between buildings and pins (Z=-0.196, p=0.845) or buildings and trees (Z=-0.517, p=0.605). Our conclusion thus is that all visualisations were equally helpful to participants in identifying and selecting popular venues.

Where the task required participants to discover unpopular venues, we removed data from cases in which participants exhibited clear outliers. We found that participants examined landmarks with the least check-ins using the building representation (m=288.61, sd=928.50). This was followed by pins (m=544.83, sd=837.14), but the difference between the two was not statistically significantly different (Z=-1.590, p=0.112). The tree visualization seemed the least helpful in examining the truly unpopular locations (m=767.44, sd=1141.86) but the difference is not statistically significantly different compared to pins (Z=-0.683, p=0.496) or to buildings (Z=-0.517, p=0.605). Hence all visualizations were equally helpful for identifying unpopular venues.

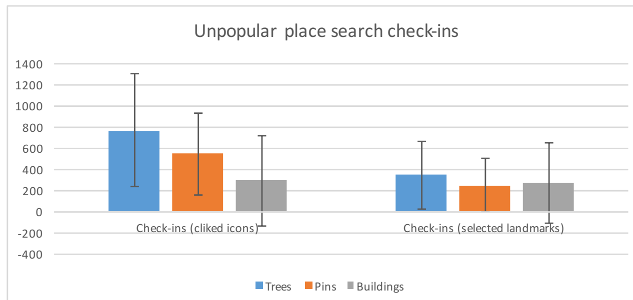

Figure 6. Average check-ins at clicked icons and selected landmarks (searching for a "quiet" place)

Finally, we compared the ability of participants to distinguish between popular and unpopular venues using the three visualisations. As can be seen from the results of statistical significance tests in Table 1, in all cases, participants were able to distinguish between popular and unpopular venues during the exploration of the map and also in their final choices.

Table 1. Statistical significance test results for comparisons between tasks searching for "busy" and "quiet" landmarks.

	Trees	**Pins**	**Buildings**
Clicked landmarks	Z=-3.516 p<0.01	Z=-3.621 p<0.01	Z=-3.516 p<0.01
Selected landmarks	Z=-3.516 p<0.01	Z=-3.516 p<0.01	Z=-3.408 p<0.01

4.3 Self-reported measures

As mentioned, we asked participants to complete a NASA-TLX questionnaire at the end of each session (Fig. 7). From this we excluded the physical effort scale as it doesn't apply to our experiment. The results are thus presented for all other scales of the questionnaire.

We found statistically significant differences in the mental axis between pins and trees (Z=-2.184, p<0.05), meaning that the mental workload was easiest with pins. In terms of temporal demand, we didn't find any statistically significant differences, meaning that our participants, despite our quantitative result findings, did not feel that the time taken to complete the tasks was different with any of the icons used. In terms of performance (i.e. their ability to find suitable landmarks for the tasks), our participants felt equally able to do so with all icons used, confirming our quantitative results.

However, they reported that they expended the least effort in achieving this performance using the pin icons, whereby a statistically significant difference was found when comparing to both trees ($Z=-2.456$, $p<0.05$) and buildings ($Z=-2.039$, $p<0.05$). Finally, in terms of frustration, our participants showed the least frustration with pins compared to trees with a statistically significant difference ($Z=-2.274$, $p<0.05$) but the difference to frustration with buildings was not statistically significant.

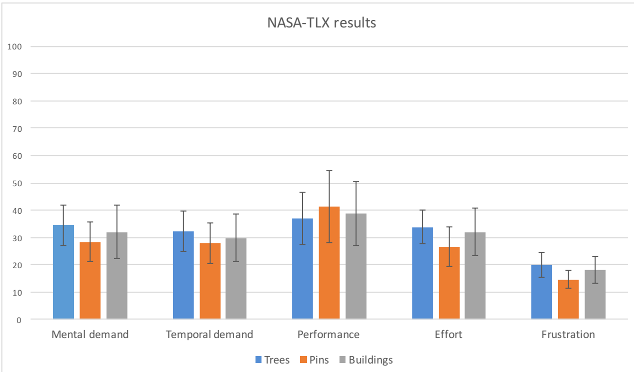

Figure 7. Responses to NASA-TLX questionnaire

Finally, we asked participants a range of questions at the end of our experiment, recorded in Likert scales. In terms of their ability to distinguish between individual landmarks on the map, the pin icons were better received, due to their slim size which limits icon overlap. In terms of being able to understand the popularity of landmarks, participants strongly preferred the building icons. The tree icons were found to be the most aesthetically pleasing but overall the most useful version was reported as the one with the pin icons. This was also verified by the response to a final question regarding which visualization participants would choose if the application was available to them, in which 59% elected the pins visualization, followed by buildings (23%) and trees (18%).

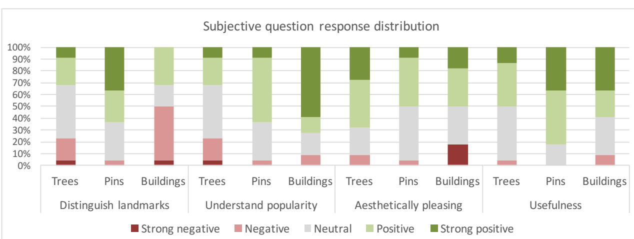

Figure 8. Responses to subjective questions

5. CONCLUSION

In this paper, we examined three different mobile map icon designs for their efficacy in conveying landmark importance to users. We created three designs based on previous literature, which indicate importance by altering the icon size in three ways: using an abstract design and continuous scaling (pins) [2], using a nature-inspired design and continuous scaling (trees) [5] and using a generative design with discrete scaling (buildings) [13]. Although we found that all three designs were successful in helping participants identify and select the best landmarks (popular or not) according to the tasks, our results indicate that the participants were best aided by abstract designs and continuous scaling, as this technique offers the most advantages in cognitive effort, task completion speed and minimization of interaction with the user interface, as indicated by both quantitative and qualitative results. The slim design and lack of visual complexity are the distinguishing characteristics of our pin icons and we should thus recommend that these characteristics are considered by designers in mobile map applications. The generative design performed closely with the pins but given the width, it often resulted in significant marker overlap which hindered users in our application, which contained a large volume of landmarks. This was an issue also with the tree icons, which additionally offered greater visual complexity. Hence we can recommend that generative markers are possibly a good choice where only a few markers have to be displayed on a mobile map. In the future, we would like to extend our work by testing the designs with mobile maps of different landmark density.

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