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Towards Personalized Pedestrian Route Recommendation Based on Implicit Visual Preference

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Abstract. Walking is an everyday, healthy, and eco-friendly mode of transportation. The visual environment of roads is crucial for pedestrians' walking experiences. However, limited research has explored modeling pedestrians' visual preferences for road environments. In this work-in-progress paper, we propose a personalized pedestrian route recommender system based on implicit visual preferences. Our work primarily consists of three parts: 1. Investigate the relationship between human eye movement and visual preferences towards the environment. 2. Explore route recommender system methods based on pedestrians' implicit visual preferences. 3. Dynamically adjust and update recommended results in response to pedestrians' real-time changes in eye movement. This recommender system framework based on implicit visual preferences also holds significant potential for numerous other domains, such as supermarkets, museums, and more.

Keywords. Eye-tracking, Gaze Modelling, Recommender System, Location Based Services

1. Introduction

Pedestrian walking is a sustainable and environmentally friendly mode of transportation that contributes to public health. Enhancing pedestrian satisfaction can increase the willingness to walk, leading to reduced CO2 emissions and contributing to environmental sustainability. Numerous studies have provided support for pedestrian wayfinding using Location-Based Services (LBS) (Huang & Gartner, 2012; Millonig & Gartner, 2011). Route recommendation is also a significant application of LBS, offering individuals more satisfactory travel routes. Early route recommendation algorithms primarily focused on minimizing a single travel cost, such as finding the shortest routes (Kliemann & Sanders, 2016). Personalized route recommendation has

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gained increasing attention over time. Most personalized route recommender systems rely on historical GPS trajectories to model user preferences (Dai et al., 2015). The visual elements of the road environment have been found to be among the factors influencing pedestrians' route choices (Sevtsuk et al., 2021). Nevertheless, hardly any research discusses the role of visual preferences for the environment in personalized route recommendation systems, possibly due to limited visual data sources.

With the rapid advancement of Augmented Reality (AR) and wearable devices, such as Microsoft HoloLens and Apple Vision Pro, it will become feasible to acquire real-time data about the visual environment and the user's visual attention in the future (Kapp et al., 2021). The interactive utilization of eye tracking enables the real-time incorporation of eye movements for Gaze-Informed LBS (GAIN-LBS) (Anagnostopoulos et al., 2017; Kwok et al., 2019). Besides, modeling visual preferences through eye movements is not a new research field. Shimojo (2003) discovered the *gaze cascade effect* that individuals' gaze progressively shifts towards the selected stimulus during a two-alternative decision-making task. Glaholt (2009)'s work validated the use of fixation times as a predictive measure for visual preferences. Previous studies, as mentioned, mainly discuss visual preferences in simultaneous comparative choice-making tasks, lacking research on non-simultaneous and non-comparative tasks.

In this research, we aim at investigating the relationship between human eye movements and visual preferences towards the environment, and explore novel route recommender system methods based on pedestrians' implicit visual preferences. This work-in-progress paper primarily addresses existing research gaps, presents research questions, and outlines the research methodology, and the expected outcomes.

2. Methodology

As illustrated in *Figure 1*, this research will be divided into three parts, each corresponding to a research question.

A. How to model pedestrian road visual preference based on eye movement?

B. How can pedestrian visual preferences improve the satisfaction of route recommender systems?

C. How to dynamically adapt route recommendations using real-time visual feedback?

The combination of these three parts will facilitate personalized pedestrian route recommendation based on implicit visual preference.

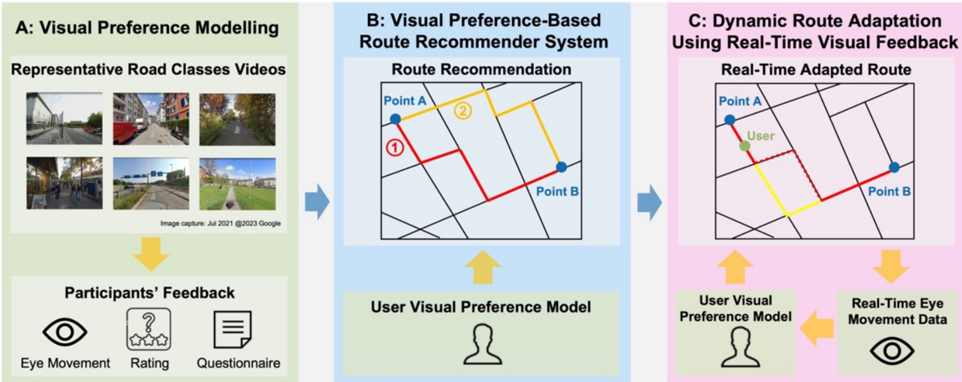

Figure 1. Outline of this research project.

2.1. Visual Preference Modelling

Previous research on visual preferences has mainly concentrated on eye movement patterns among different targets simultaneously and within the same view (Glaholt et al., 2009). However, in this study, the objective is to investigate whether there are pattern differences in eye movement when users observe different street environments with varying visual preferences. This type of non-simultaneous and non-comparative task has been rarely explored so far.

The purpose of this experiment is to explore the correlation between pedestrians' eye movement while walking in different street environments and the participants' subjective preference ratings. The experiment will be conducted in a controlled laboratory setting, simulating the process of pedestrians walking by watching street videos in an immersive environment. Concerning street video preparation, an unsupervised visual clustering model will be utilized to select the most visually distinct road class. This street model is capable of computing the visual similarity between different roads, thereby supporting the content-based route recommender system. As depicted in *Figure 1 (A)*, throughout the experiment, there will be a continuous collection of participants' eye-tracking data (e.g., scan path, fixation, saccade, pupil size, etc.) in the context of road environments. After the experiment concludes, subjective ratings of the street environment by participants will be gathered, along with questionnaires to investigate the reasons behind their ratings. In the data analysis and modelling phase, a preference model will be trained to predict users' preferences based on their eye movement behavior towards the street environment. The preference model, combined with the street model, can utilize the results from a limited set of road environment observations to generalize and predict preferences for a broader range of unobserved roads.

2.2. Visual Preference-Based Route Recommender System

This content-based recommender system suggests routes to users in alignment with their implicit visual preferences. As depicted in *Figure 1 (B)*, the route recommender system will utilize the visual preference model established in the previous experiment to predict participants' preferences for various road environments, based on their eye movement behavior in different environments. In this section, we will formulate a model to rank routes corresponding to users' preferred environments. Participants will engage with videos of various route sets (e.g. red and yellow routes in B), featuring diverse environmental conditions between the route's start and end points in an immersive device. Following the experiment, participants will be requested to provide subjective rankings along with reasons for their choices. The performance of the recommender system will be validated through a comparison of the ground truth ranking and the model's predictive outcomes. It is noteworthy that the selection of route tasks for the experiment will ensure the consistency of non-visual factors, such as route length and turns, across different routes.

2.3. Dynamic Route Adaptation Using Real-Time Visual Feedback

Users' environmental preferences are not static, and how to dynamically model and update them poses a challenge. In this section, building upon the route recommender system established in the previous experiment, we will further explore how to dynamically update recommended routes to accommodate users' evolving environmental preferences. In the experiment, once participants commence their journey, the eye-tracking device continuously captures users' eye movements to dynamically update their preferences in real-time. The recommender system will promptly adjust and update the route to align with the user's current preferences. During the experiment, the route may undergo modifications. As depicted in *Figure 1 (C)*, segments of the initially planned route (red line) have been adjusted to the new path in yellow. After the experiment concludes, participants will review a video of the originally planned route and provide feedback on whether they prefer the adjusted new route and the reasons. The performance of the real-time online system will be validated based on users' subjective evaluations.

3. Conclusion

This work-in-progress paper highlights two research gaps: 1) Generalized visual preference modeling for environments in non-simultaneous and non-comparative views based on eye movements. 2) The lack of research on route recommender systems based on visual preferences. With the aim to fill the existing research gaps， this study proposes the modeling of implicit visual preferences, the development of a route recommender system based on implicit visual preferences, and the concept of dynamically updating routes in real-time to accommodate evolving preferences. We believe that the framework of this visual preference-based recommender system can be extended to various other recommendation domains, encompassing real-world supermarkets, museums, zoos, exhibitions, and more in the future.

Acknowledgements

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The Impact of Simulation Modes on Acquiring Spatial Knowledge through Augmented Reality Landmarks on Windshield

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Abstract. Augmented Reality (AR) has emerged as a promising means to visualize landmarks for wayfinding or spatial learning. The work presented at the last symposium shows that displaying AR landmarks on windshield can be an effective way to support traveler's spatial learning in autonomous vehicles, using simulation consisting of recorded real-life driving video and added AR landmarks in an experimental setup. As the previous experiment setup was completely online, this current study intends to investigate the effects of different modes of simulation on the outcome of spatial learning. This study carries out two additional experiments, one of which is an in-person experiment using the same video-based simulation. The other experiment adopts a different simulation which is completely virtual using the head-mounted display. This study intends to compare the acquired spatial knowledge and eye-tracking measures through all three experimental setups and participant's interactions. As these three experiments represent the commonly used modes of driving simulation, an additional contribution of this study is to compare the effectiveness of different modes of simulations for experiments involving simulations of AR displays on windshield.

Keywords. Augmented Reality, Virtual Reality, Spatial knowledge, Landmarks, autonomous vehicles

1. Introduction

Many studies have pointed out the increasing popularity of using AR to visualize and superimpose additional spatial information into the physical surroundings for supporting wayfinding and navigation (see Liu et al., 2021; Keil et al., 2020). Using platforms for AR landmarks like head-mounted devices

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or smartphones, these studies assess the roles of AR landmarks on spatial learning in the indoor environment. Researchers have also suggested the use of AR landmarks on the windshield of vehicle to enhance traveler's experiences in autonomous vehicles (see Riegler et al. 2021). One main reason of using AR landmarks on windshield is to further engage travelers, as attention of travelers to surroundings in autonomous vehicles decreases significantly.

This research follows up the authors' previous work concerning the degraded spatial knowledge acquired by travelers in autonomous vehicles. Evidenced in studies investigating the acquisition of spatial knowledge using Satellite Navigation Systems (aka. GPS), driver's acquired spatial knowledge become very limited (Ishikawa, 2019; Parush et al., 2007). This situation can worsen in autonomous vehicles as travelers do not need to pay attention to the surroundings or directions at all. The previous work of the authors showed the potentials of using AR landmarks on windshield for supporting spatial learning through incidental learning (Li, 2023). The design of the landmark display builds on earlier research of visualizing unseen distant objects on smartphones (See Baudisch and Rosenholtz 2003, Gustafson et al. 2008, Gollenstede and Weisensee 2014, & Li, 2020) and on windshield through AR (Li, 2023).

The previous study, however, utilizes an online crowdsourcing platform for carrying out the experiments. Additionally, the previous study uses a real-life driving video to simulate the autonomous driving experience. Participants' computer screen can differ in size and interaction can be limited. More importantly, the experimental procedure is unsupervised. Therefore, this study intends to carry out two more experiments: one in-person experiment with the same simulation but on a large flat display and one in-person experiment with a simulation in a fully immersive virtual environment. The results can verify the effectiveness of each testing environment and inform the suitable choice of experiment setup for future studies.

2. Design

The AR landmark display used in this study employed the same design as in the previous study (Li, 2023), which adapts the suggestion of traveler's attention areas of the windshield display in autonomous vehicles (Riegler et al. 2019). Different from the visualization strategies for distant landmarks on smartphone that all edges of the screen are used for visualizing distant landmarks (Li, 2020). The windshield is divided into three portions. As shown in Figure 1, the top portion (20%) of windshield is for displaying unseen distant landmarks. The mid portion (50%) of windshield is for displaying labels for visible local landmarks. The lower portion (30%) of the windshield is for displaying auxiliary information such as street names and speed. Depending on the distance of a landmark in the environment to the traveler's location, the transparency of the landmark will gradually decrease or increase. If the distance is greater than one kilometer, a local landmark becomes transparent and not visible to the traveler. If the distance is shorter than one kilometer and a distant landmark enters the portion of windshield for local landmark display, this distant landmark becomes a local landmark.

Experiment 1 uses the same simulation from the author's study presented at previous symposium of location-based services, that is, a recorded real-world driving video with landmark graphics displayed on the windshield. In comparison, experiment 2 will develop driving simulations in an immersive virtual environment, where 3D models are being used. Participants use a head-mounted display (HMD) to get a stereoscopic view and can physically look around their virtual surroundings. The virtual simulation follows similar experience time and route characteries as in experiment 1. Each experiment consists of four simulated autonomous driving scenarios: on highway with AR landmarks; on local roads with AR landmarks; on highway without AR landmarks; and on local roads without AR landmarks. The last two scenarios serve as controlled conditions in each experiment.

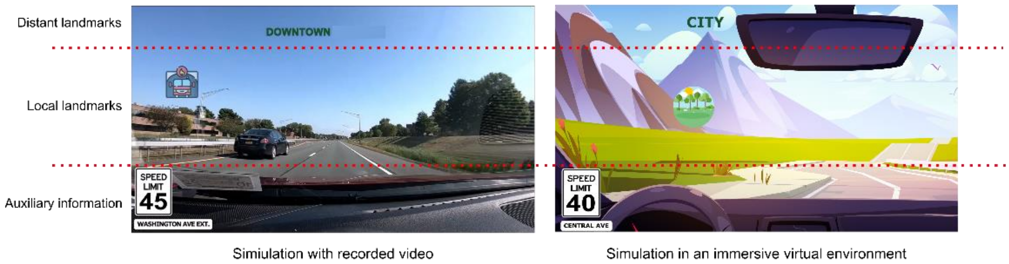

Figure 1: Illustrations of visualized AR landmarks and auxiliary information on windshield in both experiments' simulations. This example of simulation in virutal environment is designed and edited using assest from upklyak from Freekpik.com.

3. Experiment

Instead of using a crowdsourcing online platform with recruited participants from all over the world, this study is performed in a laboratory environment with participants recruited from the authors' university. Experiment 1 uses the same simulations from the previous study in an online environment to make the studies comparable. This time it adapts the same setup of Riegler and colleagues (2019) with which uses a 55 inch flat screen TV for playing the simulation. Like in the previous study, the simulation integrates recorded driving videos in real world and rendered AR landmarks using Adobe After Effects. Experiment 2 uses fully immersive virtual environments as the stimuli with participants wearing the HMD to simulate autonomous driving experiences. The experiments have been approved by the institute review board of the corresponding author's university.

Each participant will complete two scenarios (one with AR landmarks and one without) in a counter-balance order. The order of road types in each condition is counter balanced to avoid the order effect of road type. Each participant can only take part in one of two conditions: 1) highway without AR landmark (H) and local road with AR landmark (LAR); or 2) local road without AR landmark (L) and highway with AR landmark (HAR). Each simulated driving experience is approximately eight minute long which starts with the scenario without AR landmarks. Participants are randomly assigned to one condition. Participants are from the authors' universities with an expected number of 40 in each experiment. In the scenario without AR landmarks in each condition, participants simply watch the video (experiment 1) or experience the immersive virtual environment (experiment 2) as they sit in the driver's seat. In the scenario of AR landmarks, participants will first watch an example to help them understand the design before the experiment. Each participant is asked to view the driving simulation at least three times. They can view it for more times as they could not view it again once experimental tasks start in the laboratory. Eye-tracking data are collected for all participants during these scenarios to investigate the cognitive processing involved in the observation of spatial information. In the testing phase, the first task addresses route knowledge by asking participants to recall the order of landmarks along the traveled route. The second task addresses directional knowledge by asking participant to select two distant locations in the correct directions. Depending on the condition, the distant locations are indicated either by AR landmarks or signs in the environment. The third task addresses the configurational knowledge by asking participants to select the correct route configuration out of three options with the same topology. At the end of the experiment, participants complete a self-rated measure of spatial skills (Münzer and Hölscher 2011) which provides assessment of strategies used in wayfinding including: egocentric strategy, survey strategy, and cardinal strategy. Data collection will be done in the following two months to update the results.

4. Expected Results

While the in-person experiment is still ongoing and the immersive driving simulation is being finalized, it is expected that participant's performance would be different among these experimental setups. The results of both experiments will be compared with the author's previous study using a fully online testing platform with videos on participant's own computers. Participant's performance can be more accurate in the in-person laboratory setting as the screen is much larger than a home computer screen, which brings a more realistic experience to participants. It is also important to compare the effectiveness, as measured in spatial learning tasks and eye tracking, between using recorded driving video and using fully virtual simulation, as the latter condition is more flexible and controllable in experimental design.

5. Conclusion

This study compares the acquisition of spatial knowledge in autonomous vehicles by using two different experimental setups. The first one is using the same simulation as in our previous study which is created by recorded driving videos with rendered landmarks. But different from carrying it out on a fully online platform, this experiment employs in-person experiment with a large display. The second experiment also carries out in person but utilizes a fully immersive and controllable virtual environment to simulate autonomous driving scenarios. The study evaluates the effectiveness of all three setups by comparing online versus in-person experimentations and video-based verses immersive virtual simulations. The results will suggest the suitable testing environment for future studies with experiments addressing different aspects of spatial learning in autonomous vehicles.

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Representation of Local Landmarks in Bicycle Navigation Applications and their Effect on Learning Planned Routes

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Abstract. Learning and remembering a specific route in advance is beneficial to cyclists. As landmarks are known to improve route learning, we tested this in an experiment with 39 participants, where the effect of landmarks displayed as symbols or pictures is compared to no display of landmarks. Participants learned the route from a map and had to remember the route. They were shown the route on a video, simulating the bike ride. At decision points the video was stopped, and participants had to give their turning decisions and their confidence. The study revealed no significant differences between the three groups.

Keywords. landmarks, bicycle routing, user study

1. Introduction

Cycling is becoming more popular in urban and sub-urban spaces. Many cyclists face the problem of memorising route information when navigating in unfamiliar environments. Using navigation tools, such as smartphone apps while cycling, is not always an option since they should pay attention to traffic. However, getting off the bike is interrupting the trip. Thus, we designed a study to test if the way route information is shown to cyclists before a trip could influence their memory of route and hence their performance (rate of wrong turns at decision points).

The main objective of this research is to find out whether the spatial learning process of a planned bicycle route in an urban environment can be improved, in regards of better memorability, by displaying local landmarks in a routing app and by displaying them with either simple, abstract symbols or real-world pictures. We assume the spatial learning process can be improved, when specific local landmarks are shown in addition to the exact planned

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route, resulting in less direction change errors at decision points when navigating this same planned route. We also hypothesise that a real-world picture, having a higher degree of realism, leads to an increased spatial learning of the planned route compared to an abstract symbol, meaning that the route can be memorised better, resulting in less errors at decision points for changes of direction.

2. Related work

As for pedestrian and car navigation, landmarks play a central role for bicycle navigation, wayfinding and spatial learning (Burnett et al., 2001; Cheng et al., 2022; Credé et al., 2019; Duckham et al., 2010; Keil et al., 2020; Lynch, 1960; Richter and Winter, 2014; Siegel and White, 1975; Sorrows and Hirtle, 1999; Yesiltepe et al., 2021). According to Lynch landmarks are significant points of reference that are easily identifiable, contrast with their environment, and exhibit unique or specific properties making them prominent (Lynch, 1960).

Landmarks can be categorised according to scale and visibility into local and global landmarks (Yesiltepe et al., 2021). There is a plethora of properties defining landmarks: uniqueness, distinguished location, visibility, semantic salience (Burnett et al., 2001), singularity (with respect to surroundings, prominence of location, (Sorrows and Hirtle, 1999), visual salience (size, form, colour), meaning, function (Duckham et al., 2010).

Löwen et al. (2019) found that local features and global features have a positive influence on the survey knowledge. Different landmark visualisation styles (e.g., degree of abstraction) have different effects on how those landmarks get recognised and how those can affect spatial knowledge (Kapaj et al., 2021).

3. Methods

To answer the two research questions, we designed a user study, conducted from January 17 until February 14, 2022. 39 participants were recruited by Email from the first author's private and educational network, of whom 21 are male and 18 female. 70 % of the participants were between 25 and 28 years old. All participants gave their informed consent.

The study was conducted in an indoor laboratory at XXX, to allow for a more controlled environment. In addition to a large-screen projection, a bicycle ergometer was installed for the experiment. The bicycle ergometer has no resistance, so that the participant does not have to exert any effort but can simulate the bike riding process.

The maps for the spatial learning process were created with ArcGIS Pro (see Figure 1) and served as a Web Map Application in ArcGIS Online. The web maps were interactive, and participants were able to pan and to zoom between 1:100 and 1:15 000.

The video projected to a large screen represents a route of around 2.5 kilometres and lasts of about 14 minutes. It was recorded with a GoPro camera from a cyclist's perspective. At decision points the video was paused, and different arrows were displayed in the video for the possible directions. The placement of landmarks was done following the approach of *decision points* and *potential decision points* (Keil et al., 2020).

The size of the displayed landmarks was chosen, that they were clearly visible in the scale range. All symbols have the same size, resolution and same level of abstraction to ensure. Symbols of the building are coloured in the main building colour. In addition to that, all of the pictures had to be taken from the front view which the participant sees in the video.

Our experiment follows a *between-subject design* with three conditions (groups of participants): The *without* group sees a map showing the route only, and without any additional landmarks. This group represents the baseline for our experiment. The *symbols* group sees a map with additional landmarks visualised as abstract symbols (see Figure 1). The *pictures* group sees a map with additional landmarks as shown as pictures (see Figure 1). As outcome we measured the performance of the spatial learning process, measured as the number of correct turns.

We controlled for spatial abilities, demographics, geographical knowledge and bicycle experience of participants by balancing them between the three groups. Moreover, we controlled for the experiment conditions characteristics (room temperature, light etc.).

Before the experiment the spatial ability of participants was tested with the Santa Barbara Sense of Direction (SBSOD) test. The experiment was structured into three phases. In the *learning phase* the participants looked at the map according to their group (*without, symbols, pictures*) for two minutes and had to remember the route and the turnings to take. In the *performing phase* participants "drove" the route as displayed by the recorded video. At decision points participants were asked to indicate the direction they need to take to follow the remembered route (see Figure 1). Participants verbally reported their decision (A, B, or C) and how confident they are with the decision (unsure, neutral, sure) to the study conductor. Moreover, decision time, i.e., the period between the stopping of the video at a decision point and when the study conductor is informed of the direction, was recorded. Finally, in the *questionnaire phase* participants filled in a questionnaire (task, map etc.) about the two previous phases.

Figure 1. Maps for participants in *Symbols* (top) and *Pictures* group (bottom).

4. Results

Overall, our results revealed no significant improvement of the spatial learning process when landmarks have been shown on the map in comparison with no display of landmarks. Also, no significant difference could be found for the way the landmarks were displayed, i.e., as abstract symbols or as real-world pictures.

There are indications that landmarks in the beginning of the route helped more in the spatial learning process and the navigation in comparison with the ones visualised at the end.

Participants were asked to make decisions at various points, with landmarks visualized for the *pictures* and *without* groups. The medians depicted on the y-axis in Figure 2 represent the ratio value on how many decisions have been correct over the defined decisions. The analysis revealed that the *symbols* group performed the best overall, while the *without* and *pictures* groups performed slightly worse. However, when considering decisions with landmarks, the *without* and *pictures* groups performed better.

Looking also on spatial abilities, we observed weak positive correlations between performance and spatial ability pre-test scores for all groups, no significant correlation for the *without* group, very weak negative correlation for the *pictures* group, and a moderate to strong positive correlation for the *pictures* group. However, only the correlation for the *pictures* group is significant. We split participants into two groups based on the median of the SBSOD scores which was at around 5 and used it as a second factor in a *Scheirer-Ray*-Hare test. This test showed that the scores in the spatial ability pre-test significantly influenced the participants' decision-making, particularly regarding the number of correct decisions. However, only for decisions where landmarks are displayed the influence of spatial abilities is significant.

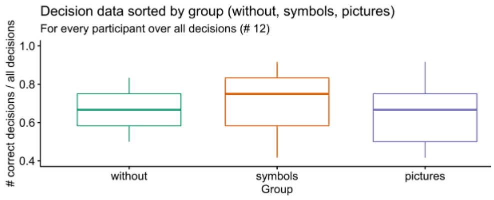

Figure 2. Decision data by group for all participants over all decisions where there are/are no landmarks visualised.

For the confidence in decisions results indicated that the *symbols* group generally exhibited higher confidence in their decisions than the other groups. However, no significant differences were found between the groups in terms of confidence.

Results for decision time are very similar. Decision times are not significantly different for the three groups. Yet, results suggest a tendency for longer decision times in the *without* group compared to the *symbols* and *pictures* groups. Additionally, the *pictures* group had slightly shorter decision times compared to the *symbols* group.

The results of the *post-experiment questionnaire* can be summarized as follows: The majority of participants from the *symbols* group and *pictures* group (26 participants) indicated that the landmarks helped them to some extent to recognize them in the video and with the spatial learning process The first four landmarks were identified as most prominent more frequently than the last three, with landmarks one, three, and four being selected the most. Over 70% of all participants (39 people) stated that they would find it useful if landmarks were displayed as symbols or images in a routing app.

5. Discussion

Our results indicate that there was no significant improvement in spatial learning when landmarks were represented either as symbols or pictures. This contradicts some previous studies suggesting that landmarks are helpful in spatial cognition. The study also analyses the performance of participants in individual decisions along the route and identifies some tendencies. The cognitive load and working memory could affect the impact of landmarks on navigation. The discrepancy between participants' perceptions of the usefulness of landmarks and their actual performance is noted, which is a common phenomenon in research.

We observed that decision time for the participants in the *without* group is marginally higher than for participants in the other groups. One explanation is that through the display of the landmarks the spatial knowledge increased (Credé, 2019, p. 6). So, through the acquired spatial learning process with the help of landmarks, there is a possibility that the answer could be given faster (Li, 2020, p. 432). In contrast, Parush and Berman (2004), stated, that the visualisation of landmarks leads to the further processing of information of the participants, which then can increase the time needed for.

Participants in the *symbols* and *pictures* group were slightly more confident with their decision. This can be explained by the fact, that the spatial knowledge increased, and the spatial learning process was improved (Credé et al., 2019) and (Li, 2020). Participants in the *pictures* group overall achieved more correct decisions than the participants performing in the *symbols* group. A study by Zhu et al. (2022) also found similar results, where the study setting was comparable. (Zhu et al., 2022, p. 677). However, it must also be mentioned that other reasons could have contributed to this result, such as the fact that the participants mostly learned the route from the beginning and that maybe the symbols and pictures in the beginning of the route have been more suitable.

Regarding limitations, the chosen route might have been too simple for most participants due to the high number of participants with a geography background, thus minimising the variability between the different groups. For a follow-up study, attention should be given to the selection of a route and landmarks. The time spent to learn the route from the map has also an important influence (hence lower the effect of landmarks). This assumption is backed up by the fact that participants in the *without* group in this study performed similarly than the two other groups.

6. Conclusions

How local landmarks may influence the spatial learning process and how the symbolisation of those can have different influences was researched in a study at the University of Zurich with 39 participants. Participants were assigned to three groups, which differed in the landmarks were visualised on a map used to learn the route. One group saw a map that additionally showed seven landmarks as abstract symbols (*symbols* group), a second saw them as real-world pictures (*pictures* group), and the third group had only route only without any landmarks (*without* group).

Although no significant results were found on whether landmarks improve the a priori spatial learning process, there are some tendencies that presentation as both symbols and pictures may help and that less time for decision-making and higher confidence may result. It should be kept in mind that a different study design (e.g., different symbolisation) could have led to different results. Future work could employ different landmarks, test other symbolisations, and use eye-tracking to determine which objects are looked at most frequently by people.

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Enhancing indoor spatial knowledge through navigation map design with landmark hierarchy

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Abstract. Landmarks are an important cognitive element in conveying route information in indoor navigation, and their extraction methods have matured. However, in the existing indoor navigation maps, the representation of landmarks is not optimal, making it difficult to obtain spatial knowledge related to navigation (e.g., landmark knowledge and route knowledge). To close this gap, we propose a conceptual model of indoor navigation map design with a landmark hierarchy containing three levels by adjusting the size and highlight of landmark expression, which should contribute to enhancing indoor spatial knowledge. As a proof of concept, a case study is being conducted to evaluate the differences in indoor spatial knowledge of users.

Keywords. Indoor navigation, Landmarks, Spatial knowledge, Map design

1. Introduction

In an era marked by rapid urbanization, especially in complex environments (e.g., airports, hospitals, shopping malls, etc.), navigating indoor spaces efficiently and confidently is a challenge, particularly for newcomers, individuals with impairments, and older people.

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Indoor space lacks semantic annotation, such as road signs as in the outdoor case (Zhou et al., 2023). However, many spatial entities contain rich semantic information around them. Spatial entities with key characteristics recognizable and memorable can become landmarks (Sorrows and Hirtle, 1999), which serve as an important cognitive element to convey route information in indoor navigation (Denis, 1997). Landmarks are fundamental to spatial knowledge acquisition, because landmark knowledge is developed before route and survey knowledge (Golledge, 1999).

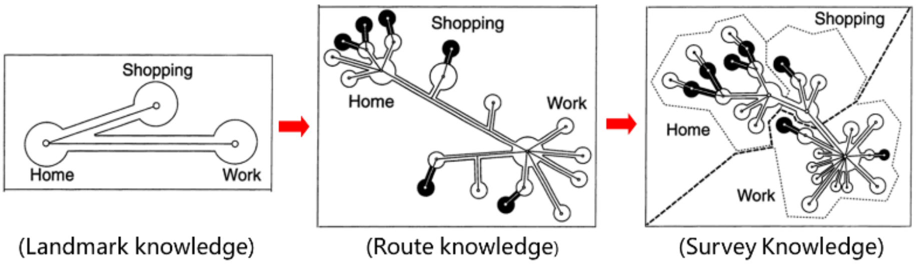

Figure 1. Anchor point theory of spatial knowledge acquisition (Golledge, 1999).

Many studies have adopted and revised the outdoor landmark salience model in indoor landmark selection (Lyu et al., 2015; Zhou et al., 2022). Despite the relative maturity of the calculation methods used for modeling indoor landmarks, there often exists confusion as to how they are represented in navigation maps, especially lacking a clear hierarchy. In the existing indoor navigation maps (Lorenz et al., 2013; Ludwig et al., 2023), the landmarks along the route have no hierarchical expression, making it difficult for users to focus on, and mentally construct spatial knowledge related to navigation.

In summary, there is a need for a navigation map with a hierarchical expression for landmarks that supports both the efficiency of navigation and the acquisition of spatial knowledge for users. Accordingly, we propose an indoor navigation map with a landmark hierarchy that is expected to enhance the spatial knowledge of users in navigation tasks. A case study is also proposed to evaluate the differences regarding the indoor spatial knowledge of users using different map designs.

2. Conceptual model of Indoor navigation map design

As illustrated in Figure 2, Ipsmap (ZIIT, 2023), which is a typical conventional indoor navigation map design, usually displays landmarks on the screen in the same size of symbol or text without hierarchy (Figure 3). In our proposed map design (Prototype map), landmarks along the route are considered to express their hierarchy containing three levels (Figure 4):

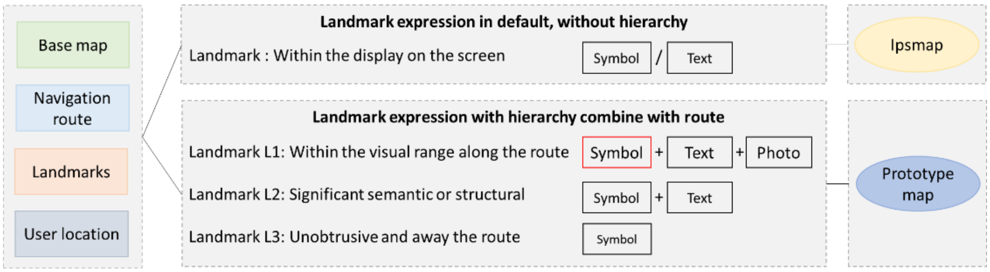

Figure 2. Conceptualized indoor navigation map design with different landmark expression.

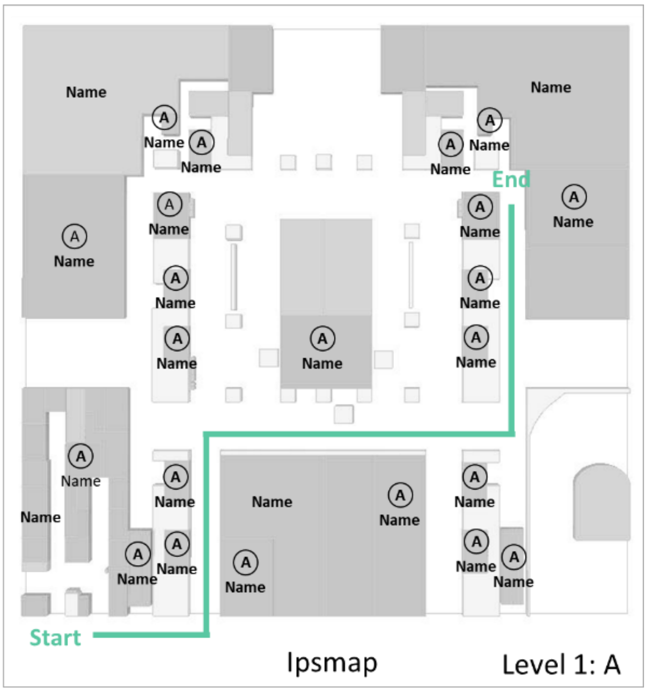

Figure 3. Conceptualization of the Ipsmap design.

Level 1 (L1, highest): The expression of landmarks within the visual range of the route should typically prioritize enlarging the size of symbols with highlights, enlarging annotations size, and adding photos to provide more detailed information. Level 2 (L2): Some significant landmarks of high semantic or structural salience in indoor space can be expressed in a second size of symbols and text to emphasize their importance. Level 3 (L3): The remaining landmarks may only be expressed using a third, smallest size of symbols.

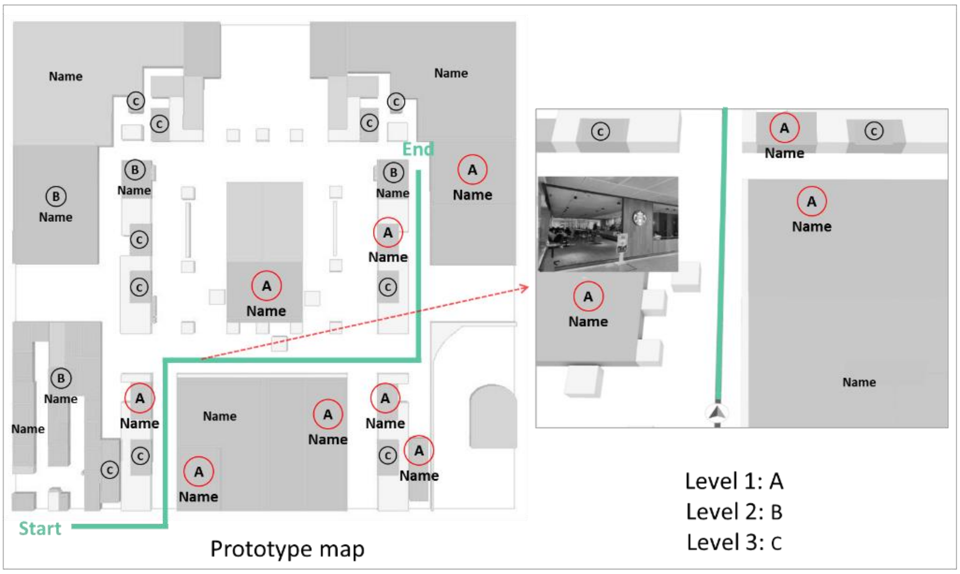

Figure 4. Conceptualization of the proposed indoor navigation map design.

3. Methodology

3.1. Map Design

Firstly, we should select the indoor landmarks in the study area. This part is derived from the previous work on indoor landmark selection based on the Analytic Hierarchy Process (AHP) (Zhu et al., 2019).

The research will employ a 2 × 2 mixed factorial design. The between-subject variable, the sense of direction of participants, has two levels: good and poor. Each participant will be asked to select different maps for navigation: Ipsmap and the Prototype map.

3.2. Evaluation Procedure and Measures

In the user study, sketch maps and landmark locating tasks can be used to assess the results of spatial knowledge acquisition (Liu et al., 2021). The whole procedure will include the following six steps: Steps 1 to 3 have already been completed, and Steps 4 to 6 have not yet been completed.

(1) Demographic information questionnaire. Each participant was first asked to fill in her/his basic information, including gender and age.

(2) Santa Barbara Sense of Direction Scale questionnaire (Hegarty et al., 2002). According to the normal distribution direction scale scores (Dong et al., 2021), a score above 3.89 can be seen as a person having a good sense of direction, otherwise as having a poor sense of direction.

(3) Recalling landmark locating tasks and sketch map drawing. The participants were asked to recall the landmark locations along the route in the base map and draw the sketch map after the navigation tasks.

(4) Pairwise comparison of navigation task completion time between the Ipsmap and the Prototype map user groups.

(5) Pairwise comparison of the correct rate of recalling landmark locations between the Ipsmap and the Prototype map user groups.

(6) Comparison of the correct rate of recalling landmark locations between users with a good sense of direction and a poor sense of direction in the Ipsmap group and the Prototype map group.

4. Case study

We selected the outpatient facility of a hospital in Nanjing, China, as the case study area. Currently, we have finished the user experiments. The pairwise comparison results will be analyzed, which will help to verify whether the proposed navigation map design can enhance spatial knowledge.

5. Acknowledgments

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A Framework for Automatic Selection of Indoor Landmarks using Machine Learning Algorithms and Shapley Additive Explanations

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Abstract. Landmarks are salient objects in an environment compared to their surroundings. However, a challenge of landmark-based navigation is selecting the most salient landmarks to include in route instructions. Current approaches mainly adopt weighted linear models, which assume that landmarks have absolute salience values. However, this contradicts the definition of landmarks as being salient in comparison to their surroundings. In this work-in-progress study, a probability-based soft classification approach is proposed to automatically select indoor landmarks. Specifically, we aggregated fundamental salience measures regarding visual, structural, and semantic dimensions from related studies to create an indoor landmark dataset. Then we, compared the performances of machine learning classifiers with several metrics and interpreted the local contributions of salience measures. Finally, we utilized a probability calibration technique that allows for finer-grained representations of indoor landmarks to include them in the route guidance process. According to the preliminary results of this study, boosting-based machine learning algorithms provide remarkable results, and functional uniqueness, category, and intensity measures are considered more important to select indoor landmarks. Moreover, our soft probability-based classification framework seems promising for selecting and representing landmarks in a fine-grained manner. However, the feasibility of the proposed framework should be further validated with user studies.

Keywords. Indoor navigation, landmark, machine learning, Shapley Additive Explanations

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1. Introduction

Landmarks are defined as prominent objects in an environment that are easily recognizable by their visual, structural, or semantic attributes compared to their surroundings (Sorrows and Hirtle 1999). Hence, including landmarks in the route instructions provides a more natural wayfinding experience, reducing the cognitive load of pedestrians and facilitating wayfinding by helping to organize their spatial mental representations (Hu et al. 2020; Zhou et al. 2022).

A challenge of landmark-based route communication is selecting the most salient objects along a particular route. Specifically, an object should be more salient than its surroundings regarding visual (e.g., color, size, shape), structural (e.g., location, centrality, visibility), or semantic/cognitive (e.g., function, uniqueness, socio-cultural) dimensions (Sorrows and Hirtle 1999) to be considered as a landmark candidate. Current approaches for selecting landmarks mainly emphasize weighted linear models. Typically, studies have adopted a linear model and a set of salience measures that consider visual, structural, and semantic dimensions to compute the salience value of a landmark candidate, following the work of Raubal and Winter (2002). The problem with the weighted linear model-based approaches is it assumes that landmarks have absolute salience (Zhou et al. 2022), which contradicts the definition of landmarks as being salient with respect to their surroundings (Sorrows and Hirtle 1999). Few studies adopted, machine learning (ML)-based approaches to overcome these problems for automatic landmark selection. In these studies, either only one algorithm was utilized to select salient landmark candidates or a classic binary classification pipeline was adopted, which hampers the fine-grained representation of landmarks (Zhou et al. 2022). Furthermore, they merely used global approaches to explain the importance of salience measures, which provides only an overall explanation of the contributions of salience measures. Furthermore, none of the existing studies examined the predictive performance of state-of-the-art ML models such as Random Forest, eXtreme Gradient Boosting (XGBoost), Category Boosting (CatBoost), and Natural Gradient Boosting (NGBoost).

To address the aforementioned research gaps, this study proposes a probability-based soft classification approach to automatically select landmarks from an indoor environment. Firstly, we aggregated fundamental salience measures from related studies. Secondly, we conducted an empirical study to collect ground-truth data for indoor landmark candidates. Then, we examined the salience measures regarding their interrelations and importance for the predictions. Next, we trained some ML classifiers, including some state-of-the-art ones, and evaluated their performances. Moreover, we compared the outputs of algorithms for statistically significant differences via statistical tests. We then used the SHapley Additive exPlanations (SHAP) method to investigate the local contributions of salience measures to explain their impact on the final predictions. Finally, we utilized a probability calibration technique that allows for finer-grained representations of indoor landmarks. Using this technique, we assessed the suitability levels of indoor objects to serve as landmarks in the route guidance process.

2. Methodology

2.1. Overview

This study aims to present a computational approach to automatically select indoor landmarks by using a soft binary classification pipeline. The framework of this "work in progress" study is given in Figure 1.

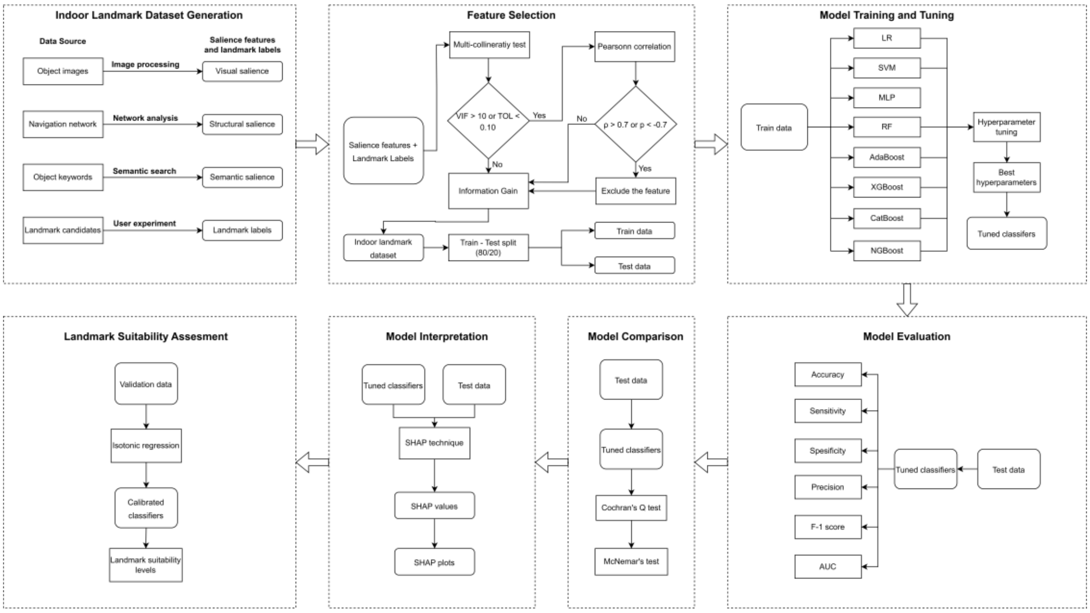

Figure 1. Framework of the study

2.2. Salience Measures

Following the conventional definition of salience dimensions (Sorrows and Hirtle 1999; Raubal and Winter 2002; Hu et al. 2020; Zhou et al. 2022), we derived the salience measures in the visual, structural, and semantic dimensions. The salience measures utilized in this study are given in Table 1.

Salience dimension	Measure	Feature name	Reference
Visual	Color	vis_color	Zhou et al. (2022)
	Intensity	vis_intensity	Zhou et al. (2022)
	Width	vis_width	Dubey et al. (2019)
	Height	vis_height	Dubey et al. (2019)
	Area	vis_area	Hu et al. (2020)
	Shape Ratio	vis_ratio	Hu et al. (2020)
	Unique Label	vis_unique_label	Fellner et al. (2017)
Structural	Visibility	str_visibility	Zhou et al. (2022)
	Permanence	str_permanence	Fellner et al. (2017)
	Distance to decision points	str_decision_point	Dubey et al. (2019)
	Proximity to floor exits	str_floor_exit	Zhou et al. (2022)
Semantic	Functional uniqueness	sem_function	Dubey et al. (2019)
	Category	sem_category	Lyu et al. (2015)
	Text	sem_text	Hu et al. (2020)
	Name prominence	sem_prominence	Hu et al. (2020)

Table 1. Salience measures used for the study (Only permanence measure for the structural category used in this work in progress study)

2.3. Indoor Landmark Dataset

A complex, multi-floor university building has been chosen as the study area to demonstrate our approach We utilized the salience measures to generate independent features for the dataset. For visual salience, the facades of landmark candidates were photographed, and Python libraries was utilized to compute them. The semantic salience measures were computed through various semantic searches. An empirical study was conducted to collect labels of landmark candidates in the study area. A survey was designed that examines the salience of a candidate in the visual, structural, and semantic dimensions. 5 participants (for this work-in-progress study) were gathered who were familiar with the study area to assess the suitability of landmark candidates.

3. Results (Preliminary)

According to the preliminary results of multicollinearity tests, none of the salience measures were found interrelated. The feature importance scores of the information gain method imply that *vis_width*, *vis_area,* and *vis_function* are the most important salience measures. The accuracy metrics of the top three ML classifiers are given in Table 2. Finally, the SHAP values for top-performing algorithms (3 out of 8) show that *sem_category*, *sem_function*, *vis_width*, and *vis_intensity* are the most important measures to select landmarks. The suitability labels provided by the tuned top-performing algorithm (NGBoost) show that approximately 42% of the candidates are "very highly" or "highly" suitable while the rest (58%) are "moderately", "lowly" or "very lowly" suitable.

ML Algorithms	Accuracy	Precision	Recall	F-1 Score	AUC
XGBoost	91.84	88.89	88.89	88.89	91.22
CatBoost	93.88	89.47	94.44	91.89	94.00
NGBoost	95.92	94.44	94.44	94.44	95.61

Table 2. Accuracy metrics of top ML classifiers used in the study

4. Conclusion

A challenge of landmark-based navigation is selecting the most salient ones. The problem with the current approaches is they assume that landmarks have absolute salience. In this study, a probability-based soft classification approach is proposed by utilizing state-of-art ML algorithms to automatically select indoor landmarks. Specifically, an empirical study was conducted to evaluate the predictive performances of ML algorithms and to interpret the local contributions of salience measures with the SHAP method. The preliminary results of this work-in-progress study show that boosting-based ML algorithms outperform others. Category, function, width, and intensity of a landmark are the most important salience measures, and our proposed soft probability-based approach is promising for automatically selecting and presenting indoor landmarks with finer-grained representations. Thus, a finer-grained representation of landmarks can be achieved by indicating the degree of confidence that a given candidate is a suitable landmark which is the limitation of a classic binary classification pipeline.

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Narrative Indoor Navigation – An Approach Using Annotated 360-Degree Camera Documentation

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Abstract. This study investigates the impact of narrative navigation and 360-degree camera documentation on indoor wayfinding. By analysing data collected through user studies, the research aims to uncover the effects of these factors on individuals' ability to navigate and remember information within indoor environments. The study utilises a 360-degree camera mounted on a helmet to capture immersive videos, and participants with diverse navigation expertise will navigate a pre-determined route. Focusing on a complex building within the University of Augsburg campus, the study aims to annotate visible indoor landmarks and explore the potential of narrative navigation and 360-degree video in enhancing indoor navigation effectiveness.

Keywords. Narrative indoor navigation, 360-degree videos, mental map, landmarks, wayfinding

1. Motivation and Research on Indoor Wayfinding and Landmarks

As an everyday task that occurs frequently, indoor wayfinding has received much attention from researchers, especially nowadays when outdoor navigation technology is developing rapidly. It is easy to see that the factors influencing the completion of this task are not only technical (e.g. location accuracy, data display, data loading, etc.) but also social (user

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characteristics, attention, external environment, etc.). This section reviews the current state of research on indoor wayfinding and landmarks over the last five years.

1.1. Social part

Several studies have explored various aspects of indoor wayfinding. Lin et al. (2019) found that repeated exposure and mental stress affect the completion of indoor wayfinding tasks in virtual reality. Li et al. (2019) simulated complex indoor environments to investigate how environmental factors influence people's route choices. Gender differences were examined by Zhou et al. (2020), revealing preferences in information attention and decision-making but not in route reading. Additionally, Wang et al. (2019) highlighted the impact of navigation systems on spatial memory, suggesting the need for system designs that minimise cognitive load and support memory retention to enhance wayfinding performance.

1.2. Technical part

Besides social factors, technological factors are crucial to assist users in indoor wayfinding tasks. Depending on the role in the wayfinding task, the technical aspects can be divided into a landmark recognition component and a localisation component.

1.2.1. Landmark identification

Zhu et al. (2019) developed a scoring system to analyse spatial object saliency, providing insights into factors influencing saliency and aiding in designing effective navigation systems. Afif et al. (2021) introduced a computer vision-based object recognition system for indoor wayfinding, enhancing navigation techniques and improving the wayfinding experience. Kim et al. (2019) proposed a navigation system combining crowdsourcing and landmarks, harnessing collective intelligence to improve navigation accuracy and information richness.

1.2.2. Positioning

Zhu et al. (2019) introduced a mobile phone video-based method for accurate indoor localisation, improving tracking reliability in complex indoor environments. Fusco et al. (2020) developed a real-time smartphone application using computer vision for indoor localisation, contributing to accurate and accessible techniques for integrated wayfinding applications. Zhang et al. (2019) proposed a framework for identifying indoor activities, enabling the development of robust activity recognition systems for personalised and context-aware indoor navigation experiences.

This study diverges from Zhu et al. (2019) by focusing on the potential application of 360-degree video range in indoor navigation. Traditional indoor wayfinding often involves searching for specific items, such as a book in a library, requiring attention and using various tools. 360-degree video recording can address this by identifying more visual cues, like specific signs or books, and creating a "mental map" that guides users directly to their desired location.

2. Methodology

This study assesses how narrative navigation and 360-degree camera documentation impact indoor navigation. By comparing different techniques, the research aims to uncover their effects and advantages on individuals' ability to navigate effectively within indoor environments. The details will be written below:

- Data Acquisition Equipment: To capture immersive videos of the indoor environment, we will use a 360-degree camera mounted on a helmet (see *Figure 3*). Continuous recording will be ensured by employing a power bank as a reliable power source.
- User Study Design: The user study will involve recruiting participants with diverse levels of expertise in navigating indoor environments. To assess their navigation abilities, a preliminary questionnaire will be administered. Participants will then be tasked with navigating a pre-determined route designed by the researchers. Following the navigation exercise, a subsequent questionnaire will be employed to evaluate participants' spatial awareness and memory recall during the navigation process. Additionally, participants will be requested to create a mental map based on their experience with navigation aided by 360-degree camera documentation. This user's study is a within-subject design. Below in *Figure 1* is the user study flow:

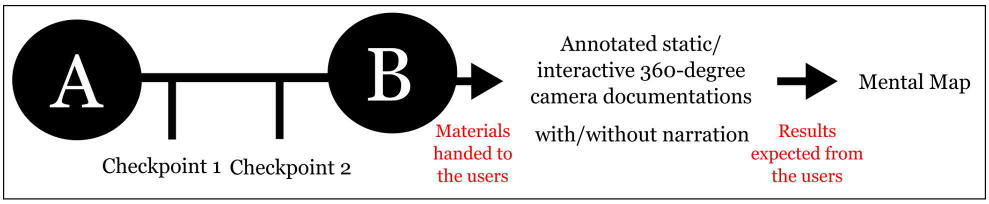

Figure 1. User Study Design Scheme (Source: Authors).

The frames or videos of the 360-degree camera documentation are methodically ordered to ensure data accuracy, facilitating a coherent narrative progression. Participants are also encouraged to annotate the locations they encounter, contributing to documenting their cognitive processes. At designated checkpoints, rewards are provided to promote engagement and motivation. All the users will be assigned to user groups based on their navigation skills, which will be measured by taking pre-questionnaires. Following *Table 1* represents the group of users we need in this study based on *Figure 1* above:

Interactive Video without narration	Interactive Video with narration	Static Frames with narration	Static Frames without narration
Expert	Expert	Expert	Expert
Novice	Novice	Novice	Novice

Table 1. User Groups (Source: Authors).

3. Data Collection and First Insights

Our case study at the University of Augsburg campus focused on the complex wayfinding within building D, which provides access to facilities like the cafeteria and library. Using an Insta360 ONE X2 camera, we captured 360-degree video footage to annotate visible indoor landmarks. Potential test subjects recorded frame numbers/IDs and pixel coordinates for reference. Two example frames of raw data are visualised in *Figure 2*.

Figure 2. Example of A Raw Data Frame (Source: Authors).

Within our annotation procedure, we integrate the option of defining video frame windows with varying pixel coordinates for the same indoor landmarks. This allows for a more detailed analysis. Our Mental Map Design incorporates a feedback loop to optimise our methodology. Our initial experiment used an Insta360 ONE X2 camera and a power bank mounted on a bicycle helmet (*Figure 3*). The investigation area includes the library, cafeteria, and lake (*Figure 4*).

Figure 3. Experimental Device (Source: Authors).

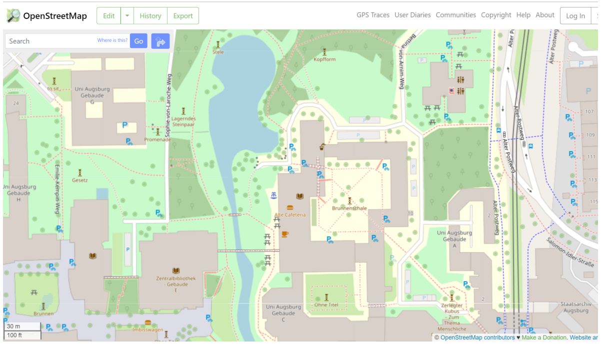

Figure 4. Study Area (Source: OpenStreetMap).

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A Comparison of Virtual Reality Locomotion Techniques in Indoor Environments

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Abstract. The proposed study explores diverse virtual reality (VR) locomotion techniques, categorized as motion-based, controller-based, and teleportation-based methods. With a focus on confined Virtual Indoor Environments (VIE) that integrate indoor cartography, 3D cartography, and VR, this research employs a within-subject design in static settings. Utilizing Unity-generated environments and HTC Vive Pro Eye headsets, controllers, and trackers, the study examines spatial cognition and user experiences to determine the suitability of the methods in this type of environment.

Keywords. Virtual Reality, Locomotion, Indoor, User Study, Spatial Cognition

1. Introduction

Locomotion in VR is one of the important aspects of building an immersive virtual environment. It is necessary to provide a means to navigate the environment for the user. It can be achieved by using a variety of hardware devices as well as different software methods.

Several criteria can categorize virtual locomotion. Boletsis (2017) propose classifying the locomotion techniques into four distinct groups. Motion-based techniques use the user's physical movement to enable locomotion and interaction in the environment, typically using continuous movement. Room scale-based techniques are similar to motion-based but aim to use the natural walking of the user for navigation in the environment. Because of this, the dimensions of the virtual environment are bounded to the user's physical space. Controller-based techniques use an artificial controller to enable the continuous movement of the user. Finally, teleportation-based techniques also use a controller, but the user's movement is realized in discrete jumps. All these types have their benefits and disadvantages.

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Even though the research on different virtual locomotion methods has gained momentum, not all aspects have been studied, especially regarding their usability in different virtual environments. One of the specific types is an indoor environment. It presents limited space with defined borders (usually represented as walls), preventing free (direct) movement and limiting environmental visibility. Indoor also has specifics regarding verticality including moving between different vertical levels (floors). For this study, virtual environments of this type are called virtual indoor environments (VIEs). VIEs can be perceived as a combination of indoor cartography, 3D cartography, virtual reality, and (in some cases) building information models (BIM). However, the combination of the unique characteristics of the VIEs and the different locomotion methods has yet to be thoroughly studied as there are not many studies combining these characteristics (Pospíšil 2023).

2. General Method

2.1. Procedure

User study will use a within-subject design with the order of locomotion techniques randomized between users. As the primary environment will be static (spatial composition and dimensions will not change), every locomotion technique will use a different path (similar in length) through the environment. This way, the impact of participants learning the spatial characteristics of the environment should be mitigated. Workflow of the experiment is shown in *Figure 1*.

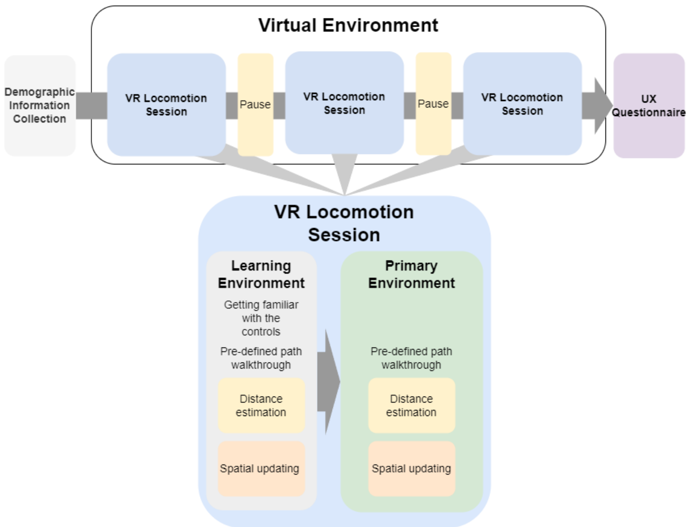

Figure 1. Workflow of the experiment

During each VR locomotion session, the participant will be asked to estimate the distance of a predefined part of the path. After finishing the whole path, participant will be asked to estimate the distance of the whole route and to point in the direction the walkthrough started. The angle between the direction participant points and the starting point will be measured to provide data about spatial updating. During the whole walkthrough, positional data and a view direction of the participant will be recorded.

After all the locomotion sessions are concluded, participants will take a questionnaire aimed to assess the user experience for all the virtual locomotion methods. For this VR Locomotion Experience Questionnaire developed by Boletsis (2020) will be used.

To have a variety in the types of locomotion methods, especially regarding the artificial vs. natural movement and continuous vs. non-continuous types, these methods will be used: **teleportation** (artificial, non-continuous), **controller** (artificial, continuous), and **walking-in-place** (natural, continuous). The study will not use a real-walking method (representing room scale-based methods) as it is technically and financially challenging when using a building/floor-scaled environment.

2.2. Materials

The user study will use an environment created by de Cock (2022), representing one floor of a semi-fictive building (*Figure 2*) as the primary environment. A less complex fictional (training) environment is used to familiarize users with the locomotion technique. Both virtual environments are developed in the Unity engine.

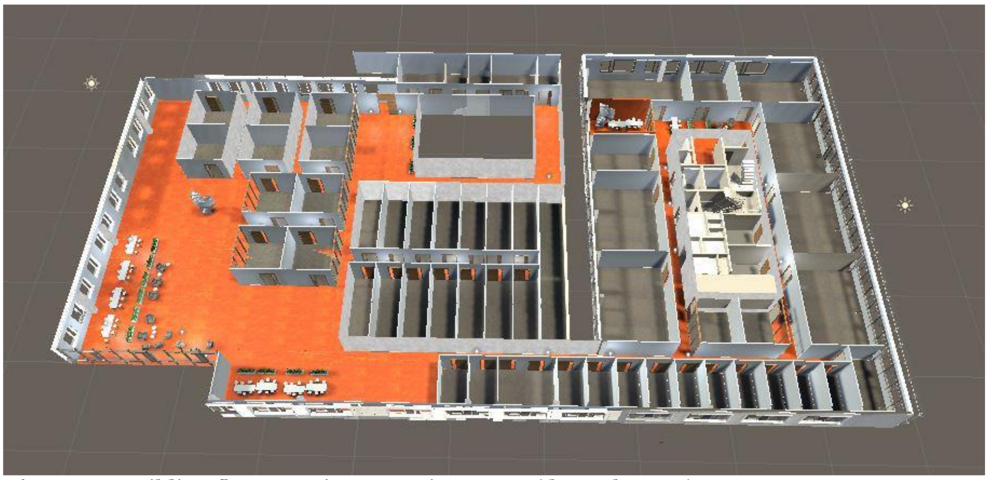

Figure 2. Building floor as primary environment (de Cock 2022).

HTC Vive Pro Eye will be used as a VR device with default HTC controllers to be used for the movement control (in controller and teleportation methods). To obtain information about movement of participant legs, Vive trackers v2.0 are attached at an ankle level and monitored by two Vive Lighthouse base stations. To translate the movement to the virtual environment, custom scripts are created in the Unity engine.

3. Conclusion

The proposed experiment aims to gather data for evaluating users' spatial cognition across various locomotion methods. This endeavour seeks to clarify the impact of locomotion on user perception and potentially determine the most apt methods for future Virtual Indoor Environment (VIE) studies. Additionally, the study assesses user experience subjectively, offering insights into the immersivity of different techniques.

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Route-Friendly Navigation With 3D Curved City Visualization

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Abstract. 3D city navigation can provide spatial information services in the rapidly changing geographical context and is widely used in commercial systems and scientific research. Traditional 3D navigation has an occlusion effects because of 3D buildings that impedes the transmission, acquisition, and perception of geographic information. This paper introduces 3D curved city visualization with visualization of unobstructed paths, customized visualization of landmarks, and multiple navigation modes into 3D city navigation. The results indicate that the proposed technique can effectively decrease the occlusion effects in 3D visual scenes, enhance users' spatial information acquisition and perception ability in 3D city navigation scenes with dynamic changes which improves users' wayfinding ability and enhances the user-friendliness of navigation.

Keywords. navigation friendly, 3D city visualization, occlusion effect, spatial cognition, wayfinding, landmark

1. Introduction

Navigation map is a comprehensive product that integrates mapping, positioning and information services, and plays an important role in path planning, space resource allocation and other fields. Based on the navigation map, 3D city navigation combines 3D urban spatial information to provide spatial information services for the rapidly changing geographical context, meeting users' requirements for 3D visualization and spatial wayfinding of navigation maps. Traditional 3D visualization methods, such as perspective projection, can cause geographical entities near the view point to block geographical entities far away from the view point, affecting the transmission, acquisition, and perception of urban environment. Many researches are developed to improve 3D city navigation from the first-person perspective

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and the third-person perspective. The use of non-standard perspective projection (Moser et al. 2008, Degener & Klein 2009, Deng et al. 2011) required a high level of expertise, which was not convenient for technical implementation; at the same time, this method lacks flexibility. Static visualization (Grabler et al. 2008) was used to simulate spatiotemporal dynamic navigation tasks. Only one kind of person perspective navigation visualization is studied (Deng et al. 2016), but it is not applicable to systems requiring multi-person perspective navigation, which is short of the user's interactivity and can't satisfy the initiative of spatial cognitive process in navigation. Visual effects (Vaaraniemi et al. 2013) were defined by designers, but it cannot meet the multiple needs of users caused by cognitive difference in multiple navigation processes. In the way-finding process, the user's movement behaviors are spatiotemporal dynamic, and the geographic location and context changes continuously and dynamically. Therefore, the navigation process is a process of dynamic cognition of geographical space. How to reduce the occlusion effect, improve the navigation effect and enhance the friendliness of navigation visualization in the dynamic and real-time changing geographical environment is the key and become the difficulty of 3D city navigation visualization research. To solve the above problems, this paper introduces the visualization of 3D curved deformation with urban environment, with the visualization of unobstructed paths, the visualization of customized landmarks, and multi-navigation modes into 3D city navigation, to improve the way-finding effects.

2. 3D Curved Visualization of Terrain Deformation

Non-standard perspective projection visualization involves changing projection mode and image fusion technology, which is not suitable for dynamic and autonomous navigation tasks. Considering that the characteristics of the electronic map itself and the representation method are very important factors (Schäfers et al. 2008), this paper introduces terrain deformation visualization into 3D urban navigation. Terrain deformation refers to the use of spatial surface function to simulate the city topography. The spatial surface function is user-defined, so the deformation can also be customized according to user needs and urban layout characteristics, as shown in *Figure 1*. In the process of navigation, the user's spatial position changes dynamically in real time, and the user's position in 3D scene also changes dynamically in real time. Therefore, this paper designs dynamic adaptive deformation with the change of user's position that has a better viewshed. As shown in *Figure 1*(b), terrain deformation of 3D city will change adaptively with the movement of user's spatial position, so that the Angle characteristics of the user's spatial perspective will remain unchanged no matter where the user drives on the route.

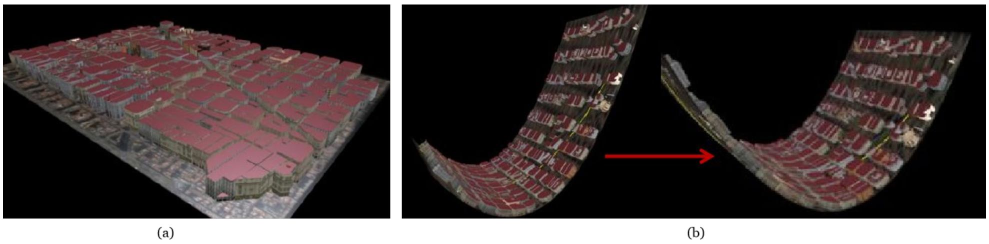


Figure 1. Visualization of terrain deformation.(a) No deformation.(b) Terrain deformation.

3. Visualization of Unobstructed Paths

As one of the spatial knowledge of spatial cognition, the cognition of route knowledge is very important. Users need to obtain the full visibility of the navigation path and the spatial relationship between the road and the urban spatial layout. In order to enhance the user's perception of route knowledge, the navigation map design should emphasize the way-finding information for user cognition, and weaken or delete the irrelevant information to user cognition that influence the access the route infomation. In this paper, the unobstructed path visualization with 3D curved city is introduced into 3D city navigation to avoid buildings from blocking the path. The principle of unobstructed visualization is to use the line of sights between the viewpoint and the sampling points on the navigation path to calculate and find 3D models that need not to be visualized. As shown in *Figure 2*(a), the path is blocked by buildings, making it difficult to acquire route knowledge. On this computation, this paper designs real-time dynamic unobstructed visualization of navigation path, that is, users can observe the navigation route at any location. As shown in *Figure 2*(b) and *Figure 2*(c), the approach keeps the enable adaptive real-time dynamic hiding or transparent occlusion. No matter how the view angle is switched, the object blocking the route is always hidden or transparent, making the path visible online.

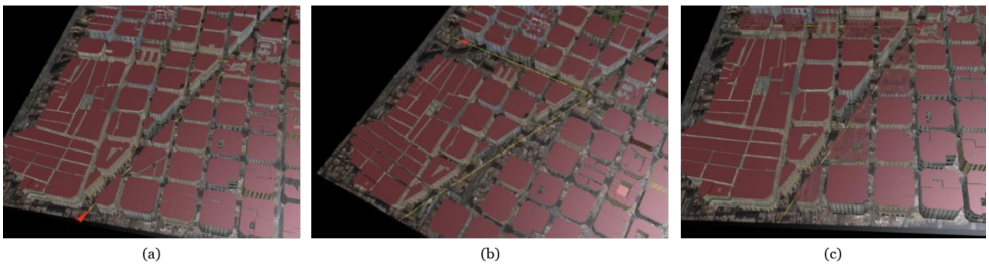


Figure 2. Route unobstructed visualization.(a) No processing.(b) Hidden visualization.(c) Transparent visualization.

4. Visualization of Customized Landmarks

Landmark, as the most basic knowledge in spatial cognition, is very important to determine the position and direction in the process of navigation wayfinding. When entering an unfamiliar environment, the users tend to use landmarks as AIDS to locate (Schafhitzel et al. 2011). Each user needs differentiation in the way they visualize landmarks of interest and landmarks of disinterest. Therefore, this paper designs the user-defined landmark labeling and landmark visualization.

Landmark selection indicates the users can select landmarks of interest according to his preferenc degree through the mouse or other input devices. Landmark custom visualization means that users can use the visualization function to highligt the selected landmark. For the more clear and familiar landmarks in the user's mental map, the landmark can be highlighted or its height or size can be raised or enlarged (*Figure 3)*. To enhance the users' spatial cognition, and users can use this as a reference to identify and determine their position and direction in the route wayfinding.

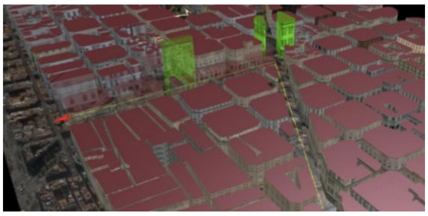


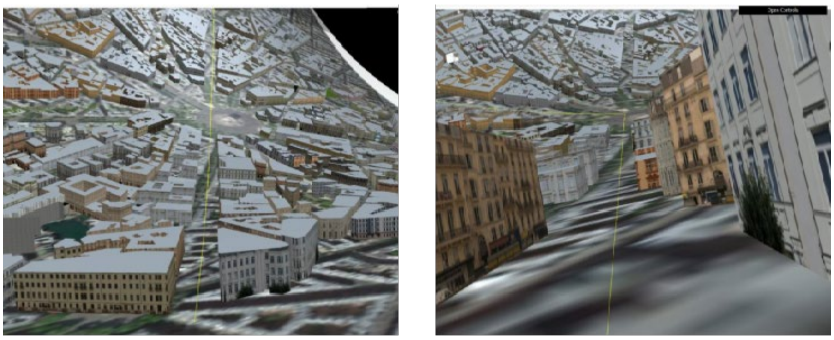
Figure 3. Landmark green visualization

5. Multiple navigation mode

First-person perspective navigation has advantages in route tracing and simulating user perspective in reality, which can bring immersive navigation experience. The third person perspective will provide the global direction of the path and the bird-view of the urban layout, which is suitable for panoramic navigation. This paper designs a variety of personal navigation modes including first-person/ third-person perspectives, as shown in *Figure 4*, which can be seamlessly switched and connected to meet users' requirements for various navigation tasks and give the system a more perfect navigation experience. 3D curved urban visualization can enlarge the view range of the ahead route with urban context that accelerate user cognition to obtain the direction and distance in wayfinding process.

6. Conclusion

In this paper, 3D curved urban deformation visualizations with path unobstructed visualization, landmark-enhanced visualization, and the comprehensive applications of multiple navigation modes are introduced in urban navigation. In future, we aim to quantitatively study the comprehensive cognitive effects of these techniques on user wayfinding and navigation in different visual environments and with the help of eye-tracking techniques.



(a) (b)

Figure 4. Multiple navigation mode with 3D curved visualization: (a) Third person view.(b) First person view.

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On the Impact of Classification Quality of Multiple Object Tracking Systems on Analysing the Path Choice Behaviour of Multimodal Traffic

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Abstract. Multiple object tracking (MOT) systems are increasingly used for acquiring comprehensive motion data relevant to many fields of traffic research. Due to an increased interest in multi-modal traffic, the ability of such systems to distinguish between different object classes is a relevant quality criterion. This work discusses different aspects of classification quality and analyses the quality of two classifying systems at the same intersection in a comparative manner. Preliminary results show that the classification might be challenging for behaviour analysis and approaches to address the challenges are discussed.

Keywords. Traffic Trajectories, Multiple Object Tracking, Object Classification, Behaviour Analysis

1. Introduction

Multiple object tracking (MOT) systems are increasingly used for acquiring comprehensive motion data relevant to many fields of traffic research (Jiménez-Bravo et al. 2022). Their ability to track every object in a particular location allows the resulting trajectory data to be used for comprehensive analyses of traffic participants' behaviour (Yuan et al. 2019), for the calibration of microscopic models (Zhao, Knoop, and Wang 2023), for infrastructure supported collision warning systems (Liu, Muramatsu, and Okubo 2018) and for digital twins (Wang et al. 2022). While early research was mainly focused on motorized vehicles, attention is increasingly given to multi-modal traffic. Especially vulnerable road users and their interaction with other vehicles are of great interest. Hence, MOT systems are required to reliably classify different types of traffic participants.

As part of our current research, we investigate methods to assess the classification quality of MOT systems while treating the generating system as a

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black box and methods to meaningfully analyse the path choice behaviour of multi-modal traffic in the presence of imperfect classification. In this work, we discuss different aspects of classification quality. We then present preliminary findings from comparatively analysing the classifications of a LiDAR-based MOT system and an optical classifier. We conclude this work by a discussion of the findings, their implications for path choice analysis, and the path choice analysis approach we are currently investigating.

2. Different Aspects of Classification Quality

The classification accuracy, i.e., the percentage of objects that the system assigns the correct class to, is a relevant quality criterion of MOT systems (Luiten et al. 2021). Additionally, the granularity of classification, i.e., the number of object classes that the system can distinguish, should be considered. A system that classifies objects into less classes might achieve a higher accuracy than a system that distinguishes more classes, but its resulting classifications might be less valuable for applications as objects with different characteristics might be combined in one class. Especially different groups of vulnerable road users can be difficult to distinguish, e.g., pedestrians, pedestrians pushing their bicycle or a baby stroller, and riders of bicycles, electric bicycles, electric scooters or different types of motorized two-wheelers. However, distinguishing these traffic participants is of great interest when analysing their behaviour.

In the case of MOT systems that operate in real-time, the stability of object classification is another quality criterion. Such systems can only use information up to the time of calculation and future information might change the classification of an object. An additional processing step is then required to decide on the final classification of an object when it is ambiguous.

3. Experiments

As a testbed for our research, we use an intersection in the City of Salzburg located at 13.0642° longitude, 47.8097° latitude. Six LiDAR sensors (31° vertical field of view at 1° resolution, 360° horizontal field of view at 0.18° horizontal resolution at 10 Hz) and a state-of-the-art perception software running at the roadside are used to detect, track the movement of, and classify traffic participants. This LiDAR-based system (LS) continuously sends time-referenced object positions and additional object attributes with a frequency of 10Hz to a server that assembles the single object measurements to object trajectories. The real-time characteristic of the LS causes classification to vary within a trajectory. Additionally, the intersection is equipped with four optical systems (OS) for detecting and classifying traffic participants. While the LS is designed to track objects through the whole intersection, each OS is focused on a specific area aiming at a reliable detection and classification there. To analyse the classifications of both systems, we fuse the classifications from one OS with LS object trajectories using spatio-temporal information. As a result, every trajectory that intersects the classification zone of the OS gets an additional classification. The layout of the intersection and the position of sensors relevant to the experiments are shown in Figure 1.

The following findings are based on data from a two-hour period in which the OS detected 718 cars, 37 trucks, 10 buses, 24 motorbikes, and 37 bicycles. The LS can distinguish vehicles, two-wheelers, and pedestrians. Table 1 compares the classification of objects between the LS and the OS.

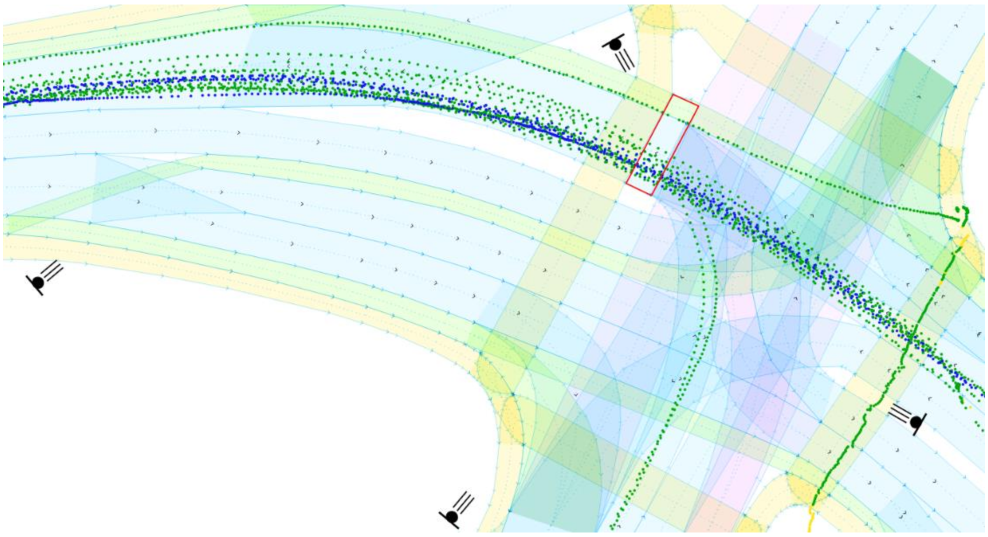
OS\LS	% vehicle	% two-wheeler	% pedestrian	% unclassified	total
truck	94.6	5.4	0	0	37
bus	90.0	0	0	10.0	10
car	99.3	0.4	0	0.3	718
motorbike	29.2	70.8	0	0	24
bicycle	10.8	86.5	0	2.7	37

Table 1. Percentages of LS object classes in terms of the most frequent classification per trajectory for each OS object class.

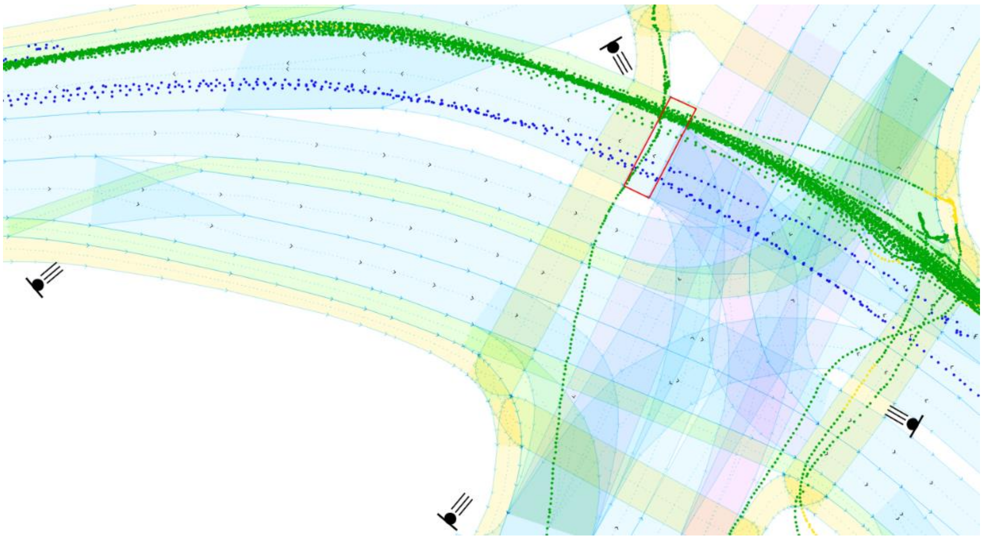
Additionally, we visualize the trajectories of each OS class for further analysis. Bicycle and motorbike trajectories are shown in Figure 1. We find that the LS classifies both OS motorbikes and OS bicycles mostly as two-wheelers and sometimes as vehicles. Some objects are classified as pedestrian momentarily, but the classification of all objects is stable enough to be unambiguous. The presence of a dedicated bicycle lane and the speed of the objects provide further indication on the classification accuracy of the systems. One OS motorbike is slowly driving on the bicycle lane after it used the zebra crossing where it also was classified as pedestrian by the LS. This could be a cyclist that pushed his bike over the crossing and then started riding. Several OS bicycles are classified as vehicle by the LS and do not use the dedicated lane.

4. Discussion

Mostly, the two systems' classifications are in correspondence. Objects classified as cars by the OS are seen as vehicles by the LS very consistently. However, OS classified motorbikes and bicycles are sometimes classified as vehicle by the LS. The granularity of the LS classification is challenging for further analyses, as it does not distinguish between bicycles and motorized two-wheelers. Fusing trajectories with OS classifications allows for that distinction, but a subclassification is not implemented either. While a subclassification of vehicles into cars, busses and trucks is common, classifying different types of bicycles, e.g., cargo or electrical bicycles, is still challenging.



a) OS classified motorbike trajectories



b) OS classified bicycle trajectories

Figure 1. LS trajectories of objects that have been classified as motorbike (a) and bicycle (b) in the red quadrangle by the OS. Point colour indicates the LS classification (blue = vehicle, green = two-wheeler, yellow = pedestrian). Coloured areas correspond to vehicle lanes (blue), bicycle lanes (green), walkways (yellow), and bus lanes (pink). Black symbols indicate the positions of LiDAR sensors.

Additionally, the accuracy of classifications is in question considering the paths of trajectories. For a concrete evaluation, ground truth information is necessary. A reclassification of objects using features derived from attributes such as speed, size, and lane choices might improve accuracy. Supervised learning with manual classifications as targets could implement this. However, using such features for a reclassification will bias analyses. For example, if the position on or off the cycle lane is utilized to distinguish motorbikes from bicycles, further behaviour analyses cannot reliably investigate how many cyclists do not use the cycle lane, as such objects would not be classified as cyclists. Hence, classification should be based on the shape of objects alone. In the presence of imperfect classification, behaviour analysis should follow an approach that does not rely heavily on a detailed and accurate classification. To this end, we look into trajectory clustering as a method to detect different path choices of traffic participants crossing the intersection from one particular side to another. This way, the focus is on the paths taken to cross the intersection. Then, we can analyse each cluster of trajectories with respect to various features, including object classes, that might explain the path choice. Consequently, we get an idea which objects (and in which situations) tend to use a certain path. First experiments show promising results.

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Bikeability and Beyond: Approaches for Measuring the Quality of Cycling

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Abstract. In this paper, we explore how the quality of urban cycling can be measured and analyzed with GIS and location-based data. We discuss different approaches and focus on measurements with ultrasound sensors.

Keywords. Cycling, sensors, GIS analyses, Bikeability

1. Introduction

Many cities want to become more bicycle-friendly for different ecological, economical and other reasons. However, the actual urban cycling experience is impaired by several factors, such as the lack of cycling infrastructure, the low quality of cycling paths, or cars that overtake to closely.

One approach to measure the quality of urban cycling is the "cycling climate" by the Allgemeiner Deutscher Fahrrad-Club (ADFC) Fahrradklimatest[1]. The test, which is actually a survey among citizens, assesses 27 criteria, which are aggregated into five major factors.

While the ADFC Fahrradklimatest gives a good first overview about which cities can be regarded as cycling-friendly and which aspects are regarded as good and bad in certain cities, there are two shortcomings of this ranking: Firstly, it is more based on subjective factors (citizens' assessments) than on actual objective measurements. Secondly, it only gives an overall score for the city and thus does not differentiate between different areas within cities. Hence, it does not show *where* exactly action should be taken.

Here is where geospatial thinking and location-based approaches come into play. In this paper, we discuss several approaches how quality of cycling can be measured with location-based data and then focus on the measurement of overtaking cars.

[1] https://fahrradklima-test.adfc.de/

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2. Related Work

The concept of bikeability as an indicator for cycling friendliness has been developed, discussed, and applied by several authors (e.g., Gehring 2017, Nielsen et al. 2018, Schmid-Querg et al. 2021, Hardinghaus et al. 2021) in different cities with different administrative areas (polygons), path segments or raster cells of equal size. Different approaches have also considered different factors that might positively or negatively influence the attractiveness of neighbourhoods for cycling activities. Factors include topography, cycling infrastructure, or landscape aspects. The importance of perceived safety and physical road properties for individual and group differences in cycling route choices have been evaluated by Hardinghaus & Cyganski (2019).

Werner et al. (2023) argue that mixed methods (that is, a mix of qualitative and quantitative approaches) studies are particularly useful to further answer cycling-specific domain questions. They identified and defined three main aspects of interests: safety (objective/perceived), stress (individual) and smoothness (simplicity, speed). The effect of passing distances in urban areas as indicators for stress and safety have recently been investigated by Beck et al. (2021) and Stülpnagel et al. (2022).

3. Measuring the Quality of Cycling: Broader Research Context

The broader context of our research is to investigate the quality of urban cycling and how it can be measured. The focus is on location-based data within the research area of the city of Würzburg.

At the time of writing, our work packages include:

1. Calculating bikeability to identify intra-urban differences in different neighborhoods of the city, based on a 100x100m raster
2. Building a cycling path cadaster with meaningful categories as a foundation for further analyses
3. Validating theoretical accessibility analyses with systematic test rides to identify the influence of topography and building structures
4. Developing methods for quantifying landscape aspects such as scenery
5. Measuring roughness of cycling paths with shock sensors
6. Analyzing smoothness by systematic speed measurements and identifying waiting times

7. Analyzing safety based on user surveys, historical accident statistics and ultrasound sensors for identifying places where cars overtake too closely

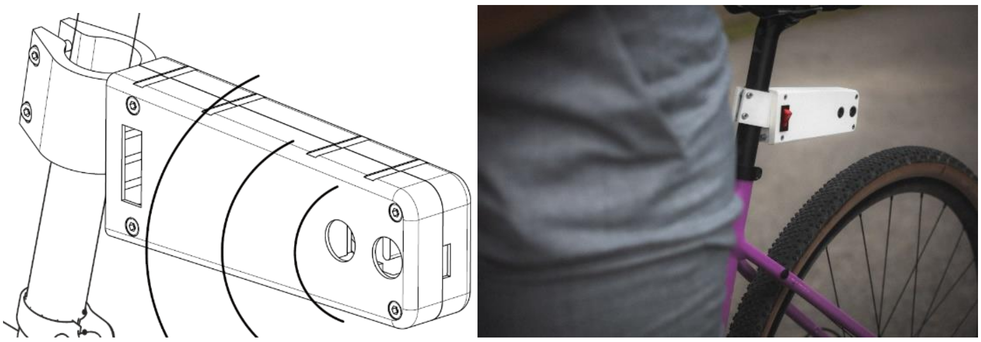
In the remainder of this paper, we are going to focus on 7), i.e., how overtaking lateral distances can be measured on-bike, that is, while cycling.

In German law, a lateral overtaking distance of 1.5m is required in built-up areas when a cyclist is overtaken. However, in reality, cars frequently overtake within a smaller lateral distance - due to impatience, ignorance, or the assessment that a smaller distance is also sufficient and harmless. This often leads to conflicts between car drivers and cyclists, which might regard this as a reduction of their personal safety.

4. On-Bike Measurements with Ultrasound Data

One popular framework for analyzing overtaking distances is OpenBikeSensor[2]. However, for our research we chose a slightly different setup for several reasons. Firstly, the production of our sensors uses the university's current resources, resulting in a 70 percent cost-reduction in comparison to the OpenBikeSensor project. Secondly, the self-developed code allows for complete customization and flexibility in terms of the functions and behaviour of the system. Finally, our setup also provides full control over the data collected, which can be beneficial where privacy is concerned.

For measuring the overtaking distances, we 3D-printed and assembled a box, and equipped it with a standard on-off switch. Inside this box, there are an Arduino board with an HC-SR04 ultrasound sensor, a GPS receiver and a SD card. This box can be mounted below the saddle of any bicycle with standard bicycle tools (Allen keys), see Figure 1.



[2] Openbikesensor.org

Figure 1. Sketch (left) and photograph (right) of our bike sensor.

The functionality of the Arduino board can be programmed with C++ code. We wrote specific code to ensure the ultrasound sensor records every object that is within a distance of 2.5 meters to the left at the height of the sensor.

Before measuring, the rider has to switch on the box and wait for a GPS fix. Then, the sensor starts recording objects which are within 2.5m lateral distance. These objects become new datasets in a CSV file, which is stored on the SD card and edited as long as the button is switched on and the location data are valid. The datasets contain several fields such as X/Y/Z coordinates, timestamp, speed, the distance of the object and a binary/Boolean “tooclose” field, which classifies whether the object was within a 150 cm distance or not (see Table 1 for an excerpt of the recorded data).

Bikenumber	Latitude	Longitude	Distance	tooclose	Time	Date	Speed
5	49.794048	9.91797	137	1	09:30:28	06.07.2023	15.73
5	49.794273	9.917084	76	1	09:30:50	06.07.2023	9.35
5	49.794277	9.917039	172	0	09:30:51	06.07.2023	12.15

Table 1. Excerpt of the CSV file that is written while recording

When switching off the box and thus its sensors, the CSV file is no longer edited. After data has been recorded, the CSV file can easily be integrated in any GIS system. Areas where objects were “too close” to the ultrasound sensor can thus quickly be identified. First successful test rides with students were performed at the Frankfurter Straße in Würzburg-Zellerau in July 2023 (see Figure 2 for a map of objects that were recorded).

Figure 2. Red dots indicate object within a range of <1.5 m, blue dots indicate objects within a range of 1.5-2.5 m.

After recording, cleaning and filtering the dataset, 908 objects remained as candidates of overtaking cars. The mean of these objects was 1.46m, the median 1.34m (standard deviation: 0.58m). These results suggests that many cars overtake at a dangerous distance, which is legally too close. It is particularly interesting that within bicycle protection lanes, the mean distance even decreased to 1.15m, and 43% of the values were less than one meter.

However, it has to be noted that not every object which is recorded as “too close” is necessarily a “dangerous” overtaking car. Firstly, these objects can also be other objects than cars (i.e., traffic lights or tram stops). Secondly, cyclists often overtake waiting cars to their right side on traffic lights. We thus already omitted measurements where the bike rider was slower than 8 km/h. A detailed speed analysis of the bike can lead to further insights here.

5. Conclusion

There are several ways in which the quality of cycling can be "quantified" by using geospatial analyses and location-based technologies such as sensors. Since more and more sensors and geospatial data are publicly available, the major challenge rather consists of combining and weighing the data, in order to create valid, reliable and objective indicators for the quality of cycling, such as bikeability indices.

Measuring overtaking distances is an important piece in the broader analysis framework for assessing the quality of cycling. While measuring objects at a certain lateral distance already works quite well, it remains a challenge to identify the subset of overtaking cars from all sorts of objects appearing within a certain distance.

It also has to be noted that it is not our aim to denounce individual car drivers. As geographers and geovisualizers, we are interested in identifying locations *where* these risky overtaking maneuvers are a problem, perhaps due to poor cycling infrastructure.

Further research should also focus on the analysis of the perceived danger of an overtaking maneuver. This issue could be tackled by giving participants the opportunity to record whether the overtaking object was regarded as dangerous or not. We hypothesize that the perceived danger depends on several factors – not only on the lateral distance, but also on the speed of the overtaking car.

We plan to enhance our measurements with mixed-methods approaches as suggested by Werner et al. (2023). Specifically, that means more user surveys and post-ride interviews are needed to identify the factors that actually are most important for cyclists regarding the quality of their cycling experience.

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Location-Allocation of Treatment Centers for Patients with Wearable Sensors

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Abstract. Nowadays, due to rapid population growth, urbanization, and an increase in the aging population, the need for an appropriate healthcare system is of utmost importance. One of the main reasons for the mortality rate among patients is their inadequate access to healthcare facilities. This research introduces a novel approach for patient's allocation. This method is based on equipping patients with smart sensors that have been developed. 8 districts in the city of Kermanshah have been examined in this study. The objective of this research is to expedite services for patients wearing wearable sensors. To achieve this goal, a location-allocation model has been developed for the patients. The results indicate that the integration of the location-allocation model and wearable sensors accelerates the provision of services to patients.

Keywords. Location-allocation, Wearable sensors, Healthcare

1. Introduction

The demand for healthcare services, particularly for the elderly and disabled individuals, is increasing due to the global population growth. The growth of the aging population has led to rising costs of healthcare and increased health-related issues. This has made the traditional healthcare monitoring system inefficient, undesirable, and inadequate (Nayak et al. 2022). Location-allocation analysis aims to find the best location for a set of demand points in a way that addresses supply and demand issues (Efiong 2019). Therefore, when planning healthcare systems, decision-makers should consider goals that involve improving access and reducing costs (Mestre et al. 2014). Wearable sensors can be utilized to achieve this objec-

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tive. Wearable sensors have gained significant interest in the medical field due to their cost-effectiveness, flexibility, lightweight, and biocompatibility (Yi & Xianyu 2022). These sensors measure physiological conditions of the body such as heart rate, respiratory rate, body temperature, blood pressure, and blood oxygenation (Baker et al. 2017). Therefore, with the rapid advancement of technology, wearable sensors have created a new opportunity for real-time monitoring of human performance today.

Considering that the location-allocation model utilizes principles of spatial analysis and optimization, the objective of this research is to increase the reliability of this model through integration with wearable sensors. The research method is as follows: First, patients are equipped with wearable sensors. Then, based on their vital signs and spatial location, the location-allocation model is implemented, and facilities are allocated to the patients in real-time.

2. Materials and Methods

2.1. Wearable sensors

In recent decades, population growth and urbanization have led to significant advancements in the field of healthcare, with wearable sensors being one of them. The present study was conducted in 8 districts of Kermanshah city, where patients are scattered throughout the city. The sensors used in this research are Apple watches. These sensors have the capability to transmit vital signs such as heart rate, oxygen level, and other health-related metrics. The process of transmitting patient information through these sensors is as follows: Firstly, the patient's information is sent to a mobile phone via Bluetooth, and then it is transmitted to healthcare professionals through Wi-Fi. The purpose of this approach is to continuously monitor the patient's health status and provide quick access to their information, including their spatial location, in order to expedite service provision.

2.2. Location-Allocation Model

Once the patients are equipped with wearable sensors, the location-allocation model will be implemented. The objective of implementing this model is to provide rapid access to healthcare facilities for patients who are unable to visit hospitals due to their physical condition. Essentially, the location-allocation model enables us to access the nearest patient in a way that minimizes the distance traveled and, consequently, the time taken to reach them. To achieve this goal, the P-Median model is used, which is a mathematical optimization model for solving facility location problems with the aim of determining the appropriate location for them and providing services to demand points. The objective function in this model is defined in a way that minimizes the total distance between healthcare facilities and patients equipped with wearable sensors. Furthermore, constraints on the number of open facilities have been imposed, stating that each patient can only be served by the nearest healthcare facility. In this study, facilities are allocated to different patients instantly and in real-time. This is done by determining the type of disease based on patient data and records previously registered, and then appropriate specialized healthcare facilities will be assigned to that specific disease. Equipping patients with wearable sensors tailored to their needs allows each patient to receive more precise and higher-quality healthcare. This approach not only improves access to healthcare services but is also economically effective as it can reduce resource wastage and prevent unnecessary service provision. It also leads to increased flexibility in society, as a facility can provide services based on the best access to a patient's location within a specific area.

3. Results

In this section, the preliminary results of integrating smart sensors and the location-allocation model are examined. The necessary patient data is obtained through wearable sensors. Additionally, information regarding hospitals is extracted using Google Earth software. Since the city of Kermanshah is divided into 8 regions, the allocation of hospitals to patients in each region is investigated.

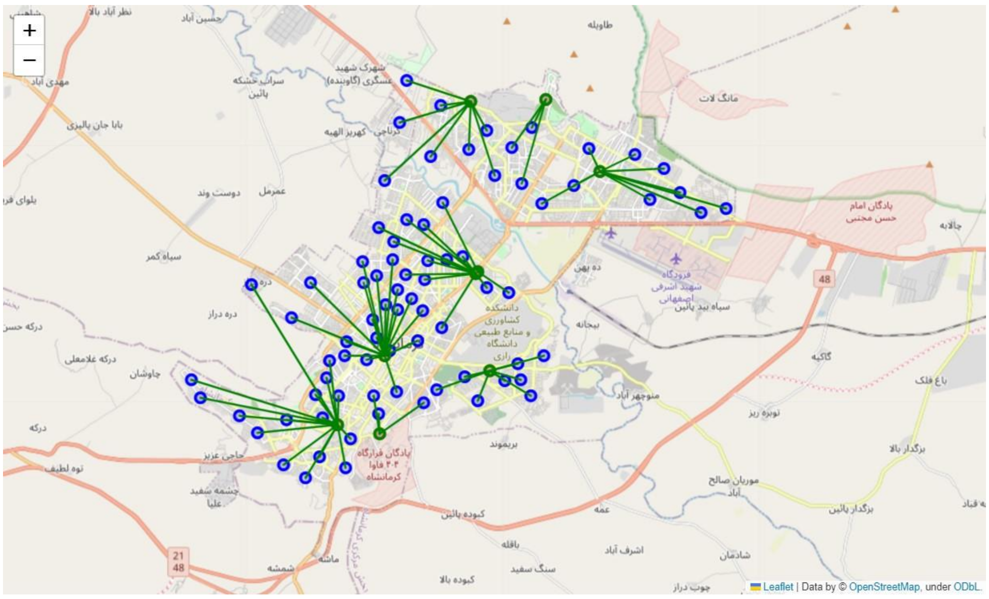

Figure 1. The result of the model implementation in different regions

Figure 1 illustrates the distribution of hospitals and patients at the city level in Kermanshah. Green dots represent hospitals, while blue dots represent patients. As can be observed in Figure 1, patients in each area have been referred to the nearest healthcare center. Unfortunately, within this geographical area, access to online traffic data was not available, and it is recommended for future research.

4. Conclusion

The aim of this study is to allocate patients with smart sensors based on their location. The methodology employed in this research involves equipping patients with smart sensors and then providing services at centers that have appropriate accessibility, taking into account their geographical position and relevant disease-related information. In a novel approach adopted in this study, it is demonstrated that swift service delivery to patients with unfavorable physical conditions can be highly effective in preserving their lives. For this reason, a location-allocation model has been utilized to enable rapid disease diagnosis through wearable sensors and quick access to centers.

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Upgrading Wi-Fi fingerprinting to 5G. A hybrid simulation case

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Abstract. This research project is an extensive study of the upgrading process of fingerprinting technology from 2.4 GHz to 5G mmWave FR2, with the primary location being a secondary school environment. The work aims to evaluate and identify optimal combinations of existing 2.4 GHz Wi-Fi, 5 GHz Wi-Fi, and emerging 5G mmWave FR2 technologies to enhance indoor localization systems. Leveraging advanced simulation software, the study explores various scenarios to achieve the most effective integration of these technologies. Early results indicate that the adoption of 5G technology faces considerable challenges in overcoming signal loss through walls, a problem less significant in the current Wi-Fi technologies. Nevertheless, it is preliminarily suggested that these barriers can be mitigated by a large-scale deployment of 5G access points (AP's). Further research is ongoing to refine the findings and develop practical recommendations for deployment in similar environments. This study holds significant implications for the design of future indoor localization systems, particularly as the global infrastructure transitions towards more sophisticated 5G networks.

Keywords. Indoor, positioning, 5G FR2

1. Introduction

The rapid growth of digital connectivity in the 21st century has needed a substantial evolution in indoor localization systems. These systems, vital for a plethora of applications ranging from building navigation to security, have traditionally relied on 2.4 GHz and 5 GHz Wi-Fi technology. However, with the advent of 5G technology, and more specifically, 5G millimeter-wave

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Frequency Range 2 (mmWave FR2), the landscape of indoor localization, is undergoing a significant shift.

Our study investigates the possibilities for indoor positioning that the relatively new the relatively new 5G mmWave FR2 and compares the results with the currently prevalent 2.4 GHz and 5 GHz Wi-Fi technology in a secondary school environment. The school's building structure, comprising numerous walls and classrooms with several obstacles, makes it an ideal setting to test the efficacy and challenges of this upgrade process.

For the realization of this work, we use a radio signal simulator (EMSlice, www.emslice.com), which allows simulating 2.4 GHz Wi-Fi, 5 GHz Wi-Fi, and 5G mmWave FR2 signals, as well as their combination. Thus, it is possible to gain insights into the synergies among the technologies, potential challenges, and optimal deployment scenarios, before the true deployment.

To ensure the veracity of our simulation results, we validated them against real-world data collected from similar settings. By correlating our simulated results with the actual performance of these technologies, we evaluated the accuracy of our simulation model and minimized the risk of misleading conclusions. Specifically, a simulation has been carried out with the EMSlice software, using a scale mapping of a secondary school as a reference. Specifically, in this center there are 6 2GHz/5GHz AP's and 38 readings have been taken to corroborate the correct functionality of the simulation software and to adjust different parameters. Figure 1 shows the position of the different AP's, as well as the points where the test signals have been taken. These signals were obtained with a Samsung 22 Ultra mobile phone, stopping at each test point for 5 seconds to stabilize the signal and capturing the RSSI power obtained. All signals were taken in a row.

The main goal of the current research is to find where to add 5G mmWave FR2 in a secondary school building for using this technology for indoor positioning.

2. Results

Following data collection and analysis, our preliminary findings have yielded results of interest in the area of indoor localization through 5G mmWave FR2 technology. In our simulation, we incorporated the use of fingerprinting with the goal of improving location accuracy in the post-compulsory school environment.

Currently, only the KNN algorithm is being used for testing. In the future, we will proceed to test different algorithms to verify their usefulness. The results of applying KNN in different contexts are presented in Table 1.

In terms of accuracy, our results thus far indicate that the use of 5G technology with fingerprinting does not provide a significant improvement over traditional 2.4 GHz and 5 GHz Wi-Fi technologies. Relative performance was determined through a comparison of the results obtained in the simulation and the data collected in the real environment, keeping the same conditions for both scenarios.

However, it is important to highlight that, although accuracy may not have improved significantly, the use of 5G technology with fingerprinting proved to be sufficiently accurate for room-level localization. This implies that, although the location accuracy may not be granular enough to determine the exact location within the room, it is effective enough to determine in which room the device is located.

Analyzing the difficulties encountered, it was found that the structure of the school building, with its numerous walls and partitions, presented challenges in the implementation of 5G mmWave FR2. For this reason, part of the work will also focus on studying the number of AP's required to achieve acceptable results. As initial work, Table 1 shows the accuracy results using the KNN algorithm on different combinations of AP's.

At the end of this study, our goal is to present optimal deployment recommendations for 5G mmWave FR2 in a real environment using simulation software to achieve both a better absolute positioning and a study on the needs of AP's to perform a positioning only at room level. A secondary objective is to produce a map of simulated RSSI signals for future use by other researchers.

	2.4GHz	5GHz	5G FR2	2.4GHz+ 5GHz	2.4GHz+5G FR2	5GHz+5G FR2	2.4GHz+5G Hz+5G FR2
KNN Precision	93.46%	87,58%	69.93%	93.46%	90.85%	86.93%	92.16%

Table 1. KNN algorithms with different wireless technologies

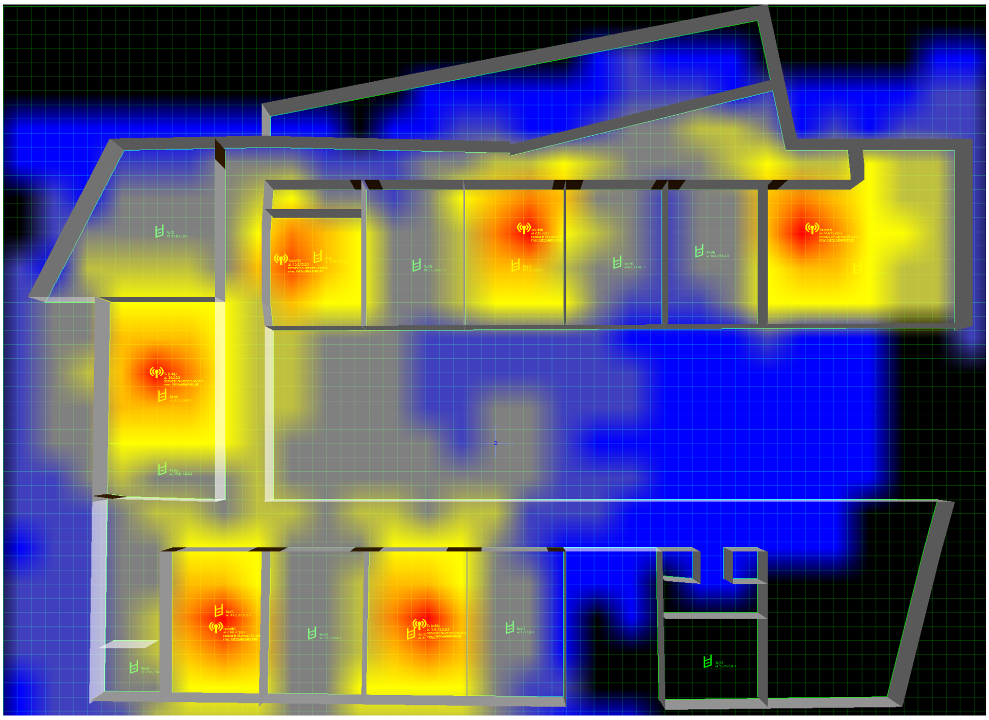

Figure 1. Map of signals in the secondary school

3. Conclusion

Our preliminary findings reveal that signal loss, particularly through walls, is more important for 5G mmWave FR2 than for Wi-Fi technologies, although it is possible to take advantage of this loss for some kind of indoor positioning applications. Another line of research of the current study is focused on whether many 5G AP's are really necessary if we only want room level positioning.

At the end of this study, our goal is to present optimal deployment recommendations for 5G mmWave FR2 in a real environment using simulation software. A secondary objective is to produce a map of simulated RSSI signals with different signal types for future use by other researchers.

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Higher accuracy for smartphone positioning: post-processing, centre points and repetition

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Abstract.

The importance of smartphone positioning for contemporary society is on the constant rise, as is the demand and potential for its higher accuracy. National mapping agencies see crowdsourcing by smartphone measurements as an interesting opportunity for data collection in the future. In this study, the purpose was to investigate the reality of smartphone positioning accuracy in the crowdsourcing context. The enhancement of plain real-time smartphone positioning was carried out by post-processing calculations with reference stations, centre point averaging and repeated measurements. The results were benchmarked against professional real-time kinematic measurements, and accuracies below 1.5 m were achieved at best by the mentioned techniques combined. The reached accuracy level is already useful for many mapping purposes and the latest developments in satellite positioning are still about to decrease measurement inaccuracies.

Keywords. Smartphone, Positioning, Accuracy, Crowdsourcing

1. Introduction

Positioning is a fundamental part of today's society, which is integrated in numerous applications. Positioning data can be collected by different smart devices including smartphones. In recent years, there have been many studies related to the positioning capabilities of smartphones (Zangenehnejad & Gao 2021) as they are the most widely spread positioning devices and quite cheap to manufacture. There have also been breakthroughs in this field. For example, a new Android operating system was released to the markets in 2016, making it possible to collect raw GNSS positioning data as required

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for more precise positioning (European GNSS Agency, 2018). Higher positioning accuracy supports more precise mapping for crowdsourcing.

In 2021, the National Land Survey of Finland (NLS) conducted a pilot study to determine if the locations of border markers of the cadastral register index map could be improved using crowdsourcing (Kettunen & Rönneberg 2022). The conclusion was that crowdsourcing did have potential in improving the locations (Kontiokoski 2022). Next, in 2022, another study was conducted to see if the positioning accuracy of smartphones could be improved, especially, using post-processing in coordinate computation (Jussila 2023). This abstract concentrates on the findings of the latter study that simulated a crowdsourcing campaign to collect the measurement data. The method is feasible for technical developers of crowdsourcing applications.

2. Methods

2.1. Test measurements

For this study, the measuring was done in different parts of Finland, where the environment differed from urban to rural areas. The measurements were taken by NLS employees using commonly available smartphones in use at the time. Since the measurements were taken by professionals, the crowdsourcing was more of a simulated experience.

The smartphone measurements were taken from border markers of the cadastral index map using the Marker Quest application in the phones. To calculate the positioning accuracy, accurate reference measurements were made on the border markers using the Real-Time Kinematic technique.

A total number of 1,889 smartphone measurements were collected from 41 different border markers, with 12 different smart devices used to take the measurements. These values are before filtering of the data.

2.2. Processing workflow

The workflow began with data preparation, in which any invalid data was filtered out and the data was formatted into a proper structure. Consequently, the post-processing calculations were run using two different software: SSRPOST by Geo++ and open-source RTKLIB. SSRPOST utilised a realisation of the PPP-RTK positioning technique and a network of reference stations. In RTKLIB, Static and DGNSS positioning modes were used with the nearest reference station data. RTKLIB is openly available but needs time to get familiar with.

In the analysis phase, the post-processed and real-time measurements were compared and analysed. Outliers were removed using the interquartile range method. For each positioning technique, the accuracy of horizontal coordinates was calculated. The positioning accuracy is the Euclidean distance between the smartphone and the reference measurement. Three types of results were analysed: 1) the positioning accuracy of individual measurements, 2) the positioning accuracy of centre points (Figure 1), and 3) the change in positioning accuracy as the number of measurements increases.

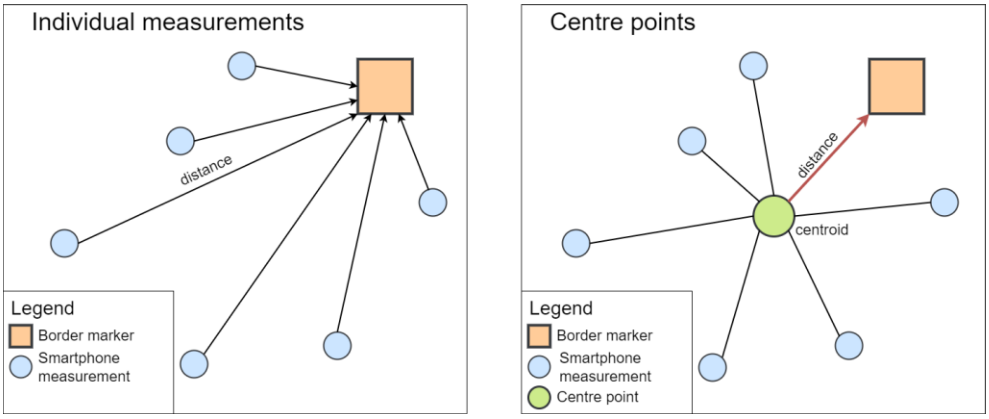

Figure 1. In individual measurements analysis, distance from each smartphone measurement to the border marker is calculated. In centre points analysis, the centre point of the measurements is calculated and distance from the centre point to the border marker is determined.

3. Results

First, the positioning accuracy of individual smartphone measurements was calculated. The results show a variation depending on the positioning technique used (Table 1, Figure 2). The least accurate results were produced by real-time techniques with 10-meter mean accuracy. The high standard deviation indicates wide dispersion of measurements around the border markers. Post-processing techniques produced results with positioning accuracies between 4–6 m. SSRPOST had the most accurate result at 3.92 m.

Second, the centre points of the measurements around the border markers were used. The results show an improvement in the positioning accuracy in all cases (Table 1, Figure 2). The real-time results improved to around 6 metres with a high standard deviation between the border markers. The post-processing accuracies improved to a range of 1.5–4 metres with SSRPOST at 1.46 m and a low standard deviation between border markers.

	Individual measurements		Centre points	
Technique	Mean (m)	Std (m)	Mean (m)	Std (m)
Real-time	9.66	12.81	5.66	6.15
Real-time DGNSS corrected	10.24	13.03	6.19	6.31
Post-processed (Static)	6.38	7.85	3.58	3.49
Post-processed (DGNSS)	4.19	3.18	2.45	1.81
Post-processed (SSRPOST)	3.92	3.44	1.46	0.88

Table 1. Positioning accuracy of individual measurements and centre points

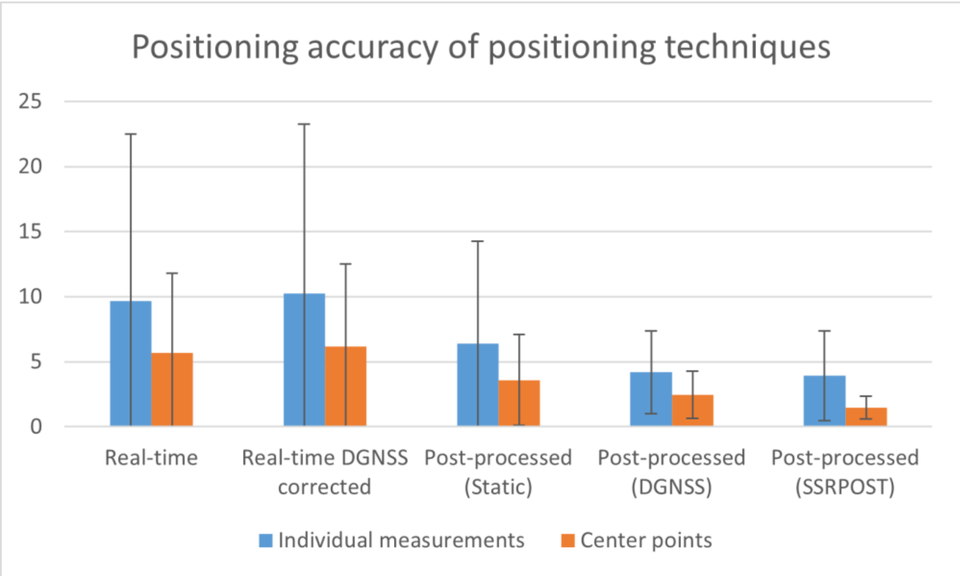

Figure 2. Positioning accuracy of individual and centre points

Lastly, this study observed the positioning accuracy change when the number of measurements increases at a border marker. The centre points of measurements were used and the order of measurements was randomised. Four different iterations were done with different sampling to see how the pattern changes, with the results showing that the most improvement occurs when around two to three measurements are used (Figure 3). The improvement slows down gradually, and after around 10 measurements the change is minimal.

Figure 3. Positioning accuracy change when number of measurements increases

4. Conclusion

This case study investigated smartphone positioning capabilities, with the results showing the potential of post-processing for developers of crowdsourcing apps. The most accurate results were achieved through post-processing and using centre points in accuracy calculations. At 1.46 metres, the SSRPOST technique produced the most accurate results. Nevertheless, there are aspects that still require improvement and further research. Therefore, the positioning accuracy of commonly used smartphone types should be further studied. New methods or the improvement of old methods to enhance accuracies are required. Moreover, in the future, the reason for any difference between the positioning accuracies between different border markers should be investigated. Overall, the results of this study prove that the applied methods can be used to improve the positioning accuracy of smartphones in the crowdsourcing context. Future satellite positioning techniques, such as Galileo's High Accuracy Service, are to still decrease positioning inaccuracies.

Acknowledgements

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Convolutional Neural Network as sensor fusion algorithm applied to IPIN2019 dataset

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Abstract. This work-in-progress explores the use of Convolutional Neural Net-works (CNNs) in a sensor fusion approach for indoor localization, a crucial component in computer vision, robotics, and navigation. CNNs have emerged in the last few years as sensor fusion algorithms, using deep learning to process multi-sensor data. We apply CNN to the IPIN 2019 competition dataset. The method consists of processing sensor data and transforming it into images, and training a CNN model for position estimation. Preliminary results show promise in specific scenarios, but the CNN approach struggles with generalization on diverse tracks.

Keywords. Indoor Localization, Sensor Fusion, Convolutional Neural Network

1. Introduction

Indoor localization faces challenges due to weak signals within buildings, leading to the ineffectiveness of Global Navigation Satellite Systems (GNSS). So it is necessary to use other available sensors to find the user's position indoor. In that, sensor fusion plays a crucial role, it enables the efficient utilization of multiple sensors to gather comprehensive and accurate information from the environment. While CNNs have been in existence

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for many years~~, their application~~ as sensor fusion algorithms is a relatively recent development. CNNs excel in extracting relevant information by leveraging spatially hierarchical features from diverse and complex data sources, including multi-spectral or multi-modal data. Specifically, researchers have reported successful utilization of CNNs for feature extraction using multiple modalities like RGB and Infrared images (Hu 2018, Li 2023). The work in (Antsfeld 2020) largely inspired us. In this work-in-progress paper, we will discuss the application of CNN as a sensor fusion algorithm to an indoor localization context using the IPIN 2019 contest dataset (Potortí 2020). We present preliminary results and provide insight into upcoming research directions.

2. Methods

This work follows a classical machine learning method: data and labels are collected, a model is trained using them, and then tested with a validation set. The model is used to predict labels for new data, and performance is evaluated by comparing the predicted labels with the true ones (Bishop 2006). Performance measures such as RMSE, MSE, and displacement are calculated. The proposed method is shown in Fig. 1. It is applied to the IPIN 2019 dataset (Potortí 2020), that are the data collected using an Android smartphone and its build-in sensors. The data are composed of time, latitude, longitude and, sometimes, altitude in format of decimal degrees, and meters respectively. The time is in milliseconds. The data collected comes from sensors such as the accelerometer, gyroscope, magnetometer, attitude (AHRS), GNSS, barometer, and the Wi-Fi intensity, among others. The labels are the ground truth of the position.

The 2019 dataset is composed by 40 tracks, each track was walked four times (e.g.T01 01.txt, T01 02.txt, T01 03.txt, T01 04.txt) often back and forth. The IPIN organizers, moreover, provided a set of geo-referenced maps of the buildings where the data were collected (Moayeri 2016, UJI-IndoorLoc 2023, Long-Term 2014).

The original data were pre-processed to separate sensor information, reduce data volume, and ensure portability across different configurations. Matplotlib and Python 3.10 were used. Data from each sensor were separated and saved in new files for easier management (e.g. 2019 T01 01 ACCE.csv for the accelerometer data, etc.). The SensorTime was used to synchronize data from different sensors, as recommended by the IPIN organizers.

The original input data were decimated and filtered to reduce both the data vol-ume and noise. All raw sensor data were down-sampled to 50 Hz, which is considered sufficient to capture user displacement. (Fig. 2 shows an ex-ample.)

In this work, the training data were augmented with the magnitude of each sensor (accelerometer, gyroscope, and magnetometer) and for each sensor an additional column with the calculated magnitude (e.g., [x, y, z, $\|v\|_2$]) was added.

CNNs are known for their capability in feature extraction from images, and in this work, we extended their application by transforming sensor signals into images. Using time windows of 1 second, we created images with 12 rows and 50 columns, representing sensor axes and their norm. The sam-pling rate was set at 50 samples per second, and padding was applied to ensure an integer number of images, thus enabling data conversion for CNN input.

This down-sampling reduce the amount of data available for training, to over-come that firstly, we reduced the time window to 0.5 seconds, dou-bling the available "images" per track. Secondly, we iterated through ran-domly shuffled batches, using each training track 2 or 3 times. These modi-fications noticeably improved our research progress.

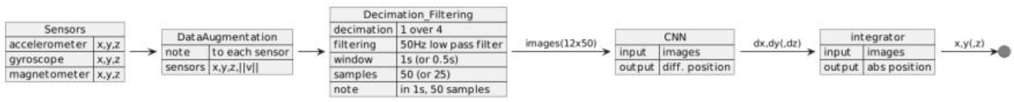

Fig. 1 From raw data to input images.

Ground truth data consist of latitude and longitude coordinates, converted to UTM coordinates. The study uses positional increments between images as labels, generating missing points based on constant speed assumption. Output labels represent user's incremental position in three dimensions, requiring integration to reconstruct the user's position during CNN's pre-diction phase.

The calibration data are collected and recorded at the beginning of each track, with the purpose to help the calibration of the smartphone. After the first initial trials, and a look at those data, it was decided to cut off the first part (35 seconds) of each track. That has led some improvement to the re-sults.

The network has been composed initially by the following layers :

```
layer1 = tf.keras.layers.Conv2D(32,(3,3),activation = 'relu',input shape =(12,50,1))
layer2 = tf.keras.layers.MaxPooling2D((2,2))
layer3 = tf.keras.layers.Flatten()
layer4 = tf.keras.layers.Dense(96,activation = 'tanh')
layer5 = tf.keras.layers.Dense(3,activation='tanh')
```

Different activation functions and varying numbers of neurons in dense layers were experimented with during the course of this work.

For training and validation, a dataset consisting of 40 tracks was prepared, with one track off allocated for validation. The data batch was shuffled, and training was performed for a maximum of 600 epochs, with a callback function to halt training if the loss did not improve for 20 consecutive epochs. Tensorflow 2.11 with Python interface, Adam optimizer, and mean squared error (MSE) loss function were used. The training process took approximately 20 minutes per iteration on a laptop with Intel Core i7-8550U CPU, 256 GB SSD, and 16.0 GB memory.

The validation set included 9 tracks from the IPIN 2019 dataset, with some tracks having floor transitions. The model's performance was evaluated on all tracks, including the validation set, using measures like standard deviation, percentile, root-mean-square error, and displacement. Integration was necessary to obtain the position, and mean square root was calculated to assess position accuracy.

3. Results and Experiments

In our experiments, we explored variations in neural network configuration, adjust-ing the number of nodes from 12 to 576. Notably, reducing network size led to longer training times and decreased performance. Increasing the number of nodes in the first layer up to 576 did not yield significant improvements. Drawing from '90s experiences, we introduced a second layer to the network, resulting in faster training and notable performance enhancements. Further improvements were achieved by changing the activation function to 'tanh'.

Even with a modest network complexity (24 nodes in first layer,12 in second) we are able to get a satisfactory result on one track, but failing to generalize to other tracks.

Increasing the number of nodes, gave us a more uniform results among tracks, sometime really good on a single track; the issue with generalization persisted.

To enhance the outcomes, we increased the number of nodes in the network (64, 96, 192, 384), resulting in some improvements but not significant enhancements. Adding a second layer improved results, although it increased training time. While the CNN showed more consistent performance across tracks, it still faced challenges in generalization.

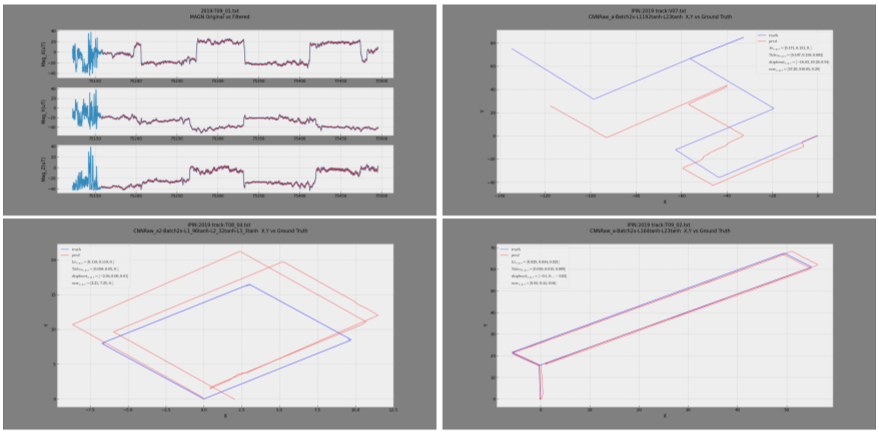

Fig. 2 Examples of input, typical prediction and Over fitting.

We observed unusually good results that raised suspicions about their accuracy. The first result was achieved by training the network multiple times on the same track, yielding remarkable performance on that specific track. The second result was obtained by training the network on a batch for two iterations, occasionally resulting in impressive performance. However, when attempting to generalize to other input tracks, the results consistently fell short of expectations (Fig. 2).

4. Conclusion

We aimed to use neural networks as a sensor fusion algorithm for indoor localization, which is a real-world problem. Recent hardware advancements enable the employment of powerful neural networks even in modern smartphones. The initial step focused on evaluating the effectiveness of convolutional neural networks (CNNs) as a sensor fusion algorithm.

A significant effort was dedicated to data preprocessing, involving the transformation of raw data from the IPIN dataset into a usable format. This included re-constructing the ground truth data and converting sensor inputs into CNN-friendly images.

The selected CNN approach yielded varying outcomes and it lefts room for improvement. It showed satisfactory performance on specific tracks but struggled with generalization to new tracks. Converting sensor data into images for preprocessing led to a loss of important information and hindered the model's ability to make accurate predictions. The model occasionally is able to compensate for drift effects in the inertial sensors. The transformation process itself resulted in a significant degradation of the original data, reducing prediction reliability. To overcome these challenges, alternative methods, such as recurrent neural networks (RNNs) or LSTM (Long short-term memory), should be explored preserving the inherent characteristics of a dynamical system, thus enhancing generalization capabilities. To improve the model's generalization capabilities, it might be beneficial to expand the dataset used for training and that means to use the data already available from the other IPIN contest..

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Indoor Mapping Using Machine Learning Based Classification of 3D Point Clouds

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Abstract. Today, indoor maps remain a valuable source of spatial information for various indoor environments. Classifying 3D point clouds from indoor environments is crucial for indoor mapping. In this study, indoor point clouds from the S3DIS dataset were classified using Random Forest (RF), eXtreme Gradient Boosting (XGBoost), Multi-Layer Perceptron (MLP), and Attentive Interpretable Tabular Learning (TabNet). The classification performances, based on overall accuracy and F1 scores, can be ranked as RF, MLP, XGBoost, and TabNet. It has been determined that machine learning algorithms can be used to classify indoor point clouds for indoor mapping.

Keywords. Indoor mapping, machine learning, point cloud

1. Introduction

The automatic generation of high-quality indoor maps for existing buildings poses a significant challenge within navigation automation, virtual reality, and robot object manipulation (Lin et al 2021). Since the as-built condition of the buildings often deviates from the original plans due to renovations, indoor mapping for existing buildings has garnered extensive research attention. Indoor maps can be considered as the output of indoor measures and serve as the foundation for most indoor-based applications. The complexity of buildings and the increasing use of indoor positioning systems also provides a strong motivation to enhance the cartographic representation of indoor maps (Nossum 2013).

Indoor mapping data acquisition refers to the measurement techniques, sensors, media, and platforms used to obtain raw data from indoor environments. The main components in acquiring indoor mapping data are hardware for data processing and sensor synchronization, typically a mapping sensor such as LiDAR (Light Detection And Ranging) or an RGB-D (Red, Green, Blue - Depth) camera (Otero et al. 2020). In this study, a backpack-

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shaped mobile laser scanning system, in collaboration with our university, was used for acquiring indoor point data. The components of this device include GPS, LiDAR, camera, processor, battery, interface, and other connection elements.

The classification of 3D point clouds belonging to indoor environments plays a significant role in the generation of indoor models (Lin et al 2021). Significant progress has been made in the recognition of point clouds belonging to outdoor environments. However, recognizing indoor scenes remains a challenge due to their confined surroundings, various structural features, and numerous obstacles such as columns and walls (Hangbin et al. 2020). In recent years, the classification of indoor point clouds using deep learning algorithms has been an active research topic. The classification performances of different deep learning algorithms on the Stanford 3D Indoor Semantics (S3DIS) dataset (Armeni et al. 2016), generated by Stanford University, were provided in the study by Lin et al. (2021).

The performance of machine learning (ML) methods in the classification of indoor point clouds for high-quality indoor mapping is one of the current research topics. In this study, indoor point clouds from the S3DIS dataset were classified using RF, XGBoost, MLP, and TabNet. It has been observed that the classes of ceiling, wall, and column, which have been classified with high performance, can be utilized for indoor floor maps. We have thus conducted preliminary work on the indoor mapping of point clouds obtained from our university, by utilizing the indoor mapping of a similar dataset such as S3DIS.

2. Methodology

Steps of the proposed study (see Figure 1): (1) Preprocessing of the S3DIS indoor point cloud dataset, (2) normalization of the point cloud data, (3) classification using ML methods, (4) evaluation of classification performance, (5) determination of object classes classified with high performance for automatic generation of indoor maps in GIS environment.

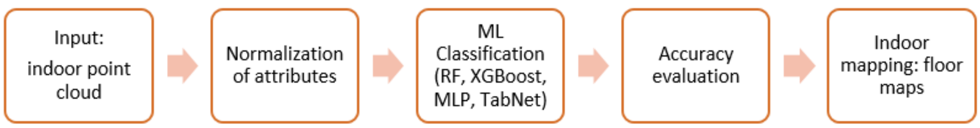


Figure 1. The framework of the study.

2.1. Preprocessing (Input and Normalization)

The classes in the S3DIS were labeled as the ceiling, floor, wall, door, window, column, table, chair, board, clutter, bookcase, sofa and beam in a discrete file format. To prevent the overfitting problem, classes were combined to create a balanced dataset. For the purpose of creating indoor maps, the classes were merged in the training and test data as follows: wall, door, window, column, and board were merged into one class (merged class-1), and bookcase, table, chair, and clutter were merged into another class (merged class-2). In total, 4 classes were obtained (ceiling, floor, merged class-1, and merged class-2). An office was used for the training (70%) and test data (30%) and 30 different offices were classified. 3D coordinates x, y, z, and RGB values are the attributes we used as inputs to the ML algorithms. Input vectors were scaled linearly by min-max normalization.

2.2. Machine Learning Classification

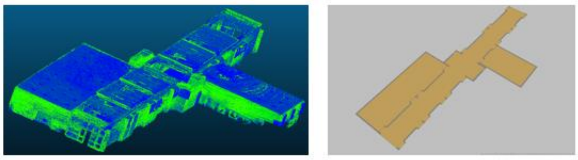
In this study, we used four ML algorithms: MLP, RF, XGBoost and TabNet. MLP is a feedforward artificial neural network. MLP is a highly popular supervised ML algorithm and forms the basis of widely used deep learning algorithms (Han et al. 2012). RF is a powerful ensemble learning method that combines multiple individual decision trees to make predictions (Breiman 2001). XGBoost is a popular boosting-based ML algorithm (Chen and Guestrin 2016). TabNet combines ideas from deep learning and attention mechanisms to effectively learn representations from tabular data and make predictions (Arık and Pfister 2020).

2.3. Accuracy Evaluation

Evaluating the prediction performance of an ML model, which is tuned with several hyperparameters defined in a search space, is an important part of the classification process. In the literature, several metrics exist for assessing the prediction performance of an ML classifier. In this study, the performance of ML models was evaluated using four evaluation metrics: accuracy, recall, precision, and F1 score.

2.4. Indoor Mapping

After the classification of indoor point clouds, polygons were obtained from the intersections of the ceiling and merged class-1 to create floor maps. Since the objects on the floor and in front of the wall create gaps (missing data) in the floor and wall classes, the floor polygons obtained from the intersections of the ceiling and merged class-1, and lowered by the wall height. The polygons belonging to the rooms and corridors were merged to obtain floor maps. In Figure 2, a sample point cloud obtained from a backpack-shaped mobile laser scanning system and a generated indoor map are given.



(a) Indoor Point Cloud (b) Indoor Map

Figure 2. Indoor point cloud of a university building obtained from our mobile laser scanning system (a) and its indoor map (b).

3. Results (Preliminary)

In this study, we used Python 3.8.8 and Scikit-learn ML library to classify the point clouds, and ArcGIS Pro 3.1 tools to produce the indoor maps. A preliminary study was conducted on the S3DIS dataset (Area 5) to test the consistency of the methods. The S3DIS dataset is a large-scale indoor point cloud dataset created by Stanford University. An office room was used for training and test data, and 30 different office rooms were classified. The accuracy metrics of the best test accuracy result (in 120 experiments: 30 spaces x 4 methods) are given in Table 1. The initial results showed that the RF method achieved an average accuracy of 86% and F1 scores of 89% for the ceiling, 97% for the floor, 90% for merged class-1, and 62% for merged class-2. The MLP method achieved an average accuracy of 85% and F1 scores of 92% for the ceiling, 97% for the floor, 87% for merged class-1, and 60% for merged class-2. The XGBoost method achieved an average accuracy of 85% and F1 scores of 86% for the ceiling, 96% for the floor, 89% for merged class-1, and 60% for merged class-2. Lastly, the TabNet method achieved an average accuracy of 83% and F1 scores of 93% for the ceiling, 82% for the floor, 87% for merged class-1, and 58% for merged class-2. Ground truth, RF classification (in Table 1) and floor map of an office room are illustrated in Figure 3.

ML Classifier	Office Room	Precision	Recall	F1 score	Accuracy
RF	Ceiling	0.98	0.98	0.98	0.93
	Floor	0.98	1.00	0.99	
	Merged Class 1	0.93	0.95	0.94	
	Merged Class 2	0.80	0.73	0.77	

Table 1. The accuracy metrics of the best test accuracy in 120 experiments (30 spaces x 4 methods).

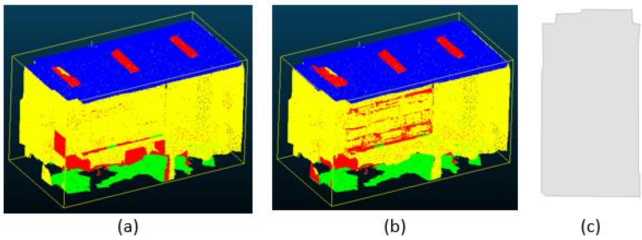


Figure 3. Ground truth (a), RF classification (b), and generated floor map (c) for an office room in the S3DIS dataset.

4. Conclusion

Classifying 3D point clouds from indoor environments is crucial for indoor mapping. The classification performances, based on overall accuracy and F1 scores, can be ranked as RF, MLP, XGBoost, and TabNet. However, the ML classification with the highest performance for each class can be utilized in hybrid solutions. In this study, it has been determined that ML classification can be used to classify indoor point clouds for indoor mapping. As a result, preliminary findings have been obtained regarding the generation of indoor maps for the test buildings of our university campus.

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Explainable AI for Urban Land Cover Classification Using Mobile Application Traffic Data

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Abstract. This research explores the use of mobile application traffic data to interpret urban land cover classification using explainable machine learning methods. The experiments using a high-resolution mobile service traffic data in Paris, France show that the hourly downlink traffic of Microsoft Office, Netflix, and Uber together with the XGBoost model can accurately classify land cover types and the SHAP values help interpret instance-level feature importance and their spatial patterns.

Keywords. Explainable GeoAI, LBS, Location Big Data

1. Introduction

Explainable AI methods have been applied in geospatial analysis such that human can understand how machine learning models use the input features to make predictions in geographical phenomenon. Common methods include tree-based explanations, game theory-based explanations, local surrogate models, and so on (Xing & Sieber 2023). In the studies of location-based services, McKenzie et al. (2015) used the information gain to understand global feature importance of temporal check-ins for points-of-interest (POI) classification. However, less attention has been paid to spatial-explicit local explanations (i.e., individual predictions and their spatial patterns). This research aims to explore what kinds of mobile service features (as proxies of human activities) are critical for interpreting urban land cover classification in different regions of cities.

2. Datasets and Preprocessing

Mobile application traffic data: In this research, we employ a high spatiotemporal resolution of service-level mobile traffic dataset in Paris, France (Martínez-Durive et al. 2023), which provides time series of the uplink and downlink traffic generated by 68 mobile applications (e.g., Instagram, Facebook, Netflix, YouTube, Microsoft Office, Google Maps, Uber, etc.) at each 100×100 m^2 grid/tile every 15 minutes. Figure 1 shows the spatial distributions of hourly downlink service traffic of "Microsoft Office" in urban area of Paris on a typical workday (March 18, 2019).

Urban land cover data: We employ the Corine Land Cover (CLC) 2018 dataset produced by the Copernicus Land Monitoring Service and coordinated by the European Environment Agency, which provides high-resolution (100×100 m^2) and thematically detailed information on land cover across Europe (Büttner 2014). The dataset contains 44 land cover classes in the hierarchical 3-level CLC nomenclature and there

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are 19 classes in the study area (as shown in Figure **2** and Table **1**). The land cover layer is further spatially joined to the mobile data service grids layer to create a unified time-series data frame for downstream explainable machine learning tasks.

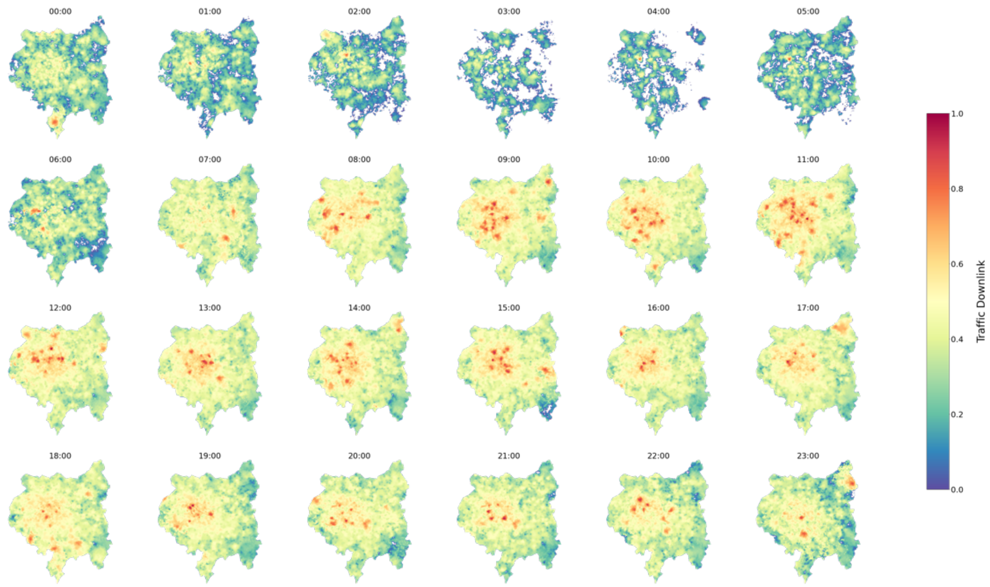

Figure 1. The spatial distributions of hourly downlink traffic of the Microsoft Office service.

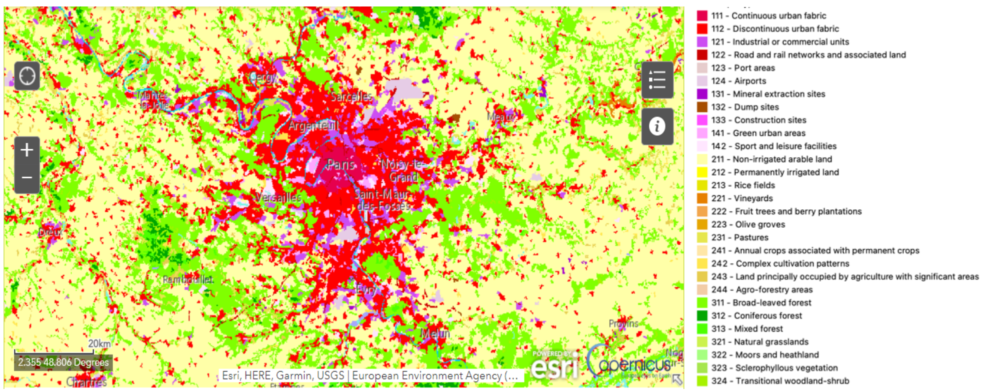

Figure 2. The spatial distributions of Corine Land Cover classes in Paris.

Table 1. Top-10 land cover classes and their distribution percentage in the study area.

Land Cover Type	**Percent (%)**	**Land Cover Type**	**Percent (%)**
Discontinuous urban fabric	52.4	Industrial or commercial units	12.7
Continuous urban fabric	11.3	Green urban areas	6.0
Broad-leaved forest	5.1	Sport and leisure facilities	2.8
Airports	2.5	Road and rail networks	2.0
Non-irrigated arable land	1.7	Water courses	1.0

3. Methods

3.1. Machine Learning Models

In this research, we employ the following machine learning models for land cover multiclass classification based on the unified time-series data of mobile service traffic introduced in Section 2.

XGBoost: is a regularized gradient boosting learning method for optimizing the ensemble of decision-trees and reducing the model overfitting. The "XGBClassifier" is trained for multiclass classification with the softmax objective and 300 gradient boosted trees with the max depth of 5.

Multi-Layer Perceptron (MLP): is a feedforward artificial neural network. We use a MLP classifier with two hidden layers of 100 fully connected neurons with a rectified linear activation function and a learning rate of 0.001.

Transformer: is a deep neural network that uses self-attention mechanisms to draw global dependencies in sequence modeling (Vaswani et al. 2017). We design a multi-head transformer neural network with 40k parameters for the time series land cover multiclass classification in this research.

3.2. SHAP Values for Model Interpretability

Then, we utilize the model-agnostic SHAP (SHapley Additive exPlanation) values (Lundberg & Lee 2017), which provide a unified approach to interpreting the above-mentioned machine learning models' performance. The *local explanation* method aims to ensure an explanation function $g(z') \approx f(h_x(z'))$ when $z' \approx x'$, where f is the original prediction model and x' is simplified inputs that can map to the original inputs x through a mapping function $h_x(x')$. The explanation function g is defined as a linear function of binary variables:

$$g(z') = \emptyset_0 + \sum_{i=1}^{M} \emptyset_i z'_i$$

where $z' \in \{0, 1\}^M$, M is the number of simplified input features, $\emptyset_i$ are the Shapley values that measure how much a feature's value changes the model 's prediction with a game-theory sampling strategy. Local explanation methods help interpret the impact of input features on individual predictions (e.g., a single sample data point or a couple of sample data points). There exist different algorithms to compute the SHAP values (Lundberg et al. 2018); here, we apply the *tree-based explainer* for the XGBoost model and the *kernel-based explainer* for the MLP and transformer models to get their corresponding SHAP values using the 'shap' Python package. Furthermore, we perform the spatial analysis to understand the spatial patterns of SHAP values of each feature on specific land cover type predictions.

4. Experiments and Results

In the experiments, we select three mobile data service apps (i.e., Netflix, Microsoft Office, and Uber) due to their popularity and they potentially represent people's stay-at-home, working, and transportation activities in the city. The unified time-series data frame contains the hourly average downlink traffic of these mobile services for each 100x100 m^2 tile/grid of Paris on a typical workday. Therefore, we have 24*3=72 features/attributes and 1 target variable (land cover type) as inputs for all the machine learning models. We then split the data with 80% for model training and 20% for testing. As shown in Table 2, the XGBoost model with accuracy of 0.91 outperforms the MLP and the Transfomer regarding the multiclass land cover classification on the testing data while their mean F1-score (macro) are very close. In the following, we only report the best performing model (XGBoost)'s interpretability.

Figure 3 shows the SHAP value computation results of top-20 most influential features on the type-specific land cover classification using the XGBoost model. Overall, both daytime and night hours of *Microsoft Office* service traffic, midnight *Netflix* and *Uber* traffic have larger magnitude of impact on the classification output of the testing data. However, the effects of those hourly features are different for specific land use type. For instance, the service traffic features "Office 1:00~1:59" has the largest impact on the "Airport" while "Office 9:00~9:59" has the largest impact on the "Industry and Commercial Units". Interestingly, the spatial patterns of SHAP values are also varying. Figure 4 shows the spatial distributions of SHAP values of the selected feratures for the classification of "Continuous Urban Fabric" type. We find that "Office 9:00~9:59" traffic has moderate positive impact across the study area but "Netflix 2:00~2:59" and "Uber 23:00~23:59" traffic have strong distinctive impacts in the urban center (mostly positive) and suburb (most negative) of the city, which demonstrates the spatial heterogeneity of individual feature importance.

Table 2. The comparison of different machine learning models' performance (accuracy and F1-score) on land cover classification for the testing data.

	Testing Accuracy	F1-Score (macro)
XGBoost	0.91	0.80
Multi-Layer Perceptron (MLP)	0.87	0.79
Transformer	0.82	0.76

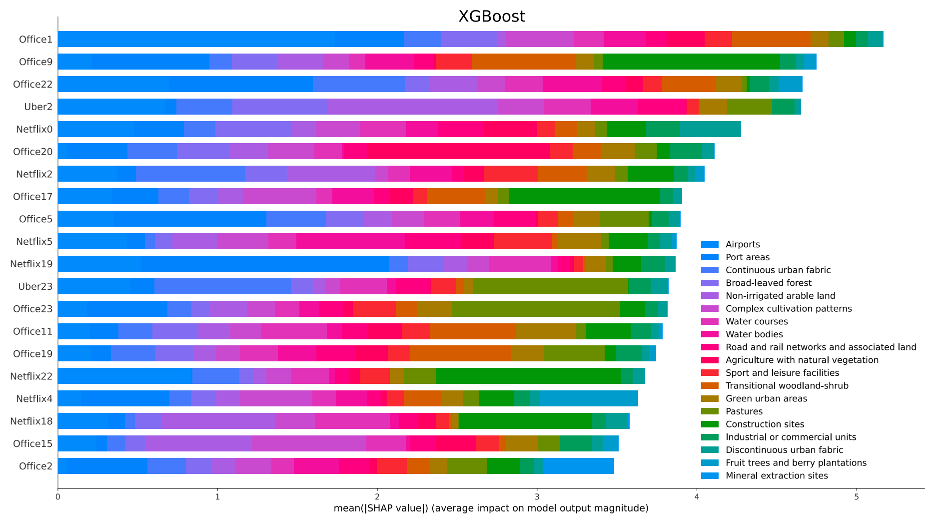

Figure 3. The SHAP values of different features for the XGBoost model.

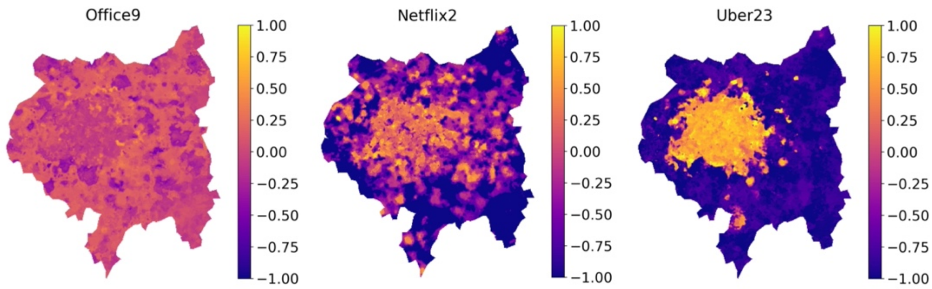

Figure 4. The spatial distributions of SHAP values of the selected feratures.

5. Conclusion

This research utilizes the model-agnostic SHAP values to interpret the instance-level feature impacts of hourly mobile application traffic in the urban land cover classification using machine learning models. The experiments using high-resolution mobile traffic and land cover data in the city of Paris show a promising performance of XGBoost in model accuracy and good interpretability with the selected temporal bands of Microsoft Office, Netflix, and Uber mobile service traffic. The results also demonstrate the spatial heterogeneity of instance-level feature importance in explainable machine learning models. Future work will further explore the interaction effects of different features and on other mobile applications as well as deeper understanding of human-environment interactions from the explainable GeoAI perspective.

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Segment Anything Model for Refugee-Dwelling Extraction with Few Samples from High-Resolution Satellite Imagery

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Abstract. Customizing Segment Anything Model (SAM) has recently attracted considerable attention in remote sensing domains. This study explores the performance of SAM-Adapter in refugee-dwelling extraction in three different refugee camps from high-resolution satellite images. The findings indicate that with scarce sample data, SAM-Adapter marginally outperforms other semantic segmentation models. This underscores SAM's promising potential for building extraction tasks when data is limited.

Keywords. Segment Anything Model, Dwelling Extraction

1. Introduction

The United Nations Statistical Commission approved multiple indicators for refugees under Sustainable Development Goals (SDGs) according to the commitment "Leave no one behind" in March 2020 (UNHCR, 2020). Providing adequate living resources such as clean water, nutritious food, medical services, and modern energy to refugees and their host communities is essential (UNHCR, 2020). Before delivering these resources, it is significant to know refugee population in need. Due to the difficulty of collecting such information on site, updated footprints of refugee dwellings from satellite imagery could be beneficial for the estimation purpose (Spröhnle et al., 2014), and thus can support urgent humanitarian operations for refugees.

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In recent years, deep learning approaches have shown high potential in extracting the footprints by learning essential features from images and annotated labels (Gao, Lang, Tiede, Gella, & Wendt, 2022). However, most research uses strong supervision that requires numerous high-quality labels beforehand.

The "Segment Anything Model (SAM)" introduced by Meta AI Research has recently garnered considerable interest. With training on an extensive segmentation dataset comprising over 1 billion masks, SAM excels at segmenting any entity within a given image (Kirillov et al., 2023). Lately, several studies have delved into evaluating SAM's efficacy in different applications for object recognition and segmentation.

SAM shows high potential in remote sensing domains yet is also challenging due to high variability in shape and size of objects (Ren et al., 2023). It is found that SAM does not outperform task-specific models on building extraction compared to trees or clouds. Hence, it's essential to augment the model's effectiveness by incorporating additional fine-tuning methods specifically for building extraction.

Currently, three primary adaptation methods are derived from recent studies (Zhang et al., 2023). They are 1) fine-tuning, 2) applying adapters, and 3) decoupling the mask decoder into two modules. Incorporating domain-specific adapters is a viable method to tailor SAM's architecture. These adapters aim to capture task-specific knowledge.

This research assesses the efficacy of SAM-Adapter (Chen et al., 2023) in extracting dwellings across three refugee camps, using two different training data sizes. The results prove that SAM-Adapter marginally outperforms other semantic segmentation models when sample data is limited. This study is currently ongoing. Associated codes can be accessible at https://github.com/YunyaGaoTree/SAM-Adapter-For-Refugee-Dwelling-Extraction.

2. Methodology

2.1. SAM-Adapter

SAM-Adapter integrates domain-specific data or visual prompts into the segmentation network through the use of efficient adapters. By melding task-specific insights with the broad knowledge acquired by the extensive model, SAM-Adapter notably boosts SAM's efficacy in intricate tasks like detecting camouflaged objects and identifying shadows (Chen et al., 2023). The codes for SAM-Adapter source from this GitHub. The pretrained model "sam_vit_h_4b8939.pth" are chosen as a foundation model in this study.

2.2. Models for ablation studies

We choose six advanced semantic segmentation models as for comparison against SAM-Adapter. These models include the Feature Pyramid Network (FPN) with 1) Mix Vision Transformer (MiT), 2) MobileNet-v2, 3) ResNet34 as their backbones, and Unet with 4) ResNet101, 5) ResNet34, and 6) MobileNet-v2. The codes for these models source from this GitHub.

2.3. Data processing

Three datasets are chosen for this study. They are from Kutupalong refugee camp in Kenya, Dagahley refugee camp in Tanzania and Minawao refugee camp in Cameroon. The dataset details about sensor, spatial resolution, retrieved date, spatial extent for training/validation/testing purposes, and number of patches in shape of 1024 by 1024 pixels are provided in *Table 1*.

It's crucial to acknowledge that there are multiple methods for sampling image data. For instance, instead of maintaining a similar spatial extent for each study site, it may be worthwhile to keep the number of generated patches consistent. It may be valuable to explore different sampling strategies such as different proportions of data. However, in this initial research, we choose this straightforward data collection approach.

Refugee camp	Retrieved date	Sensor	Resolution (m)	Data type	Extent / pixel	Nr. of patches
Kutupalong	13/02/2018	UAV	0.1	Train_Large	13283, 12489	1848
				Train_Small	6828, 5346	420
				Validation	4334, 4078	226
				Test	9844, 9420	
Dagahaley	08/04/2017	WV3	0.3	Train_Large	5754, 5074	350
				Train_Small	2010, 1944	56
				Validation	1389, 1373	7
				Test	4783, 3101	
Minawao	12/02/2017	WV2	0.5	Train_Large	3832, 4625	224
				Train_Small	1682, 1744	56
				Validation	1188, 1187	7
				Test	1817, 3165	

Table 1. Dataset details utilized in this study.

2.4. Implementation details

We evaluate the performance of the proposed approach with Precision, Recall, F1-score and Intersection over Union (IoU) of refugee dwellings. All tests were conducted on a machine equipped with an RTX3090 GPU, utilizing the PyTorch 2.0 environment. Data augmentation by random rotation and flip are applied for model training. Additional details will be disclosed in an upcoming manuscript currently in the works.

3. Results and Discussion

The accuracy assessment results for the three refugee camps are shown in *Table 2 and Table 3*. *Figure 1* provides one example of predicted results for each refugee camp from FPN-MiT and SAM-Adapter trained on "small" dataset, and from SAM without any adjustments.

From these results, it's evident that SAM, without any modifications, falls short of yielding promising outcomes. The IoU values for the three datasets are considerably lower compared to SAM-Adapter and the other six segmentation models. Nonetheless, it's also discernible that as image resolution increases, the accuracy of the predicted results improves. This discovery aligns with the observation in (Osco et al., 2023), which recommends integrating SAM with the SR (super-resolution) model to enhance its effectiveness for low-resolution images.

In summary, SAM-Adapter significantly excels over other segmentation models, notably with small datasets. For instance, while the highest IoU value among the six segmentation models for the Minawao dataset stands at 0.195, it leaps to 0.571 with SAM-Adapter. Moreover, SAM-Adapter consistently produces comparable accuracy across both dataset sizes for all three refugee camps.

Model	Data size	Kutupalong				Dagahaley			
		IoU	**F1**	**Precision**	**Recall**	**IoU**	**F1**	**Precision**	**Recall**
FPN-MiT	Large	**0.666**	0.800	0.762	0.841	**0.523**	0.687	0.784	0.612
	Small	**0.656**	0.792	0.825	0.763	**0.297**	0.458	0.429	0.490
FPN-MobileV3L	Large	0.602	0.751	0.818	0.695	0.465	0.635	0.835	0.513
	Small	0.423	0.594	0.909	0.441	0.251	0.402	0.564	0.312
FPN-ResNet34	Large	0.594	0.745	0.808	0.692	0.351	0.519	0.803	0.384
	Small	0.587	0.740	0.805	0.684	0.138	0.239	0.721	0.143
Unet-ResNet101	Large	0.574	0.729	0.669	0.802	0.505	0.671	0.670	0.672
	Small	0.519	0.684	0.764	0.618	0.140	0.245	0.146	0.758
Unet-MobileV3L	Large	0.608	0.757	0.815	0.706	0.557	0.715	0.657	0.785
	Small	0.593	0.745	0.820	0.682	0.159	0.274	0.265	0.284
Unet-ResNet34	Large	0.606	0.755	0.695	0.826	0.432	0.604	0.793	0.488
	Small	0.601	0.750	0.790	0.715	0.129	0.229	0.141	0.612
SAM-Adapter	Large	**0.733**	0.846	0.879	0.815	**0.619**	0.765	0.793	0.738
	Small	**0.710**	0.831	0.810	0.852	**0.560**	0.718	0.626	0.842

Table 2. Accuracy assessment results for Kutupalong and Dadahaley refugee camp.

Model	Data size	Minawao			
		IoU	F1	Precision	Recall
FPN-MiT	Large	**0.515**	0.680	0.648	0.716
	Small	0.194	0.326	0.621	0.221
FPN-MobileV3L	Large	0.351	0.519	0.821	0.380
	Small	**0.195**	0.326	0.668	0.216
FPN-ResNet34	Large	0.158	0.273	0.769	0.166
	Small	0.139	0.180	0.114	0.429
Unet-ResNet101	Large	0.261	0.414	0.413	0.415
	Small	0.121	0.245	0.153	0.622
Unet-MobileV3L	Large	0.278	0.435	0.857	0.291
	Small	0.129	0.228	0.424	0.156
Unet-ResNet34	Large	0.300	0.461	0.631	0.364
	Small	0.144	0.252	0.164	0.541
SAM-Adapter	Large	**0.583**	0.736	0.779	0.698
	Small	**0.571**	0.727	0.699	0.757

Table 3. Accuracy assessment results for Minawa refugee camp.

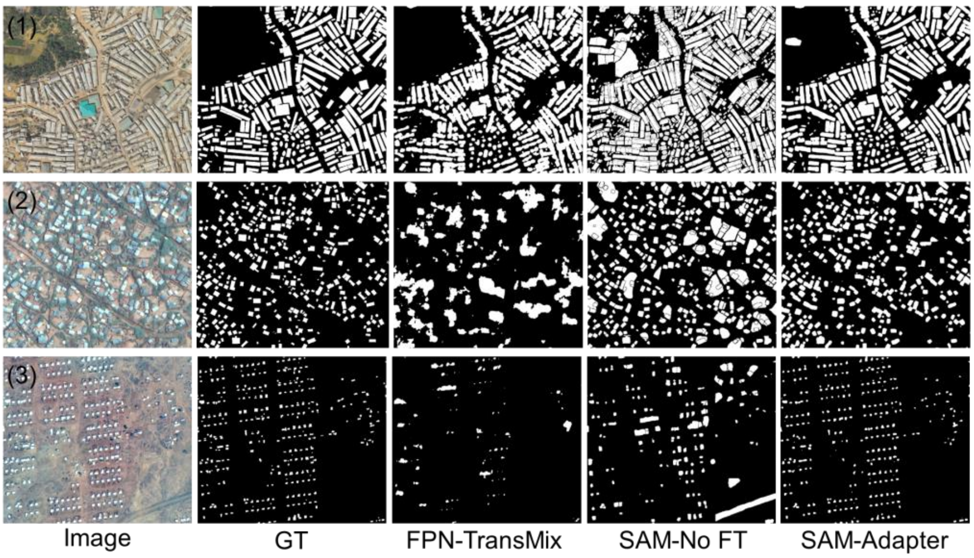

Figure 1. Predicted results from FPN-TransMix and SAM-Adapter trained on “small” dataset, and from SAM without any adjustments. From top to bottom, the images represent: (1) Kutupalong refugee camp; (2) Dagahaley refugee camp; (3) Minawao refugee camp.

4. Potential future improvements

As a pioneering study on SAM for refugee dwelling extraction tasks, there's significant room for enhancement. Firstly, enhancing the fine-tuning speed of SAM is essential. Secondly, while the SAM-Adapter's architecture is uncomplicated and easy to implement, there's some room for modifications. Thirdly, there's a potential in devising more efficient sampling strategies. Last but not least, creating SR models tailored for satellite imagery that can surpass a spatial resolution of 0.1 m could be significant for building extraction tasks.

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Estimating Area Characteristics Based on Geographic Object Positioning and Categories

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Abstract. This paper proposes a new method for estimating area characteristics, such as ease of parenting, by analyzing map images. Our approach utilizes map images that represent geographic object categories. This enables a machine learning model to infer area characteristics more accurately based on geographic object positioning and categories. We experimentally demonstrate the efficacy of the proposed method.

Keywords. Geographic Information, Machine Learning, Geographic Categories

1 Introduction

We often identify locations based on area characteristics in daily life such as the ease of parenting and shopping. For example, when people with young children move to a new city, they may want to determine whether the area is appropriate for raising them. In this situation, some people infer area characteristics from text-based content such as microblog posts; however, text content on specific regional characteristics that the user wants to know about may be scarce. For example, if most of the content is about shopping, it will not help users who want to know whether an area is appropriate for parenting. The primary aim of this research is to propose a machine learning model for estimating area characteristics. As training images, we use colored map images representing geographic object categories in color. Using these images instead of text data to estimate area characteristics allows a machine learning model to grasp geographical object positioning within the area. For example, in an area with one school and one

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station, a vector can only be expressed as (1, 1). However, map images can express various positional relationships between features. Thus, this study aims to develop a model capable of predicting area characteristics by learning colored map images that represent geographic object categories. The remainder of this paper is organized as follows. Section 2 discusses existing research related to our method. Section 3 describes our proposed method. Section 4 presents the results of the experiments and provides a discussion. Finally, Section 5 concludes the paper.

2 Related Work

The purpose of our method is to estimate area characteristics from map images representing geographic object categories. We organize existing research related to our study into two categories 1) estimating area characteristics using text data and 2) estimating methods of measurable area characteristics. Several previous studies have estimated area characteristics based on test data (Baral et al. 2018, Kato et al. 2009). In particular, Shoji *et al* (2018) proposed a model for predicting the atmosphere of a target area based on distributed representations of text as learning data. Our method uses map images instead of text data. Using this approach, the proposed model can learn the spatial relationships between features and estimate area characteristics. Previous studies have estimated numerical area characteristics (Bischke et al. 2019, Maggiori et al. 2016), such as the size of buildings (Hamaguchi & Hikosaka 2018). Our method proposes a machine learning model to estimate abstract area characteristics like ease of parenting and shopping.

3 Estimation Method of Area Characteristics using Map Images

3.1 Proposed Method

In this section, we describe the details of our method for estimating the area characteristics using a dataset consisting of map images and user reviews.

3.2 Colored Map Images

As training images, this study employed colored map images, which represent information on geographic object categories by color. Examples are shown in Figure 1. We created these training images based on the location information of geographic objects from OpenStreetMap[1] and represented geographic objects using Folium, a Python library. For example, blue regions represent schools, the red plots represent restaurants, and the green plots and regions represent transportation services such as bus stops and stations.

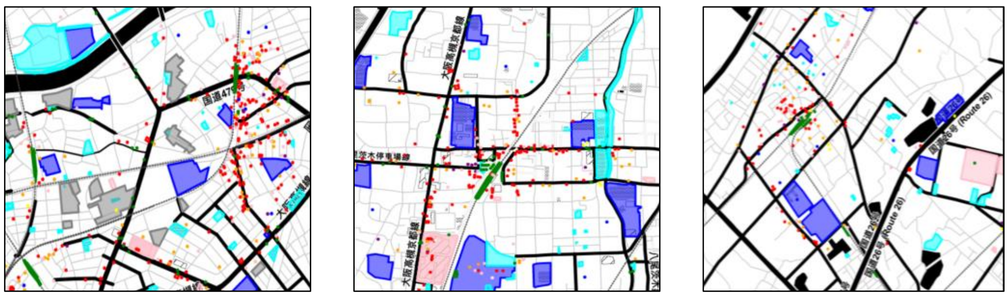

Figure 1. Examples of training images; these map images depict a part of the Kansai region in Japan.

3.3 Extraction of Area Characteristics for Training Data Set

In this paper, we employed review data of the area as labels for each colored map image. Specifically, we use the appearance rate of words that represent parenting, such as education, school, and family, as the label using the following formula:

$$P_K=\frac{t_k}{R} \quad (1)$$

Here, R denotes the total number of reviews posted for a particular area k and t_k represents the number of reviews including words related to parenting.

4 Experiments

4.1 Experiment Settings

The proposed method uses colored map images to represent geographic object categories. To evaluate the performance of the proposed method, we compared the results of the experiments using the following three map images as training images:

- Colored Map (Proposed): Images that represent object categories with color.
- Same-Colored Map: Images that represent object categories with the same color.

[1] https://www.openstreetmap.org/

- No Drawing Map: Images that do not represent geographic objects.

In this experiment, we use 1000 datasets consisting of colored map images and annotation labels. Labels were created using reviews in the LIFULL HOME'S dataset. Table 1 shows an example of the annotation labels.

Area	loccation informatioon	Review	total number of reviews	Annotation Labels
Area A	lat:32.96 lon:129.94	①There are no shops, but it is quiet and comfortable to live in. ②Because I think it's good for **children** to live in nature. ③There are many **children** in the neighborhood, so I think raising children is easy .	3	0.67

Table 1 Examples of annotation labels based on LIFULL HOME's Dataset

The dataset contained 1000 data points; 900 were used as training data, and 100 were used as test data. In this experiment, the model was evaluated by MAE and MSE for the test data. Fig.2 depicts the architecture of the neural network used in the experiments.

4.2 Results

Table 2 shows the results of the evaluation experiment. According to this result, the proposed method demonstrated higher accuracy than the other methods. These results show that representing geographic object categories is effective for estimating area characteristics through map image analysis.

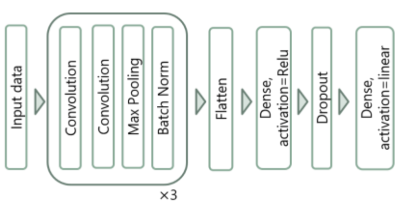

Figure 2. Architecture of the Neural Network

	MAE	MSE
Colored Map (Proposed)	0.094	0.016
Same-Colored Map	0.563	0.396
No Drawing Map	0.961	1.259

Table 2. Result of the experiment

5 Conclusion

The objective of this study is to estimate area characteristics by analyzing map images representing geographic object categories. The primary issue that we plan to address in future studies is annotation labels. Because the appearance rate of words is very simple, it is not possible for labels to reflect the characteristics of map images. Furthermore, because whether an area is suitable for parenting is very abstract, we should use indicators that clearly express regional characteristics as the label.

Acknowledgments

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Analyzing Land Use Mixing Degree using a Vector Data Cube with Hierarchical Cell: A Case Study of Seoul, the Republic of Korea

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Abstract. The type of urban land use is a very important factor in urban planning. Therefore, to quantitatively calculate the land use mixing degree, this study applied information entropy to point of interest data to perform the time-series analysis of the land use status. The visual comparison of the cell divided according to the land use mixing degree obtained using the proposed method with the current data provided by the map service portal confirmed the significance of the proposed method.

Keywords. Point of Interest (POI), National Address Information, Information Entropy, Grid Partitioning

1. Introduction

The population decline is emphasizing the need for compact cities as a new strategy in urban planning to ensure the current level of sustainability and efficiency in land use. In large cities with such high density and complex land use, various activities can be concentrated and active interactions can occur. This degree of land use mix could influence transport mode choice and shape commuting behaviors. As a variety of land uses for different functions occur within close proximity, non-auto commuting is more encouraged by the mixed land-use (Christian et al. 2011). The ability to precisely map urban land use types can significantly aid urban planning and urban system understanding. To measure the urban function mixing degree, scholars mainly calculate and analyze it from two aspects. The first is in terms of data, and it involves the use of multiple heterogeneous sources to identify and evaluate the construction of urban functional areas (Long et al. 2013, Wu et al., 2018, Kang et al., 2018, Gao et al. 2019). The second is in terms of the research methods, and it involves the use of different meas-

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urement methods to measure the urban function mixing degree, and these methods are mostly objective weighting methods, such as the entropy method, spatial entropy, mean square deviation, or land use mixing index method. These objective evaluation methods avoid the subjective judgments of researchers (Xia et al. 2020).

Previous studies apply one-size units, which are set for the whole study area, and are often inaccurate owing to spatial heterogeneity (Jing et al. 2022). The rapid evolution of cities has created new challenges in urban planning and management. Accordingly, the accurate evaluation of the mixed use of urban areas is critical, particularly at a fine scale (Cui et al. 2020). To achieve this, among various measurement methods for measuring the land use mixing degree, this study applied the information entropy (IE) method to analyze the mixing degree of each cell, and the cell was hierarchically divided according to the land use mixing degree to enable its analysis on a fine scale.

Next, the functional change of the city was examined by analyzing the land use mixing degree in a fine-scale time series. In this process, it is necessary to structure the time-series land use mixing degree generated in hierarchical cells. Therefore, in this study, a data cube recently used in the Earth observation (EO) domain was applied to refer to the time series multi-dimensional (n-D) array. The EO data, a prime source of big data, comprise large-scale and multi-source geospatial data that are acquired from orbital sensors, in-situ measurements, and simulation models (Baumann et al. 2018, Wagemann et al. 2018). An EO data cube can be defined as a time-series multi-dimensional (space, time, and data type) stack of spatially aligned analysis-ready pixels (Nativi et al. 2017). Most EO data cubes are focused on images, and discussions have emerged recently on vector data cubes or geo data cubes that can accommodate geospatial data (Gao et al. 2022, Open Geospatial Consortium 2022).

Therefore, in this study, we proposed a method for analyzing the change in land use in a city by structuring the hierarchically-analyzed land use mixing degree, that is, data cubes with different cell sizes in a time series (Figure 1).

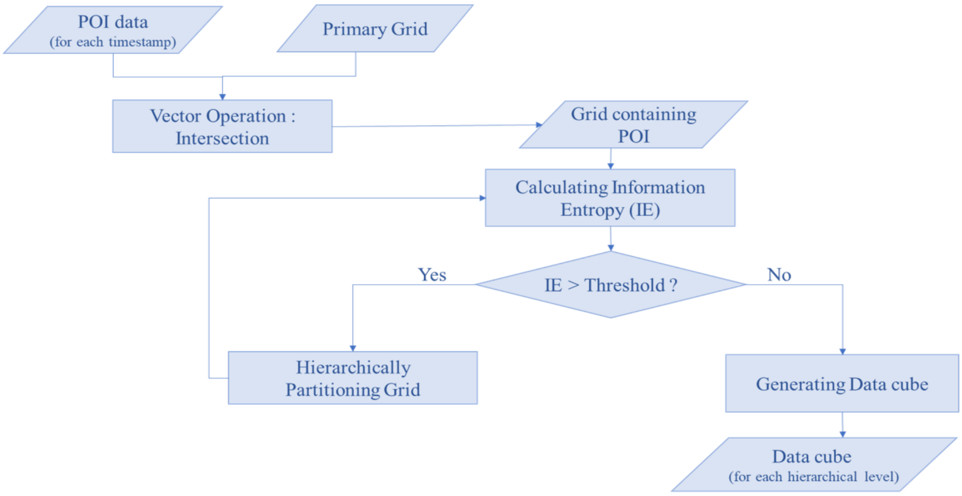


Figure 1. Workflow of this study.

2. Method

2.1. Hierarchical cells partitioning based on IE

2.1.1. IE calculation

IE is a physical concept, introduced by Shannon, to measure the disorder of a system, and to measure the complexity and balance between systems (Guo et al. 2015, Jia et al. 2016, Wei et al. 2018). In the process of analyzing the land use mixing degree, the point of interest (POI) is one of the core elements of the urban structure and form. Therefore, in this study, to calculate the IE, we combined the basic principles of IE with the obtained Seoul POI data. The specific measurement steps are as follows:

[Step 1] Identify the type of POI and count the total number of different POI types. POIs are divided into 10 categories. The total number of POIs of type k in a city is A_K (k = 1, 2, L 10), and the total number of POIs in the city is A ($A = \sum_{k=1}^{10} A_k$).

[Step 2] Calculate the IE in the city. This consists of two parts: measuring the IE of each latitude/longitude cell and measuring the IE of each cell. In this study, the dimension of the latitude/longitude cells was 1000 m × 1000 m, and there was no change in the total number of POI types in each cell. Let be the total number of POIs of type k in cell m, where M is the total number of cells in Seoul, ROK. Accordingly, the proportion of POI type k in the cell can be calculated as expressed in Equation (1):

$$P_k^m = A_k^m / \sum_{k=1}^{10} A_k^m \tag{1}$$

Based on P_k^m, the IE H^m of grid cell m can be calculated as expressed in Equation (2):

$$H^m = -\sum_{k=1}^{10} P_k^m \times \ln(P_k^m) \tag{2}$$

The complexity of the land use of the cell increases with an increase in the IE.

2.1.2. Hierarchical cells partitioning

The design was based on the hypothesis that smaller cells can more accurately represent the land use mixing degree. Therefore, an appropriate cell size should consider the mix of several functional types. The core conception of the partitioning algorithm is iteration partitioning based on the land use mixing degree measurements. According to a previous study on land use and urban planning (Wang et al. 2018), the typical spatial unit that matches most cities is 1000 m. Therefore, 1000 m was set as the initial cell size value. The partition granularity of spatial cells is determined by number of iterations. After the iteration of the model three times, the granularity size was 125 m. As a small size may result in fragments, which lead to lower identification accuracy, the number of iterations was set to 2. Therefore, the size of the smallest unit was 250 m.

The main steps of the partitioning process are as follows:

[Step 1] The first iteration was performed to create primary cells as Level 1. The study area was divided into primary cells with a dimension of W × W m, and was combined with POI data. The function-mixed degree in the primary cells was calculated using the IE. Here, W is the primary granularity.

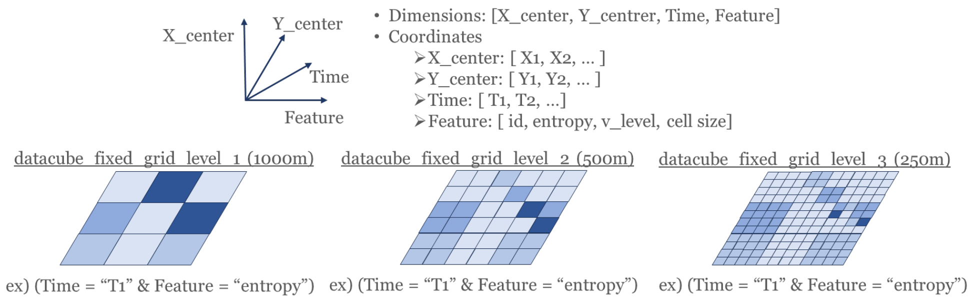
[Step 2] Another iteration process was performed to sub-divide the upper level. If the mixed degree of the units is greater than the threshold (Th1), the primary units were divided into W/2n × W/2n m, where n is the number of iterations.

[Step 3] The new-level cells are aggregated by aggregating the unpartitioned primary cells in the last level and newly partitioned cells in Step 2. Therefore, they were composed of the new level cells.

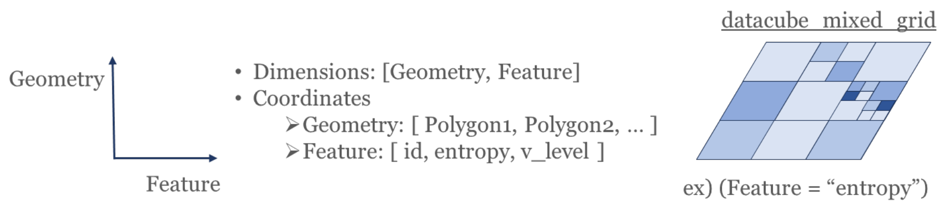
[Step 4] Determining the following loop to partition. This validates the iteration criteria by calculating the mixed degree used to determine if the next loop should be performed. Iterating Steps 2 and 3 generates the new level cells.

2.2. Generation of the vector data cube using the hierarchical cells

Here, raster data cubes refer to data cubes with raster (x and y, or longitude and latitude) dimensions, and vector data cubes are n-D arrays that have (at least) a single spatial dimension that can be mapped to a set of vector geometries. To save a hierarchical cell as a data cube, it cannot be made into one data cube because of the difference in the size of the cell. Therefore, in this study, a data cube was created for each cell size (1000, 500, and 250 m), and a feature array was added to classify the hierarchical cells into levels. Therefore, we modeled the vector data cube with 4-D arrays consisting of an X center, Y center of cell, Time, and Feature (Figure 2(a)). Features include cell Id, IE value, level value, and cell size. In addition, to visualize the land use mixing degree analyzed in time series in the hierarchical cells, a vector data cube with cell geometry as an attribute was created (Figure 2(b)).



(a)



(b)

Figure 2. Vector data cube model.

3. Test and Results

3.1. Study area and dataset

The target area of this study was Seoul, the capital of the Republic of Korea (ROK) with an urbanization area ratio of 61.39% (https://data.seoul.go.kr/dataList/569/S/2/datasetView.do) (Figure 3).

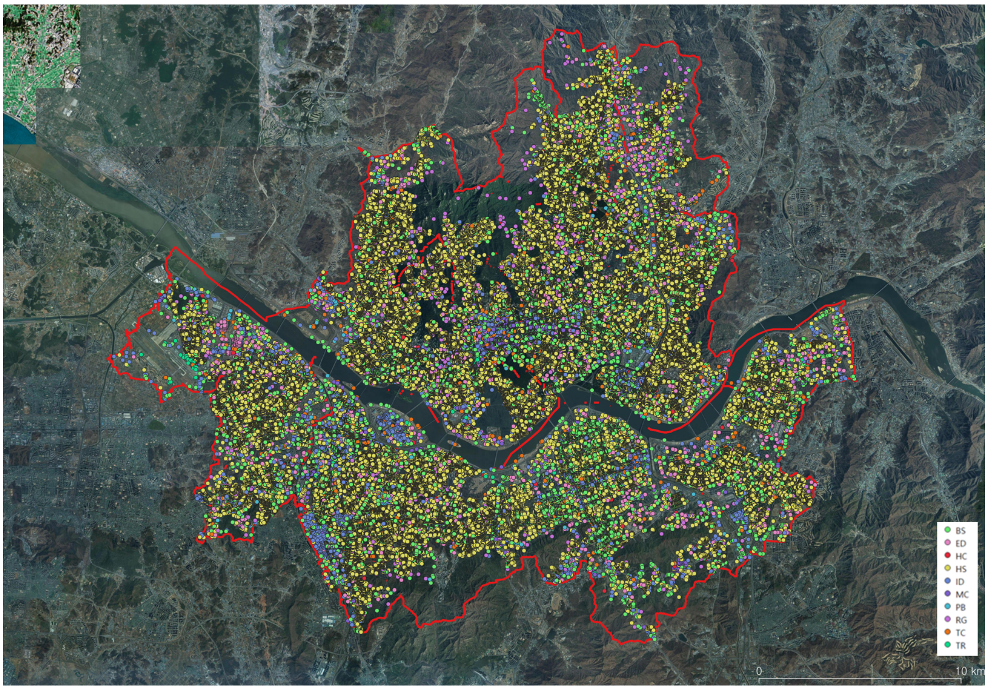


Figure 3. Study area (Seoul, ROK).

The POI data (navigation DB) and the national grid (1000 m) of Seoul provided by the Address information website (https://business.juso.go.kr/addrlink/main.do) were used (Table 1). The navigation DB includes street name address, coordinate values (X, Y) where the address is geocoded to the center of the building, and building (POI) types. Based on this, the POIs to be used for the land use mixing were reclassified into 10 categories (Table 2).

	National grid (1000 m)	POI (Navigation DB)	
Date	2022.05	2021.07	2023.05
Number of features	701	608,325	597,599

Table 1. Data sets (Source).

No.	Category	Details of the POI types
1	Business	Amusement facilities, livestock and fisheries facilities
2	Education	Educational and welfare facilities
3	Health	Hospital
4	Commercial	Catering, large shopping plaza, shopping
5	House	Residential region
6	Industrial	Factories or warehouse facilities
7	Public Service	Government, public library, senior citizen center
8	Religion	Religion
9	Tourism & Culture	Accommodation, Scenic spot, Cultural, tourism and leisure facilities
10	Transportation	Transportation facilities

Table 2. Categories of POI data.

3.2. Results and verification

The IE of the POIs crossing each cell was calculated using the primary grid (1000 m), and if the value is greater than Th1 (mean), the cells are divided, and this process is repeated twice (that is, until the cell size is 250 m). The distribution of the IE after the iteration process is repeated twice is shown in Figure 4, which indicates that the distribution is similar. According to the mean IE values, the POI data for July 2021 were 0.384, 0.394, and 0.390, and the POI data for May 2023 were similar to that of July (0.382, 0.392, and 0.380).

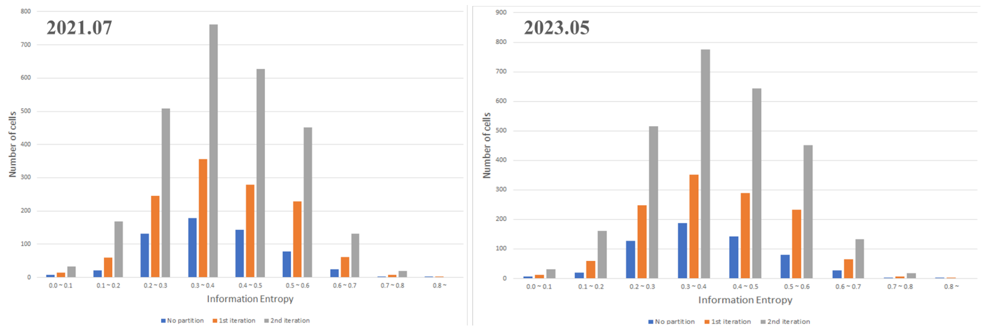


Figure 4. Distribution of the mixed degree.

However, the generated vector data cube was visualized as an array composed of geometry and features (Figure 2(b)), and time series analysis was performed (Figure 5). An increase (red) and a decrease (yellow) in the hierarchical level were observed. With a change in time, a higher level of the grid indicates an increase in the land use mixing degree of the cell, and a lower level indicates a decrease in the land use mixing degree.

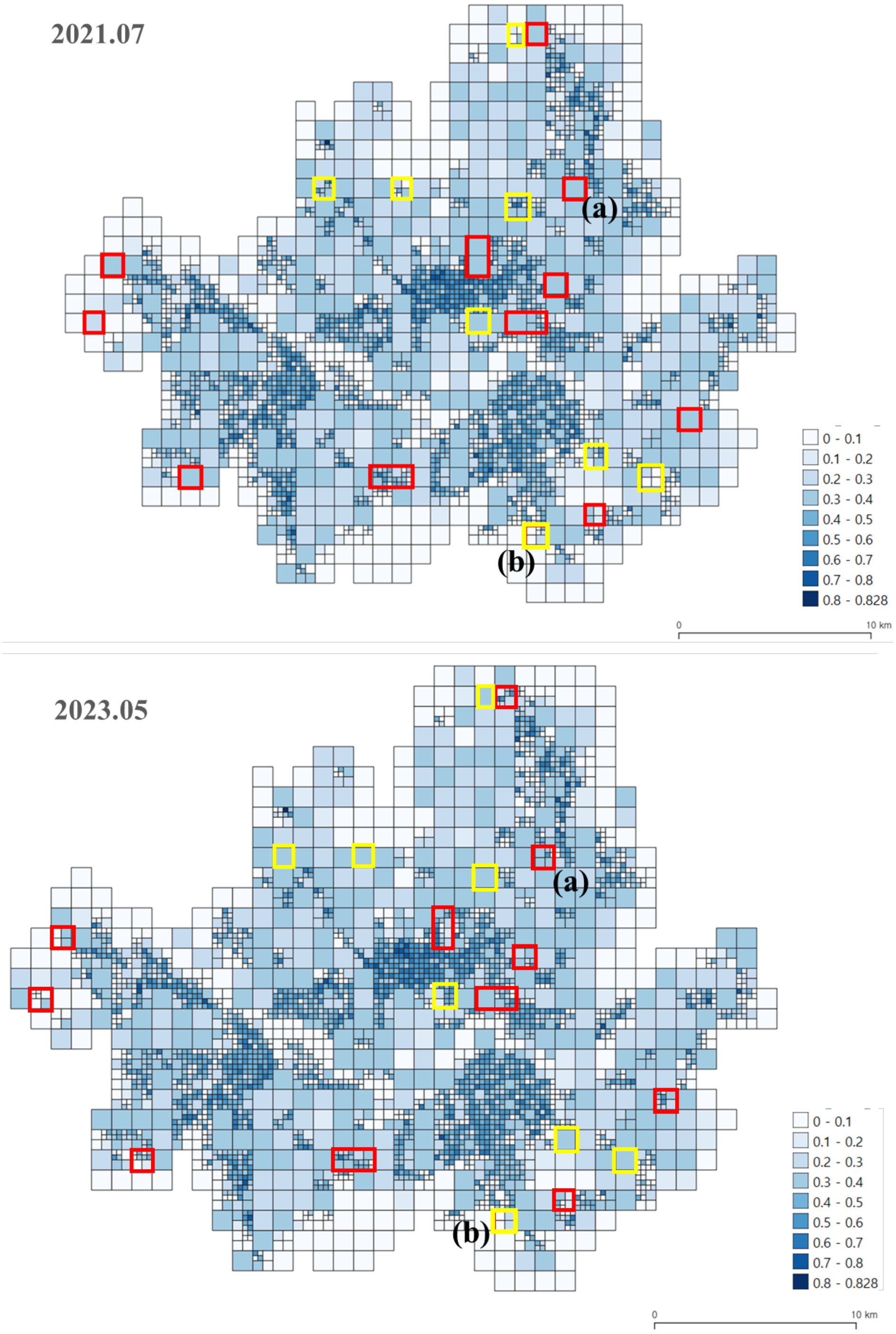
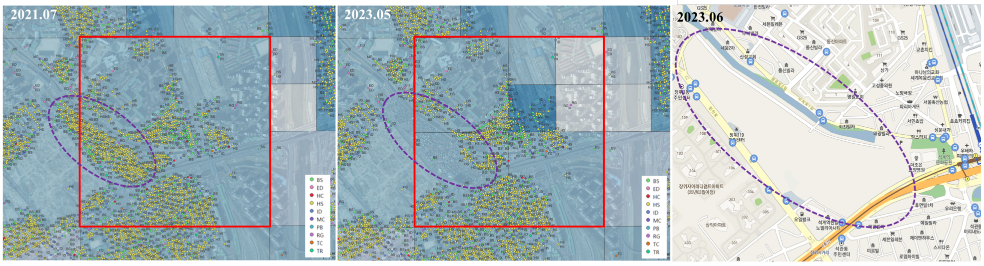
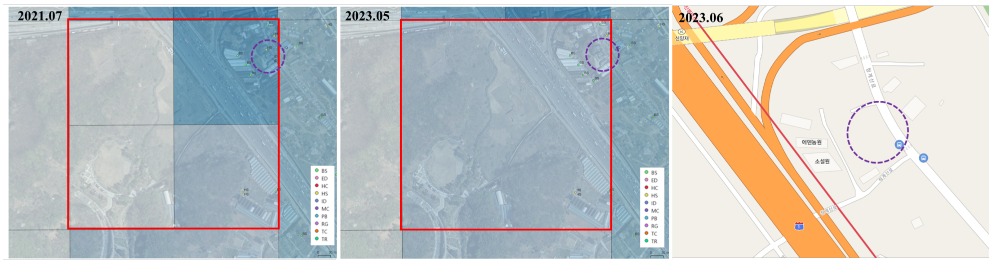


Figure 5. Vector data cube model for the time-series land-use mixing degree.

Therefore, a visual comparison was performed on the Kakao Map (https://map.kakao.com/), where a map updated in June 2023 was serviced for one of the regions corresponding to each case (Figure 6). Figure 6(a) shows an image of a cell with a higher level, which suggests that the land use mixing degree is high, as a large-scale housing complex (HS) was demolished for redevelopment (purple circle) and the POI type corresponding to the dwelling decreased. Figure 6 (b) shows am image of a cell with a lower level, and it suggests a decrease in the land use mixing degree, as an industry (ID) disappeared in 2021 (purple circle). This visual evaluation of some areas confirmed the significance of the proposed method.



(a)



(b)

Figure 6. Visible evaluation.

4. Conclusion

In this study, the time-series analysis of the land use mixing degree was performed, and the primary grid (1000 m) was divided using the IE of the POI for each cell to analyze the land use mixing degree. Furthermore, to manage the large amount of land use mixing, it was structured as a data cube discussed in EO. To this end, a vector data cube model that considers a hierarchical cell was proposed. Thereafter, a visual evaluation was performed after applying the proposed method to the POI data of Seoul, ROK, in 2021 and 2023, and the visual evaluation confirmed the significance of the proposed method. Similar to previous studies, future studies should analyze the land use mixing degree using multi-source data, and technologies for storing and managing vector data cubes should be developed.

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Analyzing problems of district-based administration using Monte Carlo simulation: the case of sex offenders notification

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Abstract. The problems of administration simply based on administrative unit that does not consider the operational purpose of the system have been consistently mentioned. For example, in the Republic of Korea, sex offenders information is notified by mail only in some regions. However, the information of sex offenders is notified based on the administrative 'Dong' of the offender's residence, so even if you live in the building next to the offender, you cannot be notified because the dong of residence is different. Therefore, in this study, the problems of administration that did not consider the realistic scope were analyzed using the case of sex offender. By expanding the distance, we derived the extent of the sex offenders notification problem. Also, in order to determine whether this problem occurred by chance at a specific point in time or a fundamental limitation in administration, Monte Carlo simulation were applied to compare the degree of problems in actual residence and random residence data.

Keywords. Administrative district, Sex offender, Monte Carlo Simulation

1. Introduction

The Republic of Korea has administrative districts such as Gu and Dong within cities and Seoul has 25 Gu and 426 Dong. Administration is handled based on them, however, administration based on administrative unit that does not consider the operational purpose of the system continues to be an issue. For example, in the field of nuclear safety (radioactive leak) crisis

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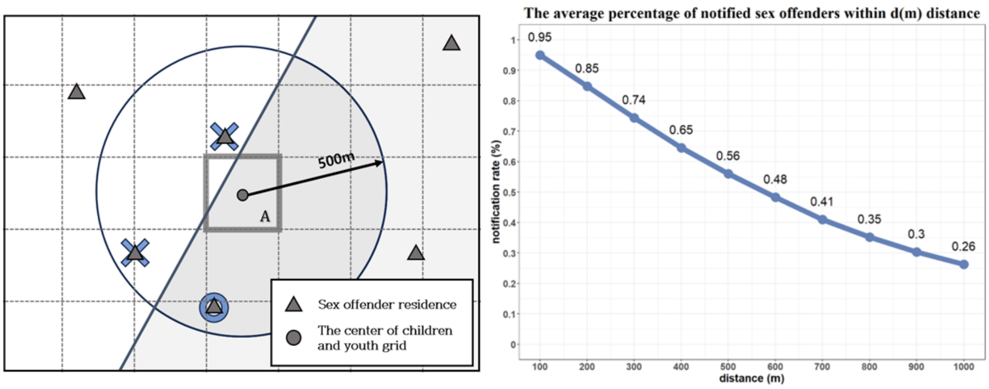
response practice manual, when a fire or radioactive leak accident occurs, the designation of the fire department is based on the administrative district. Accordingly, even though there was a 911 safety center 2km away, the center 11 km away was designated as the fire department in charge, which took more than 5 times longer to respond (Park, 2020). It was pointed out that the designation of center based on administrative districts was not suitable for safety fields requiring rapid response, so the designation of fire departments was changed based on distance.

The need to consider the distance standard when setting the scope can also be found in the issue of notifying sex offenders. In the Republic of Korea, sex offenders information is notified by mail only in some regions. Currently, the information of sex offenders is notified to household and institutions that protect children and youth in the administrative dong where the offender resides. According to Kim and Jung (2011), sex offenders are more likely to commit crimes in familiar places than unfamiliar places, and more than half of sex crimes against minors occur in areas near to the offender's residence (Gu 2023). However, the administrative dong based information notification system has a limitation in that information is not notified to residents who actually need the information, as even if the offender lives in the building next door, information cannot be notified unless they live in the same administrative dong. Therefore, in order to provide practical information, it is necessary to revise the system such as notification considering the distance from their residence.

This study aims to analyze the limitations of administrative district unit administration using the sex offender notification issue as a case. To this end, by increasing the distance centered on the children and youth grid, derive the number of sex offenders living in the nearby area, the ratio and the distance of sex offenders for whom information is not notified. In addition, to confirm that these problems do not occur only in certain residence types, Monte Carlo simulation was used to compare the degree of sex offender notification problems in the residence distribution of this study and random types. Before starting the analysis, sex offender data was referenced on the sex offender notification website(https://www.sexoffender.go.kr/), and to protect personal information, the imported data was anonymized and actual residences were not visualized.

2. Spatial analysis of the current notification system limitations

To determine the notification rate of sex offenders living nearby, analyze as shown in *Figure 1 (a)*. In Grid A, there are a total of 3 sex offenders within 500m, of which there is 1 offender for whom information can be notified, and there are 2 offenders for whom information cannot be notified because they do not reside in the same administrative district. Therefore, the notification rate of the grid A can be calculated as 33.3%. This was calculated for all grids within the study area, and the number of children and youth within the grid was applied as a weight. So, if p_i denotes the number of children and youth in gird i, a_i denotes the number of sex offenders residing in the same dong as gird i within d distance, t_i denotes the number of sex offenders within d distance from gird i, the average percentage of notified sex offenders within d distance($P(d)$) can be calculated as *Equation 1*.



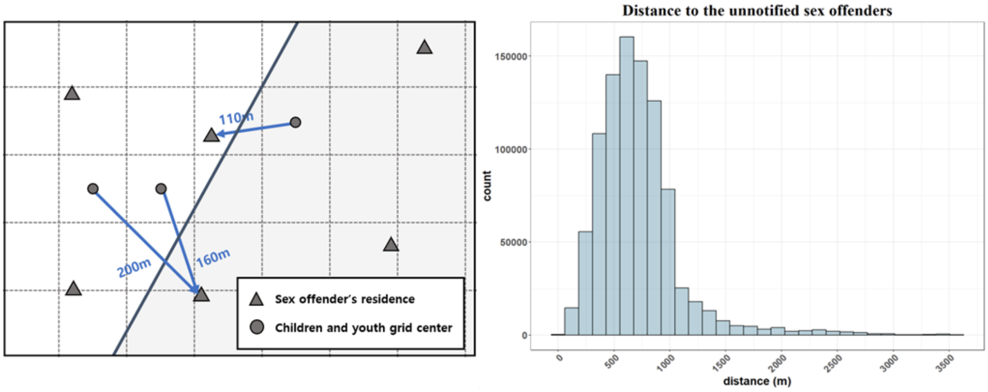
(a) **(b)**

Figure 1. (a) How to calculate notification ratio, (b) Result of notification ratio

$$P(d) = \frac{\sum_{i=1}^{n} p_i x_i}{\sum_{i=1}^{n} p_i}, \quad x_i = \frac{a_i}{t_i} \qquad (n: \mathit{Total\ number\ of\ grids}) \qquad \textbf{Equation 1}$$

Centered on children and youth grid, the calculation in 100m increments from 100m to 1km is shown as *Figure 1 (b)*. As a result of the calculation, the average notification rate of sex offenders per 500m is approximately 0.56. This means that, for example, if 4 sex offenders live within 500 m of a children and youth, half of them(2 sex offenders) will not be notified.

Next, as shown in Figure 2 (a), in order to find out how close children and youth live to sex offenders for whom information has not been notified, the distance to the nearest offenders who do not live in the same administrative district around each grid was calculated. As in the previous analysis, the number of children and youth in each grid was applied as a weight, and calculated for all grids in the study area to derive the distribution shown as *Figure 2 (b)*. As a result of the analysis, it was confirmed that approximately 255,000 children and youth(28% of the total) live within 500m of the unnotified offender.



(a) **(b)**

Figure 2. (a) How to calculate distance, (b) Distance to the unnotified sex offenders

3. Monte Carlo simulation

In the study, using residence data of sex offenders at a specific point in time, analyze the vulnerabilities of the information notification system at the administrative district unit. Therefore, it is necessary to determine whether the results appeared by chance at a specific point in time or due to fundamental limitations of information notification at the administrative district unit, because the analyzed results are dependent on the distribution of offenders' residences. Accordingly, we performed a Monte Carlo simulation-based verification that compared the results of the analysis based on the actual offenders' residence with the results of sufficiently repeated analysis based on the random residences generated by random numbers. To do this, we built a model that generate random residences and calculate the notification rate or the distance to sex offenders who were not notified in the generated residence type. The pseudocode for the Monte Carlo simulation applied to each is shown in Figure 3, and it was programmed using R 4.2.2 x64. The simulation was performed 999 times with reference to previous research. After the simulation, the results were ranked from lowest to highest. To compare the randomly generated residence-based analysis results with the actual residence-based analysis results, a 95% confidence interval was derived by excluding the top 50(or bottom 50) observations among the sorted statistics. And, if the actual residence-based analysis results were included in the confidence interval, the degree of information notification problems occurring in the two types of residence were considered to be similar, it was considered that problems similar to the analysis results would occur in any type of residence. As a result of the analysis, it was confirmed that problems similar to those in this study occur in any type of residence.

Nomenclature			
S	Number of iterations	G	Entire grid
T_j	Number of sex offenders residing within 500m from grid j	C_j	Number of children and youth in grid j
A_j	Number of sex offenders residing in same dong as grid j and within 500m	K_j	kth nearest offenders by grid j
A	Percentage of notified offenders	$D_{(j,l)}$	Distance of data j and l
C	Entire number of children and youth	D	Distance from sex offenders who are not notified

Percentage of notified sex offenders

for $\forall i \in S$
  Generate residence points in random
  for $\forall j \in G$
    $A \leftarrow (A_j / T_j) C_j + A$
    $C \leftarrow C_j + C$
  end for
  A/C
end for

Distance from sex offenders who are not notified

for $\forall i \in S$
  Generate residence points in random
  for $\forall j \in G$
    for $\forall l \in K_j$
      if $j_{Dcode} \neq l_{Dcode}$ then Calc. $D_{(j,l)}$
      break
    end for
    $D \leftarrow D_{(j,l)} C_j + D$
  end for
  D/C
end for

Figure 3. Pseudo code of Monte Carlo

4. Conclusion

In this study, the problems of administration based only on fixed areas such as administrative districts without considering the spatial scope according to the purpose of the system was examined, using the case of sex offender information notification. And Monte Carlo simulation was applied to confirm that this problem does not occur only in a specific type of residence. As a result of the study, it was possible to identify children and youth households that living close to sex offenders but were not properly informed, and it was confirmed that this problem occurs even in any residential type. Since the issue of offender information notification can be directly related to the safety of the citizens, it is necessary to properly inform the citizens who need the information. Simply setting the scope of administrative district without considering the purpose of the system has the problem of adding administrative inefficiency and inconvenience to daily life in system where distance is important. Therefore, for a practical and systematic response, it is essential to consider the spatial perspective when setting up the work area. In this respect, this study is expected to be used as basic data for improving administration simply based on administrative districts without considering realistic scope.

Acknowledgement

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Development of Carbon Spatial Map for Spatial Planning

Inho CHOI[1], Mira PAK[2], Inyoung KIM[3], Minyoung LEE[4]

Abstract. Existing greenhouse gas statistics make it difficult to establish a spatial unit reduction plan for individual regions. In addition, there are limitations in analyzing carbon emission reduction effects reflecting spatial characteristics and establishing spatial plans. Therefore, the purpose of this study is to improve greenhouse gas spatial information and statistics, develop technology, and establish a system to support carbon-neutral urban planning. Research builds carbon spatial maps and develops platforms to support carbon-neutral urban planning. This shortens the basic survey period, improves the explanation of predictive models, and supports the establishment of carbon neutral plans in demonstration cities. The results of the study can be used in various fields such as carbon neutral monitoring and carbon neutral policy establishment and are expected to be effective in urban planning such as narrowing the technology gap and establishing a foundation for Spatial management.

Keywords. Carbon Neutral City, Carbon Spatial Map, Urban Planning, Planning Support, Demonstration

1. Research background

According to the "Basic Act on Carbon Neutrality" enacted in September 2021 and the "2050 Carbon Neutral Scenario" announced in October 2021, local governments are obliged to establish and implement carbon neutral basic plans to promote carbon neutrality. Accordingly, the government and local governments have an obligation to establish GHG reduction targets and implementation plans and to check the progress.

Existing greenhouse gas statistics were written centering on emission sources, making it difficult to use them to establish spatial unit reduction plans for individual regions. In addition, the greenhouse gas inventory is currently provided at the local government level, and there is a two-year lag between collection and publication. Because of this, spatial-level data is

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needed for beneficial carbon emission reductions within a city. It is difficult to analyze the emission reduction effect that reflects spatial characteristics such as spatial structure, urban form, land use, and infrastructure of the city with only the existing (metropolitan) administrative district unit emission information, and there are limitations in establishing spatial planning.

Therefore, in order to establish a carbon-neutral city plan, local governments need to revise the basic planning guidelines for cities and counties. To this end, it is necessary to develop technology that supports spatial planning, which analyzes carbon emission and absorption status information based on spatial maps. In addition, to support the establishment of spatial policies, a separate system establishment and utilization basis must be prepared.

The purpose of this study is to improve greenhouse gas spatial information and statistics, develop technology, and build a system for carbon-neutral city planning, build a carbon Spatial map that can be used for spatial planning, and a platform that supports carbon-neutral city planning.

2. Research content

2.1. Conceptual diagram of research object

The carbon-neutral city Spatial planning support platform includes a carbon Spatial map system and is composed of various modules to support carbon-neutral city planning. This platform is designed to share and connect the functions necessary for city planning in connection with the big data-based artificial intelligence city planning establishment support system. In addition, it has been implemented so that the platform can operate smoothly by utilizing the latest information such as KLIP and greenhouse gas information system in connection with information systems in land transportation and related fields.

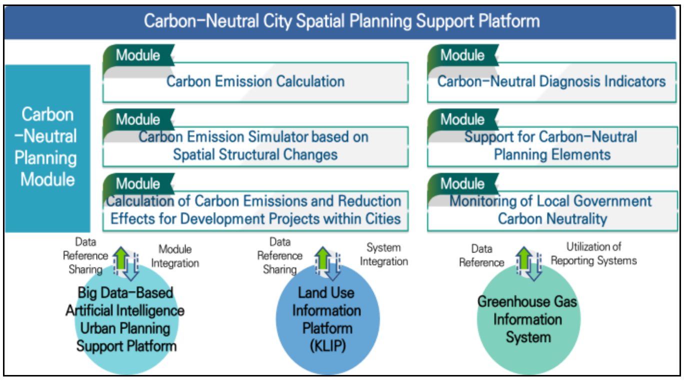

Figure 1. Carbon Neutral City Spatial Planning Support Platform Concept

2.2. Establishment and Verification of Data Acquisition Plan for Advancement of Carbon Spatial Map

In order to upgrade the carbon Spatial map, we have established a plan to secure and link source data to calculate energy use in buildings and carbon emissions in the transportation sector. This increases spatial resolution from the traditional minimum grating of 100 m to 10 m, providing more granular carbon emissions and absorption data.

In addition, we have established a plan to standardize carbon Spatial map data for each spatial unit in consideration of areas for use such as residential, commercial, industrial, and green areas. This provides carbon spatial map data in a consistent format.

By accurately calculating the energy usage and carbon emissions of the building unit and transportation sector and providing detailed carbon emission and absorption data, the quality of carbon Spatial maps is enhanced and standardized data reflecting various use areas is secured

Categories		Existing Carbon Spatial Map System	Approach for Applying Enhanced Carbon Spatial Map Model
Resolution	Grid	Minimum 100m grid	Minimum 10m grid
	Buildings	Representation using grids	Representation using grids, building forms
	Transportation	Administrative areas, linear features	Representation using grids, road linear features
	Absorption sources	Representation using grids	Representation using grids, boundaries of absorption sources
Utilization information	Buildings	Utilization of building energy usage information	Incorporation of additional characteristics at the global level, addition of variables for simulation purposes
	Transportation	Utilization of major road network traffic volume (vehicle type/fuel type/speed) information, applying emission conversion factors	Precise calculation of traffic volume up to detailed road network + addition of variables for new transportation modes, validation using private data
	Absorption sources	Calculation of forest absorption using forest area (provided by Korea Forest Service) and emission factors	Precise calculation of traffic volume up to detailed road network + addition of variables for new transportation modes, validation using private data
Inventory		Confirmation of emission quantities by administrative areas and land use zones	Creation of spatial unit inventories incorporating residential, commercial, industrial, and green areas

Table 1. Carbon Spatial map advancement model application plan

2.3. Establishment and verification of data acquisition plan

The following tasks were performed to secure basic data necessary for upgrading carbon spatial maps. First, we established statements about data sources, data refresh cycles, data types, and structures to clearly define the sources and characteristics of the data. Through this, the reliability and consistency of the data were secured.

The National Building Energy Integrated Management System collects basic information on buildings, areas of use, and road networks as well as electricity, gas, and energy usage data every month. The data collected in this way is used to calculate the building's carbon emissions.

We also measured carbon absorption in green areas using clinical maps and land cover map data from the Korea Forest Service. Based on these basic data, we design a model and data linkage structure for calculating carbon emissions and absorption.

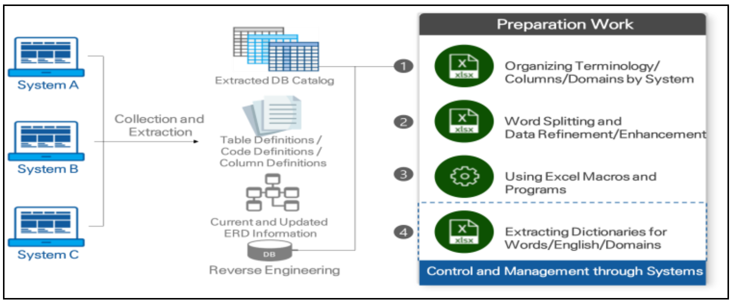

Figure 2. Metadata-related artifacts

2.4. Application of Carbon Emission and Absorption Calculation Model by Spatial Unit

In order to calculate carbon emissions and absorption, various spatial data such as buildings, road networks, use areas, and administrative areas were considered. To this end, we selected standard spatial units and developed conversion algorithms to maintain consistency and interoperability between data.

In relation to the energy usage of buildings (electricity, gas, district heating, etc.), we have developed a data set of carbon emission conversion by building units combined with various attributes such as location, use, and construction year of buildings. This creates a dataset that can be represented in the form of a building, and also takes into account the scalability of future.

This allows you to standardize various spatial data and develop conversion algorithms to accurately calculate carbon emissions and absorption. In addition, a building-level dataset can be developed and expressed according to the shape of the building, which also takes into account future scalability.

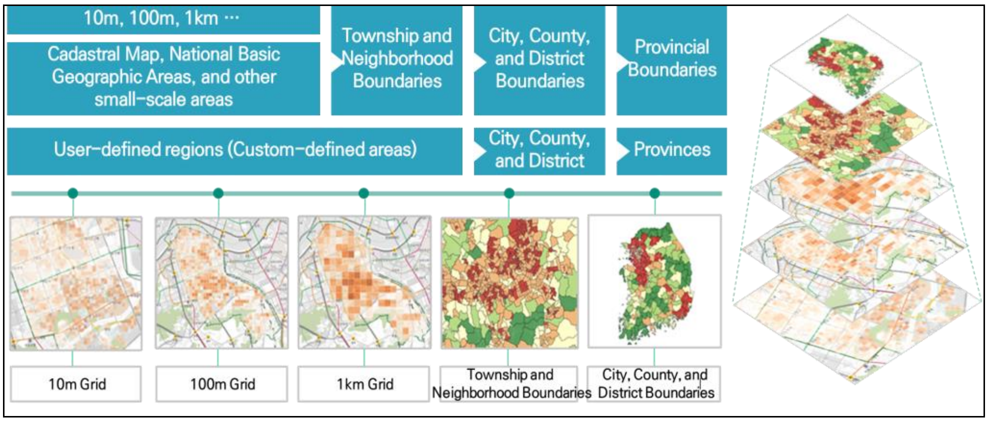

Figure 3. Carbon emission and absorption calculation model application plan by spatial unit

2.5. Implementation of Advanced Carbon Spatial Map

In order to upgrade the carbon space map, we are designing and developing systems to provide various functions and accurate information. In the past, we plan to improve the carbon space system that can only be inquired and provide flexible and accurate information through functions such as point analysis, drawing analysis, SHP file analysis, and carbon reduction modeling analysis.

Develop a methodology for producing grid-unit data used in carbon Spatial maps, and develop guidelines and manuals for users and operators of the system to promote operational and management efficiency. Through this, it is possible to provide more diverse analysis functions and accurate information by realizing the advancement of carbon spatial maps.

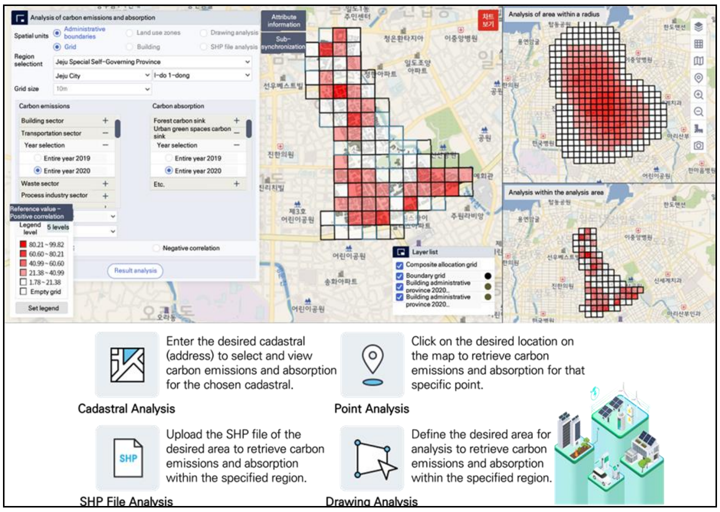

Figure 4. Carbon Spatial Map Advanced Implementation System

2.6. Design of Carbon Spatial Map System Framework

The carbon spatial mapping system framework is designed with a focus on data collection, analysis and visualization, security, and scalability.

Data Collection Module Design: A module was developed to collect source data such as energy use, traffic volume, and land use area. This module collects data in real time and stores it securely on a distributed storage system.

Data Analysis and Visualization Module Design: A module applying an analytical formula that calculates carbon emissions and absorption using stored source data was developed. This module visualizes the analysis results in a variety of ways and provides them as maps, charts, etc. This allows users to intuitively understand carbon emissions and absorption.

Security and scalability module design: Design security features for data including sensitive information covered within the system. Secure features such as data encryption, access control, and logging to ensure data confidentiality and integrity. In addition, a standard framework is established in consideration of the scalability of the system to facilitate the addition of new features and system expansion.

The carbon Spatial mapping system framework designed in this way provides comprehensive capabilities in terms of data collection, analysis, visualization, security, and scalability, providing accurate and secure carbon emission and absorption information.

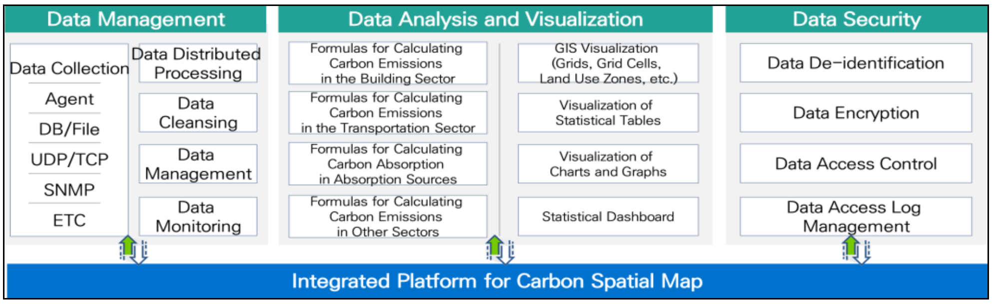

Figure 5 Design of Carbon Spatial Map System Framework

2.7. Purpose and Application of Research Deliverables

Through carbon neutral monitoring of the national Spatial unit, a carbon Spatial map system can be established to monitor carbon emissions and absorption performance of the entire country. This is used by related ministries, including the Ministry of Land, Infrastructure and Transport, to understand the current status of carbon neutrality in land Spatial.

It is also used to support the establishment of carbon neutral policies by local governments. Through spatial unitization of greenhouse gas inventories, local governments can establish carbon neutral policies based on spatial information. This helps local governments establish sustainable carbon neutral policies and contributes to reducing carbon emissions.

It is also used to support the establishment of carbon-neutral city planning. By reflecting the carbon-neutral city planning elements specified in the city county's basic planning guidelines in the city planning process, a plan aimed at carbon neutralization of the city can be established.

Finally, it is used to provide carbon neutral information to large citizens. Ordinary citizens can check the carbon neutrality of the region in their daily lives through the citizen service. This helps raise public awareness of carbon neutrality and reduce individual carbon emissions.

3. Conclusion - Expected effect

As a policy expectation effect, carbon Spatial maps can be used to evaluate the current status of greenhouse gas reduction and to set requirements for designating carbon-neutral cities. In addition, policy measures such as designating carbon emission concentrated areas, supporting spatial planning, and establishing carbon-neutral urban spatial structures can be provided to cope with local governments' obligation to establish and implement carbon-neutral basic plans.

The expected effects of science and technology can contribute to narrowing the technology gap in urban areas by introducing analysis, prediction, and optimization technologies for carbon neutrality in urban planning. It also provides a scientific technology foundation for the transition from emission-oriented management to spatial emission and absorption-based planning and management.

Economic and social expected effects can contribute to greenhouse gas reduction by building infrastructure in the city and establishing a plan to reduce greenhouse gas emissions by sector using carbon Spatial maps. In addition, greenhouse gas reduction can be accelerated by establishing a carbon-neutral spatial structure transformation strategy that reflects regional characteristics.

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Explainable GeoAI Real Time Data Model for Heterogeneous Datasets: Graph Database Approach

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Abstract. Spatial activities are described and linked to the identified place or location. In the age of the Internet of Things (IoT), a vast collection of spatial datasets is emerging. The introduction of GeoAI into spatial data analytics is changing the scope and perspective of analytical capabilities in many ways. Since GeoAI is the merging application of spatial data science, artificial intelligence, and geospatial information science, and is the highest and most advanced application of geo-enrichment, intensive heterogeneous data sources have been used. Due to the extensive open data sources generated by mobile devices, sensor data streams from static or moving sensors, satellites, the availability and sharing of data via standard APIs have now increased immensely. In this article, a graph database approach is intensively emphasized to develop an object oriented based explainable GeoAI data model in its various applications. In addition to the available data sources, large amounts of data are currently being generated by various institutions. The issue of sharing and reusing data between institutions is receiving more and more attention for various reasons. Linking datasets between different platforms creates ambiguities for both machine and human. In this article, the research mainly analysis the problems in real-time generated data management of heterogeneous spatial data in the application of GeoAI and provided recommendations.

Keywords. GeoAI, graph database, moving features, heterogeneous datasets, real time data model

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1. Literature Review

In the era of geospatial "Big Data" [1], up to 80% of big data is "spatial" with locational components attached [2]. With the advanced development in remote sensors, GPS-enabled applications and the popularity of mobile devices, as well as increasingly affordable data storage and computational technologies, geospatial big data are produced from a wide range of disciplines from commercial business to scientific research and engineering at a very fine spatial, temporal and spectral resolutions[3][4][5]. Such geotagged data in large volume, high velocity, and abundant variety that exceed the capacity of current common spatial computing platforms are defined as spatial big data [5]. The recent breakthrough in machine learning, or more generally AI and more specifically deep learning, enables a new research paradigm of data-driven science to analyses, mine, and visualize massive spatial big data (SBD) that are difficult to handle using traditional spatial analysis methods [5].

An increased availability of geospatial big data and real time generated dataset, the advancement of artificial intelligence (AI) and the availability of high computing power have created a momentum for the digital exploitation of geospatial big data real time analysis and in turn combines discipline in spatial science, artificial intelligence methods in machine learning (e.g. deep learning), data mining to extract knowledge from spatial big data. This all together emerge the new scientific discipline called Geospatial Artificial Intelligence (GeoAI) [6] [7].

The emergence of GeoAI has a significant role by developing conventional technologies AI and innovating new technologies to use the high potential geospatial big data to address ever developing new complex challenges faced in our day to day activities [6]. As the main component of the GeoAI infrastructure, an appropriated technologies can be applied to improve certain steps in the heterogeneous data management and intern maximizing the return on geospatial big datasets [6].Even though a drastic improvement have been achieved in geospatial big data analysis and geospatial artificial intelligence both in practical implementation and hypothesis analysis, the lack of high trained and labelled quality data and appropriate data management is remain the main challenge for GeoAI [17] [8].

The key challenge in GeoAI applications is scaling the integrated system to complex data scenarios. Even though GeoAI in its first inception certainly apply the AI technologies, especially those based on Deep Learning, i.e. usually require huge collections of layered and training data, GeoAI is an ideal opportunities in spatial based research challenge solutions [6]. Based on the fact that an explainable model could be the crucial variable in a predictive model, data structure is an essential factor in developing an explainable GeoAI model [6] [9] [10].

In line with the increasing use of computer analysis in artificial intelligence, more and more humans and integrated machines will work together to improve our understanding of spatial Big Data [6]. Since the biggest challenge in this emerging field of science is reliability and robustness, the degree of difficulty in model interpretability must be emphasized [6] [9] [10] [17].

To process the ever-increasing large heterogeneous open-source geospatial datasets, an advanced digital infrastructure that enables highly scalable data processing is required to provide a standardized, time-appropriate solution technology for real time heterogeneous, computationally intensive geospatial data problems [10] [11].

Figure 1. Three main components of GeoAI. (Source [3])

2. Objective

- Study on real time moving objects spatio temporal data management
- How efficient graph database for explainable GeoAI application
- Verify and explain the integration capabilities of graph database applications of GeoAI

3. Research Question

- How is data about moving objects represented in real time?
- Is explainable GeoAI better in graph database technology than in other database technologies?
- How easily is a non-spatial dataset discoverable?
- Can researchers determine and analyze the appropriate database technology for explainable GeoAI?
- How can data interoperability and automated routing be verified in a graph data model?

4. Challenges in explainable GeoAI application

In the era of geospatial big data and digital worlds, datasets from multisource devices for machine-to-machine communication are expected. How efficient in terms of computing capability, prediction model, and analysis is the key challenge when it comes to explainableGeoAI.The heterogeneity of the dataset from sensors and devices has to be edge computing capability. In this case, integrations and information exchange in the data exchange layer are traceable and identifiable [11] [13] [16].

The dataset that is currently collected and analyzed is mainly compiled in the framework of a relational database. However, the dataset that requires specifically the application of GeoAI is large-scale spatiotemporal data. A fixed data structure as a relational database for these types of datasets is challenging. A large, heterogeneous, and scalable data source is not efficient in data manipulation and analysis [12].The data management and their structure in the application of GeoAI for all kind of database illustrated that the difficulty and challenges can be easily identified. In the subsequent part of this article, a detailed practical example identified.

Efficiency, memory usage, and energy consumption could also be an extension of this article in a separate research project task. However, the challenge in explainable GeoAI is mainly the heterogeneity of the data source, data integration, and model accuracy. In the following unit, the comparisons among various types of databases are described based on scalability and performance [6] [7].

5. Database comparisons

Different types of database technologies are developed for specific and general purposes. The main database types used in research data management and analysis are relational/SQL databases, time series databases, and NoSQL databases. Even though each database is designed for its subsequent operation and goal, whether they are open or commercial tools, users and various industry and research projects have preferred their best interest and suitability for the purposes desired. The selection of a suitable database type in terms of analysis capability, computation time, scalability and integrability is distinguished in Table 1. Managing heterogeneous large spatio-temporal real time data with the appropriate application of GeoAI the outer most achievement and goal [7] [14] [15]. To give an overall view, the following table summarizes the most important comparison criteria.

Comparison Criteria	**Relational /SQL Database**	**NoSQL Graph Database**
Scalability	rigid	Flexible
Performance (Transaction)	good	good
Performance (Deep analytics)	poor	excellent

Table 1. Database type and comparison criteria (source [14])

As big geospatial datasets are generated from heterogeneous data sources such as mobile devices, social networks, and the Internet of Things (IoT), the memory is flooded with data at every moment of collections. As the cornerstone of this study, a real-time unstructured Big Data database and graph technology are explored to improve the applicability of GeoAI. NoSQL unstructured database is more weight than relational database in its characteristics such as flexibility, dynamism, agility, and explicitly integrate with hetrogenopues data source without significantly changing the whole designed setup and data integrations[13] [14].

6. Methodology

The application of explainable GeoAI was identified with respect to the geospatial research and development activities of the Leibniz Center for Agricultural Landscape Research (ZALF) and the Ethiopian Construction Design & Supervision Works Corporation (ECDSWCo). Both institutions rely mainly on spatial Big Data sources. In particular, the real-time geospatial data requirement plays a key role in crop yield prediction, soil moisture, flowering stage detection, flood forecasting, and real-time data monitoring. In this paper, we focus on case studies of soil moisture and flood prediction and monitoring. One of the goals of this research project is to develop a graph database to manage real-time spatio-temporal data on moving objects for selected projects.

6.1. Distributed Spatiotemporal Graph Database

The use of big data is the cornerstone of GeoAI. The design of the model and the implementation of the framework are the focus of this paper. This section makes the largest contribution to the development of handling heterogeneous datasets for explainable GeoAI [1] [15] [16].

In the GeoAI data platform, the data sets are mainly unstructured and come from different sources. The ideal database platform that can handle unstructured and heterogeneous data sources is NoSQL graph database. This type of database is not only characterized by its flexibility and scalability, but also allows linking non-spatial and spatial dataset features [1] [15] [16].

Currently, unstructured and semi-structured data are becoming the mainstream of advanced spatio-temporal data management. Several institutions use observations and measurements from various sensors, such as geospatial data from location-based services (LBS) and social networks, which can be stored in semi-structured and unstructured databases. NoSQL databases provide a highly accessible and scalable way to efficiently manage semi-structured or unstructured geospatial data. Therefore, the concept and framework focused on establishing a distributed spatio-temporal graph database [1] [13] [16] [17].

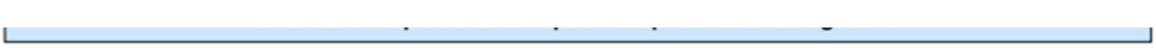

Figure 2. Distributed Graph Database and GeoAI digital Infrastructure

6.2. Data preparation

Real-time heterogeneous data management is implemented to justify the hypothesis based on the designed system selection matrix index. Therefore, the study mainly focused on soil moisture monitoring and flood forecasting. Meanwhile, datasets of any subject can be integrated and used for the demonstrable ability of handling heterogeneous data types and real-time spatio-temporal data management. Data sets from sensors and mobile devices required for soil moisture monitoring are modeled in a graph database structure. Devices such as radiometers, spectrometers, spectroradiometers, and soil moisture sensors are the main source of sensor data sets [15].

The data from moving objects, and UAVs produced large sets of information in crop yield prediction and blooming stage prediction. Variables of time-location paired knowledge stored and ready to use from graph database. These datasets require highly computing devices for processing. The volume and velocity of these big datasets are considered the scalable and integrable features of graph databases [3] [6].

Data from moving objects and UAVs provided large amounts of information for crop yield and flowering stage prediction. The variables of time-location paired knowledge data are stored in a graph database and can be used immediately. These datasets require high computational power for processing. The volume and speed of these large datasets are the characteristics of graph databases such as scalability and integrability, which can facilitate the storage and processing of large real-time datasets [3] [6].

6.3. Explainable GeoAI Analysis – real time spatio temporal data

Geospatial features of collected datasets are processed to instantiate the integration between non-spatial datasets for their maximum traceability and queriability [11]. The graph database design for explainable GeoAI is sympathetic for prediction and simulation model task. An explainable model can provide the capability to reviled the key variables and minimize ambiguity in the outcome. Connected features improve traceability and are interlinked with other features. From the geospatial data point of view, some variables could not be interlinked in the relational database. The major drawback of a relational database in explainable GeoAI application is that non-spatial data could not solely be retrieved and ready for analysis [3] [6] [10]. As depicted in the previous chapter, the usage of big data is the pillar of GeoAI .Large-size real-time dataset data cleaning, retrieving, and processing are highly efficient in graph database design.

To achieve and present AI explainability, explainable data in graph databases improve the knowledge of the data to be trained for a selected model. In addition, explainable data support the model with reasoning. We can generalize and conclude that the graph database for automated real-time ETL (extract, transform, and load) data pipeline can support data cleaning, quality detection, and data processing tasks. As shown in Figure 2, the main task of this tool is also data integration and quality control. The basic ETL pipeline is developed using the Python programming language to automate data collection from heterogeneous sources. A case study of flood prediction and soil moisture content determination of large geospatial data is used to develop the real-time ETL pipeline [19].

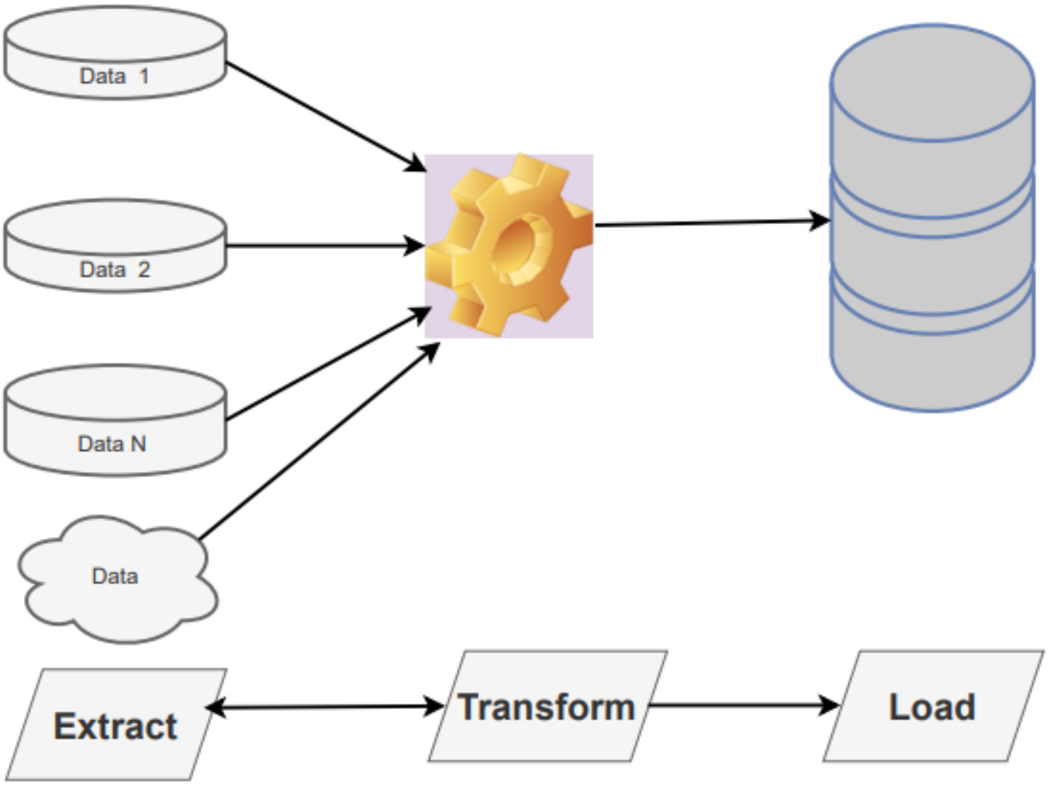

Figure 3. Real time ETL pipeline basic process

7. Conclusion

Heterogeneous data source object can be linked with each other. Knowledge derived from the large collection of the dataset discovered in support of one another. As explainable GeoAI consumes large dataset in a several layered feature, can support and provide well understandable answer to complex search queries. In the production of live stream data analysis output with an efficient performance, a distributed spatio temporal graph database set up a prominent digital real time spatio temporal infrastructure for the application of Explainable GeoAI. In the meantime, a standard data access API is maintained through the developed infrastructure and strengthen institutional inter cooperation. At the global level, where the data source in some application generated and collected worldwide, prepare a basis for the standard OGC moving features [18].

Note:

Since this project is an ongoing research project, the design of the graph database and the analysis of the real data are still in progress. The project encompasses a somewhat broader concept. The full version of the project will be available by the end of December 2023.

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Abbreviations

No.	Acronym	Description
1	**GeoAI**	geospatial artificial intelligence
2	**ZALF**	Leibniz Centre for Agricultural Landscape Research
3	**ECDSWCo**	Ethiopian Construction Design and Supervision Works Corporation
4	**SBD**	spatial big data
5	**LBS**	Location Based Service
6	**GPS**	Global Positioning System
7	**AI**	Artificial Intelligence
8	**NOSQL**	not only SQL
9	**UAV**	An unmanned aerial vehicle
10	**IoT**	Internet of Things
11	**OGC**	Open Geospatial Consortium
12	**ETL**	Extract, Transform and Load

Geodata Generation and Enrichment via ChatGPT for Location Based Services (LBS)

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Abstract. This short paper focuses on the generation and enrichment of geospatial data using ChatGPT (Chat Generative Pre-Trained Transformer, version 3, April 2023). Can we use ChatGPT to generate & use geospatial data in Locations Based Services? We conduct several example generations using the CSV and GeoJSON data formats for the feature classes points, lines and polygons. First results show the potential for educational and research purposes. The initial experiments, for example for tourism sites in Augsburg, indicate that is possible to generate geographic data, still the quality of the information is questionable. As it is generated data, it has shortages and challenges concerning for example the certainty & vagueness concerning the geographic components. In an outlook, we give first ideas for the application of the more promising approach of geodata enrichment by using ChatGPT and its possible use in location-based services (LBS).

Keywords. Artificial Intelligence Chatbots, Geodata Generation, Location-Based Services, ChatGPT, Geographic Data

1. Introduction

In recent years, the popularity of using generative AI in education and research has changed. As artificial intelligence chatbots are able to facilitate the academic writing process and improve readability in different languages, we can expect qualitative changes in selected outcomes of texts and software. The latter refers to the ability of ChatGPT (Chat Generative Pre-Trained Transformer) to optimize language use - even for programming

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languages. These expectations are currently being confirmed more and more, as in an initial study by Taecharungroj (2023).

In this work in progress research, we investigate the possibility of using ChatGPT to generate geospatial data in different feature classes such as points, trajectories, lines and polygons. The focus of this work is on generating geospatial data for the purpose of providing test applications for location-based services. This can be seen as an alternative method for the case that no or only sparse geodata are available. It also applies to the presence of geodata with only little attribute information. Thus, besides the generation of geodata (and the associated attribute information), another idea would be the enrichment of already existing geodata with additional attributes.

One possible application for ChatGPT is the enrichment of geodata for tourism sites. It could provide an option for capturing local knowledge (along with event information). This is partly related to ongoing research activities on the formalization of Points of Interests (POIs), such as by Psyllidis et al. (2022), and would in our opinion greatly benefit current developments.

Geodata Generation via ChatGPT – Selected Examples

The steps for creation and enrichment are provided by using ChatGPT prompts. We document our previous steps mainly using the responses and data sets generated by ChatGPT.

1.1. Generation of Point Data – POIs as an Example

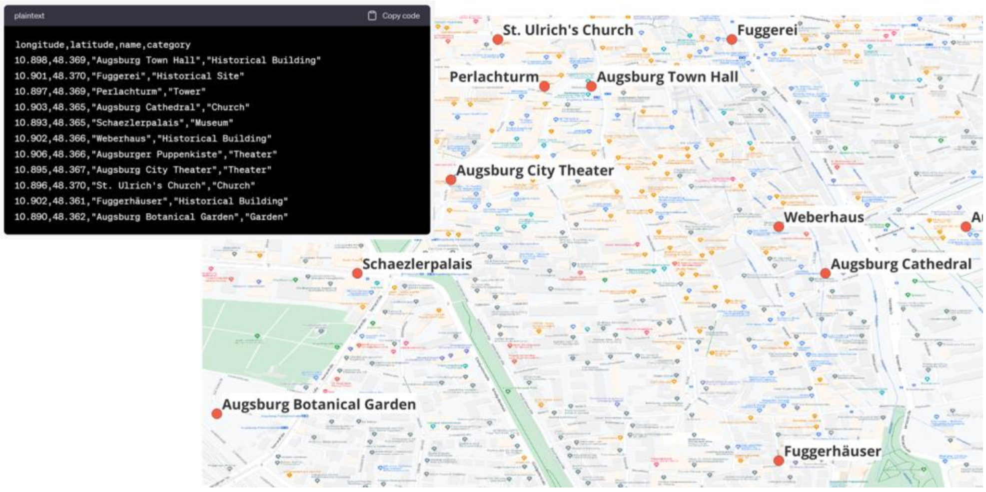

Figure 1. Visualized CSV file of landmarks in Augsburg, Germany.

In *Figure 1* we see a visualization of 11 landmarks (tourist sites) in Augsburg, only a few of which actually correspond to the exact location (prompt: "Create a csv file of all landmarks in Augsburg"). This could indicate that the quality of the location data is rather low. Nevertheless, the selection of landmarks in Augsburg, Germany, is acceptable (based on local knowledge).

1.2. Generation of Trajectory Data Sets

Figure 2. The generated trajectory of Odysseus with labeled events and directional arrows (based on a CSV file).

In *Figure 2*, (prompt: “create a csv file with the trajectory of Odysseus with record number, longitude, latitude, time stamp, year, name of location, name of event, time duration of Odysseus’ stay at the specific location”). In this case, selected events from the novel are well represented, but other attribute data - especially the timestamps - are inappropriate.

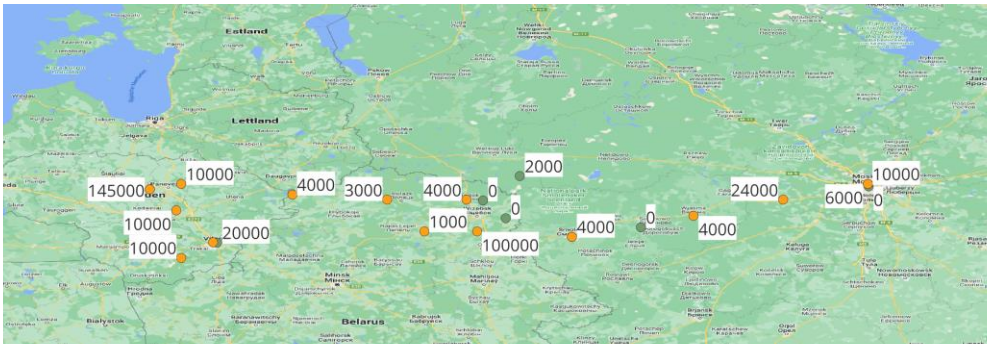

Figure 3. Recreating the data of Minard's map for Napoleon's Russian campaign (in orange) with labels showing the number of troop losses after every battle (compare to the data in green for Napoleon's Russian campaign in 1812).

In *Figure 3*, we compared the data in Minard's map with the losses of Napoleon's army (prompt: "create a csv file Minards map"). The locations of the battles partially match and, surprisingly, so do selected records from the historical map. On the other hand, the data on Napoleon's campaign of 1812 (in green in Figure 3) show far less detailed information.

1.3. Generation of Lines and Polygons

Figure 4. Generation of a line segment (in Magenta) representing the length of the reflection lake in Washington D.C..

Figure 4 shows surprising information: the reflection lake is shorter and not in the right place, but relatively close to the location of the reflection lake in Washington D.C. (prompt: “create a GeoJSON file with a line segment between the start and end of the reflection lake in Washington DC”).

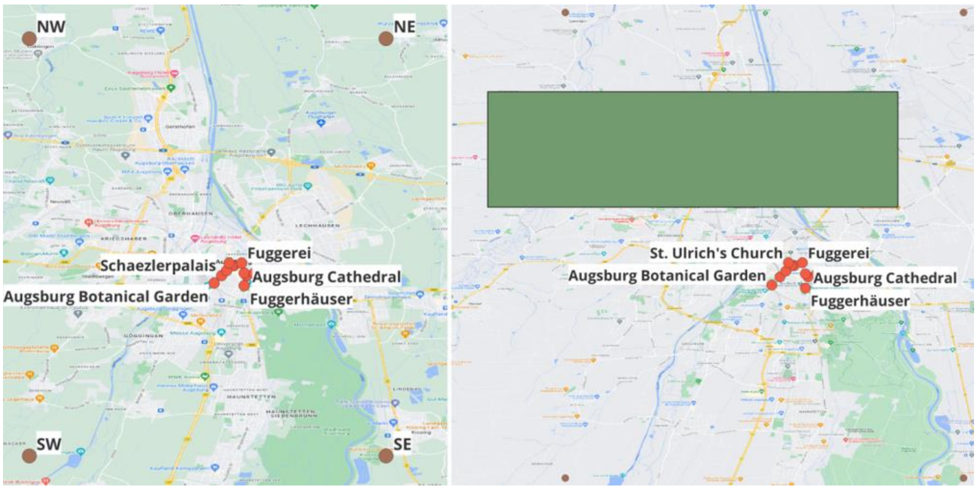

Figure 5. Examples for a bounding box around the German city of Augsburg with 4 cornerpoints (based on a CSV file) (left) and another attempt with a polygon (based on a GeoJSON file) (right).

Figure 5 shows the two tested approaches to polygon generation, resulting in a CSV file (left) and a GeoJSON file (right) with different dimensions and shapes (prompt: "create a csv file with four corner points of a bounding box around Augsburg"; "Create a GeoJSON file with a bounding box around Augsburg"). Nevertheless, there is a close proximity to the real city boundaries of Augsburg, Germany.

Geodata Enrichment through ChatGPT?

The development in this field is highly dynamic. It seems impossible to predict how the development will continue. Still, we can conclude that it is possible to generate geospatial data with the ChatGPT AI algorithms. As expected, these yield different qualities. Rather "fuzzy" concepts like "top 10 sights' seem to be generated in a reasonable list, geocoding seems reasonable on a large scale (e.g. the market place in Augsburg is not exactly on the right coordinates, but "approximately" in the right area. Nevertheless, the exact coordinates are not correct. Features that are measured in space (e.g. reflections of lakes or country borders) are created with estimated coordinates. These features are not geocoded correctly.

The idea of enriching geospatial data with generative AI differs from traditional approaches by selectively adding or extending attribute information for specific features. Jang et al. (2023) propose enriching geospatial data with place identities that can incorporate local knowledge, including dynamic components such as event information. This approach can benefit voluntary mapper initiatives such as the one presented by Polous et al. (2015). Our focus is on enriching point data on landmarks in Augsburg and establishing relationships between landmarks and POIs in OpenStreetMap (OSM). The formalization of POIs (Psyllidis et al. 2022) could benefit from AI-generated information enrichment. We are also exploring web-scraping approaches (Brenning & Henn 2022) to enrich scraped data with additional information during the scraping process.

Another avenue worth considering is the use of linked open data and semantic web approaches to generate and enrich geospatial data. Freely accessible databases such as Geonames (Ahlers 2013) offer analysis possibilities for location and street information.

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Early Insights into Location-Allocation Decision-Making using Ensemble Learning

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Abstract. The COVID-19 pandemic underscored the significance of geography in health emergencies, spotlighting the need for optimized spatial decision-making. This paper introduces a novel, data-driven approach to spatial decision-making, leveraging gradient boosting to derive data-informed weights for a Weighted Linear Combination (WLC). The goal is to pinpoint optimal locations for vaccination centres in Flanders, Belgium. Drawing from prior work, we present a foundation for the required number of centres, and then focus on determining the most suitable locations within Flanders. Utilizing a dataset of 91 centres, our ensemble learning technique dynamically determines criteria weights. Criteria that are socio-demographic or mobility oriented are considered. Our methodology, termed Ensemble Analysis for Criteria Trade-offs (ENACT), offers a comprehensive framework, targeting dynamic location-allocation scenarios. Using derived weights, we identify regions with the highest suitability scores for vaccination center placement. The high model performance metrics underline its reliability, with caution on potential overfitting. The study comes with a roadmap for enhancing the methodology's comprehensiveness in future research, suggesting the integration of more criteria and GIS optimization techniques for actionable health infrastructure planning.

Keywords. Multi-Criteria Decision Analysis, Gradient Boosting, COVID-19 Vaccination Strategy

1. Introduction

The COVID-19 pandemic has emphasized the role of geography in health crises. As the virus spread and responses varied, the importance of geo-

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graphical information science and systems (GIS) became clear (Higgs 2004, Li 2020). Historically used for healthcare planning (Lyseen et al. 2014), the unique challenges of the pandemic spotlighted the limits of traditional spatial decision-making(Parvin *et al.* 2021).

Traditionally, multi-criteria decision analysis (MCDA) has been favoured for spatial decision-making, relying on expert-informed criterion weightings. In contrast, our paper introduces an adaptive approach using the gradient boosting ensemble method. This innovative technique dynamically assigns weights to criteria in a Weighted Linear Combination (WLC), providing data-driven insights for spatial trade-offs. We apply this method to Flanders' vaccination strategy, pinpointing optimal vaccination centre locations based on these data-driven weights.

In the context of Flanders, a region of Belgium hard-hit by COVID-19, this paper builds on two central themes. First, we draw from prior research that determined the optimal number of vaccination centres based on the interplay between vaccine distribution and mobility costs. While these insights set a strategic foundation for the number of centres needed, the specifics of this research are detailed elsewhere (Beckers *et al.* 2021). Our current focus then shifts to spatial modelling, aiming to pinpoint the most suitable locations for these centres within Flanders, given its unique demographic and geographic features.

In response to the pandemic's urgency, the Flemish government swiftly set up 91 vaccination centres throughout Flanders, a number which notably exceeds our previously suggested optimal count in (Beckers *et al.* 2021). Nevertheless, we harness the spatial distribution of these 91 centres, using them as a foundational dataset for our ensemble model. By applying gradient boosting—a renowned supervised ensemble learning method in site suitability analysis (Sahin 2020, Yin *et al.* 2020, Wei *et al.* 2023) —we extract criteria weights for a Weighted Linear Combination (WLC). This approach yields empirically-supported weights for each criterium, offering a more data-driven decision-making framework.

Specific criteria were determined, based on literature (Alemdar *et al.* 2021, Guida and Carpentieri 2021, Song *et al.* 2022) and input from stakeholders, knowledgeable about spatial planning, mobility, and vaccination policy. These were either socio-demographic in nature or mobility-oriented. They include mean population age, node value public transport (Vlaamse Overheid - Departement Omgeving - Afdeling Vlaams Planbureau voor

Omgeving 2021), population density, road proximity, and hospital accessibility[1].

Positioned to offer a robust, adaptable, and comprehensive framework, we present our idea as the Ensemble Analysis for Criteria Trade-offs (ENACT). This method targets the intricacies of location-allocation decision-making in dynamic scenarios. The COVID-19 pandemic, with its vast logistical challenges and the imperative for effective vaccine distribution, presents an ideal backdrop for the implementation of such a methodology. This data-driven approach retroactively tries to depict a nuanced image of Flanders' vaccination strategy, aiming to ascertain the optimal spatial positioning of vaccination centres—retaining only the most strategically located—based on learned criteria weights.

The sections that follow delve into the methodology. In the preliminary results, we aim to illuminate how a gradient boosting ensemble model, yielding dynamically estimated weights for WLC, offers nuanced solutions for location-allocation dilemmas. Our discussion culminates with an assessment of the first outcomes, an exploration of potential pitfalls, and insights into the future potential and evolution of the methodology.

2. Methodology

To construct a comprehensive suitability model for the optimal placement of vaccination centres in Flanders, we acquired a collection of socio-demographic and mobility data. All of these criteria were normalised on a scale from zero to one, and processed across Flanders at a spatial resolution of 1x1 kilometres, resulting in a series of raster grids. In parallel, a binary dataset was developed to indicate the presence or absence of existing vaccination centres, which served as our labelled training data for the ensuing ensemble learning phase.

The main objective of this research is to amalgamate the criteria grids in a suitability raster, S, using the Weighted Linear Combination (WLC) method. The difficulty is determining the best weights for each grid in this combination. Formally, our targeted suitability score, S, for any given cell in the resulting raster map is articulated as $S = \sum_i w_i \times x_i$ where w_i represents the weights attributed to each factor and x_i denotes the scores (values) of the cells within the criteria grids.

[1] In the rare case a severe allergic anaphylactic reaction would occur after vaccination (McNeil and DeStefano 2018), it is important that the patient can be taken to the nearest hospital as soon as possible.

The methodology section details our ensemble learning technique using gradient boosting, with current vaccination centres in Flanders as the labelled training data. This approach refines criteria weights for optimal vaccination center placement. In gradient boosting, decision trees iteratively learn, with each tree building upon the errors of its predecessor. For example, while the first tree might focus on population density, subsequent trees might consider factors like travel time to the nearest hospital. After all trees offer their insights, their decisions are combined, with higher weights given to more predictive factors. The resultant feature importances indicate each factor's contribution to the model's prediction capability.

Next, the feature importances derived from gradient boosting are translated into weights for each criterium. This fusion of data-driven insights with the WLC method provides a more empirical and precise avenue for synthesizing decisions.

Beyond the determination of the criterium weights, the gradient boosting algorithm can several other insights regarding model performance. Metrics such as accuracy, and F1-score (a harmonic mean of the precision and recall) were adopted to provide a quantitative understanding of the preliminary model's prediction capability.

The code implementing the ENACT methodology is publicly available and can be accessed at https://github.ugent.be/cartogis/ENACT.

3. Preliminary Results

Using the gradient boosting technique, weights were derived for each of our criteria. These weights provide insight into the relative importance of each criterium in determining suitable locations for vaccination centres. The computed criterium weights are: mean population age: 0.096, node value collective transport: 0.203, population density: 0.215, road proximity: 0.440, and hospital accessibility: 0.046.

A composite suitability map was generated by employing the WLC method, utilizing the derived criterium weights. This map reveals regions in Flanders with the highest suitability scores, indicating optimal areas for vaccination centre placement. The visual representation of the composite map can be observed in Figure 1.

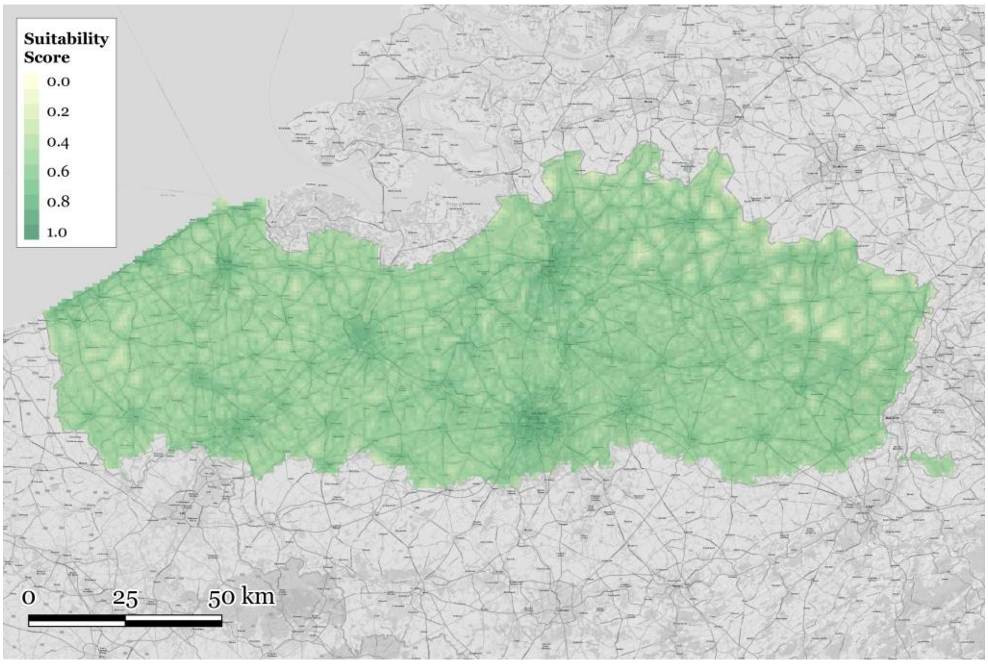

Figure 1. Composite map of the normalized suitability score, indicating suitability for vaccination centre placement.

Ultimately, the model performance metrics were calculated, yielding an accuracy of 0.97 and an F1-score of 0.97.

4. Discussion

The methodology employed in our study leveraged gradient boosting to derive weights for various criteria, illuminating the relative importance of each factor in the identification of optimal locations for vaccination centres in Flanders. The criteria weights suggest a pronounced importance of road proximity (0.440), which underscores the significance of accessibility via primary transportation networks. Socio-demographic factors like mean population age (0.096) and population density (0.215) also played vital roles, alongside mobility-driven metrics like node value for collective transport (0.203). However, it is notable that hospital accessibility, a seemingly crucial factor, carried a lesser weight (0.046). This counter-intuitive result underlines the importance of using data-driven models to inform our decision-making process, as they can often uncover non-obvious relationships in the data.

Our composite suitability map, constructed using the WLC method and our derived criteria weights, visually encapsulates the regions in Flanders that are most amenable for vaccination center deployment. This visualization serves as a foundational layer in spatial decision-making processes.

The model's accuracy and F1-score, both standing at 0.97, highlight its effectiveness in classifying suitable areas. However, these high-performance metrics also raise potential concerns about overfitting. A model that fits training data too closely might not generalize well to new, unseen data. This underscores the importance of model validation, hyperparameter tuning, and other regularization techniques to ensure a balance between bias and variance and prevent overfitting.

Several considerations can be incorporated in future iterations of this research to enhance its comprehensiveness and applicability. The first one is the integration of hard criteria. Our model is driven by soft criteria focusing on mobility and socio-demographics. Incorporating environmental constraints as hard criteria could be pivotal. For instance, regions with environmental protections might be strictly unsuitable for infrastructural developments, irrespective of their scores on soft criteria. Such constraints can also assist in undersampling the majority class – in this case, all the "0s" in the labelled dataset dominate and can overshadow the minority "1s", potentially leading to model biases. Addressing this imbalance can result in a more balanced dataset for model training. A second consideration is expanding the criteria. A more nuanced picture might emerge by integrating additional socio-demographic and mobility factors such as car ownership, disability rates, poverty levels, etc. These variables can enrich the model by accounting for more segments of the population, ensuring inclusivity in the decision-making process. A third consideration covers the transition from suitability to allocation. The current methodology yields a suitability map, which, while invaluable, doesn't directly translate to optimal spatial location-allocation of the centres. In future work, leveraging this suitability map as an input to optimization techniques like the p-median problem can bridge this gap. Such an approach would meld traditional GIScientific techniques with supervised learning models, producing robust and comprehensive spatial solutions.

In conclusion, our study lays the groundwork for a data-driven, GIS-enabled approach to vaccination center placement in Flanders. By integrating further criteria, optimization techniques, and refining the modelling process, future research can provide actionable insights for health logistics and infrastructure deployment.

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Shared Dockless E-Scooters in the City: System Analysis and the Novel Management Policy.

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Abstract

We present an initial analysis of Tel Aviv's Shared Dockless E-Scooters (SDES) system operation. The SDES system consists of three interacting components: operators, scooters, and users that act within the constraints defined by the regulator – Tel Aviv municipality. Our analysis reveals under-supplied and over-supplied areas, proves that the users prefer routes with a higher share of the bike paths, and, operationally, exposes street segments where these paths are most lacking. Data analysis evokes a novel shared e-scooter regulatory policy that focuses on the control of long-unused scooters.

Keywords. Location-Based Services, Shared Urban Mobility, Shared Dockless e-Scooters, Urban Transportation Policy.

1. Introduction

The Shared Dockless E-Scooters (SDES) were first introduced in Singapore in 2016 and are expanding all over the world (Bikeshare, 2023; Statista, 2023; E-scooter, 2023). Most of the cities successfully accommodated this new transportation mode and only a few have banned it. Overall, scooter trips mostly substitute trips with public transport and walking; the average ride distance varies between 2 and 3 km; when riding, SDES users prefer bike paths; while the non-users are mostly concerned about safety issues, like riding on the sidewalk or against the traffic (Li et al, 2022). The long-term municipality's goal is to make the SDES easily available to the users while preserving safety and non-conflict interaction between the riders and non-riders. This demands a spatio-temporal assessment of the interactions between operators, scooters, and users.

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2. The Data

Our study is based on the anonymized trip data collected by the Tel Aviv municipality using the POPULUS software (Populus, 2023) that employs the Mobility Data Specification format (MDS, 2023) for storing geo-located trip data. We analyze 730K rides made during 22 working days of March 2023 with 7500 e-scooters operating over the 52 km² city area populated by 480K residents and visited by the same number of visitors. The routes of 10% of the trips have a full GPS presentation at a 10-second frequency. The data on scooters supplied by five city operators are combined. Figure 1 presents the workday dynamics of the SDES use and their speed.

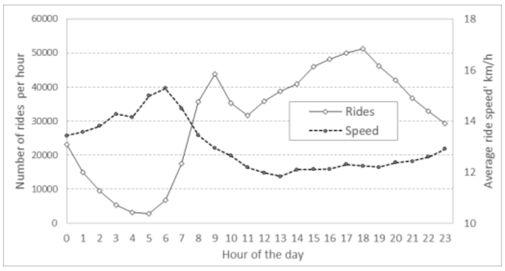
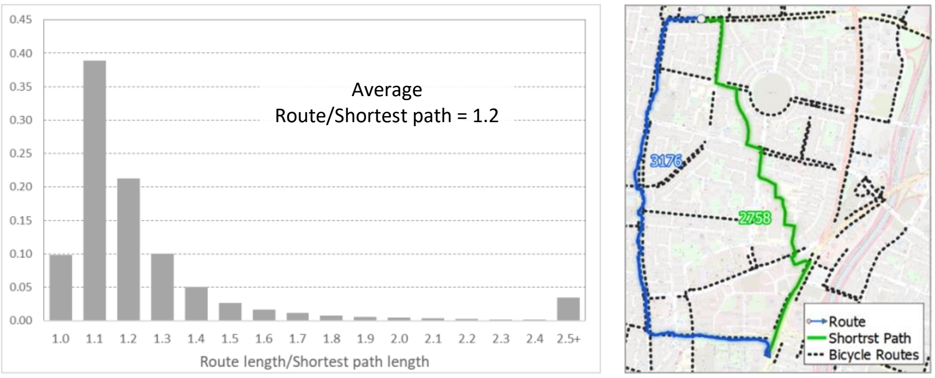


Figure 1. The workday dynamics of the SDES use and e-scooter speed in Tel Aviv

3. E-Scooter Users' and Operators' Behavior

3.1. How do riders choose a route?

About 90% of riders' routes essentially deviate from the shortest paths (Figure 2a). The view of individual trajectories, like in Figure 2b, suggests that riders may prefer routes with a higher share of the bike paths.



a b

Figure 2. (a) The ratio of the actual route to the shortest path length; (b) Example of the chosen route and the shortest path between the rider's origin and destination

The results of the riders' route choice analysis are presented in Figure 3, where (1) the share of segments with the bike path in the actual route is essentially higher than in the shortest path and grows with the increase in the route length, and (2) the speed on the segments with a bike path is on average ~20% higher than on those without. These differences are steady in the hours of the day. The by-product is a map of the street links' usage (Figure 3c) that will serve to establish the priorities for bike path construction.

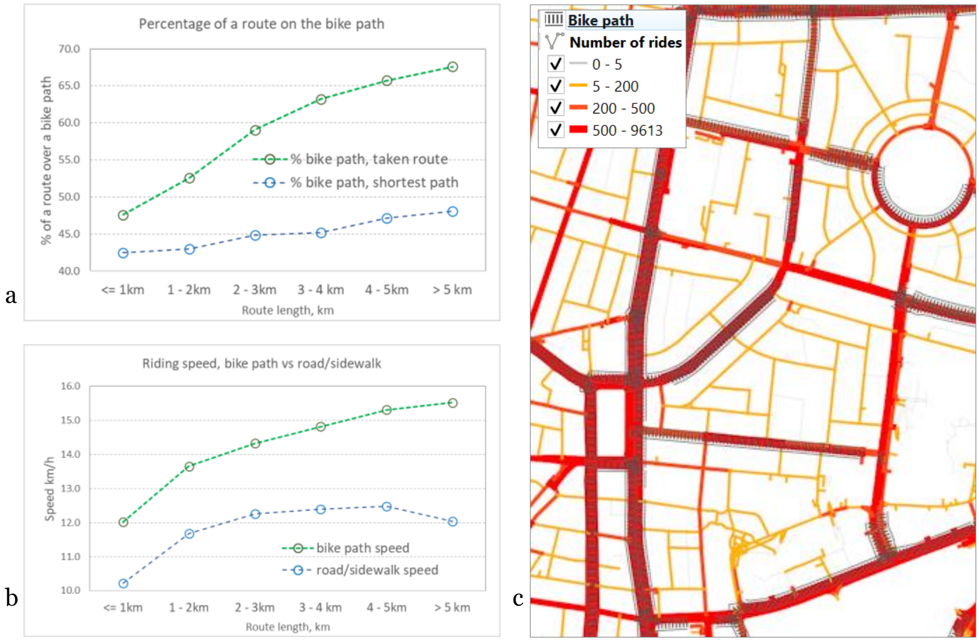


Figure 3. (a) The share of the bike paths in the actual and shortest path; (b) The speeds of the riders on the bike path and non-bike-path parts of the route: (c) Monthly utilization of street segments by riders

3.2. Users' Demand and Operators' Attempts to Match It

On average, each scooter is used 3-8 times a day, and its parking time essentially depends on the location (Figure 4).

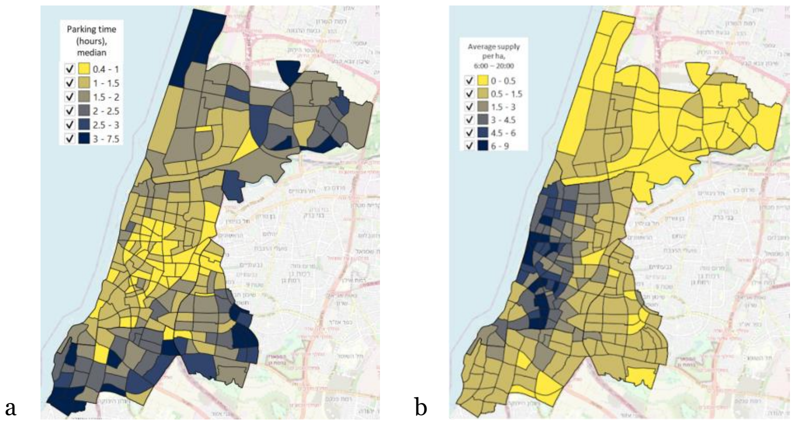


Figure 4. Tel Aviv Traffic Analysis Zones (TAZ) by (a) the median parking time, an indicator of users' demand; (b) e-scooters supply per hectare.

In addition, scooters that are parked (1) close to the bike paths or (2) in the parking cells are used 20%-25% more frequently than those parked far from the bike paths or cells.

The operators know the areas of high demand and focus on supplying scooters there. However, they overdo it, and the share of scooters allocated at “hot” parking cells (ones with short average parking time) that are not activated for long is essential (Figure 5a), while in the areas of low demand, scooters that are not used for long are located randomly (Figure 5b). Notably, the same scooters are repeatedly chosen or ignored (Figures 5c, 5d).

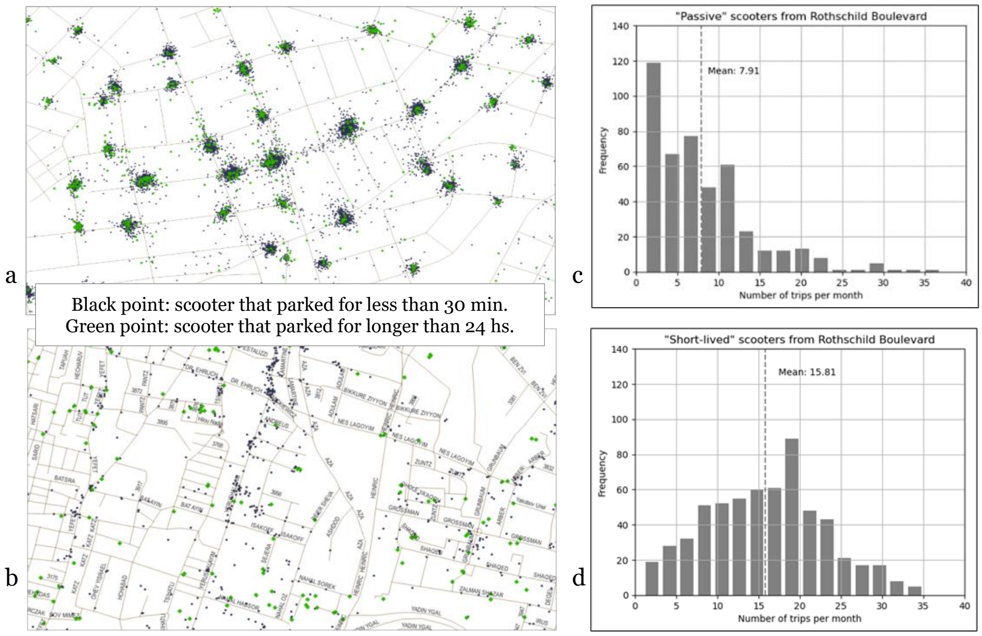


Figure 5. Locations of scooters that were used again after less than 30 minutes of parking (black dots) and were not used for 24 hours (green dots) in the areas of (a) high and (b) low demand (b); the monthly number of rides with scooters that (c) at least once were not used for 24h or longer and (d) at least once were used after less than 30 min parking.

We thus hypothesize the Mohring-like demand-supply feedback (Bar-Josef et al, 2013): Operators over-supply vehicles to the high-demand areas that guarantee a stable profit. Given the fleet limitation, this entails an under-supply and a subsequent decline in demand in the rest of the city.

Figure 6 thus completes Figure 4, by displaying the demand-supply relationship and separating between TAZ of possible under- and over-supply:

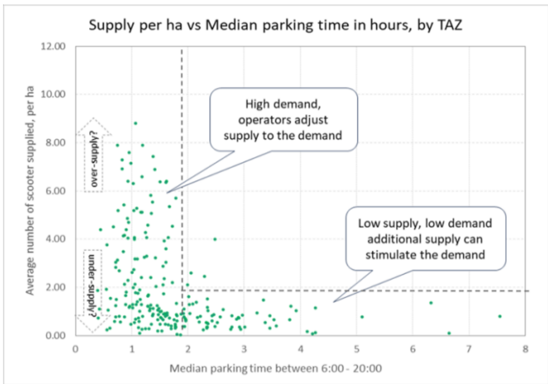


Figure 6. The relation between the demand and supply, by TAZ, with the domains of possible over- and under-supply.

3.3. Policy proposal

The current Tel Aviv scooter policy is based on two principles: (1) each operator's fleet is limited to 1800 vehicles and (2) an operator must allocate 6% of its fleet to the economically low-status city south. We suggest a policy that is based on two other principles: (1) establishing parking cells all over the city, and (2) operators are obliged to relocate scooters that have not been used for long to the nearest parking cell in the under-supplied area.

4. Conclusion

High-resolution analysis of the Tel Aviv shared e-scooter data exposes the inherently complex dynamics of this system. Based on the basic features of the riders' and operators' behavior, we propose a novel policy for scooter management in the city.

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Station-level demand prediction for bike-sharing systems planning with graph convolutional neural networks

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Abstract. Accurately predicting bike-sharing demand at the station level is of paramount importance to facilitate station planning and enhance the efficiency of bike-sharing systems. In this study, we develop graph convolutional neural networks (GCNN) to predict station-level bike-sharing demand by modeling the spatial dependence of stations in two ways, namely trips and nearest neighbor, and compare the prediction performance with three machine learning models, including multiple linear regression, multilayer perceptron (MLP) and random forest. The two GCNNs and three machine learning models were implemented and evaluated using a bike-sharing trip dataset in Zurich, Switzerland. The results show that the GCNN model based on the graph structure built by k nearest neighbor achieves the best prediction performance. The way of modeling spatial dependence of bike-sharing stations presents an influence on the prediction. This research is beneficial for decision-making in establishing new stations to support bike-sharing systems planning.

Keywords. Bike-sharing demand prediction, graph convolutional neural networks, spatial dependence, machine learning

1. Introduction

Bike-sharing systems (BSS) have been operated and popularized in many cities worldwide, aiming to reduce transport-related carbon emissions and promote sustainable urban mobility (e.g., Li et al., 2021). Although the adoption of BSS brings environmental and social benefits, unbalanced usage of bike-sharing raises concerns (e.g., inefficient resource allocation). Demand prediction plays a crucial role in BSS planning by helping opera-

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tors optimize their resources, improve customer satisfaction, and ensure efficient operations (Boufidis et al., 2020). Predicting demand accurately allows BSS to allocate bikes and docking spaces effectively, thus reducing instances of overcrowding or empty stations and improving users' satisfaction.

The current bike-sharing demand prediction is mainly implemented at three levels of research units, namely cluster, area, and station (Xiao et al., 2021). In this paper, we focus on station-level bike-sharing demand prediction. As a typical spatial regression problem that relies heavily on observed variables across geographic space, station-level demand prediction has attracted notable attention in the fields of GIS and transportation (e.g., Lin et al., 2018; Yang et al., 2020). Since bike-sharing stations are usually distributed irregularly across the space, it is necessary to model and understand the spatial dependence effects of stations on demand prediction. Graph-based deep learning that explicitly models the relationships among connected locations can be an effective tool to deal with the problem (Zhu et al., 2021). Although graph convolutional neural networks have been used to predict bike-sharing demand, the existing studies are mainly concentrated on short-term prediction using historical demand time series (e.g., Lin et al., 2018; Xiao et al., 2021). In addition, little attention has been paid to examining the influence of graph structure (e.g., neighbor-based, distance-based) on demand prediction with GCNNs.

To fill the gap, this study is dedicated to systematically modeling the spatial relationships of bike-sharing stations and developing GCNNs in different graph structures to predict station-level bike-sharing demand based on influencing factors. The developed GCNNs are tested using the bike-sharing trip dataset in Zurich, Switzerland. Since the proposed method is not constrained by historical demand data, it could serve as a planning tool for municipal urban planners and operators to establish new stations in bike-sharing systems.

2. Data and methods

2.1. Data

The public bike-sharing (PBS) trip dataset is collected from a service provider company in Zurich, from May 27 to July 7, 2022. Each trip records the following attributes: id, start/end time, start/end longitude, start/end latitude, start/end station id, distance, and duration. In addition, land use, points of interest (POI), public transport stops, population density, and employment density datasets are also collected from open geoportals to calculate the influencing factors.

2.2. Variables

Previous studies (e.g., Eren and Uz, 2020) have indicated that bike-sharing studies are related to various influencing factors, such as built environment, public transport, socio-demographic factors, and weather conditions (e.g., temperature and precipitation), etc. In this study, 16 variables are calculated to describe the influencing factors and used to train GCNNs and machine learning models, as shown in Table 1. To estimate the variables at the station level, a 300-meter buffer is created for each bike-sharing station based on prior knowledge.

Categories	Variables
Urban built environment	Bike lane density, Land use mixture, Education density, Tourism density, Healthcare density, Entertainment density, Sports density, Accommodation density, Errand density, Dining density
Public transport	Public transport stop density, Closest distance to bus stops, Closest distance to railway stations, Closest distance to tram stops
socio-demographic factors	Population density, employment density

Table 1. Variables for influencing factors.

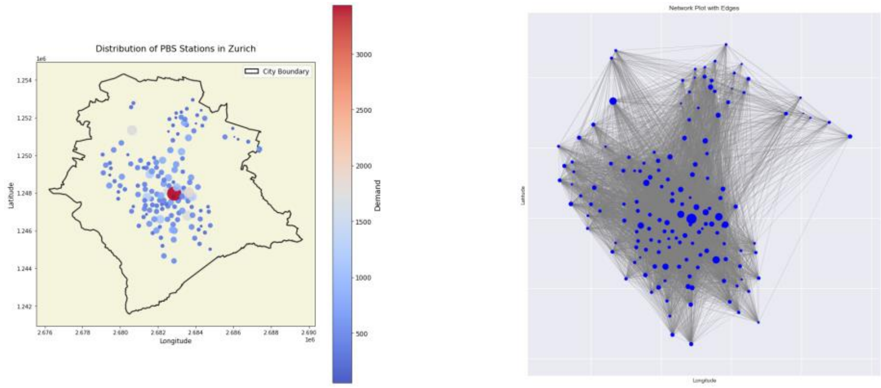
2.3. Model description

A Graph Convolutional Neural Network (GCNN) is a deep learning technique designed for the analysis and processing of data structured as graphs (Kipf and Welling, 2017). In a graph, entities are represented as nodes, and the relationships between entities are captured by edges connecting these nodes. A GCNN leverages the inherent graph structure to perform convolutions and learn hierarchical representations directly from the graph data. Zhu et al. (2021) further proposed the use of spatial regression graph convolutional neural networks (SRGCNN) as a deep learning paradigm in spatial regression analysis.

As an invariant of convolutional neural networks (CNNs), GCNN applies convolutional operations to node features and adapts these operations to the irregular graph structure compared with grid-like data in CNNs. Therefore, graph structure has a significant influence on the prediction performance. In this study, we attempt to model the spatial dependency effects among bike-sharing stations and thus construct graph structures in two ways. The first graph structure is constructed based on whether trips occurred between two stations. One edge is added to the corresponding nodes if there are trips occur between two stations. The number of trips between them can be the weight of the edge. The second graph structure is built based on k nearest neighbor inspired by the study (Zhu et al., 2021).

3. Experiment and results

The GCNNs are developed based on the two graph structures and tested using the station-level demand and influencing factors in Zurich. Figure 1 (a) shows the spatial demand distribution across bike-sharing stations. The stations with high demand are mainly concentrated in the city center. Figure 1(b) displays the graph structure based on whether trips occurred between two stations.



(a) Demand distribution (b) Graph structure

Figure 1. Demand distribution across stations and the graph structure.

The two GCNNs (i.e., $GCNN_{trip}$ and $GCNN_{neighbor}$) are implemented and validated by comparing with three machine learning models, including multiple linear regression, MLP regressor, and random forest regressor, in terms of Mean Square Error (MSE), Root Mean Square Error (RMSE) and R-squared. In this study, the entire dataset is split into 80% training data and 20% percent test data. Table 2 shows the prediction performance comparison of the five models in terms of the three evaluation metrics. It can be observed that the $GCNN_{neighbor}$ model achieves the best performance. It implies that the graph structures that model the spatial dependence of bike-sharing stations have a significant influence on the prediction using GCNN.

Models	**Evaluation metrics**		
	MSE	RMSE	R^2
$GCNN_{trip}$	328452.56	573,11	0.58
$GCNN_{neighbor}$	**306828.62**	**553.92**	**0.60**
Multiple linear regression	353501.13	594.56	0.03
MLP	342384.41	585.14	0.06
Random forest	320748.70	566.35	0.12

Table 2. Prediction performance comparison of different models.

4. Conclusion

In this study, we developed the GCNNs to predict the station-level bike-sharing demand by modeling the spatial dependence of stations in two ways: trips and nearest neighbors. Using the datasets in Zurich for evaluation, the results indicate that the graph structure that models the spatial dependence of bike-sharing stations influences the prediction. Overall, the developed GCNNs present potential for accurately predicting demand. For our future work, distance-based spatial dependence modeling will be exploited in the prediction of GCNNs. In addition, spatial analysis of errors will be conducted to examine how the underestimated or overestimated errors are distributed across space, thereby further improving the prediction performance of the models. Finally, the generalizability and transferability of the GCNN models will be investigated by applying them to other cities.

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Mobility during the Pandemic: the Swing Tilted to One Side

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Abstract. Researchers usually divide counties into the Democratic and the Republican in analyzing human mobility during the COVID-19 pandemic in the US. However, the Swing counties remain a blind spot. Our study reveals that the Swing counties highly resemble the Democratic, but considerably differ from the Republican with respect to the change in mobility volume. People living in the Swing and the Democratic counties consistently reduced traveling during the first wave. Towards the end of it, residents in the Republican counties started increasing traveling. In 2748 out of 3101 counties, the abrupt drop took place on the same day, March 16th, 3 days before the first stay-at-home order. Our findings highlight the role of political affiliation in shaping people's travel behavior and demonstrate the lag in public health policy.

Keywords. Human mobility, Political affiliation, the Swing

1. Introduction

Many countries adopted non-pharmaceutical interventions, such as travel restrictions and social distancing to curb the spread of the COVID-19. The effectiveness of these policies was subject to public involvement (Chan et al., 2021). The response to the travel restrictions varied among people (McKenzie et al., 2020). Political preference might influence individuals on how they perceived the risk of the virus and whether they chose to travel less (Hsiehchen et al., 2020). Grossman (2020) asserted that when a governor tweeted to call for reducing unnecessary traveling, residents in the Democratic counties were more likely to act. Barbalat (2022) further suggested that residents in the Republican counties traveled more as the restrictions tightened.

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In the US, political polarization has exacerbated over the past 2 decades (Jung et al., 2017). The COVID-19 pandemic in the United States was as much a political problem as a public health problem (Clinton et al., 2021). Previous work mainly focused on the comparison between the Democratic and the Republican. While a survey by the Guardian[1] suggested that most Americans did not feel represented by the Democrats or the Republicans. We thus aim to analyze the human mobility pattern in the context of the Swing, the Democratic, and the Republican counties by investigating daily mobility volume during the first wave of the pandemic.

2. Methodology

2.1. Definition of Swing

The 2016 and 2020 US presidential election voting data at county level are retrieved from MIT Election Data Lab[2]. A county is considered Swing[3] if it did not consistently support the candidates from the same party. It is considered Democratic if the Democratic candidates won both the elections (Jung et al., 2017). Otherwise, it is Republican. We divide 3101 counties into 78 Swing, 467 Democratic, 2556 Republican. We notice that the ratio of the Swing to the Democratic and that of the Democratic to the Republican are both approximately 1/6. The small number of the Swing does not diminish its importance.

2.2. Characterization of Mobility Change

Our source data are the dynamic origin-destination matrices at county level synthesized by Kang (2020) from the SafeGraph[4] mobile phone data. We process the data to derive the daily mobility volume indices of 3101 counties (7 out of 3108 contiguous counties are excluded due to missing data). The indices of each county are then normalized by dividing its average. The normalized indices fall between 0.45 and 1.95. A normalized index smaller than 1 suggests that people travel less than the average. Thereafter, we refer to the normalized indices simply as the mobility volume.

[1] https://www.theguardian.com/us-news/2016/oct/25/american-political-parties-democrats-republicans-representation-survey

[2] https://electionlab.mit.edu/data

[3] https://www.polyas.com/election-glossary/swing-states

[4] https://www.safegraph.com/guides/mobility-data

2.3. Identification of Structural Break

A structural break in time series is a significant change in the parameters of linear regression models (Güler et al., 2019). Having observed an abrupt change in the mobility volume, we apply radial basis function (Harchaoui & Cappé, 2007) to detect breakpoints. With the detected breakpoints, we perform piecewise time series analysis on the mobility volume. *Figure 1* illustrates the difference between a single regression and piecewise regressions. We gauge the change in the mobility level by comparing the average mobility volume before and after the breakpoint. We measure the rate of the change by the slope coefficient of a piecewise regression. Three indicators of each county are thus synthesized: *Mobility Volume Difference*, *Before-break Trend*, and *After-break Trend*. We perform the Analysis of Variance (ANOVA) and t-test to compare the Swing, the Democratic and the Republican counties with respect to each mobility indicator.

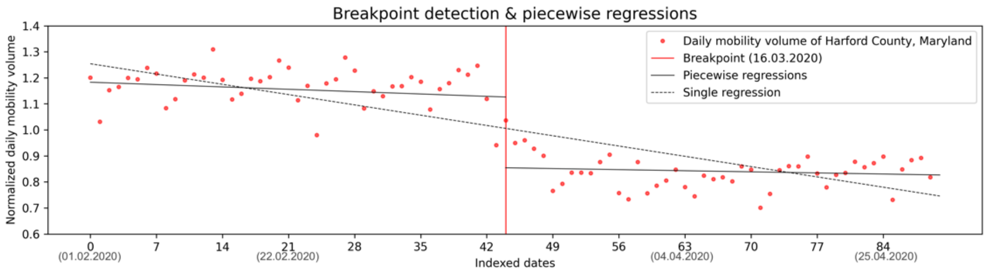

Figure 1. Harford County, Maryland is taken as an example to show the difference between a single regression and piecewise regressions.

3. Result

The mobility volume exhibits a weekly pattern, with the peak on Friday and the valley on Sunday. However, it deviates from the pattern and decreases monotonically in the week of March 16th (*Figure 2*). The breakpoint detection finds that 2936 out of the 3101 counties have one breakpoint. In 2748 counties, the breakpoints are on the same day, March 16th.

To minimize the impact of the weekly pattern, the mobility indicators are calculated with a tumbling window of 6 weeks (42 days). ANOVA and t-test suggest that the Swing counties are the same as the Democratic but different from the Republican regarding each of the three mobility indicators (*Table 1*). All the mobility indicators are negative except for the *After-break Trend* of the Republican counties. The magnitudes of all the indicators are greater in the Swing and the Democratic than the Republican.

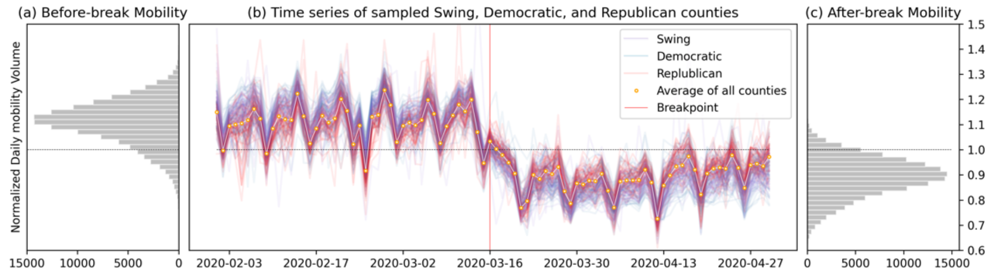

Figure 2. (a): Histogram of the daily mobility volume of all counties before the breakpoint. **(b)**: Mobility volume time series of randomly sampled 50 Swing, 50 Democratic, and 50 Republican counties. **(c)**: Histogram of the daily mobility volume of all counties after the breakpoint.

	Mean			T-test		
	Swi.	Dem.	Rep.	Swi. – Dem.	Swi. – Rep.	Dem. – Rep.
MVD	-0.2605	-0.2688	-0.2118	***	***	***
BBT	-0.0006	-0.0008	-0.0001	***	***	***
ABT	-0.0003	-0.0005	-0.0002	***	***	***

Table 1. Left: Descriptive statistics of mobility indicators: Mobility Volume Difference (MVD), Before-break Trend (BBT), and After-break Trend (ABT), in the Swing (Swi., N=76), the Democratic (Dem., N=420), and the Republican counties (Rep., N=2252) with a tumbling window of 6 weeks (42 days). **Right**: Pairwise t-test results (*** $p < 0.001$).

4. Discussion

We leverage mobility volume to characterize human mobility and presidential election voting data to define the political affiliation of each county. We utilize three indicators to quantify the level and the rate of the change in mobility volume. The *Mobility Volume Difference* suggests that the level of the change in mobility volume is greater in the Swing and the Democratic counties than in the Republican. Likewise, the *Before-break Trend* reveals that the rate of the change in mobility volume is greater in the Swing and the Democratic counties. The positive *After-break Trend* suggests that people living in the Republican counties had started traveling more while others kept avoiding traveling. However, our study did not consider the spatial dependence of mobility and political affiliation. This should be addressed in the future.

5. Conclusion

This study investigates the change in mobility volume in the Swing, the Democratic, and the Republican counties during the first wave of the

COVID-19 pandemic. The results suggest that the Swing and the Democratic counties are the same but different from the Republican concerning each of the 3 mobility indicators, *Mobility Volume Difference*, *Before-break Trend*, and *After-break Trend*. The Swing and the Democratic counties experienced the greatest change in mobility volume and a constant decreasing trend throughout the study period. Whereas the Republican counties had smaller change and observed an increasing trend after the breakpoints. The majority of the breakpoints are on the same day, March 16th, 3 days before the first stay-at-home order. We conclude that people took actions simultaneously and political affiliation had a greater impact on mobility volume than the travel restriction policies.

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Development of Aggressive Driving Detection Method for two-wheeled vehicles

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Abstract. In the rapidly growing two-wheeled vehicle industry, there is an increasing need to detect and prevent aggressive driving behaviors. In this study, we propose an effective method to identify aggressive driving behaviors of simulated two-wheeled vehicles using limited data from the Carla simulator. We focus on two types of aggressive driving behaviors: sharp turning and sharp lane changing. By utilizing acceleration, angular velocity, and position data, we establish a foundation for detecting these behaviors. For sharp turning, a multi-stage classification method is adopted using gyroscope and acceleration data. Sharp lane changings are detected using an XGBoost model.

Keywords. Two-wheeled vehicles, aggressive driving detection, sharp turning, sharp lane changing

1. Introduction

The rapid growth of delivery services calls[2] for improved safety measures for two-wheeled vehicles, given the substantial increase in their usage. Despite a decrease in overall traffic fatalities, fatalities involving two-wheeled vehicles are rising, indicating the need for enhanced safety precautions. Existing methods for assessing safe driving behaviors mainly focus on four-

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[2] In 2022, the delivery services market in South Korea reached approximately $23,000 million, exhibiting a remarkable growth of 973% compared to 2017, with a steep annual growth rate of 162% (Statistics Korea).

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wheeled vehicles, leaving a gap for two-wheeled vehicles. The absence of data collection systems for these vehicles necessitates the use of simulation technology and AI to detect aggressive driving behaviors (Ministry of Land, Infrastructure and Transport, 2022). Such behaviors are difficult to assess due to limited data and the distinct nature of two-wheeled vehicles.

To address this gap, we aim to develop a method to detect aggressive driving behaviors in simulated two-wheeled vehicles using the limited available data. Given the limitations of onboard detection devices for two-wheeled vehicles, we rely on simulation data encompassing speed, acceleration, and angular velocity.

2. Aggressive Driving Detection

In this study, the detection criteria for aggressive driving on two-wheeled vehicles were narrowed down to sharp turning and sharp lane changing. *Figure 1* illustrates the temporal changes in the Z-axis gyroscope values for rapid turns and abrupt lane changes. During a rapid turn, the value experiences a maximal change over approximately 1 second, while during an abrupt lane change, a single significant change occurs over 0.5 seconds.

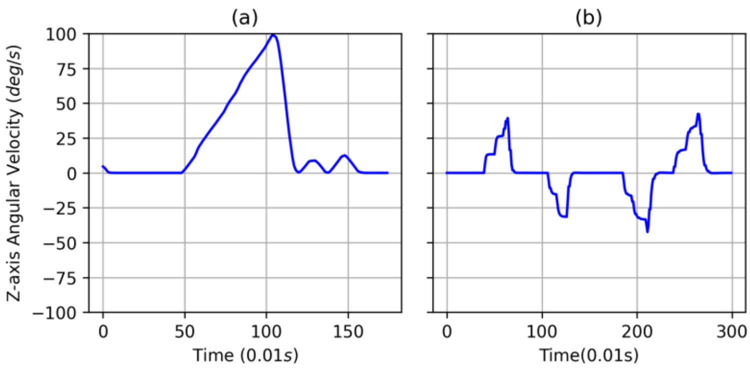

Figure 1. Z-axis gyroscope signals used for sharp turning(a) and sharp lane changing(b) detection.

To detect aggressive driving, sensor data(acceleration, angular velocity, and position information) extracted from the Carla simulator[3] was chosen considering the feasibility of onboard installation on real two-wheeled vehicles.

[3] The Carla simulator is an open-source simulator designed for autonomous driving research. In this study, various aggressive driving scenarios and trajectory data that would be difficult to collect on actual roads were generated and analyzed using the simulator.

However, criteria for defining rapid turns and rapid lane changes can be subjective. In this study, the classification of rapid turns and abrupt lane changes was performed by dividing them into four categories. To achieve this, a labeling task was carried out by conducting a survey with 100 participants, including both ordinary individuals and traffic experts.

2.1. Rapid Turning

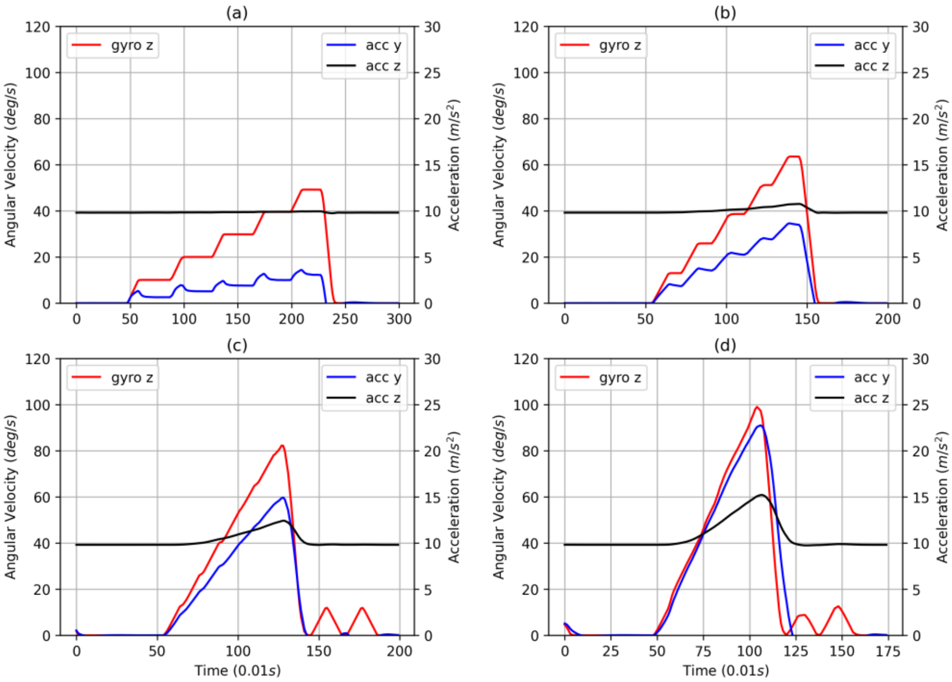

Figure 2. Inertial sensing data used for sharp turning detection. Data obtained from Carla simulator, and (a), (b), (c) and (d) are the level (1~4) of sharp turning defined in the survey, respectively.

	Time	Max. Gyro-Z	Max. Acc-Y	Max. Acc-Z
Sharp Turn (L1)	2 (s)	30 - 50 (deg/s)	0 - 5 (m/s^2)	-
Sharp Turn (L2)	1 (s)	50 - 70 (deg/s)	5 - 10 (m/s^2)	-
Sharp Turn (L3)	1 (s)	70 - 90 (deg/s)	10 - 15 (m/s^2)	10 - 12.5 (m/s^2)
Sharp Turn (L4)	1 (s)	90 - (deg/s)	15 - (m/s^2)	12.5 - (m/s^2)

Table 1. Table for sharp turning criteria.

Rapid turns can be detected using gyroscope and acceleration data (R. Gao et al., 2022). This study considers both the Y and Z-axis acceleration values in addition to the Z-axis gyroscope values to differentiate between stages of rapid turns. *Figure 2* illustrates the changes in Z-axis gyroscope, Y-axis acceleration, and Z-axis acceleration values across different stages of rapid turns. As the stage of rapid turning increases, the Z-axis gyroscope value changes sharply, and both Y and Z-axis acceleration values demonstrate increased fluctuations. Based on these observations, this study defines the criteria for rapid turns as shown in *Table 1*.

2.2. Sharp Lane Changing

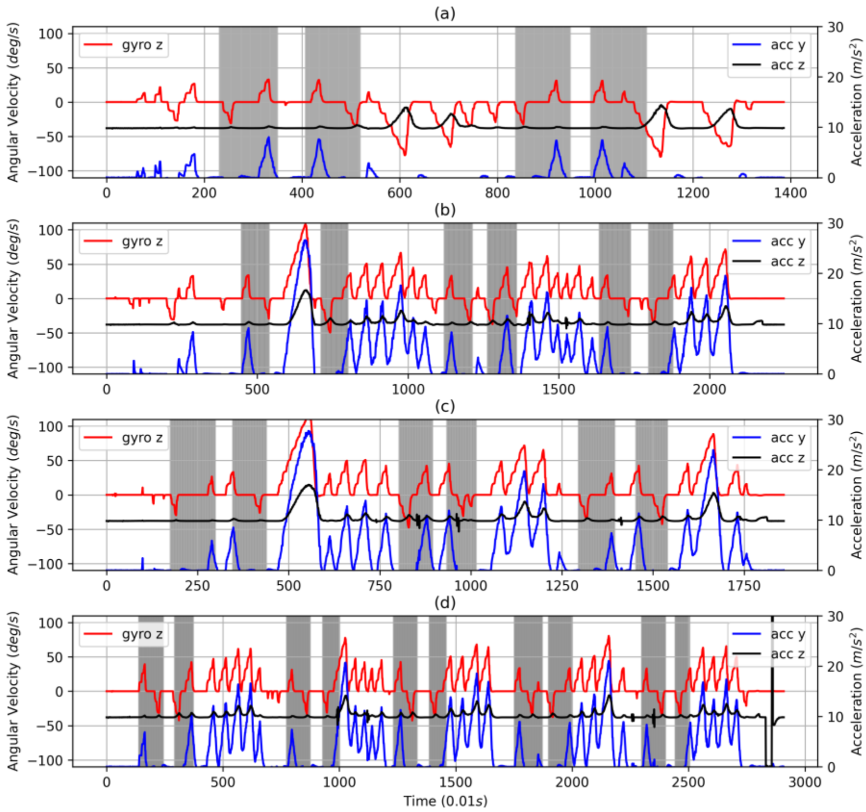

Figure 3. Inerial sensing data used for sharp lane changing detection. Data obtained from Carla simulator, and (a), (b), (c) and (d) are the level (1~4) or sharp lane changing defined in the survey, respectively. The gray section judged to be a sharp lane changing in the survey.

Sharp lane changes exhibit a back-and-forth pattern due to the nature of vehicle movement (R. Gao et al., 2022). *Figure 3* illustrates the staged sharp lane changing. It's noticeable that the Z-axis gyroscope value oscillates around 0(deg/s) during sharp lane change segments(gray). However, there are many cases where the Z-axis gyroscope value oscillates but doesn't correspond to an abrupt lane change, and the acceleration value is also inconsistent. This indicates the difficulty of establishing a straightforward definition for abrupt lane changes due to their complex and non-linear nature. Moreover, sharp lane changes tend to oscillate rapidly from left to right in a short period, making it challenging to define solely based on observation.

Because of these reasons, we propose an XGBoost model to detect sharp lane changing. The XGBoost classification model results for staged abrupt lane changes are presented in *Table 2*.

Class	Precision	Recall	F1-score	Class	Precision	Recall	F1-score
Normal	0.97	0.99	0.98	*LC (L3)*	0.97	0.84	0.90
LC (L1)	0.95	0.92	0.93	*LC (L4)*	0.85	0.88	0.87
LC (L2)	0.89	0.80	0.84				
Accuracy	0.95						

Table 2. Table for evaluating XGBoost classification model results for sharp lane changing. *LC* is a sharp lane change and *L1* to *L4* are in that level.

3. Conclusion

In conclusion, we developed a method using Carla simulator data to detect aggressive driving behaviors. We focused on rapid turns and sharp lane changes as indicators of aggression. Our approach involved a multi-stage classification for rapid turns and an XGBoost model for sharp lane changes, both showing promising classification accuracy. To validate our findings, we plan to apply and test our method with actual riders, ensuring its practicality and effectiveness in real-life situations.

Acknowledgement

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Weight Determination of Two-wheeled Vehicle Driving Evaluation Factors using AHP

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Abstract. As the frequency of two-wheeled vehicle driving and related traffic accidents increase, the need for two-wheeled vehicle safety management is emerging. However, the development of quantitative indicators that comprehensively consider various behaviors of two-wheeled vehicle driving has been limited. In this study, 11 evaluation items, such as signal violation, reverse lane driving, central line violation, and speed violation were defined, and the weight was determined using the AHP technique. As the result, helmet violation (0.158), speed violation (0.124), and pedestrian close driving (0.122) had the highest weights. It is expected that the development of two-wheeled vehicle safe driving indicators will be possible through the derived risk criteria and weights.

Keywords. Two-wheeled vehicle, AHP, Driving evaluation

1. Introduction

As the frequency of use of two-wheeled vehicles and delivery related traffic accidents increased, the need for active response to the safety problems of two-wheeled vehicle has been increased. In previous study, dangerous driving behaviors for four-wheeled vehicles are defined and safe driving evaluation system based on the weight of each behavior has been developed (Ministry of Land, Infrastructure and Transport 2022). However, the development of indicators that comprehensively and quantitatively consider various characteristics of two-wheeled driving is limited.

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Therefore, in this study, weights of each item are calculated for 11 evaluation items of two-wheeled vehicle driving. To calculate individual weights for each item, analytic hierarchy process (AHP) was used, as it is an effective method for calculating importance for several criteria and items. In addition, simulation videos similar to reality were used for items such as rapid acceleration, rapid deceleration, rapid turn, rapid lane change, which are difficult to survey with verbal expression.

2. Methodology

2.1. Two-wheeled vehicle driving evaluation items

The items for evaluating two-wheeled driving were defined by analyzing the types of two-wheeled vehicle accidents and law violations through the Traffic Accident Analysis System (TAAS), the survey on two-wheeled vehicle traffic law violations by the Korea Transportation Safety Authority, and two-wheeled vehicle violation status data by the Korean National Police Agency. The 11 finalized evaluation items are: signal violation (not following a traffic signal), central line violation (crossing the center line on a roadway), helmet violation (not wearing helmet), pedestrian close driving, sidewalk driving, reverse lane driving (driving in the opposite direction of a lane), speed violation (exceeding the speed limit of a roadway), rapid acceleration, rapid deceleration, rapid turn, rapid lane change. For each item, several methodologies were used to detect violations from the trajectory data. Evaluation items such as signal violation, central line violation, helmet violation, and pedestrian close driving are detected through object detection by deep learning models using real-time video and sensor data. Reverse lane driving, speed violation, and sidewalk driving are determined by GPS-based location data with pre-generated GIS road and sidewalk data including direction and speed limit. For rapid acceleration, rapid deceleration, rapid turn, and rapid lane change, simulation video data with different speeds, accelerations, and angular velocities for each item were produced, and then risk criteria were derived through a questionnaire. The data collected by motion sensors is then compared to the risk criteria to determine the degree of violation.

2.2. Derivation of weight for each evaluation item

In this study, the AHP technique is used to derive items weights for the two-wheeled vehicle driving evaluation. It is one of the MCDM (Multicriteria Decision Making) methodologies that determine the best alternative or the ranking of alternatives when there are multiple evaluation criteria and multiple alternatives. The AHP technique was developed by Saaty (1988), and after structuring a complex situation in a hierarchical form, the importance of each element can be derived.

Weight derivation using the AHP proceeds in the following five steps:

- Step 1: Create a hierarchy of evaluation items.
- Step 2: Construct a pairwise comparison matrix based on the survey.
- Step 3: Calculate the weight of the main criteria and sub criteria by comparison matrix for each respondent.
- Step 4: Perform a consistency check.
- Step 5: Calculate the weight of each item for the entire response result.

As a first step, the decision-making hierarchy is created as shown in *Figure 1* by classifying 11 evaluation items into three categories: traffic violation, pedestrian threat, and reckless driving. The 0th layer is two-wheeled vehicle driving evaluation, the 1st layer is category (main criteria), and the 2nd layer is evaluation item (sub criteria).

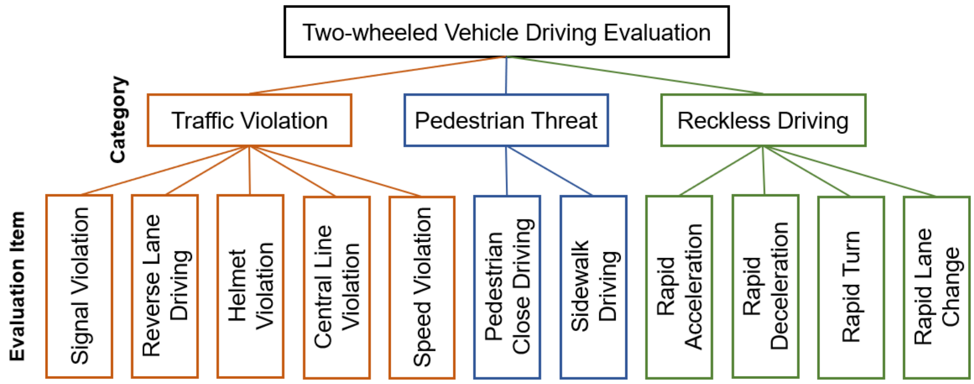

Figure 1. Hierarchy framework for two-wheeled vehicle driving evaluation.

In the next step, (traffic violation - pedestrian threat), (traffic violation - reckless driving), and (pedestrian threat - reckless driving) pairs are formed and surveys are conducted by category. Based on the results of the category pairwise comparison questionnaire, a comparison matrix is constructed, and the weight of each category is calculated. A weight matrix is calculated in the same way for the evaluation items constituting each category.

Through consistency ratio (CR), the logical consistency of each respondent's response result is verified. When CR > 0.1, it is judged as a consistent response, and in this study, the consistency ratio is calculated through a web-based survey form so that the respondent can review the response values if it is greater than 0.1 and revise his or her response instantly.

After the above process is repeated for each criterion of each respondent, a comparison matrix is aggregated using the geometric mean for all respondents. Then, the consistency of the aggregated matrix is checked, and the local weight matrix of the evaluation items is multiplied by the category weight to calculate the global weight for each evaluation item. In this process, the number of evaluation items for each category is not the same: traffic violation - 5 items, pedestrian threat - 2 items, and reckless driving - 4 items. If the number of each sub criteria constituting each main criterion is different, a serious error occurs in AHP analysis, so a process for adjusting this is necessary (Choi 2020). Therefore, as in *Equation 1*, the adjusted weight RW_{ij} of evaluation item j belonging to category i is calculated.

$$RW_{ij} = \frac{W_i \times W_{ij} \times N_i}{\sum_{i=1}^{n} \sum_{j=1}^{m} (W_i \times W_{ij} \times N_i)}$$

W_i : $weight\ of\ category\ i$

W_{ij} : $weight\ of\ evaluation\ item\ j\ belonging\ to\ category\ i$

N_i : $the\ number\ of\ evaluation\ items\ belonging\ to\ category\ i$

Equation 1

In the case of evaluation items belonging to reckless driving category, which are rapid acceleration, rapid deceleration, rapid turn, and rapid lane change, the risk criteria are not defined and evaluation according to the degree is necessary. In addition, it is difficult to survey to establish such risk criteria by verbal expression. Therefore, using a high-performance driving simulator, videos were implemented with different degrees of speeds, accelerations, and angular velocities, and risk scores between 1 and 5 for each video were collected through survey responses. Based on the response results for each video type, the risk criteria for each item were statistically calculated.

3. Results

A survey was conducted targeting 100 people composed of experts and ordinary people through a web-based survey form. *Figure 2* shows the weights of two-wheeled vehicle driving evaluation items derived from the survey. The weight for each category was high in the order of traffic violation, pedestrian threat, and reckless driving, and was derived as about 0.380, 0.365, and 0.255, respectively. As for the weights of each evaluation item, helmet violation, speed violation, and pedestrian close driving were the highest at about 0.158, 0.124, and 0.122, respectively. The risk criterion for the reckless driving category was derived as the average risk score for each video type. In the case of rapid acceleration, the average risk score was calculated as 0.87, 1.07, 2.05, 3.12, and 4.18 for the five types from the lowest risk video to the highest risk video, respectively.

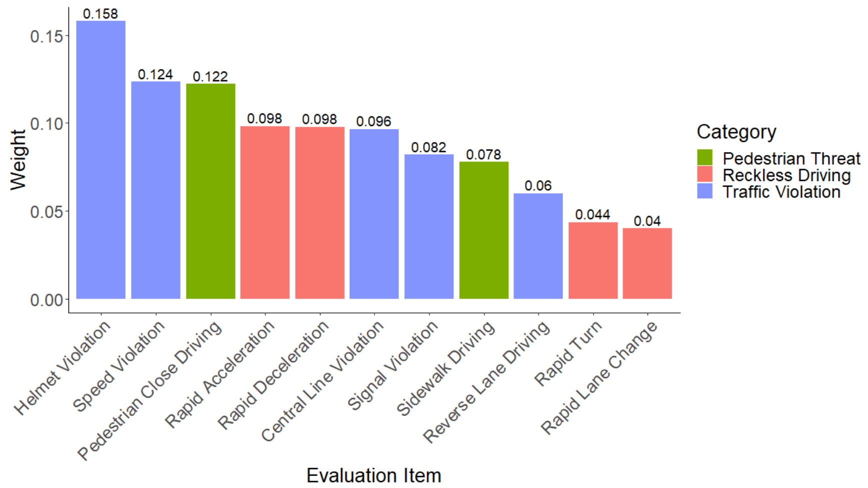

Figure 2. Two-wheeled vehicle driving evaluation item weight calculation result.

4. Conclusion

In this study, individual weights of 11 items for two-wheeled vehicle driving evaluation were derived through a survey using AHP. In addition, for the reckless driving category, the risk criteria were defined through simulation videos. Currently, a safe driving index for two-wheeled vehicle is being developed by considering the calculated weights and risk criteria comprehensively. The final goal is to quantitatively evaluate how safely (or dangerously) a two-wheeled driver traveled over a specific distance.

Acknowledgement

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Spatial Knowledge Graph for Analyzing Traffic Accident Data

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Abstract. Various attempts are being made to effectively manage and utilize the considerable amount of traffic accident data generated in real-time. A knowledge graph, which organically integrates different contexts based on their relations using graph structures, is a good alternative for managing accident data. This study proposes a traffic accident spatial knowledge graph (TA-SKG) that integrates road-level spatial context to manage detailed traffic accident information. Additionally, a test graph was constructed using emergency response activity data and road networks, and several use-cases for TA-SKG were presented.

Keywords. Traffic accident, Knowledge graph, Graph database

1. Introduction

Road accidents significantly disrupt traffic flow, cause a substantial number of casualties, and damage road infrastructure. To develop prevention strategies, accident patterns can be identified by analyzing accumulated accident records. Consequently, effective management and utilization of accident data collected through various devices is becoming crucial.

Diverse data can be integrated using a knowledge graph, which represents various entities and their relations on a graph structure and provides logical explanations of the relationships between entities (Wang et al. 2019). Analyzing accident data requires comprehensive handling of multiple relevant factors and various contexts; thus, knowledge graphs have been constructed using textual or structured traffic accident data for accident management and analysis (Wang et al. 2019, Liu et al. 2021, Yuhang et al. 2021, Liu & Yang 2022, Zhang et al. 2022).

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The locational and topological characteristics of the roads where accidents occur are important factors for accident analysis. Therefore, both road-level spatial context and detailed accident information must be integrated for effective management. However, most previous research has focused on handling the coordinates of the accident locations or spatial characteristics at the urban level.

In this study, a knowledge graph model was proposed to manage traffic accident data by integrating road-level spatial context of accidents. Specifically, a conceptual graph model was designed to include both the characteristic information of accidents and the temporal and spatial knowledge. Additionally, a graph database was constructed for the test area using emergency response activity data and road networks. The suitability of the proposed model was examined through traffic accident analysis and avoidance routing tests using the generated database.

2. Knowledge Graph Model for Traffic Accidents

Entities are defined based on various aspects of traffic accident contexts (Table 1). Specifically, the proposed model represents the accident attributes, temporal and environmental characteristics, and locational and topological features of the occurrence points.

Entity	Description	Attribute
ACCIDENT	Traffic accident	id, latitude, longitude
COUNTRY, CITY, ZONE	Administrative districts where the accident occurred	name
PLACE	The place category where the accident occurred, such as highway, residential road, etc.	place type
FSTATION	The fire station that handled the accident	station, center
CAUSE	The cause of accident	description
TYPE	The type of accident, e.g., Car-to-Car, Car-to-Person, etc.	type
REPORT	The accident report	report number
YEAR, MONTH, DAY, WEEK, HOUR	The time when the accident was reported	time
JUNCTION	The junction of the road	latitude, longitude

Table 1. Core entities of the TA-SKG.

Reported accidents are represented by the ACCIDENT node, whose attributes are the latitude and longitude coordinates of the occurrence point. ACCIDENT serves as a core entity and is connected to other entities through the appropriate relationships. By categorically modeling accident-time information, the accident information can be easily classified temporally, such as by year or day of the week. Based on the accident type, the ACCIDENT node is connected to the corresponding TYPE node through the TYPED_AS relationship. Similarly, the ACCIDENT node is connected to the appropriate CAUSE node through the CAUSED_BY relationship based on the accident cause and to the PLACE node through the OCCURRED_AT relationship based on the occurrence point category. Additionally, the CONDITION entity includes environmental factors at the accident time, such as temperature, humidity, and visibility, and is connected to the ACCIDENT node through the AFFECTED_BY relationship.

In addition to connecting the ACCIDENT nodes to the occurrence place information after decomposing the place into country, city, and zone, the road-level spatial context of the detailed occurrence point is reflected in the model by combining the road network with accident information. The node-edge of the network corresponds to JUNCTION-CONNECT in TA-SKG, representing the topology of roads. The intrinsic attributes of road segments, such as road hierarchy, maximum permissible speed, and number of lanes, can be stored as properties of the CONNECT relationship. The ACCIDENT node is connected through a LOCATED_AT relationship to the two JUNCTION nodes of the road where the accident occurred. Accounting for the road direction, the connection is created from the start node of the road and passes through the ACCIDENT node to the end node (Figure 1). If an accident occurs at a junction, the node is bidirectionally connected only to that single JUNCTION node through an OCCURRED_AT relationship. Consequently, various spatial analyses of accident points can be performed using integrated spatial context. For example, the coordinates stored within the JUNCTION nodes and the network distance stored within the LOCATED_AT relationship can be used for accident-avoidance routing.

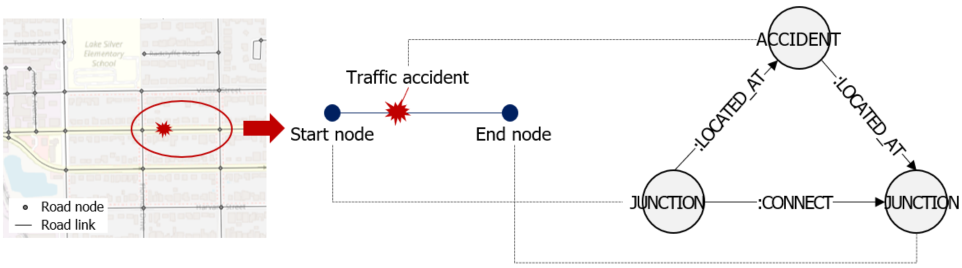

Figure 1. Relationship between accident and junction nodes.

3. Applications

This section introduces the use-cases of TA-SKG. Here, the TA-SKG was constructed as neo4j graph database using emergency response activity data comprising information regarding accidents that occurred in Seoul, South Korea, in 2022. Simultaneously, a spatial graph was constructed for Seoul based on the node-edge connectivity information obtained from the OpenStreetMap (OSM) network.

First, the graph enables easy information retrieval of specific accidents and generates accident descriptions. As shown in Figure 2, relevant information can be found by exploring nodes connected through various relationships related to a particular accident. Moreover, by employing relationship types and node labels, the following descriptions can be readily generated:

- At 1 AM on Saturday, February 26, 2022, a traffic accident was reported. The accident occurred on the highway in Guemhodong-4Ga, Seoul. It was a Car-to-Facility accident and was handled by the Dongdaemun fire station.

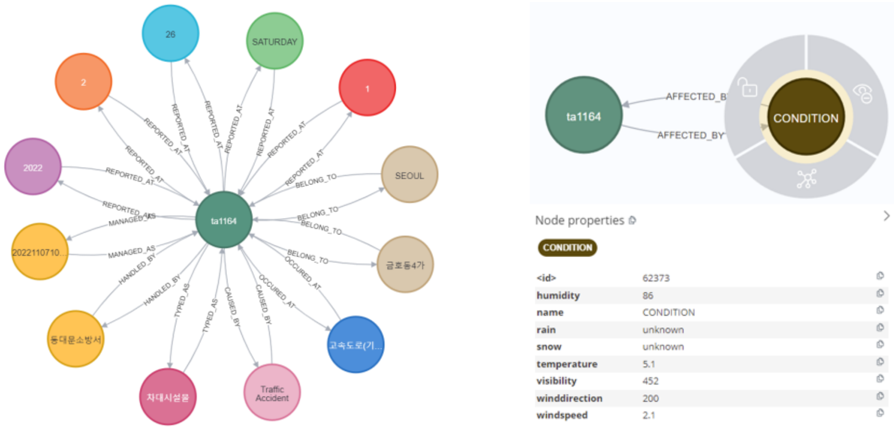

Figure 2. Example of an accident retrieval result.

(a) (b)

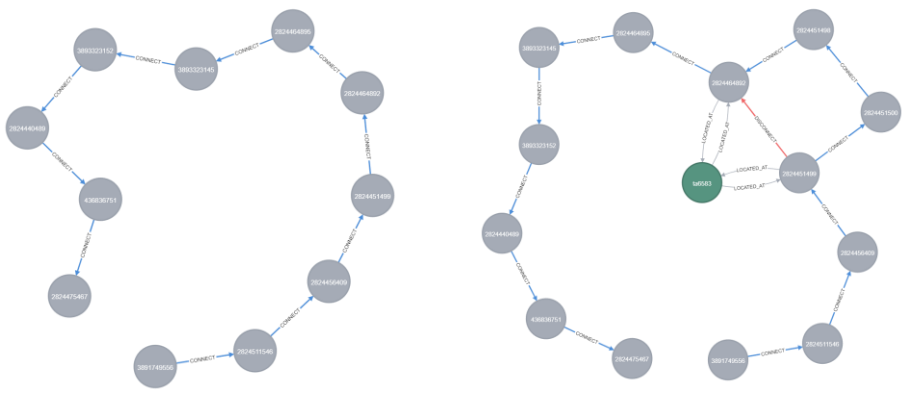

Figure 3. Result of accident-avoidance routing: (a) without and (b) with accident.

Figure 3 shows the result of avoidance routing using TA-SKG after setting an arbitrary path through the road where the accident occurred. It can be seen that the route bypassing the link with an accident is rederived after changing the relationship type (CONNECT to DISCONNECT) between the two nodes (IDs: 2824451499-2824464892) where the accident occurred (Figure 3b) and re-projecting the graph.

Accident information can be easily classified using various node labels, allowing accident pattern identification. Furthermore, temporal analysis of accidents, such as identifying the time of day with the most occurrences, can be performed through time-related entities and relationships.

4. Conclusion

This study proposed the TA-SKG, which combines traffic accident information with road-level spatial contexts. In subsequent research, the data model will be modified to allow integration with existing ontologies of relevant knowledge graphs. Furthermore, the TA-SKG will be expanded using unstructured data sources such as SNS data or accident report documents.

Acknowledgment

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Large-scale Planning Tool for Mobility Hubs – Data Requirements and Open Data Availability

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Abstract. Mobility hubs can contribute to a user-friendly and sustainable mobility by facilitating the use of public transport and shared services. Despite their potential, the planning of such hubs is often hampered by inefficiencies, as planning is done on a case-by-case basis. This is further complicated by data limitations and the lack of appropriate planning tools. Therefore, we are developing a comprehensive and open data-based planning tool for mobility hubs that includes all essential planning steps. In order to assess the availability of the required data for the implementation of such a tool, we defined a methodology and applied it to the selected open data sources. This paper presents a preliminary concept for mobility hub location planning, delineates the required data, and finally summarizes the results of the data quality assessment.

Keywords. mobility hubs, decision support system, open data

1. Introduction

A growing trend in urban areas is the shift towards shared mobility and on-demand services (Machado et al. 2018). In rural areas, however, traditional forms of mobility dominate, with up to 70% of trips being made by cars (Nobis & Kuhnimhof 2018). The main barriers to public transport in these regions are a lack of information and missing services for the first and last mile and during off-peak hours (Rehme et al. 2023). Mobility hubs, which consolidate various mobility services in one location, usually near of a public transport stop, promote intermodal mobility and can reduce dependence on private transport (Frank et al. 2021). Despite their benefits, they are rare in rural areas. Planning of mobility hubs is complex, requiring decisions

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about appropriate locations, type and number of mobility and other services, infrastructure, and consideration of budget constraints (Frank et al. 2021).

To support mobility and urban planners in the large-scale deployment of mobility hubs, we are developing an open data-based planning tool that integrates location planning and hub configuration. This paper explores the feasibility of the planning tool and presents its rough concept as well as an assessment of selected open data sources. It is structured into an introduction, a short literature review, the concept of the planning tool, an assessment of the data quality, and finally a conclusion and further work.

2. Literature Review

The literature identifies two dominant methods for location planning of mobility services: accessibility measurement and optimization-based planning models (Frank et al. 2021). Geurs and Van Wee (2004) define accessibility as how land use and transportation systems allow individuals or groups to reach destinations using various transportation modes. Optimization-based planning models provide structured decision support for the location choice of mobility hubs (Frank et al. 2021). Despite the advantages of such integrated approaches, they are rarely applied in practice due to their complexity, so that hubs are often designed on a case-by-case basis (Möller et al. 2018). In the literature, different typologies and recommendations for the equipment of mobility hubs are presented (Roukouni et al. 2023). However, most of the methods and typologies mentioned above have been developed and applied mainly in urban regions. This may reflect poor data availability in rural areas.

Data quality plays a critical role in information systems and decision-making processes. The Open Knowledge Foundation (2023) defines open data as data that can be freely used, modified, and shared by anyone for any purpose. Data quality, according to DIN EN ISO 9000:2015-11, refers to how well data meets specific requirements. Various dimensions of data quality are discussed in the literature, with accuracy, validity, completeness, and timeliness, among others, identified as core aspects (DIN EN ISO 19157, Sebastian-Coleman, 2013, Klinkhardt 2021). Depending on the use case, the relevance of the quality dimensions may vary. Klinkhardt (2021) provides a comprehensive synthesis of quality standards for geographic databases with a particular emphasis on completeness and thematic accuracy for geoinformation. In order to measure data quality, it is necessary to define requirements for the data and tools to monitor the extent to which the data meet these requirements (Sebastian-Coleman, 2013).

3. Concept of the Planning Tool

3.1. Method

The first step in mobility hub planning is the evaluation and ranking of potential locations. These are initially all existing public transport stops. The planning approach focuses on the rural regions of Germany, including small towns, medium-sized towns and central cities. Through a literature review, relevant factors for assessing the potential of a location were identified, such as the number of points of interest in the catchment area, the potential demand (derived from the number of passengers, population density), and the frequency of public transport. In addition, mobility hub projects were analyzed and expert interviews were conducted to validate the planning factors. The most frequently mentioned factors were integrated into the planning concept and the required data inputs were derived.

3.2. Partial Concept and the required Data

Figure 1 summarizes the work flow for the location planning including the required data inputs. The goal of this planning step is to provide the planner with an overview of the potential sites including relevant information and a site ranking based on the total potential per stop. The total potential value per stop can be determined on the basis of only one influencing factor, e.g. passenger numbers, or on the basis of several factors, which can be additionally weighted by the planner. Based on the total potential values of the stops, the planner can select the most suitable public transport stops and then proceed to the individual planning, i.e. configuration of the mobility hub.

The individual planning is based on a mobility service recommendation matrix and a potential number of users per mobility service.

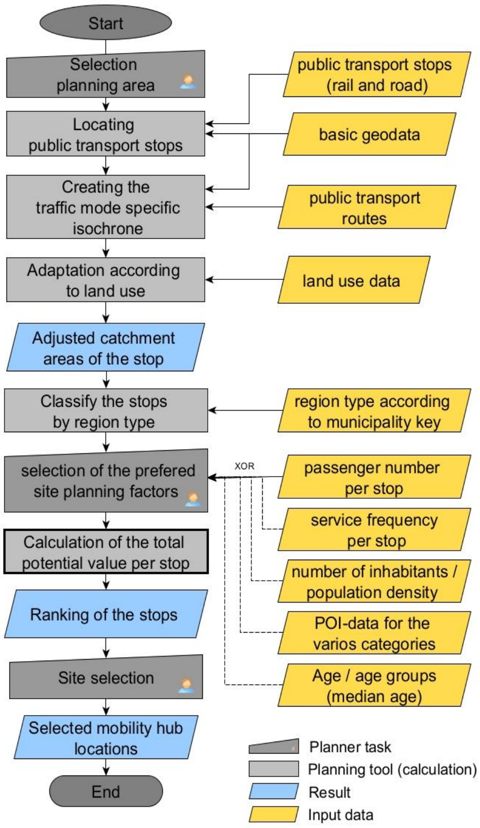

Figure 1. Concept of the location planning.

4. Data Quality Assessment

The quality assessment of the available data sources is based on the relevant quality criteria for data, see chapter 2. Particularly relevant for the use case and therefore included in the evaluation were the criteria availability as open data, suitability of the data format, and transferability (scalability) of the data sources to all of Germany. These were assessed as exclusion criteria with a "Yes" or "No" answer. Data sources were researched using an unstructured internet research and suitable ones were selected based on the above criteria. Additional criteria – Completeness and Accuracy (thematical and positional) - were rated on a scale from 0 to 2 (0 - low fulfilment degree, 1 - medium fulfilment degree, 2 - high fulfilment degree) in terms of meeting the planning tool-specific requirements. Furthermore, the criterion complete-ness was weighted with a factor of 0.7 and the criterion accuracy with a factor of 0.3, because inaccurate information (e.g. minor deviations of the location) is generally less critical for the expected planning results than completely missing information. In the next step, the selected sources were evaluated using the above scale. For this purpose, data were qualitatively assessed by the research team.

Table 1 shows an excerpt of the data source assessment and its results.

Type of data	*Assessed Source*	*Exclusion criteria*	*Comple-teness*	*Accuracy*	*Usability score*
Basic geodata (roads, traffic routes, etc.)	Open Street Map (OSM)	Yes	2	1	1.7
Federal state and munici-pal borders, etc.	State survey-ing offices	Yes	2	2	2
Land use data	OSM	Yes	1	2	1.3
Regional rail transit stops	OSM	Yes	2	1	1.7
Points of interest (POI)	OSM	Yes	2	2	2
Population density	Eurostat	Yes	2	2	2

Table 1. Assessment of the suitable open data sources. Legend: 0 = low fulfilment degree, 1 = medium fulfilment degree, 2= high fulfilment degree.

The sum of the weighted criteria gives the total usability score. The score of the OSM data refers to the data format "point", which was considered sufficient information for the implementation of the concept. The data quality assessment found that open data sources exist for most of the required data and that they meet the minimum requirements. The overall usability scores vary between medium and high levels of fulfillment of the criteria by the datasets. This means that the available open data are of sufficiently good quality and can be used for the planning tool. The only missing data is the number of passengers. This can be estimated based on population density or completely replaced by other influencing factors, see chapter 3.2.

5. Conclusion and further work

The feasibility of a large-scale open-data planning tool for mobility hubs was confirmed for the location planning step. The next step is to finalize the concept for single hub configuration and to collect the necessary data. To configure a mobility hub, the number of potential users per mobility service in the catchment area has to be estimated. The required data for this, such as the intention of the users to use the different mobility services, will be collected through a survey, as it is not available as open data at the required level of detail. The validation of the collected data will be performed at a prototypical mobility hub in a rural region. Finally, the concept will be implemented as a web application.

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Towards gaze-supported emotion-enhanced travel experience logging

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Abstract. Experience logging helps people to create a digital archive of their daily activities. As technologies advance, modern devices make it easier to include various elements into travel logs, including emotions. We propose research on a novel topic utilizing eye tracking features and physiological signals to detect travelers' emotions in the wild and to develop a visualization prototype for travel experience logs.

Keywords. Eye tracking, emotion, experience logging

1. Introduction

Experience logging is a way to record daily life activities. Its purpose is to work as a memory aid and help users better reflect upon past events (Belimpasakis et al. 2009). The idea of digitally recording life experience dates back to the 1940s when Bush (1945) imagined a man in the future wearing a camera on his forehead and taking pictures of valuable moments. Nowadays, Location-Based Services (LBS) (Huang et al. 2018) enable users to record travel logs which typically include trajectories, text, and media (Huang et al. 2015).

Although emotions play a major role for a memorable travel experience (Moyle et al. 2019), they are rarely included in current LBS for travel logging. Understanding travelers' emotions is an important challenge, as emotions can indicate travelers' behavior and motivations behind their activities (Goossens 2000). Outside of the tourism research field, emotion itself can also provide us with additional information about how people perceive their surroundings, enabling us to adapt the environment to people's needs (Gartner 2010, Resch et al. 2015).

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Self-report survey is one of the most popular methods to log emotions (Chiou et al. 2011). It is simple and straightforward but sometimes lacks precision (Li et al. 2015). Complementary, eye tracking (Lim et al. 2020) and other physiological sensors (Hadinejad et al. 2019) have been suggested for emotion recognition - sensors which have also gained increasing interest in the LBS literature recently (Anagnostopoulos et al. 2017, Kwok et al. 2019).

However, research on using eye tracking and physiological signals for emotion-enhanced experience logging in LBS is still missing. In this work-in-progress paper, we outline research on detecting emotions during traveling using a multimodal approach and developing a visualization prototype for travel experience logs. We tackle the following research questions:

- Q1: Does a combination of eye tracking and physiological signals enable us to detect emotions more accurately than each of them alone?
- Q2: How can we detect a traveler's emotions in the wild?
- Q3: How to design a visualization for emotion-enhanced travel experience logging that can help users recall critical events?

2. Background

2.1. Experience logging

Early applications of experience logging focus on providing a supplement to memory with video and audio including Remembrance Agent (Rhodes & Starner 1996). These systems capture events passively without user interventions. But they often require the user to manually select or annotate events subsequently.

Blum et al. (2006) developed the inSense system, with an algorithm using location and other features to classify events in real time. When a possible interesting moment is detected, the system takes a picture and records a short audio clip, which can be a memory aid for the users.

Kalnikaite et al. (2010) investigated how experience logging could help us remember past events. Participants were asked to use a camera for two weeks to capture their daily activities, and later do a recall test. Results show that locational data supports inference of past events whereas images are associated with directly recalling events.

2.2. Emotion detection

Two types of features are dominant in emotion detection: physiological signals and eye tracking. Emotions are believed to be associated with autonomic nervous system physiological responses (Levenson 2014), thus they can be detected by changes in physiological signals. Commonly used physiological signals include electroencephalography, electrodermal activity, electrocardiography, blood volume pulse, and skin temperature (Bota et al. 2019). These signals can be easily recorded with wearable sensors or devices. Similarly, eye movements allow us to infer about a user's attention and could possibly reveal emotions associated with certain moments (Lim et al. 2020).

Most of these emotion detection studies were performed in the lab with different types of stimuli including video, audio, image, and text (Badshah et al. 2017, Deng & Ren 2021). However, few studies perform emotion detection in an outdoor environment. This has left a research gap among the current studies.

3. Research outline and challenges

We propose research on using eye tracking features and physiological signals to detect emotions evoked during travelling and developing a travel experience log visualization prototype, using emotion as a context. It can be divided into three steps as shown in *Figure 1*.

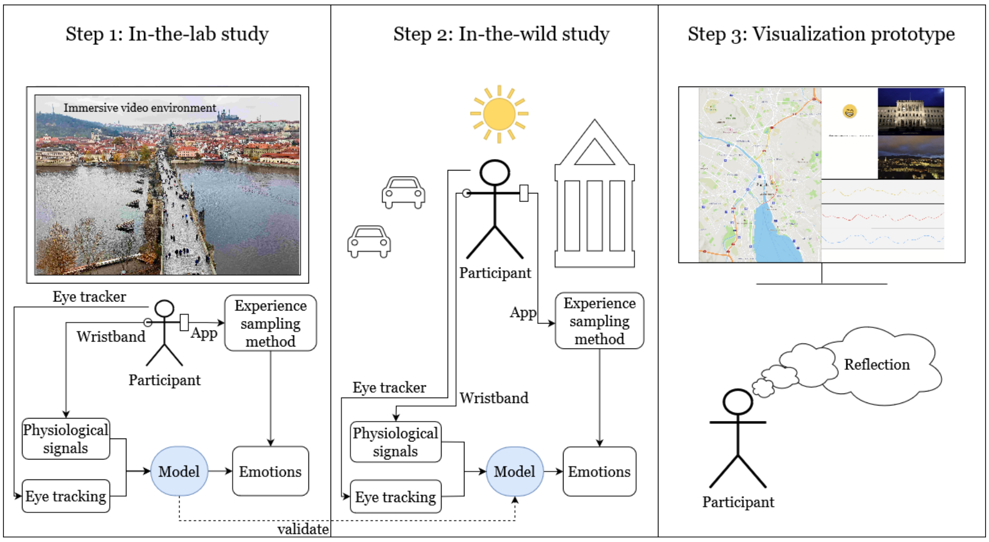

Figure 1: Project overview

First, a controlled lab study will be conducted to test if a multimodal approach can detect emotions more accurately. During the study, participants will be shown video clips of a traveler's pedestrian egocentric perspective in an immersive video environment (Schröder et al. 2023). An eye tracker for collecting eye movement data and a wristband for collecting physiological signals will be used. Experience sampling method will be used to complement ground truth emotions using the circumplex model of affect (Russell 1980) after each video. Machine learning models will be trained for emotion detection. In step 2, a study in the wild will be performed to validate and improve the trained model, with nearly the same experiment setting except a longer time interval for sampling emotions. Finally, a visualization prototype for travel experience logs will be developed. The traveler's GPS tracks are overlaid on a base map, with emotion annotation generated by the trained model displayed. Users can also input annotations either as a correction or complement. We plan to compare different visualization and interaction methods for this tool.

Several challenges lie within the study part, especially during the in-the-wild study, where illumination could have a significant effect on pupil size. How to distinguish pupil size changes due to emotion or illumination needs to be further studied. This could potentially lead to a context-aware emotion detection model that can adapt itself according to lighting conditions in the wild. The in-the-wild study must also be carefully designed to ensure that different types of emotions are evoked during the travel.

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Visualizing Eye Movement Data of Web Maps: The ET2Spatial & ET2GIS & ET2QGIS Tools

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Abstract. This paper addresses the issue of costly analysis of eye-tracking data over dynamic interactive stimuli. The introduction offers a brief insight into the addressed issue. Afterwards, it describes the ET2Spatial tool that allows to capture and georeference eye movement data during user interaction with web maps. The main part describes 13 features of the ET2GIS tool that facilitate the visualization of dynamic data in ArcGIS Pro and QGIS environments. Both tools have the potential to be extended and can be used for usability studies of interactive cartographic stimuli as well as for the analysis of human interaction and cognition with web maps.

Keywords. Eye-tracking, Map Interactivity, Utility, Georeferencing, User-logging, GIS

1. Introduction

Cartographic eye movement research has evolved from static to dynamic map displays. Słomska's 2018 study highlighted that over a third of stimuli used in cartographic research are interactive, with a growing number of publications in cognitive cartography. Additionally, eye-tracking, used in in almost one fifth of the GIS usability studies reviewed by Unrau and Kray (2019), is considered a significant method for such research. The cartographic community is working to improve eye-tracking data analysis. Notable tools include EyeMMV for analyzing eye-tracking data (Krassanakis et al. 2014), EyeMSA by Burch et al. (2018) for sequence alignment, and ScanGraph (Dolezalova & Popelka, 2016) for eye movement similarity comparison, useful in multiple domains including cartography and education. However, challenges persist. Eye-tracking with interactive stimuli is time-consuming and data-intensive. Traditional eye-tracking mechanisms strug-

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gle with interactive media, and creating dynamic areas of interest (AOIs) is labor-intensive. Tools like the one by Papenmeier and Huff (2010) aid in drawing dynamic AOIs, but rapid changes in interactive web media content make manual annotations impractical. Research into eye-tracking and interactive web maps has grown, focusing on understanding cognitive processes with dynamic maps. Innovative methods include a combination of eye-tracking and transforming gaze coordinates to geographic coordinates for more accurate analysis. Yet, current tools lack the ability to analyze gaze data from a spatio-temporal perspective despite its similarity to real-world geographic movement datasets. There's limited research on open-source eye-tracking solutions for dynamic maps. One tool, 3DgazeR (Herman et al. 2017), addresses eye-tracking in 3D environments by calculating 3D real-world coordinates for each gaze point. Ooms et al. (2015) presented a framework capturing the essence of challenges in this field, offering desktop-based user data logging solutions. FeatureEyeTrack from ETH Zurich (Göbel et al. 2019) is a tool aiming to simplify eye-tracking data analysis for dynamic online mediums, integrating eye-tracking with interactive web map functions.

2. Tools for eye movement data conversion to GIS

2.1. ET2Spatial

In 2022, a study introduced the ET2Spatial tool (Sultan et al. 2022) designed to capture and georeference eye movement data during web map interactions. This tool's primary purpose is to convert user gaze locations on the map into real-world coordinates. A significant motivation behind this research was the traditional eye-tracking software's limitation in consolidating data from multiple participants interacting with web maps into a unified file. The tool also allows for the visualization and comparison of multiple users' data simultaneously on a basemap, which was not possible with traditional eye-tracking software. The tool combines eye movement data with user action data, such as mouse clicks, user inputs, and displayed map extent and zoom level, which are recorded through logging. The tool uses Google Maps API v2, and the main program is written in Python. The ET2Spatial tool converts the points from screen coordinates to geographic coordinates, and the next step is file conversion and export. The tool generates a separate file for each participant, identified with the participant ID. The converted raw gaze points and fixation points files are provided as outputs for each participant. The main file formats considered for exports in the ET2Spatial tool are Geojson and Shapefile. The tool generates a CSV file as a byproduct for an alternative entry into GIS software. Geojson and Shapefile are popular file formats in the GIS community and are compatible with most GIS software. Geojson can also be easily visualized with mapping libraries and APIs such as Leaflet, Mapbox, and Google Maps. The tool has expanded current knowledge by providing a new approach to inspecting eye-movement data as spatial features, subjecting them to traditional spatial operations and comparing them to standard techniques provided by eye-tracking software. The tool has also highlighted the need for more research in this domain and the development of tools to address the issue of analyzing eye-tracking data on interactive web maps.

2.2. ET2GIS

Following that, the ET2GIS toolbox was developed for Esri ArcGIS Pro 3.0+, which offers the creation of a toolbox using the ModelBuilder environment. The objective of the tool is to facilitate the import of output data from ET2Spatial into the ArcGIS Pro software and provide various methods of gaze data visualization. A Project template was designed for repeated work with the toolbox. This template includes the ET2GIS toolbox, both 2D and 3D maps with locked and unlocked zooming, as well as four basic base maps from Google Maps (Roadmap, Satellite, Terrain, and Hybrid). The tool ET2GIS includes 13 functions (Figure 1). Most of the tools were inspired by typical visualizations of eye-tracking programs (e.g. Heatmaps, Scanpaths, Areas of Interest, etc.). However, visualizations that are not commonly available in eye-tracking programs are also available (e.g., Space-time cube or Zoom Level Clustering). The output from ET2Spatial provides a separate file for each participant and task.

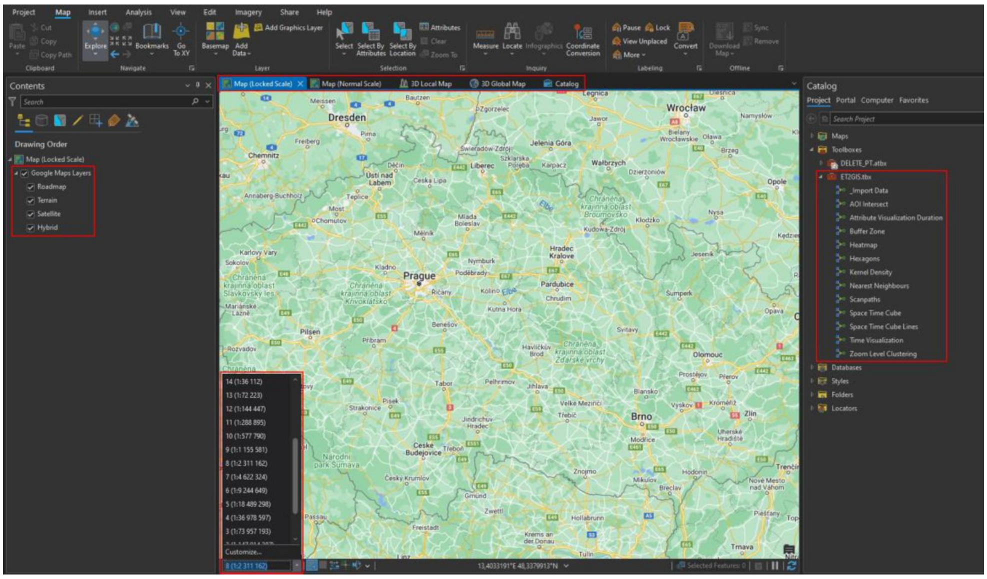

Figure 1. List of 13 functions in Project Template environment.

The next step involves **Import Data tool**, designed to consolidate data from multiple participants and tasks to streamline subsequent analyses and visualizations. The **AOI Intersect** tool allows to create areas of interest for the investigated stimulus, based on this, might be determined how many fixations belong to each area of interest. The **Attribute Visualization Duration** displays the fixation using Duration Time, which displays, using a graph, how long the respondent looked at a particular location. The **Buffer Zone** creates a circle around the defined point based on the distance parameter and displays the fixations that are inside the circle. The **Heat Map** visualizes the density of fixations using a continuous gradient. **Hexagons** offer visualization of the density of fixation points and raw points within hexagons, which can reveal a cluster of points overlaid that might otherwise be overlooked. **Kernel Density** is similar to the Heat map; however, while the Heat map only visualizes existing vector data, the Kernel Density tool works with a newly created raster layer, which can be further utilized, for instance, in a raster calculator. **Nearest Neighbours** displays the cluster of nearest fixations, determined by the average distance between the fixation and its closest neighbor. **Scanpaths** represent the order and duration of fixations for each respondent. The tool creates two new layers: the first shows the fixations in different colors for each participant to represent the fixation duration and its order, while the second layer links the line fixations based on their order. The **Space Time Cube** visualizes fixations in 3D space using the time feature. Similar to the Scanpaths tool, the **SpaceTime Cube lines** create lines using the Points To Line tool, but in 3D space, reflecting the time feature of the data. These lines are color-coded by a participant. **Time Visualization** allows users to view eye-tracking data over time via the Time tab, which allows visualization controls such as playback speed, rewinding, and more. The **Zoom Level Clustering** tool allows to visualize participant fixations according to the zoom level based on predefined map scales and the range of scales for which the data is displayed.

2.3. ET2QGIS

Besides ET2GIS, we are currently working on a similar tool written in Python that will enable us to perform spatial analyses of eye movement data in the environment of QGIS. The advantage of this approach is that QGIS is an open-source application and that all functionalities might be accessible through a single window. Since it is still a work in progress, only the possibility to import data and create AOIs is currently available.

3. Conclusion

This contribution presents the tool solving the problems of eye-tracking analysis on dynamic interactive web maps and their subsequent visualization. Traditional eye-tracking systems struggle to analyze dynamic content. The evaluation of static stimuli does not meet current needs for analysis using eye tracking in interactive environments such as web maps. There has been limited research on this topic, and even fewer free, open-source tools are available to address the issue. Therefore, the ET2Spatial was used to convert ET data collected in interactive maps, and both ET data analysis/visualization tools (ET2GIS and ET2QGIS) were developed.

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A Framework and Practical Guidelines for Sharing Open Benchmark Datasets in Cartographic User Research Utilizing Neuroscientific Methods

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Abstract. This paper presents a structured approach to creating benchmark datasets and proposes guidelines for open-data sharing in the field of cartographic user research using neuroscientific methods including but not limited to eye tracking, EEG, and fMRI. The unique complexities introduced by geospatial data and maps make geospatial tasks fundamentally different from those encountered in the experimental psychology or cognitive visualization domains. We argue that datasets capable of addressing specific cartographic problems possess significant value and hold the potential to become benchmarks. For instance, studying the cognitive load and strategies employed by map users during various map tasks can provide valuable insights for map design and serve as benchmarks in developing complexity algorithms for cartography. We emphasize that benchmarks should be tailored to specific scientific issues rather than solely focusing on data standards. Such benchmarks not only contribute to map usability research but also play a pivotal role in developing predictive models that consider the visual attention and map use capabilities of users. Researchers across domains bear the responsibility of actively seeking concrete methods to encourage the open sharing of experimental data, complemented by high-quality metadata. By fostering the creation of benchmark datasets and promoting open-data sharing, collaboration is enhanced, cartographic research advances, and the scientific community is empowered to effectively address cartographic challenges.

Keywords. Eye tracking, EEG, fMRI, cartographic user research, open data benchmark dataset guidelines

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1. Introduction

Research methods in cognition and neuroscience, such as eye tracking, EEG (electroencephalogram), and fMRI (Functional Magnetic Resonance Imaging), have greatly enhanced our comprehension of visual attention, cognitive processes, and problem-solving strategies. Through their direct and objective assessment of eye movements and brain activities, these methods have become increasingly prevalent in spatial cognition and map usability research. They have demonstrated their efficacy as powerful instruments in evaluating the visual attention capabilities of map users. For instance, De Cock *et al.* (2022) performed an eye tracking usability study in VR to investigate the interaction between route instruction types and building configuration on cognitive load during indoor route guidance. Keskin *et al.* (2020) studied the memorability of map landmarks by assessing the influence of a set of visual variables (i.e., location, size, shape, color), task difficulty, and expertise on recognition using eye tracking and EEG. Qin & Huang (2022) investigated the cognitive processes of map users during different map tasks (i.e., global search; distance comparison; route following and route planning), integrating both overt (visual attention through eye tracking) and covert (neural activities through EEG) perspectives, with the hypothesis that distinct eye movements and brain activities are associated with different map tasks. Dong *et al.* (2022) used fMRI to investigate the relationship between human brain activities and the spatial and temporal characteristics of public transport travel whereas Liu *et al.* (2019) investigated the influence of regular and irregular road network patterns on spatial cognition using fMRI.

Compared to standard behavioral measurements such as response time and accuracy, the added value of neuroscientific methods (*e.g.*, eye tracking, EEG, fMRI) lies in providing a deeper and more nuanced understanding of how our eyes and brains interact with maps, allowing for more targeted and effective interventions to gain insights into map users' behaviors and possibly improve map usability and map usage related capabilities. When combined with other physiological measures (*e.g.*, galvanic skin response (EDA/GSR), skin temperature, heart rate, *etc.*) or user-generated feedback such as (digital) sketch maps, they enhance the understanding of spatial cognition processes, limitations and capabilities of map users (Keskin *et al.*, 2018; Xu *et al.*, 2022). These methods can also be complemented by qualitative user feedback such as structured interviews, pre- and post-test questionnaires. In this context, it is important to consult the existing review guidelines and suggestions for mixed methods research in map usability and cartography (Roth, 2015; Štěrba *et al.*, 2014).

It is not straightforward to design a neuroscientific user experiment. Preparing all the equipment, experimental tasks and stimuli, instructing participants, collecting, preprocessing, analyzing, and making sense of the processed data requires a lot of time, expertise and effort. Despite the great endeavor, such data seems to be disposable only after one or two publications and left somewhere in the lab where it becomes another data island with limited external connectivity. In the meantime, some other researchers might be going through the same process for similar data and map reading tasks. Therefore, we must prioritize open data and open science efforts for cartographic user studies. This involves publishing raw experiment data (*e.g.,* eye tracking, EEG, fMRI, *etc.*), defining possible causes and solutions for a lack of user data benchmarks, and repurposing collected datasets as benchmarks. One possible reason for the lack of such data benchmarks for cartography is that existing benchmarks are typically used to serve computational models and they fail to replicate the similar results when it comes to complex stimuli as maps and unique tasks involved in map reading. However, if the dataset is collected to address a specific cartographic problem, and recorded during map reading, it can have significant value and the potential to become a benchmark. For instance, cognitive load and cognitive strategies of map users during different map tasks can be used as inputs in map design or can be used as benchmarks for developing complexity algorithms in cartography. Overall, benchmarks should be aimed at specific scientific issues rather than just data standards. Such open benchmark datasets for map usability research can then provide several benefits in terms of:

- Accessibility: Open benchmark datasets can increase accessibility to research findings, particularly for researchers who may not have the resources to collect their own data.
- Reproducibility & Transparency: By sharing data openly, other researchers can attempt to replicate the findings of a study and build upon them, as well as save time and resources by avoiding the repetition of similar experiments.
- Collaboration: Encouraging collaboration between researchers working on similar problems, open datasets can foster collaboration and improve the credibility, quality, and accuracy of the research, and with multi-purpose datasets, this can also happen in cross-disciplinary.
- Innovation: By providing a shared resource for testing and improving new methods and algorithms, open datasets can lead to innovative solutions, *e.g.*, *further analysis as well as exploring new methodological approaches (e.g., by including new indices and/or aggregated visualization methods, and predictive AI algorithms) can help the process of computational modeling of visual attention for this specific type of visual stimuli.*

1.1. Existing datasets in general *vs.* datasets for geospatial tasks

There have been several efforts to provide open datasets, such as MIT/Tuebingen's Saliency Benchmark (Kümmerer *et al.*, 2018) which is one of the largest repositories that provides a collection of eye-tracking data and saliency maps for various types of stimuli. They plan to include other eye movement benchmarking tasks with an initial focus on scanpath prediction in free-viewing and visual search settings. However, many open eye movement datasets including MIT/Tuebingen's Saliency Benchmark typically lack information for task-driven cognitive assessments. They are largely tailored for saliency analyses of general images (*e.g.*, Tliba *et al.*, 2022), and are not diverse enough to address complex cartographic visualizations and their associated tasks. Recently, there has been increasing recognition of the value of open datasets in the cartographic usability domain. For instance, **EyeTrackUAV2** was created to study how the participants' visual attention was influenced by the UAV videos under free viewing and surveillance viewing (i.e., object detection) tasks. It includes a large-scale eye tracking data (*i.e.*, gaze position, fixation duration, and saccade amplitude) from 30 participants watching 43 videos of UAVs recorded from different perspectives and at different speeds. **CartoGaze** (Keskin *et al.*, 2023) contains a comprehensive and reproducible set of large eye movement data from a controlled memorability experiment with 38 participants balanced in age and gender, along with 37 corresponding map stimuli, AOI files, task descriptions, and full procedural details of data collection and analysis framework. **GeoEye** (He *et al.*, 2023), on the other hand, constitutes 110 college-aged participants' eye movement data when free viewing 500 geospatial images, including thematic maps, remote sensing images, and street view images, which demonstrate the scientific benefits and applications in saliency prediction and map user identification. The development and provision of more varied datasets remain essential to expand the scope of cartographic research and make it possible to study new and emerging topics.

Despite EEG and fMRI research producing a wealth of data that can be used to study brain functions and activities, such data can be difficult to access and use. In recent years, there has been a growing movement to make brain imaging data more accessible through publicly available datasets.
Here we list some of the useful open datasets and repositories available for eye tracking, EEG, and fMRI research and/or co-registration of those:

- A list of all public **EEG datasets (github)**: This repository includes EEG data from a variety of tasks, including visual perception, memory, and motor control (Agarwal, 2023).
- **Donders Data Repository**: is designed to accommodate brain imaging (*e.g.*, fMRI, MEG, EEG, *etc.*) research data management workflows throughout the research life cycle. It ensures the long-

term preservation of large datasets from a variety of tasks, including language, attention, and emotion, and helps researchers adhere to the FAIR (Findable, Accessible, Interoperable, and Reusable) principles and Radboud University's research data management policy (URL 1).
- **The SJTU Emotion EEG Dataset (SEED)**: is a collection of EEG datasets provided by the BCMI laboratory for emotion recognition (URL 2).
- **Radboud Coregistration Corpus of Narrative Sentences (RaCCooNS)**: the first freely available corpus of eye-tracking-with-EEG data collected while participants read narrative sentences in Dutch. The collection is intended for studying human sentence comprehension and for evaluating the cognitive validity of computational language models (Frank & Aumeistere, 2022).

There is still a growing body of research into brain imaging research and to the best of our knowledge, no open brain imagining datasets have been published for cartographic tasks. Therefore, future research should focus on the data sharing standards that are needed for benchmarking.

2. Proposed structure

Standardization plays a crucial role in facilitating reliable and reproducible research outcomes. Data standards/principles such as FAIR exist but how applicable is it to address the research questions in neuroscientific user studies, yet in the cartographic domain? A key aspect of achieving standardization in neuroscientific user research is the implementation of detailed documentation for shared data, along with the development of empirically derived guidelines. Geospatial data and maps present unique complexities that differentiate them from traditional stimuli subjected to experimental psychology or cognitive visualization. Therefore, it becomes imperative to address these differences and adapt existing standardization practices to suit the specific requirements of geospatial tasks. In this context, we propose a comprehensive structure for benchmark datasets and present guidelines specifically tailored to open-data sharing in neuroscientific user research related to cartography to foster greater consistency and generalizability of research outcomes.

2.1. The characteristics of benchmark datasets

For the reusability of the shared datasets, information about the participants' characteristics, recording device, experimental tasks, stimuli and conditions are bare minimum, in order other words, “must-have”. Here we list and detail all the dimensions that are "nice-to-have" and to be taken into consideration while reporting metadata related to datasets:

1. Controlled conditions
    - Medium/display: mobile (smartphone, tablet), laptop and/or desktop with integrated or standalone webcams
    - Performance for data collection and system specification: data quality, claimed error and calibration accuracy of the recording system and device
    - Input modality: the means by which a user interacts with a computer or other electronic device. It can include various input methods such as a keyboard, mouse, touchscreen, joystick, voice recognition, or gaze control
    - Recording devices: remote/screen-based or mobile eye trackers, webcam eye trackers, standalone EEG recording modules (*e.g.*, EEG caps & electrodes), or headsets with integrated eye tracking, VR, AR capabilities, EEG, fMRI, or other sensors
    - Extraneous variables such as lighting conditions, noise, shielded room, impedance, curiosity about the experimental procedure and equipment
2. Well-defined tasks and research questions
    - The purpose of the experiment with keywords defining the study as this is useful for others to access the datasets
    - Full procedural details of the experiment (*e.g., perhaps a standard flowchart can be prepared if not released with a research paper*)
    - Free viewing vs. task-specific
    - In labs or in real-world environments
    - Visuospatial or perceptual tasks
    - Trial tasks, orientation, and task instructions
    - Task design (*e.g.*, randomized block design, event-related design, *etc.*)
    - Task duration and total recording length as it is important due to fatigue, performance, and focus. Typically experiments should not take longer than 45 min for eye tracking and no longer than an hour for EEG or fMRI
3. Well-defined data
    - Artifact-free (if so, preprocessing steps) or raw data
    - The data quality
    - Sufficiently large data samples to ensure the generalizability of the results
    - The data format and compatibility
    - Detailed documentation including data collection, preprocessing and analysis protocols, and open codes for such analysis

- Attaching relevant scientific research if applicable and/or other relevant references
- Data specific descriptions:
  Eye tracking specific: dominant eye, resolution (60Hz, 120Hz, *etc*.), fixation recognition algorithm/parameters
  EEG specific: resolution, the number of electrodes, the type of electrodes, their spatial distribution (*e.g*., 10-20 system)
  fMRI specific: the number of channel head coils, repetition time (for functional/structural images), echo time (for functional/structural images), layer scan

4. Well-defined stimulus properties:
   - Screen map (mobile, laptop, desktop), animation, web-service
   - 2D, 3D or XR
   - Static, dynamic, interactive
   - Size, position, and format of images or other media used in the experiments
   - Visual or task-related manipulations if applicable
   - Experimental stimuli preparation details (*e.g.,* source, authorship, existing or new)
5. Well-defined participant characteristics
   - Sample size: we often need a large sample size for EEG and fMRI due to noise but optimization is important when using mixed methods
   - Individual characteristics of the participants (age, gender, education), additional tests to classify participants based on spatial abilities (*e.g.,* NASA TLX), if needed
   - Special concerns: Color blindness, users with other disabilities
   - Self-reports, pre- or post-test questionnaires, and structured verbal interviews
6. Well-defined metrics
   - Behavioral metrics: response time, response accuracy
   - Eye movement metrics: fixation- or saccade-related, AOI- (area of interest) specific metrics, scanpaths, heatmaps
   - EEG: time-domain: Event-Related Potentials (ERP) (*e.g.,* P300); frequency-domain: Power Spectral Density (PSD) (*e.g.,* hemispheric differences: Frontal Alpha Asymmetry (FAA)); time frequency-domain: Event-Related Synchronization& Desynchronization (ERS/ERD)
   - fMRI: Blood Oxygen Level Dependent (BOLD) Signal (*e.g*., changes in whole-brain or AOI), Functional Connectivity
7. Ethics
   - Asking local ethics committees for permission if needed
   - Adhering to ethical standards, including obtaining informed consent from participants and protecting their privacy.

- Anonymization of participants' data

With above metadata being listed, we would like to emphasize that it is important to make pre-processing and analysis steps clear, available and somewhat transferrable to other use-cases. Hence, linking shared datasets with published scientific work is the ideal approach. For instance, the open EEG dataset collection published by Popov *et al.* (2018) portrays a good example of sharing the metadata, as well as all raw data, metrics, and analysis scripts necessary to reproduce the results of the original study.

2.2. The guidelines for sharing data openly

- Accessibility: The data should be stored somewhere accessible to a wide audience.
- Stability: The data provider should make sure the data is taken care of and always accessible (at least within certain years).
- Safety: The data provider should make sure there is no malware that might attack its users.

3. Conclusion

Open data and open science for cartographic user studies are essential to improving the quality and accessibility of cartographic research. We must prioritize these initiatives in order to ensure that our research is as rigorous and impactful as possible. Benchmarks that are useful for addressing specific cartographic issues not only create value for map usability research but also are essential parts of the development of predictive models considering the visual attention and map use capabilities of map users. The biggest responsibility for us researchers in all domains is to seek concrete ways to encourage ourselves and the community to share experimental data openly with high-quality metadata.

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The Importance of Communication with Missing Data with Colours of Map for Decision-Making

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Abstract. Missing data is a growing issue in data-driven studies. This study focuses on measuring the importance of communication with missing data and the perception of missing data with colours to find better solutions to potential problems in research with datasets with missing data. Understanding the significance of the interaction with missingness may help us to improve the visualisation of missing geospatial data. We have created a survey that includes some sentences, terms, graphs, maps, and colours we can encounter in daily life. However, all these expressions have some missingness in measuring participants' perceptions and decision-making mechanisms. One hundred-one respondents from different demographics, all from the UK, participated in the survey. It aims to improve the visualisation of missing geospatial data using the results of this research for future studies. But, in this paper, we specifically focus on the perception of representation of missingness with different colours on maps. We observed some differences depending on the gender, age, and education categories of the participants. In the gender-aged analysis of this study's results, a significant difference was observed, especially in the perception of a specific colour.

Keywords. missing geospatial data, communication with missing data, visualisation of missing data

1. Introduction

All scientific disciplines may experience challenges with missing data (Graham, 2009). Most surveys and a significant number of experimental data have an issue with missing data (Scheffer, 2002). Studies in which missing data are represented by the terms negative space, silence, dark matter, dark data, and a black hole have been examined in different disciplines such as physics, astronomy, genetics, political science, social media, art, psychological science, online shopping, medical science, security of living spaces ((Hand, 2020, Buetow, 2009, Dawid et al., 2006, Huggett, 2020, Lieberman, 2016, Luo et al., 2012, NASA, 2022, Noelle-Neumann, 1977, Smith, 2018, Wong, 2011)). Although they all describe missingness with different terms, the effect of the missingness may cause unintended consequences for all of them. Significant challenges can be posed by missingness in the results of the statistical studies. The potential that the missing data in the observable dataset may significantly impact the procedure or results of the research makes them highly crucial. Because a lack of data in the dataset may be of importance that can affect the result of the whole study in the opposite way, these difficulties caused by missing data may also affect the reliability of the study. A study's statistical significance can be reduced by missing data, which can also lead to skewed predictions and incorrect results (Kang, 2013). Even though we cannot see or record these data, they can significantly influence our choices and actions. The consequences may be fatal when we are unaware of the missingness (Hand, 2020). Therefore, to minimise the negative effects of missing data and contribute to the development of new imputation methods, it may be necessary to examine in more detail how the missing data should be represented in the best way. However, since little research has been observed to find the best way to represent missing geospatial data, this paper focuses specifically on the perception of colour representation of

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missing data. This indicates a need to understand the various perceptions of visualising missing data using colours on maps. In addition to the terms representing missingness in different fields, colours can represent missingness in some areas. The effective use of colours to represent the data helps to show the patterns of the data and their relationship with each other (Brewer, 1994). In cartography visualisation, colours can be defined as the most effective graphic variable that can increase communication, transmit information, and enable seeing a large amount of information on a single map without negatively affecting the intelligibility of the map (Štěrba and Bláha, 2015). The colours used in map visualisations represent an item or specification on the ground, for example, where water is usually represented by blue (Rosenberg, 2019). Although colours were generally used for decoration on maps in ancient times and real maps were left uncoloured, today, colours are used to convey statistical information about many data (Rother). People's perception of colours is very different from each other and is difficult to measure (Bláha and Štěrba, 2014). The perception of colours can cause people to feel different emotions, just as red is usually a warning by representing a danger (Chesneau et al., 2005). As a result, decision mechanisms may be affected. However, colours may not always represent data or information, but in some cases a deficiency situation.

1.1. Research Aims & Questions

We aim to understand if there is a difference between different groups to perceive missingness on a map. Depending on our results about perceiving missingness, we can find the best way to visualise missing geospatial data. However, we need to understand the importance of missing data before visualising missing geospatial data. Communication can be the best way to analyse the significance of the missingness in geospatial data science. To understand the importance of communication with missing data, it is necessary to choose the best way. To observe the impact of communication with missingness and its effect on scientific studies, we decided to observe the impact of missingness for the participants using the sentences, colours, and terms we use in daily life before augmented and virtual visualisation methods. In summary, our main purpose in this study will be to observe how the participants communicate with missing data in colours. As a result, it is thought that by evaluating the significance of communication with missing data, presenting these data to the participants using technologies such as augmented reality and forming a basis for understanding the importance of communication.

In addition to the data sets used in scientific studies, we may experience many missing data in our daily lives, whether we are aware of it or not. These data can affect our decision mechanism depending on their meaning and importance. This paper evaluated the part of preliminary results of the continuing study to find the best way to visualise missingness in a 3D environment. Therefore, we aim to get answers to the survey question that we examine for this paper to the following question:

- Is there any difference between demographics based on the perception of missing data with colour?

2. Method

In our study, we aimed to understand the significance of interacting with missingness and visualising missing data; a survey was created that includes missing data based on different aspects that participants would come across in everyday life. With different questions in the survey, we aimed to measure users' perspectives and decision mechanisms for lack of data or data uncertainty.

We specifically planned to observe if different colours of missing data on maps in different datasets make sense to participants for this paper. We observe how the missing data on the map in the survey affects the perspectives on the cases and how the importance of the colour or hatches can be perceived according to the types of missing data. Participants were expected to evaluate these deficiencies by reflecting the missing data on the number of data given depending on colour.

It is planned to measure whether the users perceive the colours or hatches as a deficiency and how they evaluate them, and to observe which missing data is more important or unimportant depending on participants' age, gender, and education level, with the results of survey questions. Depending on the idea that visualisation can be one of the effective methods to measure the perception towards missing data, we designed our question with the colours and hatches we used on the map we created. We asked the participants to indicate what the colours and hatch symbols used in different countries on the map mean to them (Figure 1). We designed the answers, so they have two choices, whether a colour represents missing or available data. As a result of this survey, the participants evaluated eight colours (pink, orange, turquoise, black, green, grey, white, cloud blue/grey) and two hatches (dot and line).

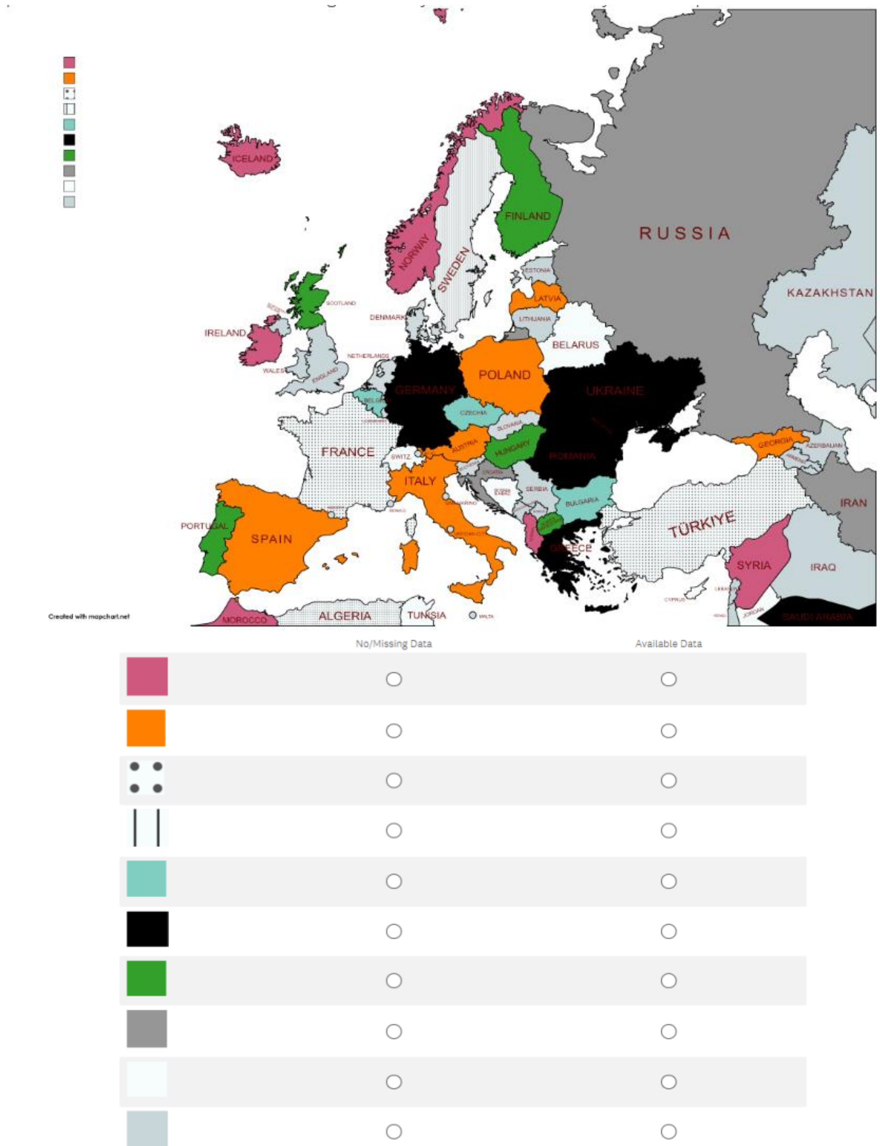

Figure 1 Survey Question – asks participants to indicate whether the colours and patterns used for the map's visualisation represent "available data" or "no/missing data" for them.

3. Results

This study is aimed to observe whether the missing data perception of colours on maps is different between men and women. It was observed that 51 of the survey participants were male, and 50 were female. The age information of the participants was expected in the form of four different categories: "18 - 29", "30 - 44", "45 - 59", and "60+" in the question asked to the participants. According to the initial observations from the survey data, when the participants with different genders perceived different colours on the maps as incomplete data based on their age groups, no significant difference was observed between the male and female participants. As a result, gender-based participants in four different age group categories were divided into two groups, below middle age and over (Table 1), and it was observed whether men and women in these age groups exhibited other behaviours in perceiving the representation of missing data with colours. Our preliminary results show a significant difference between men and women over middle age in perceiving the "black" colour as missing (Figure 2), even though there is no significant difference in perceiving other colours and hatches. We are still in the initial analysis stage of our study, and as the next step, we will observe how the participants with different demographics perceive the missing data from the colours on the maps.

	18 - 44	45+
Female	31	19
Male	16	35

Table 1. Number of Participants

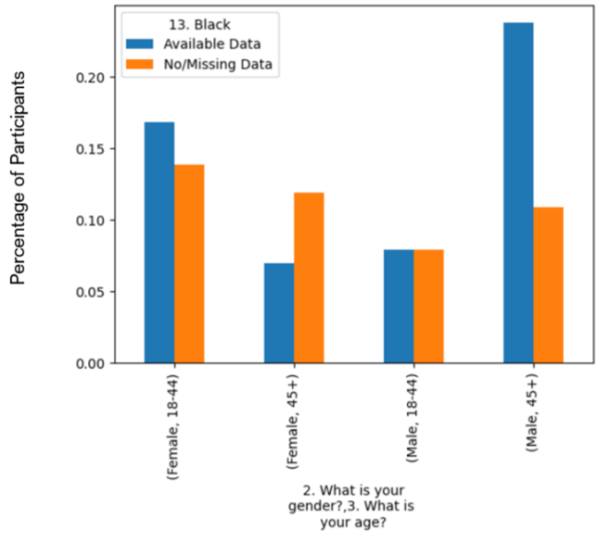

Figure 2. Perceiving “Black” colour on the map

4. Future Works

The purpose of this study is to understand better and examine whether there is any difference in perceiving missing data in colours on the map for different demographics such as age, gender, and education. Findings from this study may have important implications for developing a study to communicate and visualise missing geospatial data. We need to understand the importance of communication with missing data and the importance of missing data and to measure how important missing data is in decision-making. It is planned to determine the effects of missing data based on location, time, colours, and amount separately depending on the age, gender, and location data of the participants as a next step with survey results. Moreover, since the presentation of many colours together on the map designed for the survey may cause different effects on the perception of the participants and may confuse them, it is planned to continue the study to observe the isolated representation of each colour to measure the perception of the participants in a more understandable way that the different colours represent the missing data, as a next step of this study. The results of these studies will form the basis of the next step, the visualisation of missing geospatial data using augmented reality and virtual reality technologies. In addition, by analysing the results of other questions in our survey, we will lay the foundation for finding the most appropriate way to visualise missing geospatial data in a 3D environment using AR technologies.

5. Acknowledgements

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A Comparative Analysis of Locative Audio for Mobile Cartography: A Preliminary Study

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Abstract. In this preliminary study, we present a comparative analysis of locative audio design and technology for mobile cartography. Locative audio describes the placement of sound into the landscape, and is now widely supported in mobile technology using the device's GPS and other spatial sensors. Sound cartography occupies a relatively small space in cartographic research in favor of visual methodologies, despite the growing relevance to both mobile-first and inclusive cartographic design. We analyzed 38 locative audio tours by five criteria: app technologies, tour characteristics, visual representations, sonic representations, and interactions. In the presentation, we present the preliminary design insights and future directions derived from the comparative analysis.

Keywords. Locative audio, mobile cartography, location-based services, sense of place, comparative analysis

1. Introduction

This paper introduces a comparative analysis of locative audio design and technology for mobile cartography. *Locative audio* describes the placement of sound into the landscape (Behrendt 2015). Analog locative audio long has been used in art installations to support an immersive sense of place (Aceti 2016; Fedorova 2016). Digital locative audio is now widely supported through mobile technology, using the device's GPS and other spatial sensors to deliver sounds to mobile devices as users are moving (Indans, Hauthal, and Burghardt 2019). Locative audio is particularly popular in mobile *guided tours* that lead users through a sequence of points of inter-

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est, with audio supplying context on the historical, geographic, and otherwise invisible dimensions of the visited places (Roth et al. 2018).

Sound cartography drew some interest early in the digital revolution (e.g., Krygier 1994; Golledge et al. 1998), but since has occupied a relatively small space in cartographic research in favor of visual methodologies (Schiewe 2014). Audio and other multi-modal forms of representation and interaction are particularly relevant to mobile-first cartographic design, where visual attention is divided between the map and environment with sound potentially offloading visual complexity to promote safety (Roth et al. forthcoming). Finally, research on locative audio is an ethical imperative for inclusive cartographic design, with translation from visual to audio promoting accessibility for non- or low-sighted users in both mobile and non-mobile use contexts (Shum et al. 2016; D'Ignazio and Klein 2016)

In this paper, we present a comparative analysis of 38 guided tours that include locative audio (henceforth described as *locative audio tours*). This research is the initial step in a user-centered design process to design a series of audio-enhanced guided tours about recent and planned green infrastructure projects in the City of Milwaukee, Wisconsin, a collaboration between the University of Wisconsin Cartography Laboratory and the University of Wisconsin Sea Grant Institute. We present our comparative method design in the next section, discuss preliminary results in the third section, and conclude with future direction in the final section.

2. Method

2.1. Sample

Comparative analysis (sometimes "competitive analysis") is a usability engineering method that critically compares a sample of related designs or technologies by their content and functionality (Nielsen 1992). We primarily collected our sample from the top-ranked mobile applications listed in AndroidRank.org and SensorTower.com. To prevent bias towards a particular platform or template, we sampled only the two highest-rated locative audio tours from the same source. We appended this list through keyword search of "locative audio tour", "locative audio story", and "location-based audio story" in the Google Play Store and iOS App Store.

We identified six inclusionary criteria for the comparative analysis: 1. Published and fully-functional (i.e., not beta-ware); 2. Includes audio; 3. Includes an interactive map; 4. Includes an offline version (i.e., "armchair" mode; Behrendt 2015); and 5. Includes one suggested audio route.

2.2. Codes

We developed five categories of codes form the competitive analysis based on a literature review of locative audio and sound cartography:

1. **App Technologies:** Basic identification—including categorization as applied by the app store category as well as Behrend's (2015) locative audio taxonomy—the underlying mobile mapping technology (after Roth et al. 2014), and platform availability.
2. **Tour Characteristics:** Travel modality, route characteristics (e.g., linear, non-linear, branching; after Röber et al. 2006), site characteristics (e.g., total number of POIs, total audio clips), and geofencing triggered upon entering versus leaving the site.
3. **Visual Representations:** Basemap type, egocentrism, user symbolization, POI symbolization, route symbolization, context layers, map elements, and multimedia (all based primarily on Abraham 2019).
4. **Sonic Representations:** Narrator type (e.g., objective outsider, subjective local, real interviews, fictional characters; expanded from St Clair 2018), sense of place or "embeddedness" (e.g., historic, nature, culture, community, or futuristic background sounds; expanded from Fedorova 2016; St Clair 2018), and sonic variables (after Krygier 1994; MacEachren 1995).
5. **Interactions:** Interaction operators (after Roth 2013), differentiated by user- versus location-triggered.

3. Preliminary Results

Figure 1 provides the preliminary results from the comparative analysis.

App Technologies: The majority of locative audio tours use proprietary technologies including the Google Maps (14/38), Mapbox (13/38), Apple Maps (2/38), and Mapy.cz (2/38) APIs. While we could not identify the underlying technology of seven locative audio tours, only 9/38 use fully open source technologies. Although most locative audio tours are advertised as "Travel and Local" in the Google Play Store and iOS App Store, we observed a greater diversity of purposes following the Behrend et al. (2015) taxonomy, with the most common categories including touristic (24/38), historical (17/38), cultural (17/38), and educational (10/38). Most locative audio tours support offline (37/38) and remote "armchair" modes (33/38), indicating the importance of having fail-proof and preview options to avoid connectivity issues and promote uptake, respectively. However, only 10/38 are responsive between mobile and non-mobile devices, a surprise since we designed our own past guided tours using responsive design frameworks. This finding illustrates the broader shift towards mobile-first over responsive design, particularly for delivery of larger files such as audio.

Tour Characteristics: The majority of the locative audio tours are designed for an outdoor walking modality (27/38), with personal automobile (7/38) the only other modality supported by more than three locative audio tours, an opportunity since some modalities like tram, bus, train, and airplane are chauffeured and do not exhibit the same split attention and safety concerns. Most locative audio tours follow a linear sequence (32/38), with only five non-linear and none using a branching sequence. This perhaps suggests a preference towards linearity for users unfamiliar with the tour location, but also a potential gap for experimenting with non-linear and branching storytelling forms to support transformative experiences in known landscapes. Notably, the majority of locative audio tours supply tour directions through external links to other wayfinding apps (25/38) or as part of the audio recording (22/38), but relatively fewer provide route directions as text (14/38) or visually in the map (3/38). The latter is quite surprising, but perhaps indicates a limitation of route calculation in existing tools supporting locative audio. Finally, the majority of sampled locative audio tours trigger audio content when reaching a POI (25/38) or not at all (10/38), with only one tours triggering audio about the next POI when leaving a POI; the latter design strategy could be effective for longer audio recordings providing background context between sites.

Visual Representations: Most locative audio tours use vector street basemaps (30/38), suggesting a more urban focus, or at least a focus on navigation on roads versus trails. Fewer locative audio tours take advantage of egocentrism to orient the user, with only half (19/38) centering the map on the user and six reorienting the map so that forward is up, with no tour supporting both forms of egocentrism. However, the current user location (36/38) and orientation (25/38) are commonly symbolized on the map. Interestingly, the sampled locative audio tours more commonly symbolize POIs by their absolute sequence (19/38) than their relative sequence (11/38) or non-linear categories (7/38), a finding that perhaps reinforces emphasis on tour linearity. The route most commonly is represented in its entirety (27/38), with only three highlighting the route just between sites, none highlighting just the remaining route, and eight locative audio tours not depicting the route at all. As above, this lack of dynamic symbolization may be a limitation of existing software (excepting WeGoTrip, which appears to support dynamic symbolization). Notably, additional context layers are not commonly included on the sampled locative audio tours, with 9/38 including additional point layers beyond the POIs and no tour including additional line or polygon layers. While this could indicate a preference towards simplicity to avoid confusion along the tour, it also might suggest a design opportunity to better integrate the POI multimedia content into the map itself. Map elements are more common however, with 24/38 indicating north—important given the use case of wayfinding—and 10/38 indicating scale—perhaps more important as the distance increases with a travel modality change away from walking. Legends are not common given minimal inclusion of thematic context layers. Finally, the photos (35/38) and text (27/38) are the most common non-audio multimedia supplement, indicating access of POI content through detail retrieval. The ability to share content on social media also is common (27/38), perhaps unsurprisingly so given emphasis on mobile-first design. Advanced forms of multimedia are not common despite their relative discussion in the literature.

Sonic Representations: Objective outsider narration is most common among sampled locative audio tour (32/38). However, we found the limited examples (four each) of subjective local, real interviews, and fictional character narration to be more interesting, suggesting a missed opportunity to bring multiple perspectives and creative solutions into the narration. Cultural-presentation is the most common non-narrative audio for developing sense of place, presented primarily (although not exclusively) in the form of music. As with narration, we qualitatively found the examples, while limited, of historical/archival (6/38), nature-present (3/38), and community-present (3/38) non-narrative audio to add rich texture to the experience. Only 17/38 locative audio tours intentionally use the sonic variables, most commonly varying the timbre (12/38), loudness (8/38), or order (7/38) of the non-narrative audio. Interestingly, two locative audio tours use the sonic variable location, playing stereo sounds from the left or right audio channels to create an embodied locative audio experience.

Interactions: Nearly all locative audio tours implement zoom (38/38), pan (37/38), and retrieve (35/38), with nearly two-thirds also implementing rotate (26/38). This is an expected finding, as zoom, pan, and retrieve are the most common operators supported in "slippy" web maps. Common inclusion of rotate is logical given the focus on wayfinding, and supplies further evidence that rotate should be considered a separate map browsing operator from reproject. Other operators are less common, indicating an emphasis on interface constraint to keep the UI simple. Overall, fewer operators are triggered by location through geofencing. Retrieve (28/38) and pan (23/38) are the most common location-triggered operators, expectedly so as they update the map position and activate new content for a POI. However, zoom (9/38) and rotate (4/38) are not commonly part of geofencing; this perhaps makes sense for zoom, as a scale change when arriving at a POI may be disorienting, but less so for rotate where map orientation can be updated based on the user's orientation. Interestingly, calculate, while infrequent, is more commonly a location- versus user-triggered operator, included in four locative audio tours to calculate the route to the next POI.

Figure 1: Preliminary results of the comparative analysis.

Future Directions

As stated above, the comparative analysis is the initial step in a user-centered design process to design a series of locative audio tours about recent and planned green infrastructure projects in the City of Milwaukee, Wisconsin. We identified Echoes and VoiceMap from the comparative analysis as two candidate platforms for our locative audio tours given their overall utility and stability. We also are developing a third, open source solution based on Leaflet.js and plan on field testing the three alternatives on a case study walking tour on Shorewood, WI, green infrastructure before expanding to the complete suite of walking, biking, and bus guided tours.

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Recommend Places by Spatial and Non-Spatial Features

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Abstract. Places are described by users that make a huge number of textual contents. This work proposes a novel method for place recommender system based on the integration of semantic space and geographic space. To achieve this goal, salient features are modeled as directions in a domain specific semantic space. Finally, these directions and geographic distances can be used to rank places according to corresponding features.

Keywords. Semantic Space, Geographic Space, Place Recommendation.

1. Introduction

Concept of place, which is based on the experienced and observed space (rather than the commonly used geometric conception), is currently gaining attention (Purves et al. 2019; Wagner et al. 2020). The users of social networks provide a huge amount of textual content about places (Ballatore & De Sabbata 2020). Location-based recommender systems provide relevant suggestions to users by integrating location information (e.g. mobile GPS data), into algorithms (Quercia et al. 2010). These could include recommendations for hotels, restaurants, parks or other places or events near the user's location (Ye et al. 2011). Place recommendation would not recommend only near places but can be different according to the context. For instance, a recommender system of tourism should focus on attractiveness of places rather than their locations. In other words, these systems focus only on the general area of places, not on their exact locations. In addition, a place may be very attractive, but it is so far away that tourists will avoid

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visiting it. Hence, this paper aims to propose a novel method for place recommender systems based on spatial and non-spatial features derived from textual contents. Our fully unsupervised approach contains three main steps requiring only a bag-of-words representation of online reviews of places as input.

In this paper we focus on information about what happens at a place or place functionality, in particular the activities that are associated with or afforded by a place. To achieve this goal, salient features would be modelled as directions in a domain-specific semantic space. Such domain-specific semantic spaces could be used to suggest items in recommender systems (Karimi et al. 2022, Abbasi & Alesheikh 2023). These directions can be used to rank objects (in this case, places) according to corresponding features. In addition, geographical coordinates will construct the geographic space to consider the distances between user and places.

2. Methodology

The general workflow of the proposed method is shown in Figure 1.

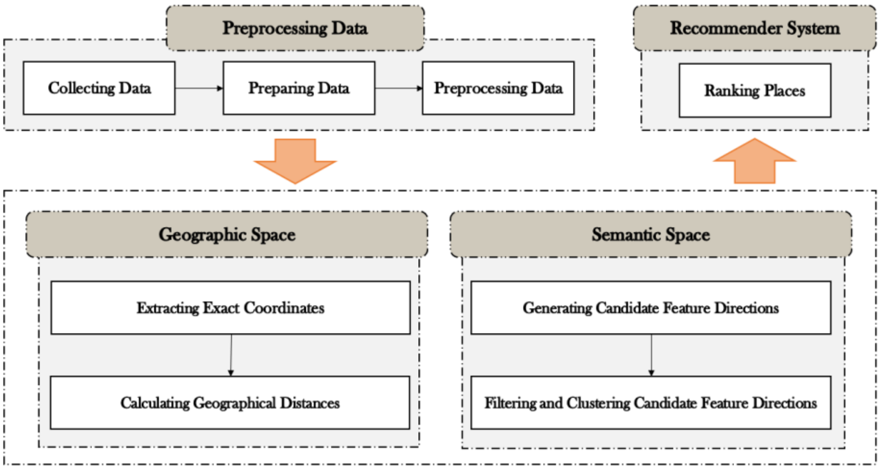

Fig. 1: The general workflow of the proposed method

2.1. Data

We are going to propose a method to online reviews of different places to recommend places based on their attractiveness and distance to user or another attraction. In the first step, places and their corresponding user reviews are extracted for New York City (NYC) by web crawling in Tripadvisor website, which were available in October 2020. Then, some preparing analysis is done to clean data and obtain useful dataset. Therefore, places without geographic locations, places out of the study area, duplicate places and reviews, or places whose type is not "*attraction*" are removed. Afterward, to preprocess the user reviews, which are incredibly unstructured, each review is converted to lower case and tokenized. Then, punctuations and stop words are omitted. Finally, all tokens are lemmatized, and a bag of words (BoW) is created.

2.2. Constructing the Geographic and Semantic Spaces

In the second step, a cluster of words is used to define each feature (similar to LDA topic modeling but more flexible than it). Since there is not a priori knowledge about the most salient features, we consider all nouns, verbs and adjectives that are sufficiently frequent in the BoW representations of the places as candidate feature labels. These BoW representations of places are applied to learn a semantic space. This semantic space model salient features (e.g., how attractive a place is?) as directions. We will quantize the documents with respect to words by assigning the TF-IDF weighting scheme. Then, the vectors would be introduced into Multi-Dimensional Scaling (MDS) technique to construct a domain-specific semantic space. Each document in this semantic space is a point derived from MDS, where more similar points are located closer. Afterward, the most common words for topic Attraction are extracted by utilizing LDA to avoid sparse representation of the documents. Then, we will classify the space using a Logistic Regression binary classification to put a hyperplane in the space to distinguish those points (i.e., place documents) containing the given word and/or those lacking the word. The direction perpendicular to this hyperplane is the direction towards the given attribute (e.g., attractiveness). We will subsequently determine the most salient features in the considered domain, and their corresponding directions using the method from (Derrac & Schockaert 2015). Then, we evaluate the quality of the candidate feature directions using the accuracy of logistic regression classifier. For places with the accuracy of more than 50%, we rank places according to their distances to the hyperplane. The more the distance in the positive direction, the more the place is a tourist attraction. Hence, different places are ranked based on the probabilities.

Spatial information is significant in place recommendation systems among other non-spatial attributes. In the next step, geographical locations would be introduced to the model to consider the distances between user and places and the pairwise distances between places. Finally, these geographic and semantic spaces would be integrated to rank and recommend places according to the corresponding features (e.g., how attractive and close a place is).

3. Results and Discussions

After preparing data, around 482 attractions and 95661 user reviews are obtained for further analysis. We applied different python libraries such as Beautiful Soup, RE, NLTK, Gensim, Scikit-learn, and Matplotlib. Different MDS Dimensions are applied to find the best semantic space (5, 10, 15, 20, 50). The results demonstrate that D =15 will lead to better results, while increasing the dimension will not make significant improvement, but will require high computational cost. Table 1 shows the top 10 attractive places which are ranked based on the proposed method using the semantic space.

id	categoryType	Distance
1	[Sights & Landmarks]	81.44360911
2	[Muesums]	76.17219418
3	[Sights & Landmarks]	52.18535502
4	[Sights & Landmarks]	51.357416
5	[Other]	46.25181251
6	[Concerts & Shows]	45.07901105
7	[Other, Nature & Parks, Sights & Landmarks]	41.15674603
8	[Concerts & Shows]	40.97252379
9	[Fun & Games, Nature & Parks, Sports Camps & Clinics]	36.1009389
10	[Nature & Parks, Sights & Landmarks]	36.04665008

Table 1. The top 10 attractive places ranked in the semantic space.

It is worth mentioning that the authors are working on the combination of geographic space to semantic space to rank places based on the spatial and non-spatial features derived from travel websites. The thematic view of ranking places in semantic space is represented in Figure 1.

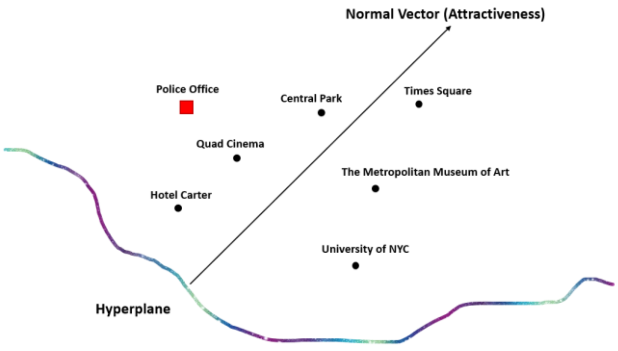

Figure 1. The thematic view of ranking places in the semantic space.

4. Conclusion

We introduced a method to rank places based on salient features. These features are modeled as directions in a domain-specific semantic space. Also, we are trying to integrate the geographic space to semantic space to design and implement a recommender system which is more applicable in tourism management. The proposed approach can help users to find places which are more attractive and closer to visit.

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User Perceptions of GeoAI in a Comfort-based Route Planner: Preliminary Results and Design Considerations

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Abstract. In this work in progress, we apply a first step in a user-centered design framework to assess the user requirements surrounding the use of AI in a thermal comfort-based navigation application. Initial findings from a survey of 129 participants in Europe suggest that users would like general information about how a navigation application is using AI, with the option to access more detailed information, but care less about the details of the uncertainty of the prediction. Furthermore, designers should take care to clearly describe data security and use practices and explore ways to address doubts about reliability and accuracy. Additionally, our results encourage further development of routing services focused on diverse factors other than time and distance.

Keywords. user perception of GeoAI, user-centered design, GeoAI

1. Introduction

GeoAI is the integration of geospatial science and artificial intelligence (AI) (Gao, 2021). It is playing an increasing role in spatial data collection and processing, in information extraction and analysis, and in quality assessment of geodata (Richter & Scheider, 2023; Herfort et al., 2023). As a technical solution, GeoAI has been used for human-centered smart city planning to improve the efficiency of urban services (Mortaheb & Jankowski, 2023). In environmental health, GeoAI has been applied to model and capture the built environment to address various factors that affect health (Kamel Boulos et al., 2019). Meanwhile, recent projects in LBS are incorporating variables like pollution, noise, safety, and greenness into route calculation (e.g. Hecht

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et al. 2021; Heidelberg University, 2023; Helle et al., 2021), and applying GeoAI methods could be useful for these dynamic variables.

Several guidelines exist for designing human-AI system interfaces (e.g. Amershi et al., 2019; Cheng et al., 2019). However, to our knowledge, human-AI design considerations have not yet been explored in the LBS community. On the one hand, usability engineering offers guidelines that are relevant to mobile applications with AI, such as Nielsen's (1992) usability heuristics for UI (e.g. "visibility of system status"). On the other hand, human-AI design recommendations may not be deemed as pertinent given the often efficiency-prioritized use case of navigation applications.

Our project *CoolStreet* is a proof-of-concept route planner for pedestrians and cyclists which is being developed collaboratively with Climateflux GmbH, following a streamlined user-centered design (UCD) process, as outlined in Roth et al., 2017. The project aims to predict the outdoor thermal comfort of different routes based on deep learning models using a variety of urban and climatic data sources.

This work in progress focuses on a subsection of a user requirements survey developed in the realm of the CoolStreet project, specifically related to two research questions: Do users want to be informed when a navigation application is using AI? What concerns or suggestions do they have? The feedback from our initial survey provides potentially transferable insights into how users would like to be informed of the use of AI in a comfort-oriented navigation application design.

2. Method

As a first step in assessing user needs and preferences for our use-case, an online self-reported user requirements survey was deployed. The broad survey aimed to evaluate current patterns of mobility relating to thermal comfort, the use-contexts of users' current navigation tool, user preferences about the use of AI, and to gather feedback and ideas about the initial proposal. This paper focuses on the subsection of the survey related to user perception of AI.

First, users were given a detailed description of the use-case and shown a prototype of the application. It was clarified that AI was used for efficient prediction of the thermal comfort of each route and that no personal data was used for the calculation. Then users were asked a series of open- and close-ended questions relating to whether they would like to be informed about the use of AI in the application, and at what level of detail. They were also asked if they would like to be informed about the uncertainty of the AI prediction of shade along the route, as well as the desired level of detail. Participants could also indicate additional features or capabilities they would like to see from a navigation application using AI, as well as any concerns they might have. These text answers were analyzed using thematic content analysis and sub-themes were identified (Braun & Clarke, 2006).

While the initial proof-of-concept will focus on the city of Munich, it is planned to develop the API into a city-independent solution. Therefore, the survey was distributed publicly via posted flyers, snowballing, social media, and email invitation. Over 90% of respondents were based in Europe, with the majority from Germany, Switzerland, and Austria and will be the focus of the preliminary results presented in this paper.

3. Preliminary results

129 (female = 59) inhabitants of Europe with ages ranging from 18-74 answered, though half (52%) of the respondents were 25 to 34 years old. 64% reported that they “have a basic understanding of AI,” while 27% “have advanced understanding of AI and related concepts.”

Participants most frequently use public transport in urban areas (100 responses). Walking and cycling were the second and third most frequently used modes of transport, with 64 and 57 responses respectively. Most users selected two or more answers for this multiple-choice question. 37% of participants walk between 30 minutes to an hour on average per day in a typical week. The rest of the answers were evenly balanced from under 30 minutes to over two hours per day. Participants spend less time per day cycling, with 46% spending less than 30 minutes and 24% between 30 minutes and an hour. Six participants skipped the question. Interestingly, 85% of participants indicated Google Maps as their most frequently used navigation tool.

3.1. Keep the user informed

After receiving a detailed description about how AI is used in the application and a prototype, users were asked “While using the application, how much information would you like to have about its use of AI?” (*Figure 1a*). The vast majority would like to be informed, indicating either that “just a basic explanation of the use of AI” is okay, or that they preferred “detailed information on why and how AI is being used.” *Figure 1b* shows responses to the question “Would you want to see the uncertainty of the prediction?” Here, a general explanation is relevant to most.

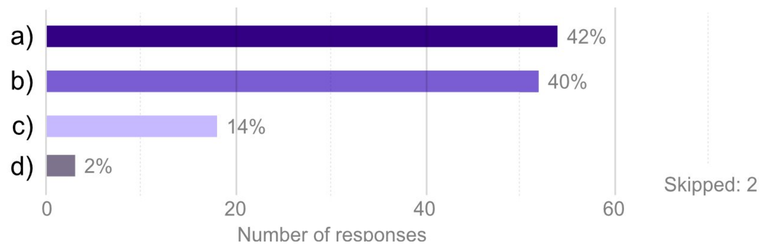

Figure 1a. How users want to be informed about the use of AI in the application. Answer choices in the survey were: a) "I want detailed information on why and how AI is being used in the application," b) "just a basic explanation of the use of AI is okay," c) "I don't care to know about the use of AI in the application," and d) "other."

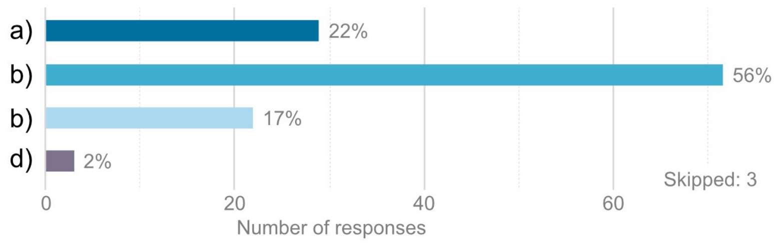

Figure 1b. How users want to be informed about the uncertainty of the AI prediction in the application. Answer choices in the survey were: a) "I want detailed numbers and visualizations on the prediction of the AI," b) "just a general explanation of the uncertainty is okay," c) "as long as it's reliable, I don't care about the details," and d) "other."

3.2. Concerns and doubts about AI

Results from the thematic analysis are summarized in *Figure 2*. Main concerns consisted of data security *("How do I know that no data is really being collected from me?"),* lack of control *("I want to decide myself")* and that context matters for how users feel about the use of AI *("not in this case").* Primary expressions of doubt related to reliability *("I would just always questioning if the suggested AI route is the best" [sic])* and accuracy *("can it derive more or less accurate results?").*

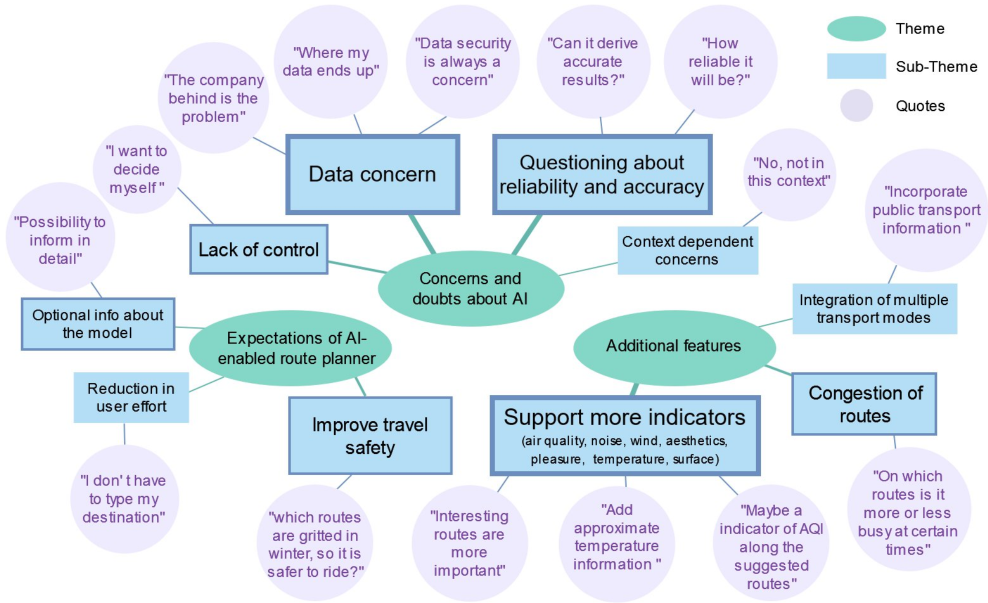

Figure 2. The result of theme analysis. The thicker the border of the polygon, the more users discussed that theme. No borders indicate fewer than four mentions, thin borders between five and eight, and thick borders more than nine mentions.

4. Discussion

Our preliminary findings related to user perceptions of AI in a navigation application for thermal comfort-based travel in the city indicate several design considerations. While narrow in use-context, we argue that these considerations may be transferable to other use-cases in the field, potentially "stimulat[ing] new considerations for future projects" (Roth, 2019).

Users want to be informed about the use of AI, even if it is only involved in real-time calculation of urban shading and is unrelated to personal data. Some want a detailed explanation about why and how it is used, while others accept a general explanation. Designers should consider including both, allowing a drill-down approach for those who want to learn more. Providing an appropriate level of detail may also assuage doubts or concerns among users, given that some indicated their lack of concern as contextual. Interestingly, the participants were less concerned about being informed in detail about the uncertainty of the prediction, with the majority preferring a general explanation. In our survey, "uncertainty" was referred to only in the context of "uncertainty of the prediction," without a detailed explanation of the AI concept. Given the range of experience with the topic of AI amongst the participants, this should be clarified in the future.

Attention should be given to explaining data security practices clearly and transparently. More than a third of participants indicated data concerns such as third-party access, how their data is used, or company intentions as concerns, despite receiving explanation that the use of AI was unrelated to their personal data. Details on data security should be sufficiently detailed and very easily accessible for the users that would like to learn more.

Users are interested in multiple route criteria beyond the shortest or fastest. This has been explored in the LBS research community (e.g. Hecht et al., 2021; Helle et al., 2021; Novack et al., 2018; Quercia et al., 2014), but there is a need for sustainable solutions such as APIs (done only to our knowledge by Helle et al., 2021), given that some in our study mentioned not wanting to download another application. It also speaks to the individuality of user preferences, maybe indicating a need for multiple additional route qualities, presented simultaneously, allowing users to opt-in to those they are most interested in.

Finally, many users expressed desire for a comprehensive multimodal transport network that incorporates live updates from local transport associations, as well as visualization of congestion along street, cycle, and pedestrian ways.

5. Conclusion

We conducted a broad user requirements survey for the development of a comfort-based navigation application. In this work in progress paper, we present the preliminary results of a subset of the survey focusing on user perception of the use of AI in the application. We discuss our results and offer design considerations for further research. Development continues with analysis of the complete user requirements survey, derivation of user personas, and initial prototyping.

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Geoprivacy Platform: First Experiences from an Open Service for Sharing Personal-level Location Data

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Abstract. The Geoprivacy platform is a service for sharing sanitised personal-level location data as open data. At the moment, it runs as a pilot service of the Geoportti Research Infrastructure. Our LBS conference presentation will briefly review the technical solutions developed for the platform and focus on privacy issues raised during the development of the platform, legal aspects tackled during the development of the service, and summarises the first experiences gained during the autumn 2023 on the interest of the public audience towards the service. For others who have a vision of setting up a similar service, we'll provide lessons learned during the development process.

Keywords. GPS, GNSS, trajectory data, cycling, privacy-preserving data publishing, VGI, open data

1. Introduction

The current climate goals and the ongoing green transition mean that societies must reduce their overall consumption to a sustainable level. Ambitious decarbonisation objectives will be impossible to achieve without a sustainable urban mobility transition, as in cities the traffic, and especially road transport, is the source of 26% of GHG emissions (DESTATIS 2022). The perfect solution would be to increase the share of cycling and walking, which alleviates traffic congestion and reduces GHG emissions and pollution, thus making cities attractive and functional at the human scale. In addition, cycling demonstrably provides health benefits for cyclists (Oja et al. 2011), and the problem of the non-inclusivity of cycling as a transport mode

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can be mitigated (Aldred et al. 2016). Therefore, all efforts and investments to promote cycling and walking should be considered, including making cities more suitable and safer for cyclists and pedestrians. Furthermore, to achieve a real revolution in urban mobility, we need to create a better and more supportive cycling environment for all people, not just enthusiastic cyclists (Aldred et al. 2016). It is crucial to direct the scarce public resources for developing and maintaining infrastructure to the most cost-beneficial targets. One critical and currently underused source of supporting data is the volunteered geographic information (VGI) provided by pedestrians and cyclists using global navigation satellite systems (GNSS) enabled devices to track their personal mobility (Nelson et al. 2021). Despite the known challenges of VGI, such as participation inequality (e.g., Bergman and Oksanen 2016), the data appears to have vast utilisation potential (e.g. Oksanen et al. 2015, Brauer et al. 2021).

In today's modern society, smartphones and wearable devices integrated with GNSS receivers have become an integral part of everyday life. Individuals use various applications to record their movement as trajectory data. These trajectory datasets would offer invaluable insights into the patterns of non-motorized mobility within urban areas, but the EU's GDPR (EU 2016) and individuals' privacy concerns have hindered the innovative use of personal-level trajectory data. The utility of commonly seen heatmaps from various service providers (such as Strava, Endomondo, and Suunto) has already demonstrated their effectiveness in traffic planning. This approach offers a pragmatic means of harnessing spatially aggregated trajectory data without infringing on privacy concerns, as highlighted by e.g. Sainio et al. in 2015. While more versatile services, such as Strava Metro (Strava 2022), do exist, their usage is currently restricted to "organisations responsible for active transportation infrastructure or those influencing planning processes positively." This limitation excludes start-ups and researchers who could potentially introduce innovative applications for utilising the data.

This has been the basis for us to find solutions for sharing sanitised personal-level location data as open data. As the first step of the process, we created a survey where attitudes towards sharing personal location data and concerns related to privacy protection were investigated (Jokinen et al. 2021). Based on the results of our survey, there seemed to be a positive inclination towards contributing personal tracking data to a privacy-preserving open data repository. The majority of survey participants valued their privacy and emphasised the need for robust data safeguarding measures. The primary driving force behind contributing data appeared to exist around the anticipation of enhancements in biking and pedestrian infrastructure. However, these improvements are geared towards the long term, which raises the question of how immediate feedback could be provided to contributors.

Encouraged by the outcome of the survey, we started designing and implementing a service enabling citizens to donate their personal tracking data and share it in a sanitised form where all data revealing personal identity has been removed (e.g. Mäkinen et al. 2022a and 2022b, Brauer et al. 2023). In May 2023, the pilot service was launched for the public as a Geoportti Research Infrastructure service.

2. Our solution: Geoprivacy platform

The current version of the Geoprivacy platform (Figure 1) has four modules: 1) the Donation module, 2) the Sanitation module, 3) the Statistics module, and 4) the Open Sharing module. Within the Donation module, users have the capability to contribute their trajectory data by uploading it via the designated donation webpage (supported formats: .gpx and .fit). The Sanitation module eliminates personal identifiers from the contributed data, including potentially identifying spatial and temporal attributes. Engaging with the Statistics module grants users access to descriptive statistical summaries derived from their uploaded data. Lastly, the Open Sharing module packages the sanitised trajectories of all users into a downloadable collection database accessible to all registered users and users of the Fairdata IDA service (https://ida.fairdata.fi/).

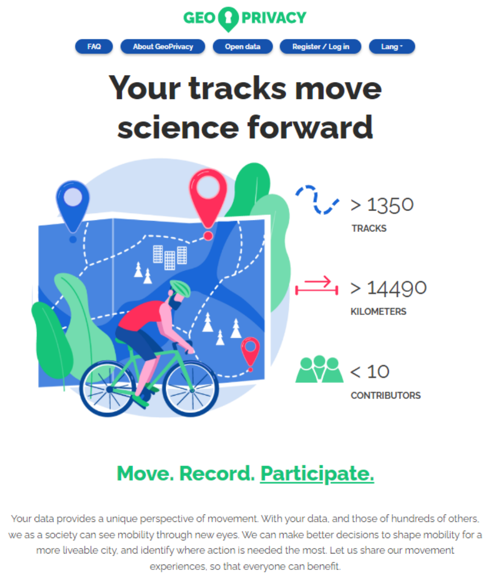

Figure 1. The opening page of the Geoprivacy platform as seen on Aug 31st 2023.

Upon the arrival of data to be processed at the backend, we employ two distinct methods for the purpose of sanitation. Initially, we undertake

trajectory truncation, which hinges on the nearby buildings situated at the trajectory endpoints, as well as potential prolonged pauses along the trajectory route. This truncation procedure is executed using the S-TT algorithm (Brauer et al. 2022). The effective implementation of this method necessitates comprehensive building data pertinent to the specific geographical region under consideration. Consequently, during the pilot phase, trajectory donations can solely be accommodated for trajectories within Finland and only within relatively densely populated areas. Subsequently, the second method involves **temporally shifting the truncated trajectories** (Brauer et al. 2023). The method aligns the first point of each trajectory to the nearest predefined time of the day; these times are defined at regular 6 h intervals. This temporal alignment makes linkages between the obfuscated trajectories and external datasets, such as surveillance camera recordings, significantly more challenging.

3. First experiences of the service

At the time of writing the abstract, the service has been open to the general public for some weeks, but marketing of the service in social media channels is still work to be done. The LBS conference presentation will briefly review the technical solutions developed for the service, and focus on privacy issues raised during the development of the platform, legal aspects tackled during the development of the service, and summarises the first experiences gained during the autumn 2023 on the interest of the public audience towards the service. For others who have a vision of setting up a similar service, we'll provide lessons learned during the development process.

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