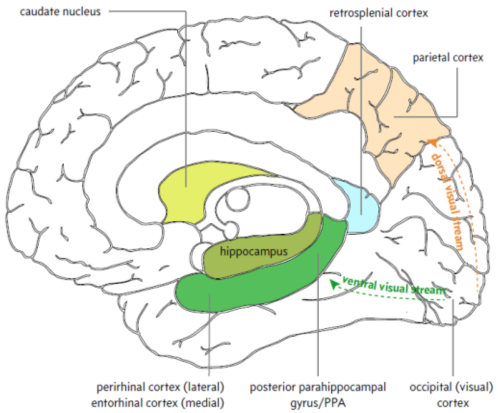
Research on Landmark Cognition for Pedestrian Navigation Services

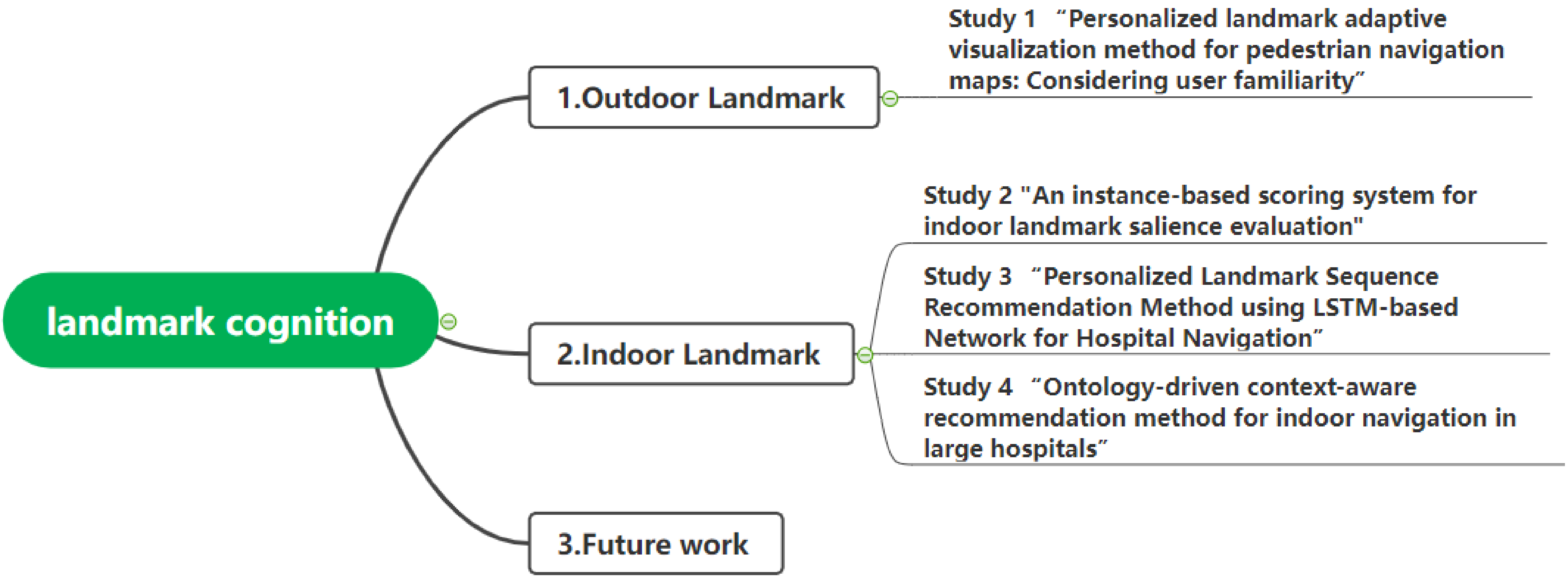
Litao Zhu[1,2], Jie Shen[1]

[1] School of Geography, Nanjing Normal University, Nanjing 210023, China

[2] Research Group Cartography, Vienna University of Technology, 1040 Vienna, Austria



CONTENTS


landmark cognition
1.Outdoor Landmark
Study 1 “Personalized landmark adaptive visualization method for pedestrian navigation maps: Considering user familiarity”
2.Indoor Landmark
Study 2 "An instance-based scoring system for indoor landmark salience evaluation"
Study 3 “Personalized Landmark Sequence Recommendation Method using LSTM-based Network for Hospital Navigation”
Study 4 “Ontology-driven context-aware recommendation method for indoor navigation in large hospitals”
3.Future work

PART 01 Outdoor landmark

Study 1

Zhu, L., Shen, J.*, Zhou, J., Stachoň, Z., Hong, S., & Wang, X. (2021). **Personalized landmark adaptive visualization method for pedestrian navigation maps: Considering user familiarity**. Transactions in GIS

1. Introduction: Landmarks

Any sufficiently prominent object can be considered a landmark. The definition of indoor landmarks and outdoor landmarks is **unified**.

Spatial cognition research indicated that landmarks, as key elements of wayfinding, can **reduce navigation time** (Golledge, 2003), **decrease error rates** (Goodman et al., 2004), improve **route learning** (Tlauka & Wilson, 1994), **reduce user cognitive load** and **increase confidence in navigation decisions** (Millonig & Schechtner, 2007).

Indoor Landmarks (Ohm, 2015).

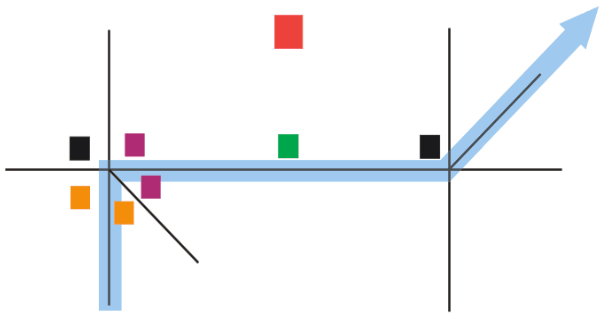
1 Introduction: Landmark salience

Landmark salience is the nature of the landmark itself, the strong contrast with the surrounding environment resulting in the attraction to people (Presson & Montello, 1988).

Landmark salience is divided into **Visual**, **Semantic**, and **Structural** (Raubal & Winter, 2002)

Visual

Semantic

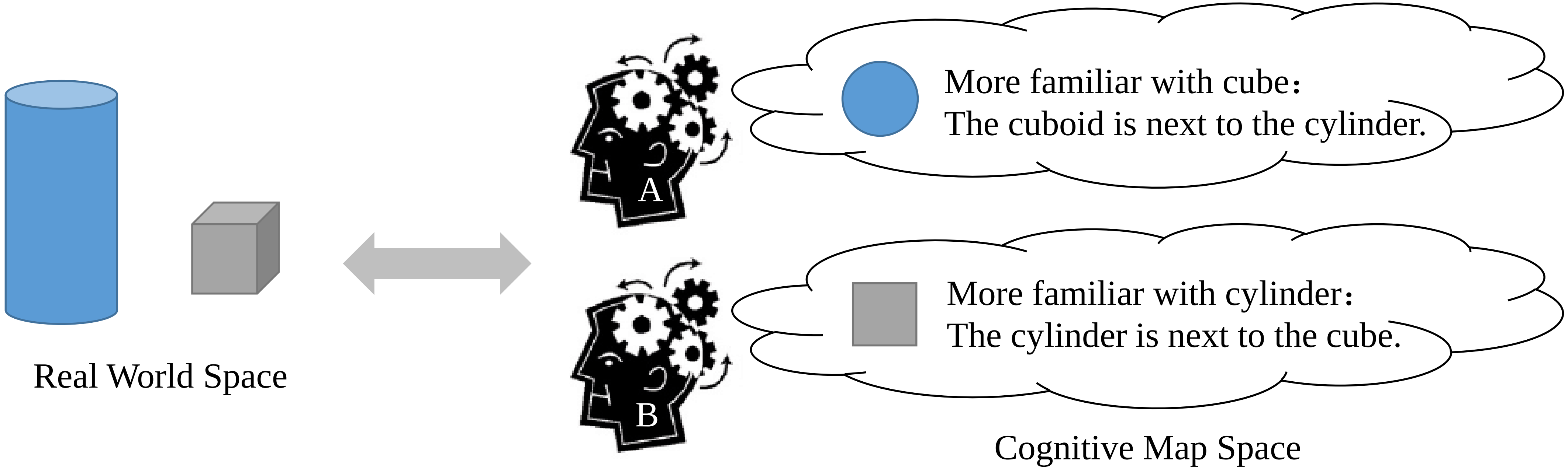


Structural

Landmark salience

2 Motivation

Empirical studies indicated people with different levels of familiarity have different preferences for **landmark selection** and **representation**. Spatial familiarity is an important variable related to personalized navigation but is often ignored.



The motivation is to investigate **landmark selection and visualization preferences** of people and apply the results to the landmark-based pedestrian navigation system.

3 Research questions

In this study, we propose **a personalized landmark adaptive visualization method considering user familiarity**. We focus on two research questions:

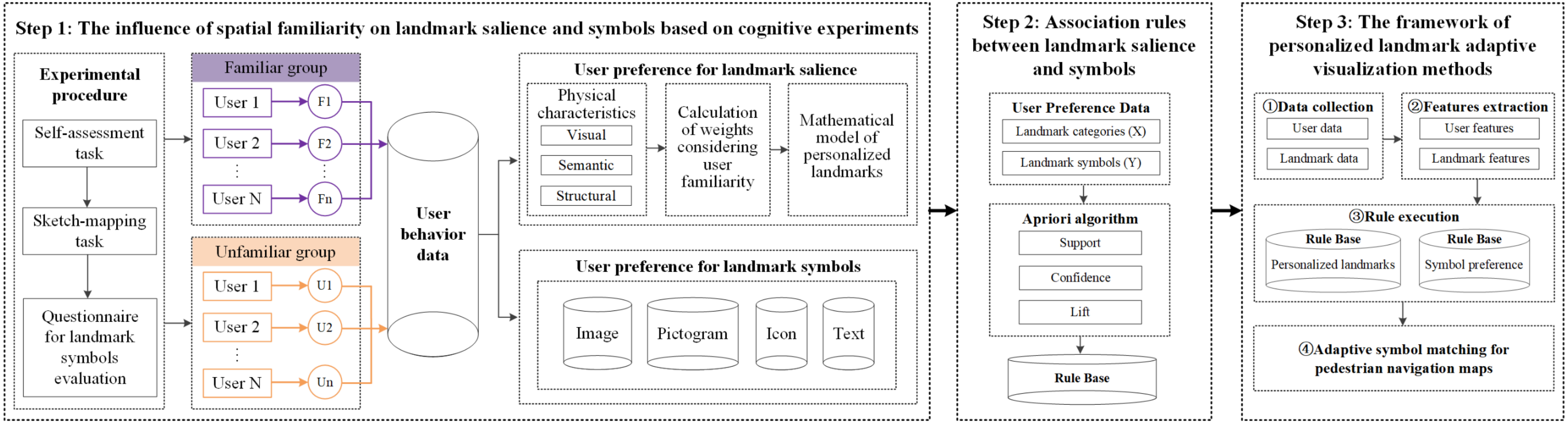
1. How to select **personalized landmarks** for target users.
2. How to realize the **adaptive visualization** of landmarks in pedestrian navigation maps.

4 Methodology

Step 1: The influence of spatial familiarity on landmark salience and symbols based on **cognitive experiments** is explored.

Step 2: **Association rules** between landmark salience and symbols are mined.

Step 3: A personalized landmark **adaptive visualization method** based on these rules is proposed.



The framework of methodology

4.1 Step1: Cognitive experiments

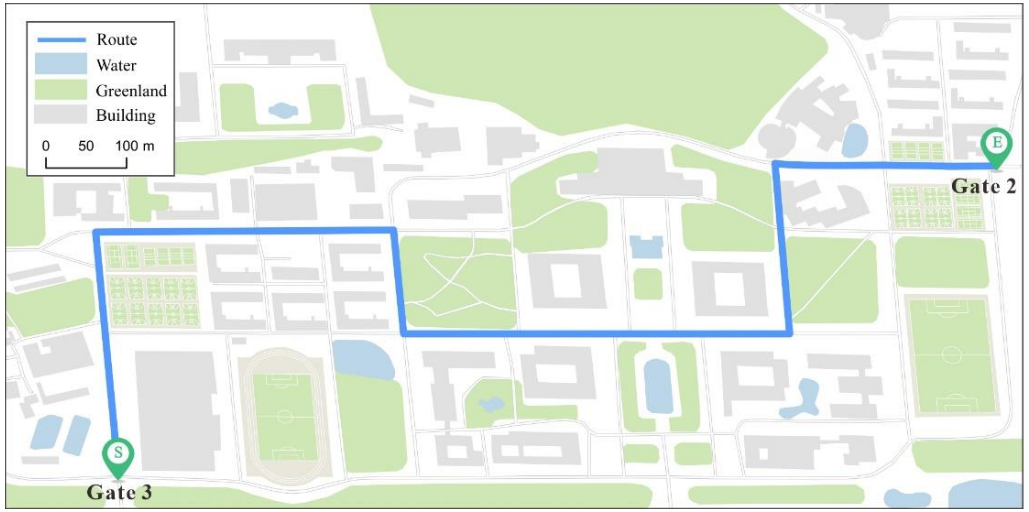
The aim is to explore the influence of spatial familiarity on landmark salience and symbols.

(1) Participants

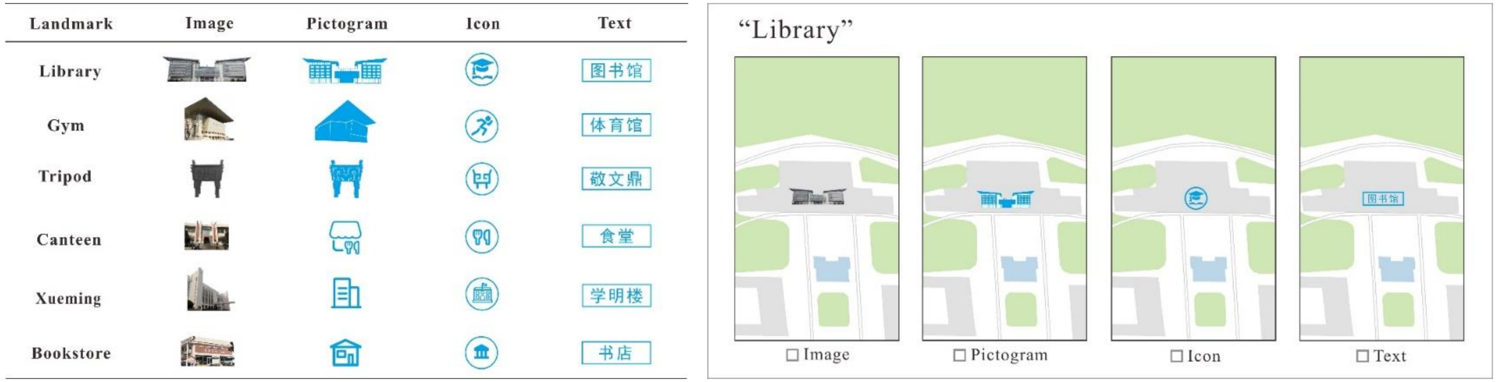
Familiar group (27) vs. Unfamiliar group (24)

(2) Materials and Procedure

- Self-assessment task: Santa Barbara Sense-of-Direction Scale (SBSOD) and two additional questions (about visits and mapping ability)
- Sketch-mapping task
- Questionnaire for landmark symbols evaluation



Study area.

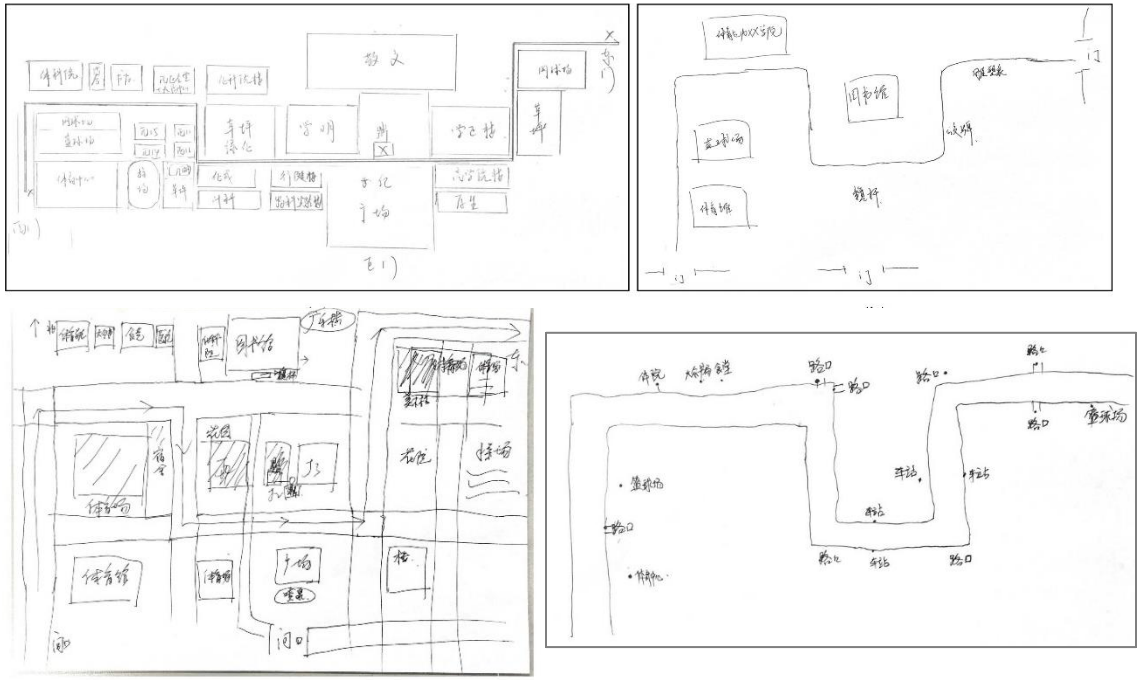


Landmark symbols

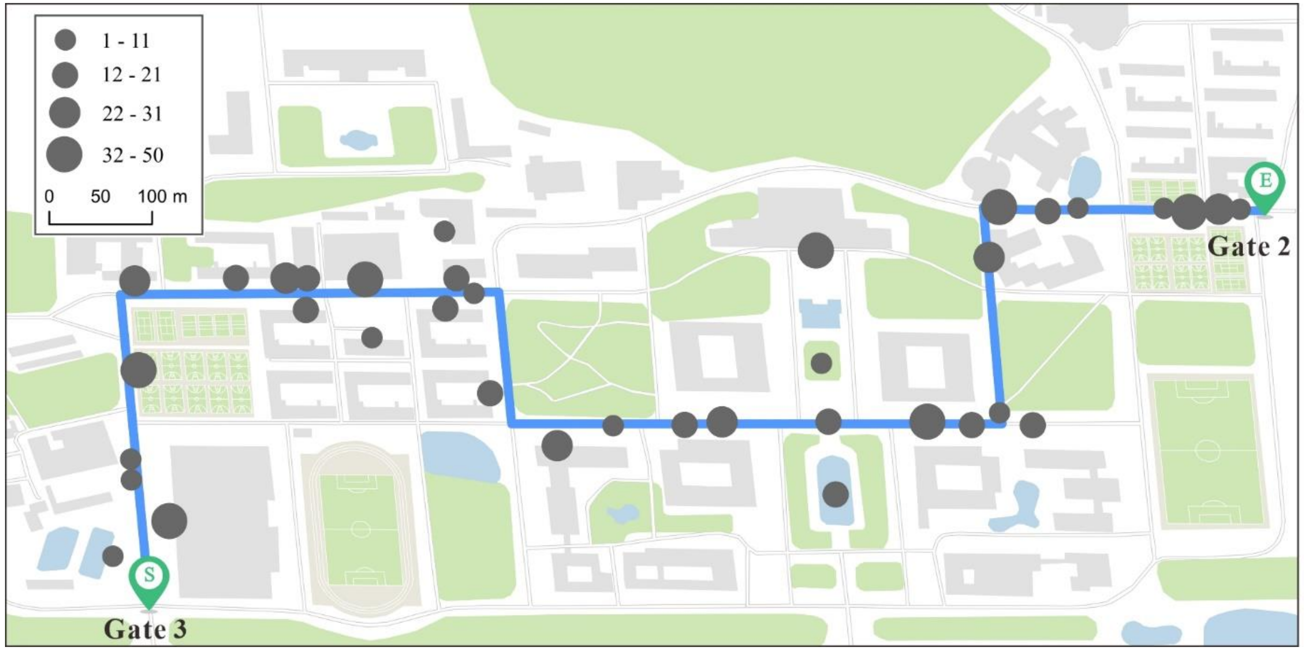
4.1 Step1: Cognitive experiments

Result 1: Analysis of sketch mapping task.

The t-test results indicated a significant difference ($t = 3.70$, **$p = 0.001 < 0.05$**) between the familiar group ($M = 16.93$, $SD = 5.14$) and the unfamiliar group ($M = 11.58$, $SD = 5.15$). It showed that the level of environmental detail provided by familiar and unfamiliar people **varied substantially**.



Examples of sketches drawn by the familiar group and the unfamiliar group



The results of landmark extraction

4.1 Step1: Cognitive experiments

Result 2: Mathematical model of landmark salience. $S_L = W_{vis} S_{vis} + W_{sem} S_{sem} + W_{str} S_{str}$

For the unfamiliar individual, $W_{vis} : W_{sem} : W_{str} = 5:2:3$

For the familiar individual, $W_{vis} : W_{sem} : W_{str} = 3:5:2$

Result 3: the preference for landmark symbols.

The results showed significantly different proportions of landmark symbol selection between the familiar group and unfamiliar group ($\chi^2 = 172.3$, $p = 0.000 < 0.001$). Table 5 presents the descriptive statistics of the preference rates of the familiar group and the unfamiliar group for different landmarks..

Image

Table 5 Summary of landmark symbol evaluation

Group	Image (n, %)	Pictogram (n, %)	Icon (n, %)	Text (n, %)	χ^2
Familiar (N=27)	76 (16.63)	53 (11.60)	139 (30.41)	189 (41.36)	172.3***
Unfamiliar (N=24)	176 (63.31)	25 (8.99)	29 (10.43)	48 (17.27)	

χ^2 refers to a Chi-square test, ***p < 0.001

Icon | Text

4.2 Step2&3: Personalized landmark adaptive visualization method

(1) Data collection, including user data, landmark data, and the range of the map.

(2) Features extraction, including user features and landmark features.

(3) Rule execution, it aims to identify the personalized mode of user interactions with pedestrian navigation maps based on user familiarity using association rule mining.

Table 7 Association rules between landmark salience and symbols

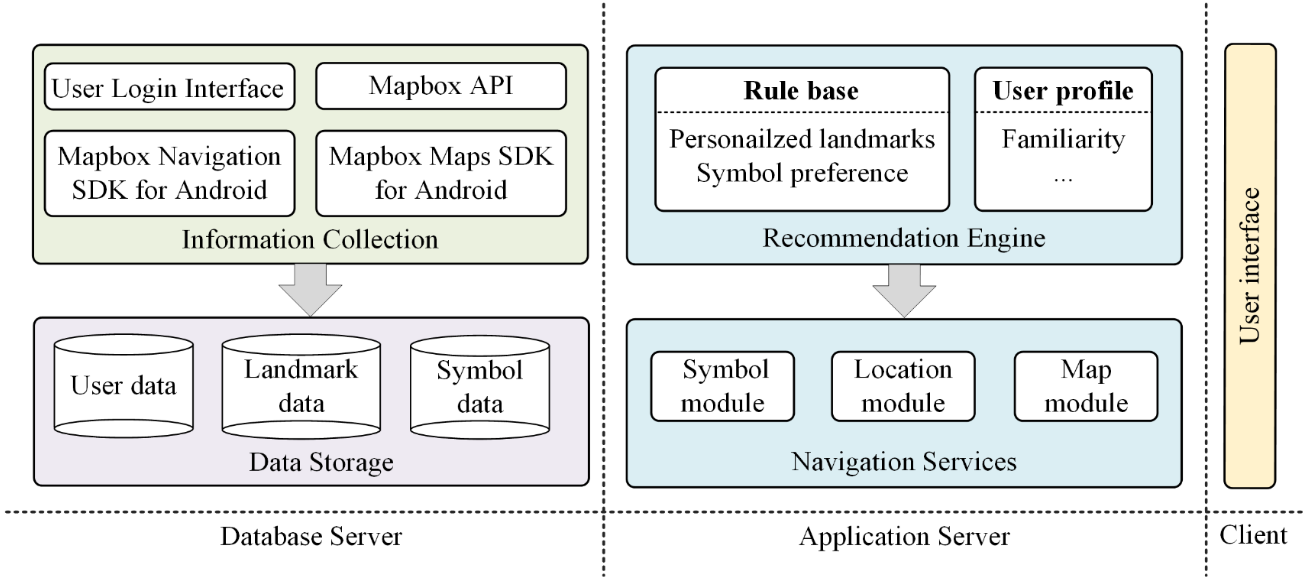
Rule	Semantic Association Rule	Sup.	Conf.	Lift
Rules related to familiar user				
R_1	$Semantic \Rightarrow Text$	0.21	0.46	1.12
R_2	$Visual \Rightarrow Text$	0.15	0.38	0.92
R_3	$Structural \Rightarrow Icon$	0.06	0.36	1.20
Rules related to unfamiliar user				
R_4	$Visual \Rightarrow Image$	0.29	0.62	0.97
R_5	$Semantic \Rightarrow Image$	0.27	0.67	1.06
R_6	$Structural \Rightarrow Image$	0.08	0.58	0.92

5 Verification experiments

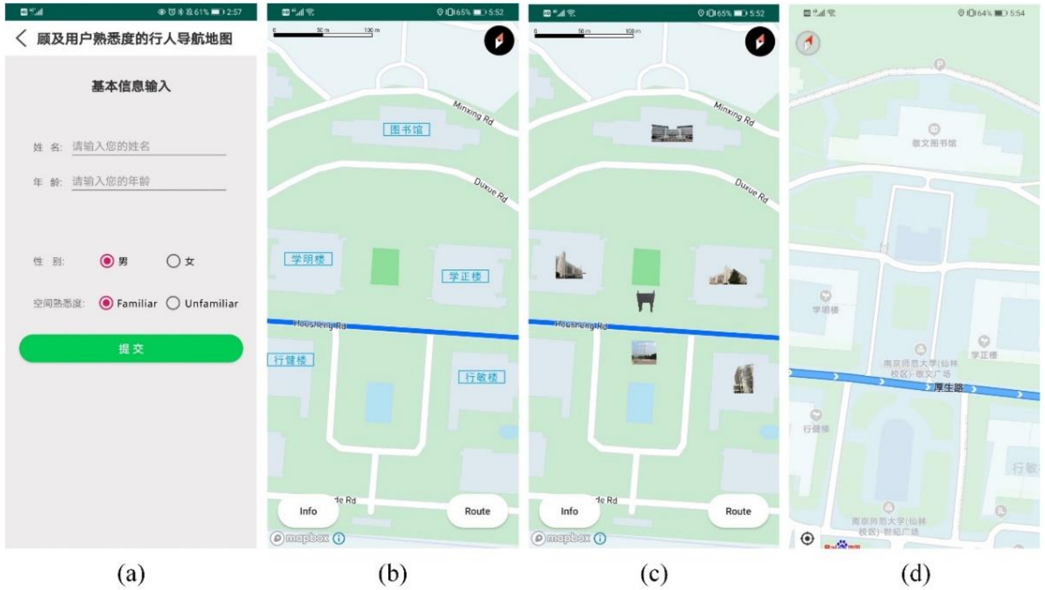
(1) Prototype system

(2) User experiments

- Participants: Familiar group (14) vs. Unfamiliar group (14)
- Materials: the prototype vs. Baidu Map for Mobile (BMM).
- Procedure: Pedestrian navigation task; and System Usability Scale Questionnaire



Prototype system

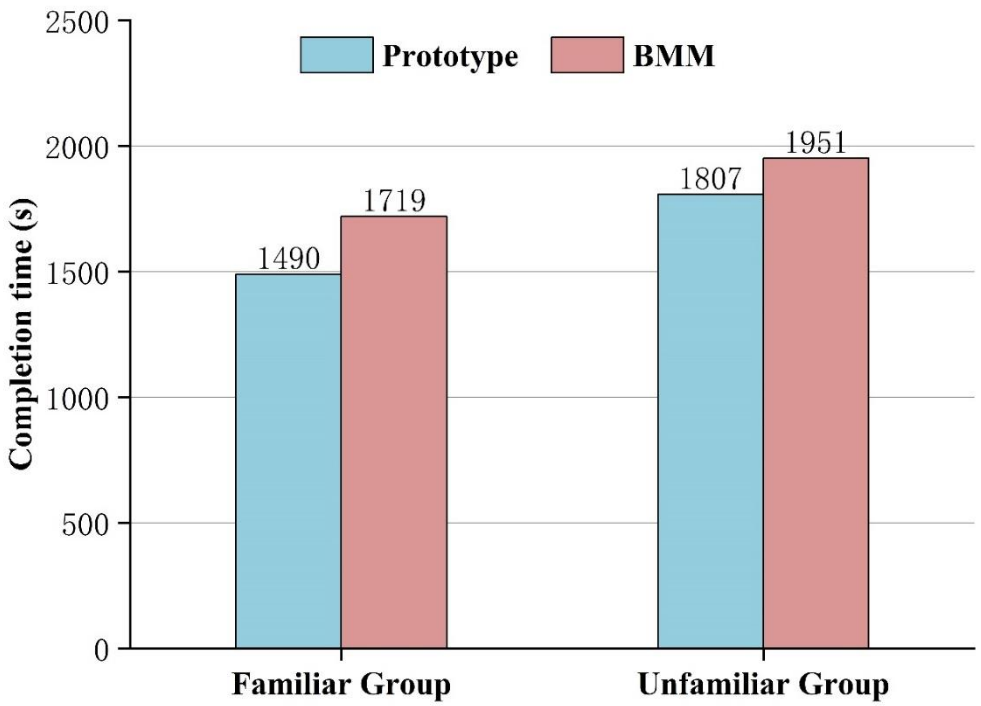


The prototype vs. Baidu Map

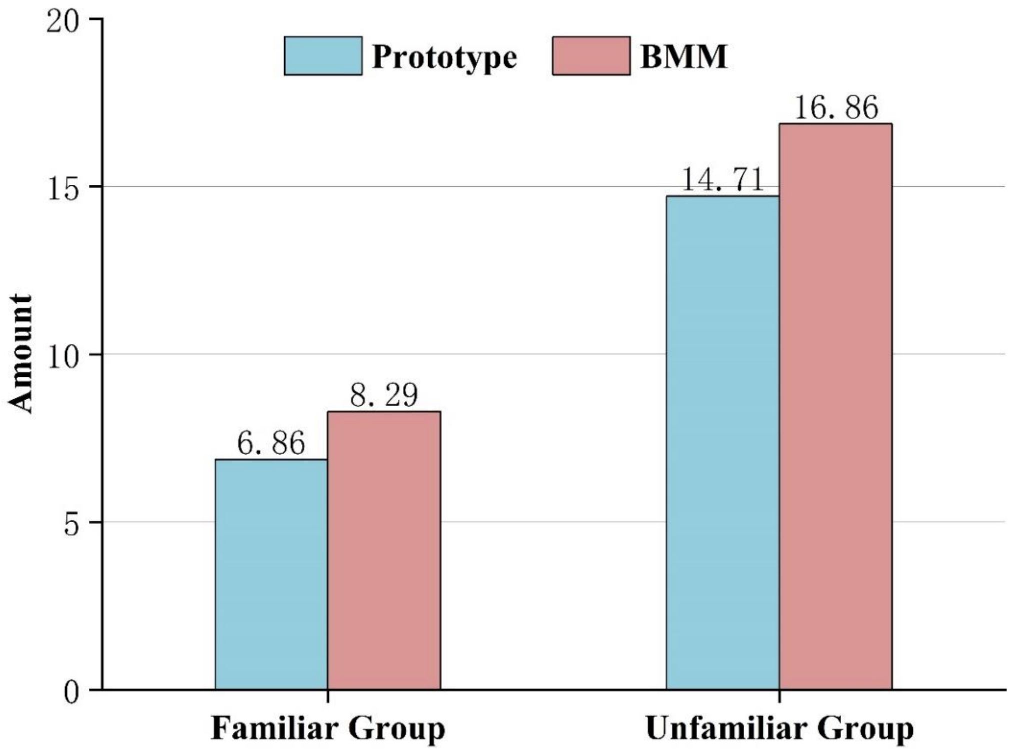
5 Verification experiments

(3) Results

- Time efficiency
- The number of map views
- Analysis of the System Usability Scale (SUS)



The average completion time

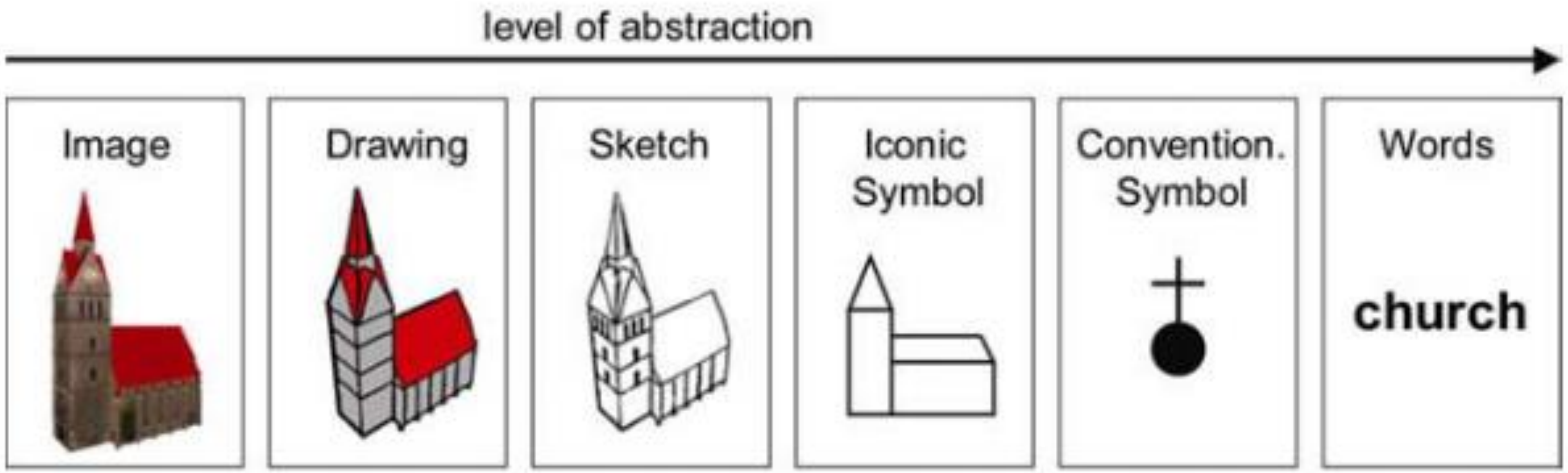


The average number of map views

6 Discussion

Using landmarks in maps helps users identify their location (Hile et al., 2008). Previous studies proposed the user-centered visualization method for outdoor landmarks (Elias & Paelke, 2008).

However, few studies have explored the visualization of indoor landmark symbols.



Landmark symbols (Elias & Paelke, 2008).

PART 02 Indoor landmark

Study 2

Zhu, L., Švedová, H., Shen, J.*, Stachoň, Z., Shi, J., Snopková, D., & Li, X. (2019). **An instance-based scoring system for indoor landmark salience evaluation**, Geografie, 2019/2.

1 Research questions

This study proposed **an instance-based indoor landmark salience evaluation method** to address the lack of indoor landmark salience evaluation methods. We focus on two research questions:

1. How to **evaluate the landmark salience** in the indoor environment.
2. How to **verify the usability** of indoor landmark salience evaluation results.

2 Methodology

- Propose indoor landmark indicators and scoring system
- Calculate landmark salience weight using AHP

Table 1 – Indicators and indoor landmark salience measurements

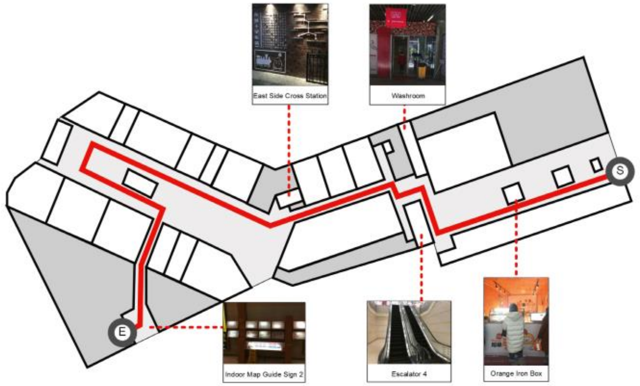
Type	Indicator	Measurement	Degree of Attractiveness
Visual	Physical size (α)	$\alpha \in \{1, 2, 3, 4, 5\}$	$S_{vis} = w_\alpha S_\alpha + w_\beta S_\beta + w_\gamma S_\gamma$
	Prominence (β)	$\beta \in \{1, 2, 3, 4, 5\}$	
	Availability of a unique label (γ)	$\gamma \in \{1, 2, 3\}$	
Semantic	Familiarity (δ)	$\delta \in \{1, 2, 3, 4, 5\}$	$S_{sem} = w_\delta S_\delta + w_\zeta S_\zeta + w_\eta S_\eta$
	Description length (ζ)	$\zeta \in \{1, 2, 3\}$	
	Uniqueness (η)	$\eta \in \{T:1, F:0\}$	
Structural	Spatial extent (ϑ)	$\vartheta \in \{T:1, F:0\}$	$S_{str} = w_\vartheta S_\vartheta + w_\iota S_\iota + w_\kappa S_\kappa$
	Permanence (ι)	$\iota \in \{T:1, F:0\}$	
	Location importance (κ)	$\kappa \in \{1, 2, 3\}$	

$$\boxed{S_{sum} = w_{vis}S_{vis} + w_{sem}S_{sem} + w_{str}S_{str}}$$

From w_α to w_κ refers to the weights of the nine evaluation indicators obtained from the AHP.
From S_α to S_κ refers to the standardized score of the nine evaluation indicators.

3 Experiment and Result

To verify the usability of the proposed method, we applied it to a shopping mall (Nanjing, China) using questionnaire and a headquarter (Brno, Czech Republic) using eye-tracking.



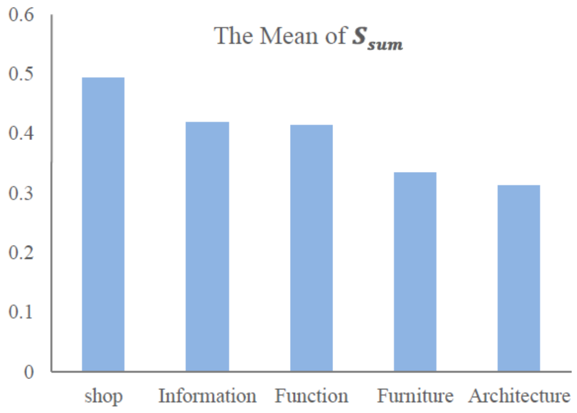


Figure 5. The mean landmark salience for each type

(Nanjing, China)

Figure 6. Examples of the study area at the Headquarters of Masaryk University (Brno, Czech Republic)

Table 6. Results of Evaluated Overall Average Landmark Sa¨

saliency category	landmark	decision point	overall average salience
most salience	fire extinguisher	1	0.53
	stairs	4	0.53
	green evacuation sign	4	0.53
medium salience	door	3	0.51
	green evacuation sign	1	0.50
	green evacuation sign	2	0.50
	sign 2nd floor	3	0.50
	sign 2nd floor	4	0.50
	window	3	0.49
	window	5	0.49
	door	5	0.49
least salience	stairs	2	0.46
	white door	5	0.44
	radiator	3	0.40
	radiator	5	0.40
	flowers	5	0.36
	flowers	3	0.32

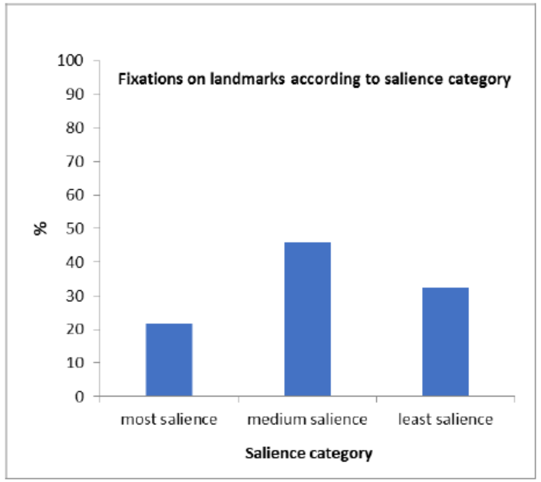


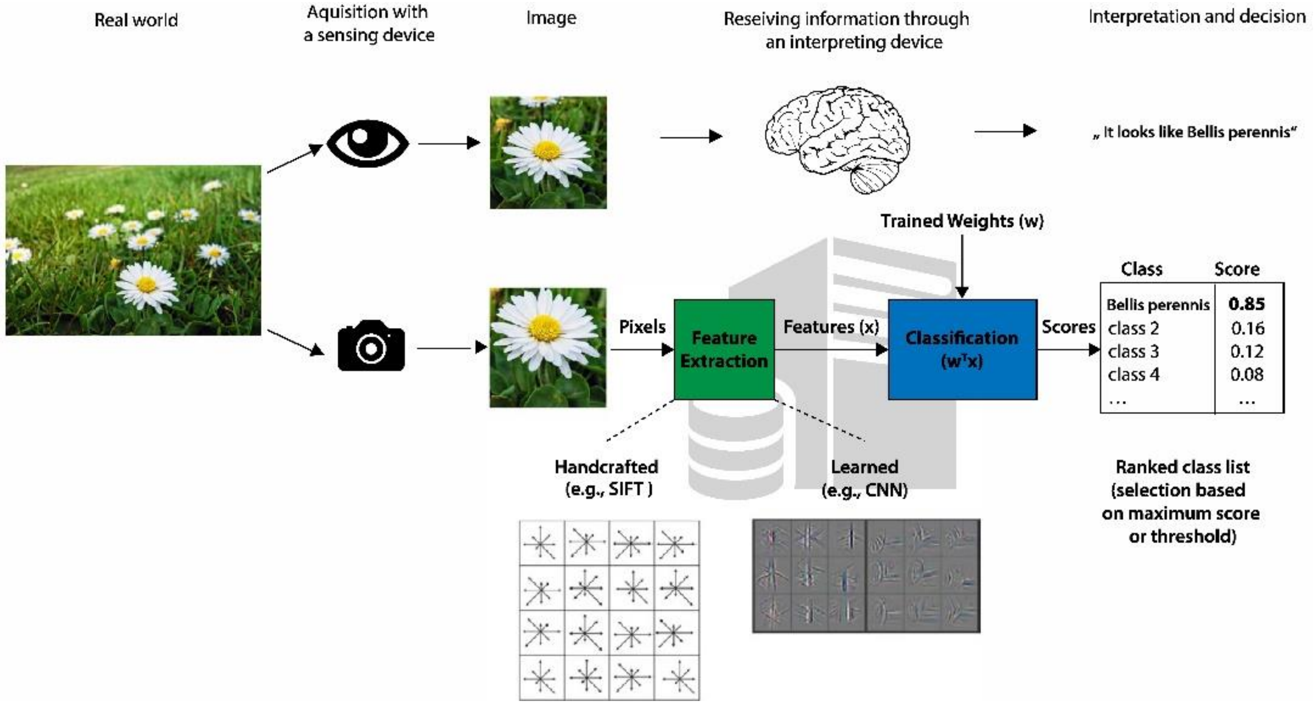
Figure 10. Fixations on landmarks according to salience category

(Brno, Czech Republic)

4 Discussion

In this paper, the landmark indicators are scored by users and the weights are scored by experts. The proposed method is tedious and complicated. The process need to be repeated for each scenario.

In future work, **we will consider using machine learning methods to automatically identify indoor landmarks.**



Typical human and computer vision pipelines (Wäldchen & Mäder, 2018).

P_{ART} 02 Indoor landmark

Study 3

Zhu, L., Shen, J., Gartner, G., & Hou, Y. (2021). **Personalized Landmark Sequence Recommendation Method using LSTM-based Network for Navigating in Large Hospitals**. Abstracts of the ICA, vol. 3.

1 Introduction: The market for hospital navigation is considerable

1. A large number of Chinese hospitals

China has a total of **35,394** hospitals.

2. A large number of total hospital visits

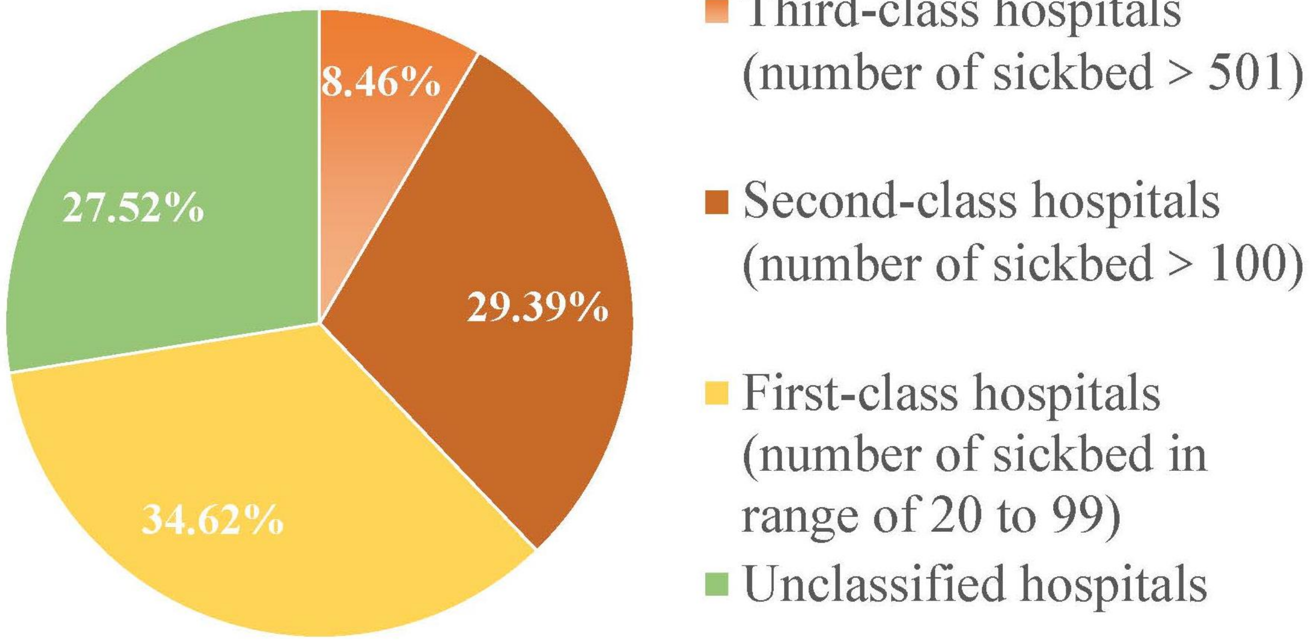
In 2020, **3.32 billion** visits

In 2019, **3.84 billion** visits

In 2018, **3.58 billion** visits

In 2017, **3.44 billion** visits

In 2016, **3.27 billion** visits

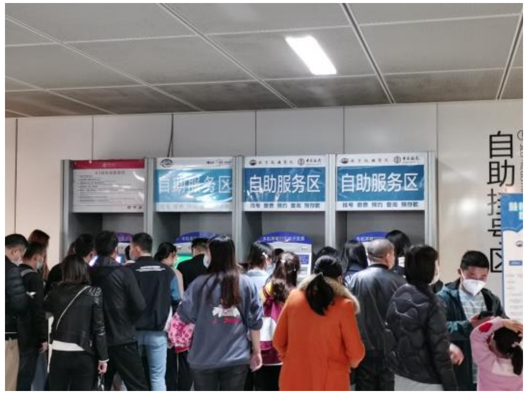


3. In 2017, the National Health Commission of China requires that the informatization construction of hospitals includes indoor navigation.

The hospital navigation market is at least €2.1 billion

1 Introduction: The hospital navigation

- **Indoor space** of the hospital is unique in that most of the facilities are related to the task of medical visits.
- **The users** (patients/visitors) who use hospital navigation are unique. They usually accomplish many tasks under time constraints and discomfort.
- **Hospital guidance information** contains a great deal of medical terminology and knowledge.

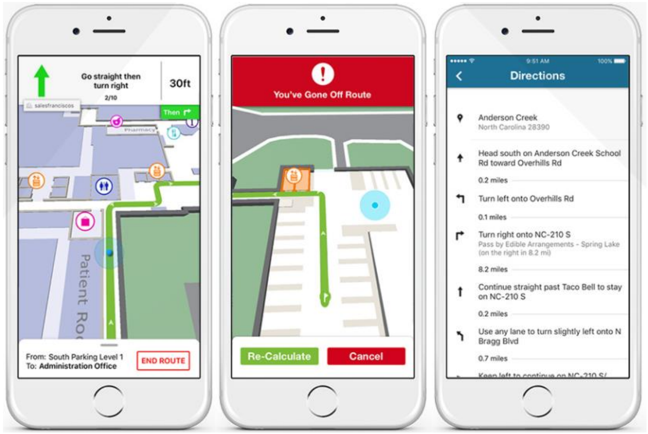


In summary, **the specificity of hospital navigation** lies in its close connection with **user behavior, medical processes, and hospital space (departments)**.

1 Introduction: Hospital navigation APP

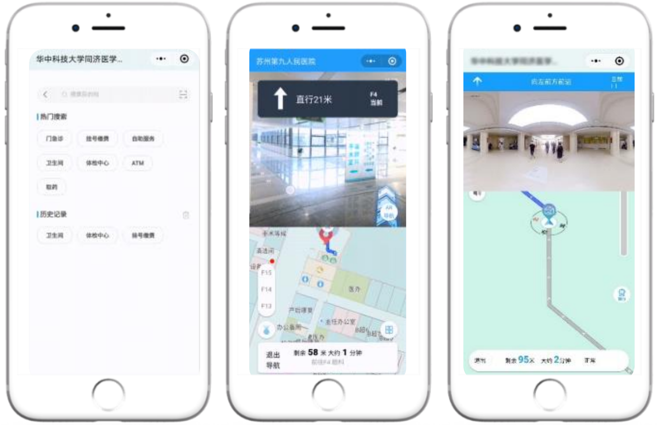
Hospital navigation apps are medical wayfinding tools for specific visitors or patients who visit the hospital for any purpose.

Gozio Health
https://www.goziohealth.com/



MediNav
https://medinav.eu/home/

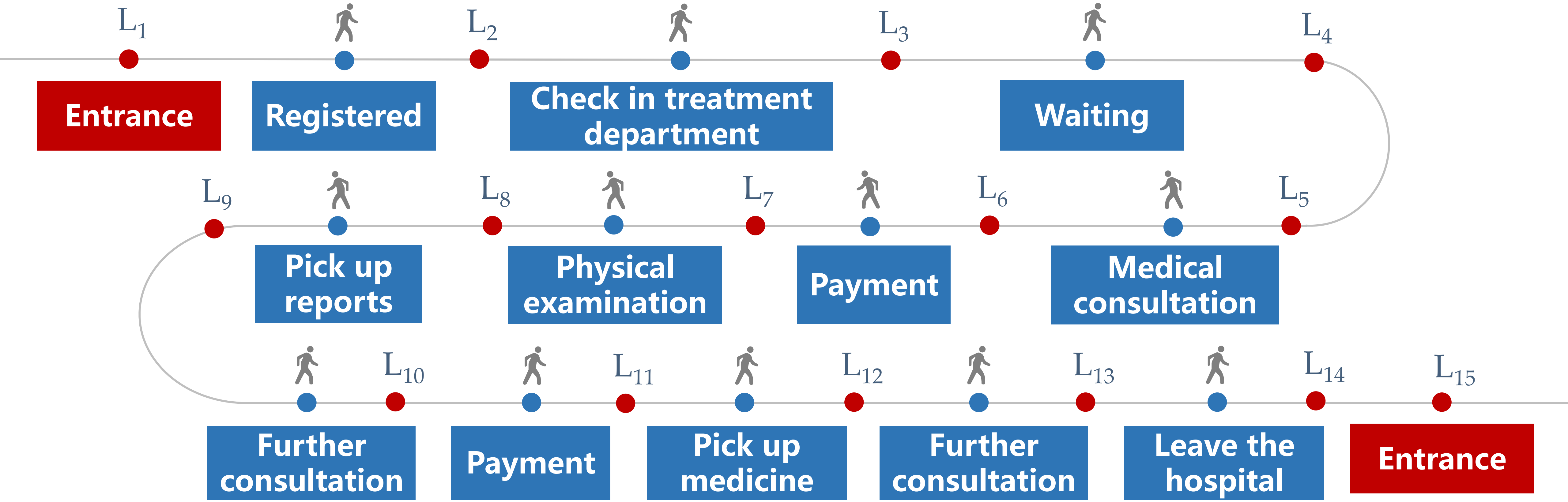
IPSMAP (China)
https://www.ipsmap.com/



JoySuch (China)
https://www.joysuch.com/

To the best of our knowledge, few landmark-based pedestrian navigation systems have been developed for hospitals.

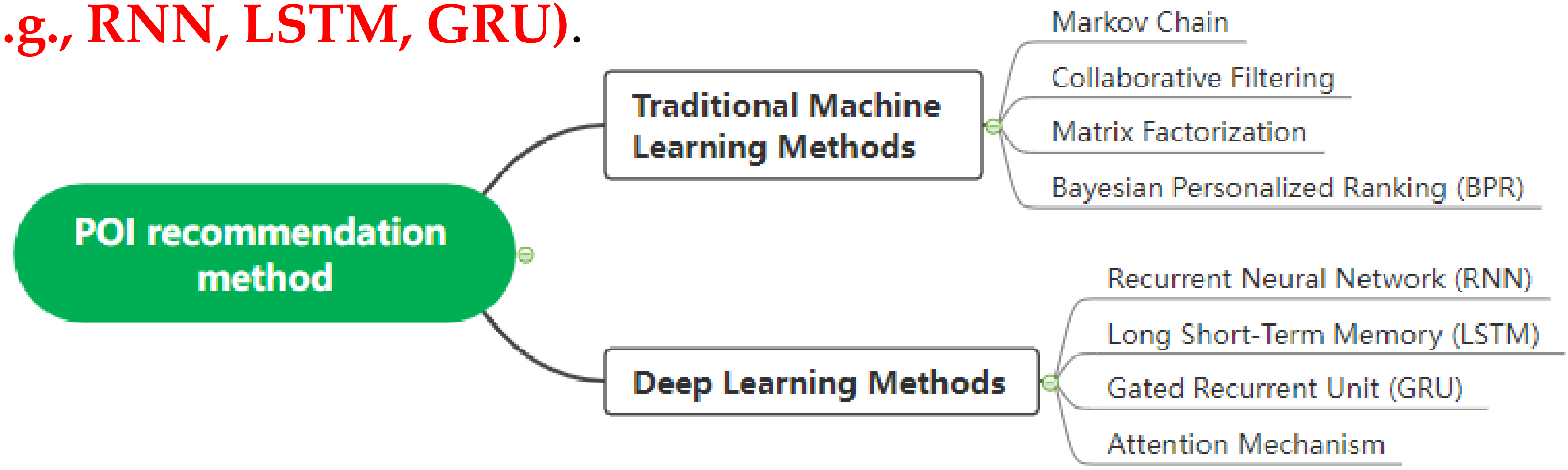
1 Introduction: Behavioral analysis of medical visits



- Location Sequence, Time Sequence, Location Hierarchy, Location Distance, and Medical Treatment Sequence
- Semantic Trajectories (i.e., Landmark **Sequence**)
- User **preference** which related to the disease and task.

1 Introduction: Landmark recommendation method

- **93% of user behavior** is predictable (Song et al., 2010). Hospital landmark sequence recommendation is also closely related to user behavior.
- Existing studies on personalized landmark recommendations are mainly used for outdoor travel recommendations, **but few studies for navigation and wayfinding.**
- The POI recommendation methods include traditional machine learning and **deep learning (e.g., RNN, LSTM, GRU)**.



We **adopted RNN** to model landmark sequences for recommendation due to their superiority in capability of processing the sequential data.

Song, C., Qu, Z., Blumm, N., & Barabási, A. L. (2010). Limits of predictability in human mobility. Science, 327(5968), 1018-1021.

2 Research questions

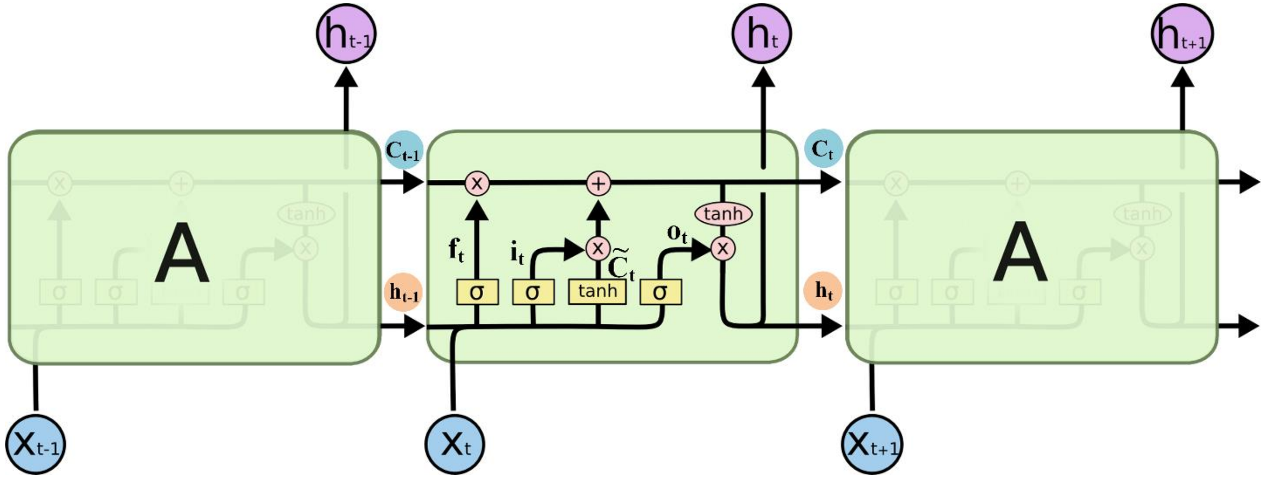
Inspired by research on POI sequence recommendation methods, we propose a **landmark sequence recommendation method using LSTM-based network for hospital navigation**. We focus on two research questions:

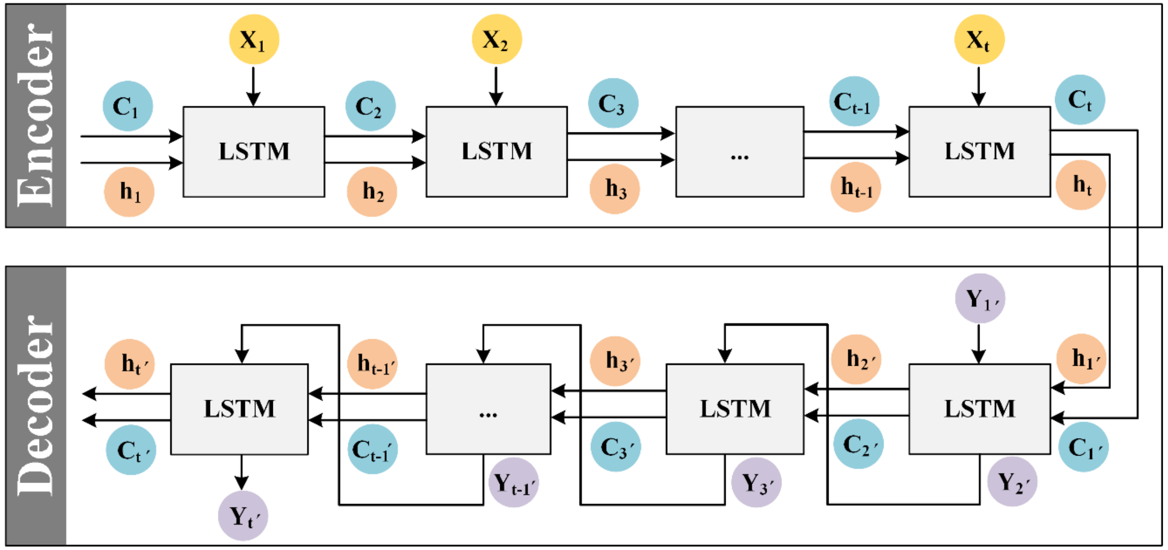
1. How to **model** the **complex sequential users behavior** in hospital navigation.
2. How to develop an **indoor landmark sequence recommendation algorithm** for hospital navigation.

3 Methodology: The research framework

We propose an indoor landmark sequence recommendation method for hospital navigation based on **LSTM with an attention mechanism**.

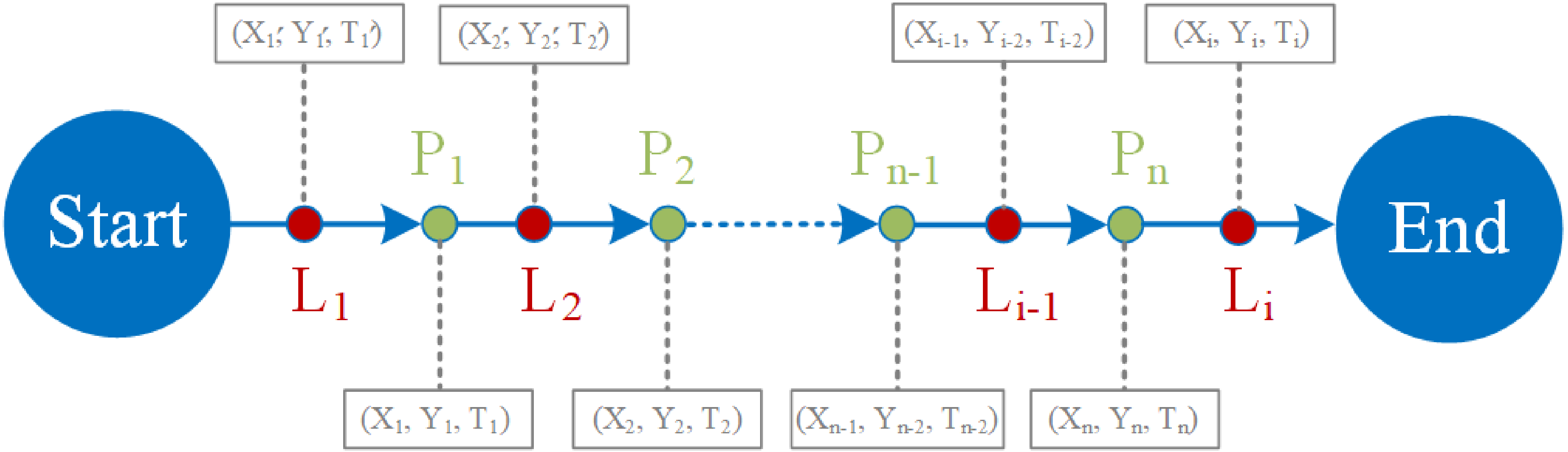
The research framework can be divided into **three modules**: input, attention-based encoder–decoder LSTM model, and output.





4 Experiments: Indoor trajectories

- Let $P=\{P_1,P_2,\ldots,P_{n-1},P_n\}$ represent **indoor trajectory** consisting of n points data and the information on its location (latitude and longitude coordinate) and timestamp. Let $L=\{L_1,L_2,\ldots,L_{i-1},L_i\}$ represent **semantic trajectory** consisting of i landmarks data and the information on its location and timestamp.
- A user behavior sequence is a list of three-tuples.



4 Experiments

Step 1: Indoor trajectory data collection and processing

↓

Step 2: Extraction of indoor landmark sequences

↓

Step 3: Identification of evaluation metrics

↓

Step 4: Baseline Methods

↓

Step 5: Parameter Setting

↓

Step 6: Analysis of results

The process of experiment

Table 1 Example of indoor trajectory data

UserID	Time	X	Y	FloorID
0000A321373	20200907091031	13483****	45392****	1
0000A321373	20200907091046	13483****	45392****	1

Table 2 Example of semantic trajectory data

UserID	Semantic	Time	X	Y	FloorID
0000A321373	Gate9	20200907091031	13483****	45392****	1
0000A321373	Guidedesk	20200907091052	13483****	45392****	1

5 Discussion

Contributions

- we proposed **a novel hospital landmark sequence recommendation framework**;
- we incorporated **an attention mechanism into the LSTM**, which helps to capture the correlation between different landmarks.

Outlook

In the future, we will do further research work in the following aspects:

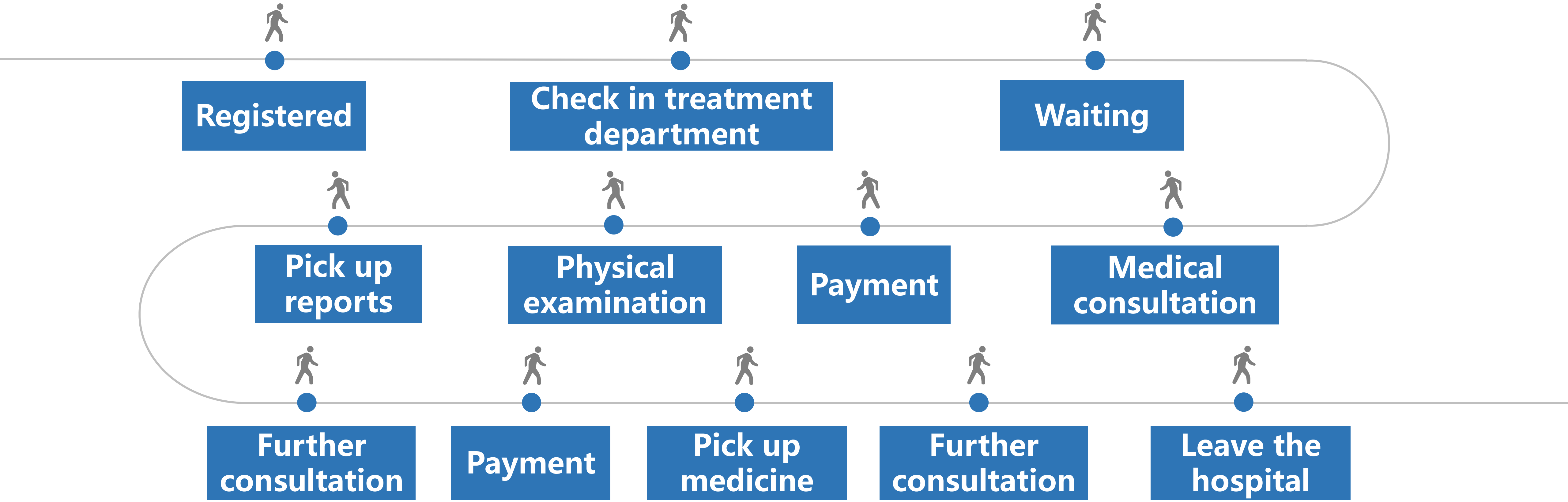
- Refining the experiment
- Applying the proposed model to more complex hospital scenarios to verify the performance of navigation.

P_{ART} 02 Indoor landmark

Study 4

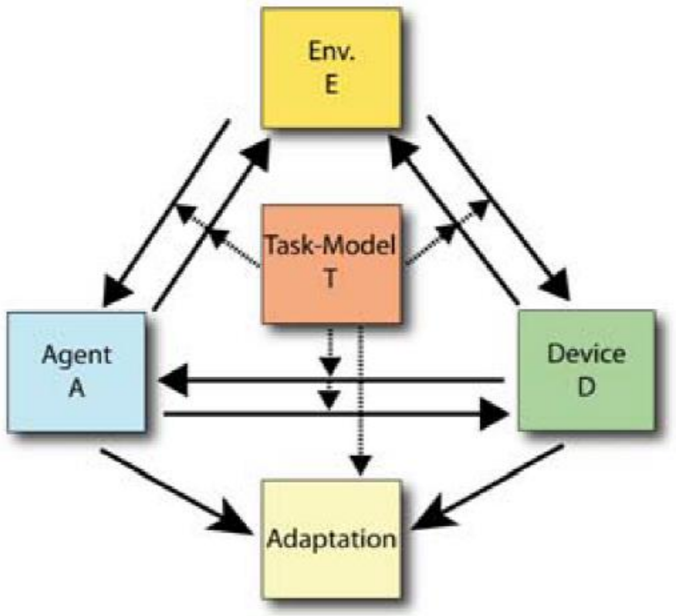
Zhu, L., Shen, J., & Gartner, G. (2021). **Ontology-driven context-aware recommendation method for indoor navigation in large hospitals**, LBS 2021: Proceedings of the 16th International Conference on Location Based Services (pp. 23–26).

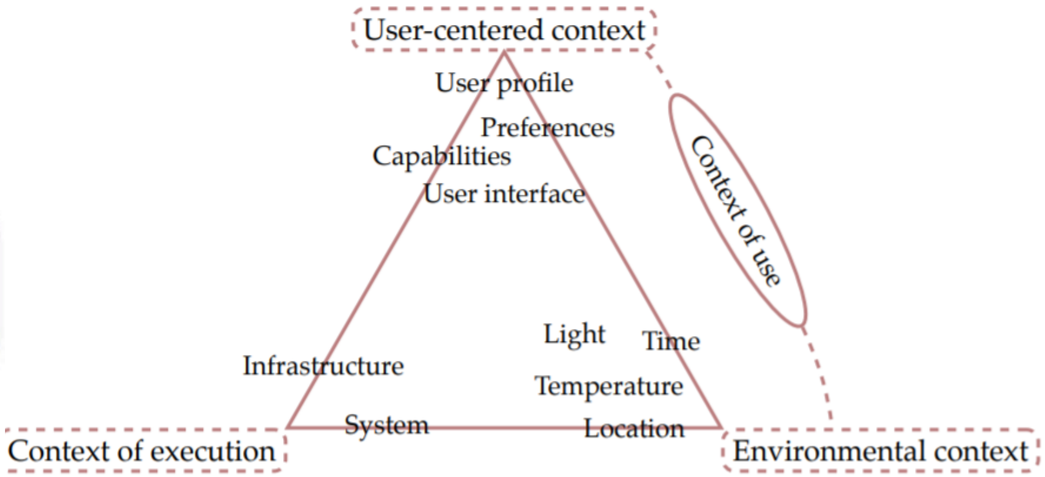
1 Introduction: Analysis of user behavior

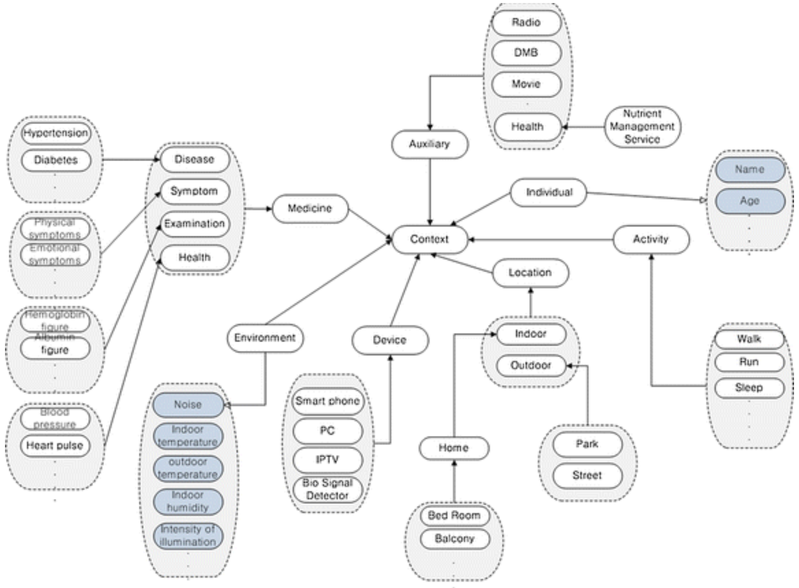


There are some contextual information in the hospital navigation: **individual, location, time, department, facility, medical process, medical services, medical knowledge, schedule, navigation services.**

Q1: what is the context model for hospital navigation?







Context model for outdoor navigation (Richter et al. 2010).

Context model for indoor navigation (Afyouni et al. 2012).

Healthcare context model (Kim et al. 2014).

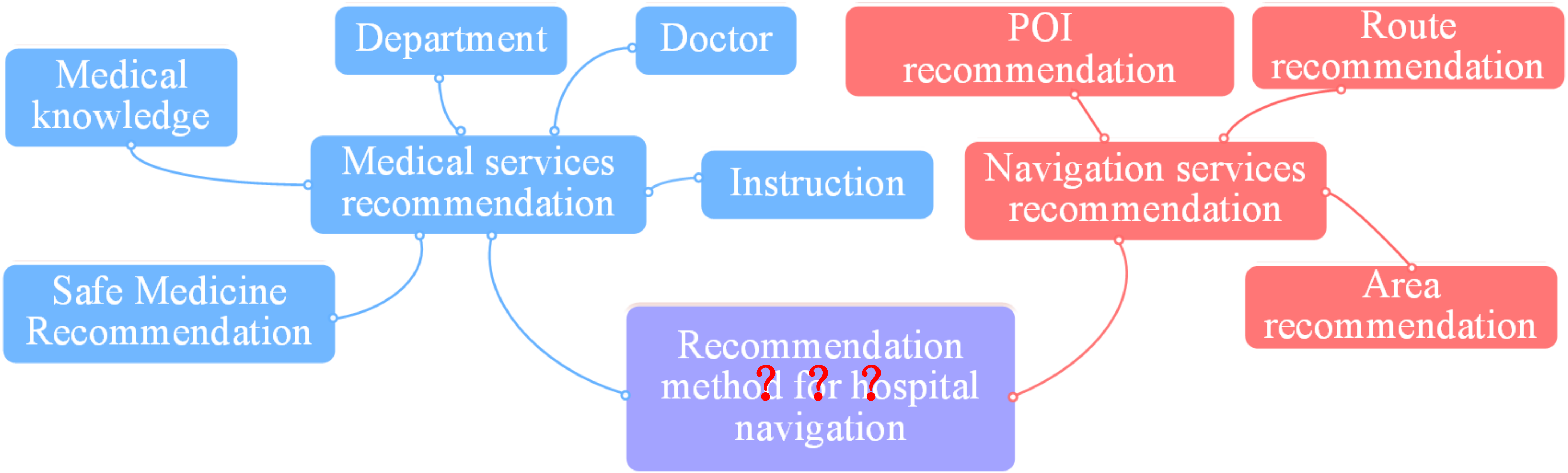
The lack of the context model for hospital navigation.

Richter, K. F., Dara-Abrams, D., & Raubal, M. (2010, September). Navigating and learning with location based services: A user-centric design. In Proceedings of the 7th International Symposium on LBS and Telecartography (pp. 261-276).

Afyouni, I., Ray, C., & Christophe, C. (2012). Spatial models for context-aware indoor navigation systems: A survey. Journal of Spatial Information Science, 1(4), 85-123.

Kim, J., & Chung, K. Y. (2014). Ontology-based healthcare context information model to implement ubiquitous environment. Multimedia Tools and Applications, 71(2), 873-888.

Q2: what services are recommended by systems?



Lack of the recommendation method that combines medical services and navigation services.

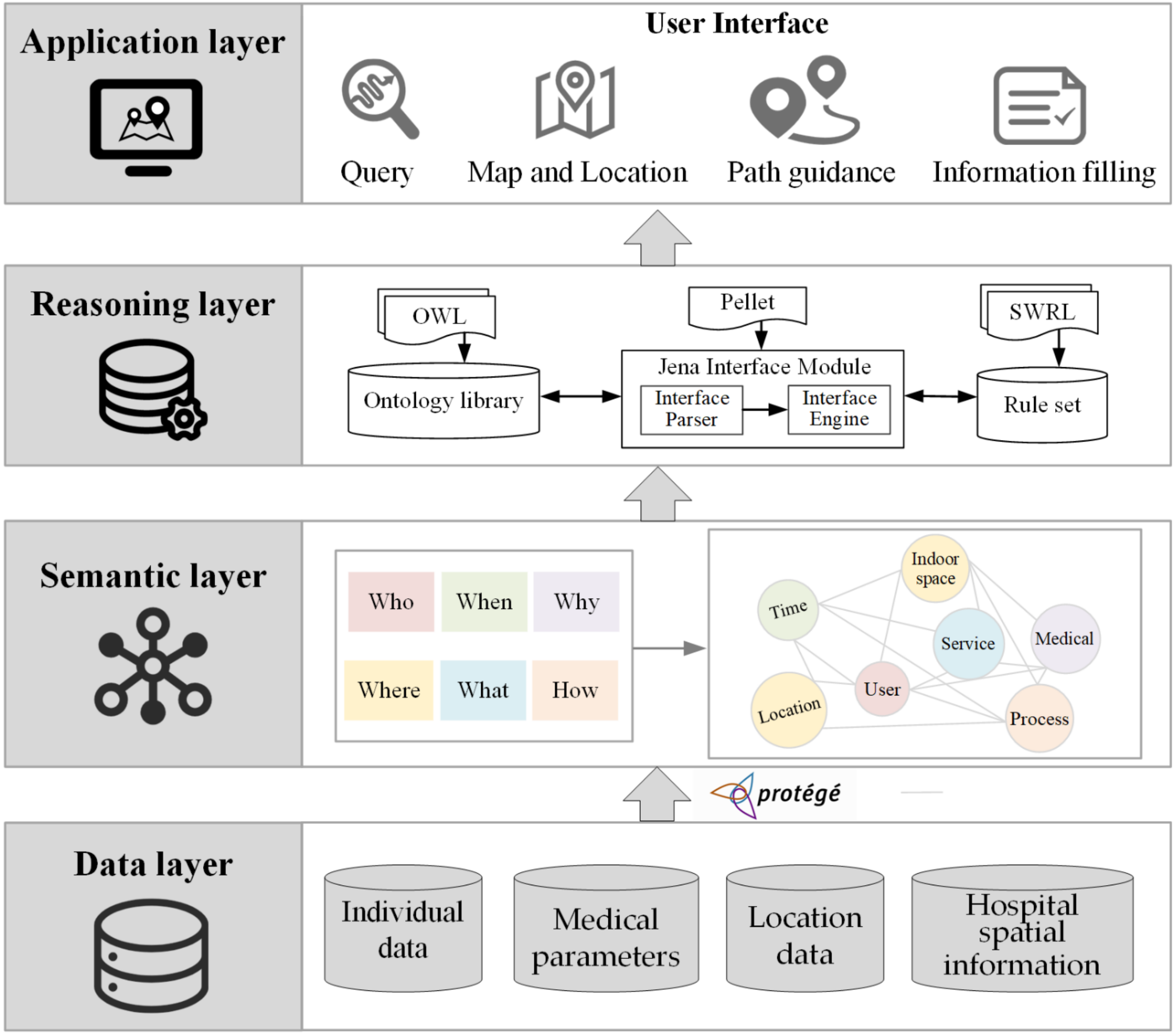
2 Research questions

In this study, we propose an **ontology-driven context-aware recommendation method for hospital navigation** that adapts to dynamically changing needs, tasks, and processes for various users. We focus on two research questions:

1. How to develop a **context model** for hospital navigation?
2. How to realize **personalized service recommendations**?

3 Methodology: Research Framework

We designed the framework of **an ontology-driven context-aware recommender system** as shown in the Figure.



4 Discussion

Contributions

- **Developing a context model for hospital navigation using ontology** to complete the complex medical processes and provide personalized navigation services;
- **Developing a personalized recommendation mechanism** using SWRL rules to infer contextual information.

Outlook

In the future, we will do further research work in the following aspects:

- Developing a prototype system
- Applying the proposed method to hospital scenarios.

PART 03 Future work

Future work

In the future research on landmark-based pedestrian navigation service should involves:

- Design user cognitive experiments to evaluate indoor landmark selection and symbols
- Design a user-center indoor landmark visualization method
- Understand the needs of different types of users for indoor navigation
- Design a more user-friendly the interface for hospital navigation
- Dynamic recommendation of landmarks based on context-aware.

Thanks！
Any question？

Funding:

- National Key R&D Program of China (2021YFE0112300);
- National Key R&D Program of China (2016YFE0131600);
- National Natural Science Foundation of China (NSFC) (No. 41871371);
- The State Scholarship Fund from the China Scholarship Council (CSC) (No. 201906860035).

Litao Zhu

School of Geography
Nanjing Normal University

181301028@njnu.edu.cn

shenjie@njnu.edu.cn
http://schools.njnu.edu.cn/geog/person/jie-shen