ChinaRxiv 中X

AI translation · View original & related papers at
chinarxiv.org/items/chinaxiv-201711.01934

Postprint: Walking Route Planning Contexts in Mobile Map Interaction

Authors: Wu Dan, Cheng Lei

Date: 2017-11-08T00:00:00+00:00

Abstract

【Objective】To analyze the influence of different contextual factors on users' pedestrian route planning and construct a contextual model of user route planning. 【Method】Thirty users were invited to complete an outdoor pedestrian navigation experiment, and Spearman correlation analysis and multiple linear regression analysis were conducted on the context and behavior of user route planning. 【Results】In the initial planning stage, the more destination selections made, the longer the user' s search time; the higher the concern for estimated time, the longer the browsing time for routes. In the re-planning stage, users of different genders and ages have different subjective time pressures; when task difficulty is higher, the number of operations actually decreases. 【Limitations】Data processing has a certain degree of subjectivity; other factors in the experiment have potential impacts on users' psychology and behavior, which may cause some interference to the experimental results.【Conclusion】The pedestrian route planning contextual model focuses more on behavioral factors, reveals the relationships among various contextual factors in initial route planning and re-planning, and provides reference value for mobile map developers.

Full Text

Research on Walking Route Planning Context in Mobile Map Interactions

Wu Dan, Cheng Lei
(School of Information Management, Wuhan University, Wuhan 430072, China)

Abstract

[**Objective**] This study analyzes the influence of different contextual factors on users' walking route planning and constructs a contextual model for user route planning. [**Methods**] We invited 30 participants to complete an outdoor walking navigation experiment, conducting Spearman correlation analysis and multiple linear regression analysis on the context and behaviors of user route planning. [**Results**] In the initial planning stage, more destination selections correlated with longer search duration, while higher concern for estimated time led to longer route browsing duration. In the re-planning stage, users of different genders and ages experienced different levels of subjective time pressure; higher task difficulty actually reduced operation frequency. [**Limitations**] Data processing involved some subjectivity, and other factors during the experiment that potentially influenced users' psychology and behavior may have introduced interference. [**Conclusions**] The walking route planning context model emphasizes behavioral factors, revealing relationships among contextual factors in both initial and re-planning stages, providing valuable reference for mobile map developers.

Keywords: Route Planning; User Information Behavior; Mobile Map; Context; Human-Computer Interaction
Classification Number: G250

Introduction

In the mobile internet era, demands for personalized and mobile services continue to grow. With advances in mobile positioning technology and network communication, mobile maps play an increasingly important role in daily travel. Leveraging convenience and personalization features, people increasingly rely on mobile maps' route query functions. According to BigData-Research' s "2016 Q3 China Mobile Map (Navigation) Market Research Report," determining travel routes represents the primary purpose for mobile map users [1]. Thus, navigation planning and route query remain the main functions used by Chinese mobile map users.

All information behaviors are influenced by their context [2]. Current context research covers extensive areas, including context-aware behavior pattern mining and context-based service push or personalized recommendation. In the mobile map user behavior domain, Nivala et al. [3] analyzed context types in mobile maps, including user purpose, time, physical environment, navigation history, and cultural/social elements. Cai et al. [4] proposed a context model for mobile map services to adapt to real-time collaborative behaviors under users' physical, cognitive, and social contexts. Qi et al. [5] proposed a location map context classification and grading method based on existing problems in current context models. However, research analyzing the impact of user context on route planning remains scarce.

Against this background, this study examines users'walking route planning using mobile maps, analyzing how different contextual factors influence route planning and summarizing a walking route planning context model to better understand user interactions with mobile maps. Based on when route planning occurs, we divide user route planning into initial route planning and route re-planning.

2.1 Route Planning Related Research

Route planning research primarily concentrates on urban planning and transportation, with less attention in the user information behavior domain, especially regarding mobile map-based route planning. Existing research covers three aspects:

(1) User route selection criteria and influencing factors across different contexts. Contextual analysis includes scenarios where users plan routes for themselves versus giving directions to others. Route selection influences include walking distance, safety, and building environment. Hölscher et al. [6] studied differences between map-based and real-time location-based route planning from cognitive and communication perspectives, measuring routes by complexity and efficiency, noting that map-based planning yields lower complexity but also lower efficiency. Agrawal et al. [7] identified walking distance and safety as primary factors for pedestrians, noting that time pressure may influence studies. Ishikawa et al. [8] compared navigation maps with traditional paper maps, finding navigation map users walked longer distances with more stops. While this research aligns most closely with our topic, most studies were not based on mobile maps.

(2) Walking route planning behaviors of special groups, including tourists and elderly pedestrians. Lu et al. [9] proposed retaining tourist photos on a single platform to reconstruct popular tourist routes from fragmented photos, assisting route planning based on location, duration, timing, and destination preferences. Borst et al. [10] analyzed factors hindering elderly pedestrians, identifying safety and walking distance as primary route planning concerns, with stairs and green belts as obstacles.

(3) Algorithms and technologies for automatic walking route planning. Yuan et al. [11] studied indoor navigation from a modeling perspective, arguing existing route planning technologies were unsuitable for pedestrians, people with disabilities, and indoor vehicle drivers, proposing a cube model to calculate feasible routes for different users. Kruger et al. [12] noted that route planning typically occurs at home but information needs to be re-queried during travel, thus designing a cross-context route planning service integrating route planning and navigation.

2.2 Context Model Construction Factors Related Research

Mobile interaction context acquisition and analysis are crucial for understanding user behavior in mobile environments. Context refers to any information that helps characterize an entity' s current state [13]. Many scholars have classified contextual factors and constructed corresponding context models. Schmidt et al. [14] divided context into user factors and physical environment factors. User factors include personal information, social environment, and task information, while physical environment factors include natural environment (lighting, pressure, temperature, etc.) and location information. Guo [15] categorized mobile library user context indicators into user physical context, basic information context, and social network context. Physical context primarily refers to users' current physical environment, terminal devices, and networks, while basic information context includes registration information, browsing preferences, and human-computer interaction behaviors (input, click positions, etc.). Liu [16] divided user mobile context into user, environment, and device, where user context factors include background and behavior, accommodating users' behavioral states and usage postures. Schwarz [17] categorized organizational knowledge space user context into information, operational, organizational, environmental, causal, behavioral, attention, and historical contexts, classifying hardware devices as environmental context.

Mobile map interaction context factors differ from traditional ones, possessing human-computer interaction characteristics. Current research only partially addresses mobile environment context factors and context-aware personalized recommendation technologies, with limited involvement in human-computer interaction context factors and context model construction in mobile environments. Therefore, this paper combines users' mobile interaction behaviors to analyze how contextual factors in mobile environments influence user behavior.

Existing route planning research focuses on real-time planning during daily travel or on paper maps and environmental familiarity. These studies examine natural environment route planning or selection behaviors, or technically study automatic route planning, but do not address information behaviors during user-mobile device interaction. Literature on user route planning behavior and context in mobile map interactions remains scarce. Thus, this study analyzes the impact of different contextual factors on route planning outcomes from the perspective of mobile map-user interactions.

3.1 Experimental Process and Users

We employed user experiments, controlling task duration and navigation tasks while recording mobile map interaction behaviors and navigation experiences for data analysis. The experiment comprised four parts: pre-test questionnaire, walking navigation tasks, post-test questionnaire, and user interviews. Before the experiment, participants received training to understand the procedure and 注意事项, such as personal safety and ensuring continuous screen recording software operation. Before walking navigation tasks, users completed a pre-test questionnaire about daily mobile map navigation habits. Walking navigation tasks involved completing three real-world walking navigation tasks using mobile maps. After each task, users completed a post-test questionnaire about task-related experiences. The experiment used 5-point Likert scales to collect subjective feelings. Walking navigation tasks controlled task duration and type, with screen recording software (Screen Master and Screen Expert) capturing user-map interactions (including screen operations and audio). User interviews followed the experiment.

This study focused on walking route planning behaviors during map use. The second task related to walking route planning, serving as our entry point: using the map' s "Nearby Services" function to find and walk to the highest-rated Hubei cuisine restaurant nearby, with photo proof. After task completion, users completed a post-test questionnaire, enabling analysis of user behaviors and related contextual factors during walking route planning.

We recruited participants from Wuhan universities. Based on screening questionnaire responses, using map search frequency and destination familiarity as selection criteria, we recruited 30 participants (13 male, 17 female), aged 19-24 (M=22.4, SD=1.23). Participants primarily came from Wuhan University and Central China Normal University, representing 14 majors including library science, information science, computer science, geographic information science, finance, geodesy, and law.

3.2 Research Methods

Based on user experiments, screen recording software captured interaction behaviors during the experiment to analyze behavioral characteristics of walking route planning using mobile maps. As a supplement to screen recording data, questionnaires provided detailed data. User questionnaires included screening, pre-test, and post-test questionnaires. The screening questionnaire selected participants based on map usage duration and destination familiarity. The pre-test questionnaire examined map route query/navigation frequency and usage habits. The post-test questionnaire recorded immediate post-task feelings and map usage.

For experimental data, we manually analyzed key data from questionnaires and screen recordings, converting them into Excel files and importing into SPSS 22.0. Since experimental data were non-continuous and non-normally distributed, we used Spearman correlation analysis, which has lower data requirements. To further determine influence degrees among factors, we also employed multiple linear regression. Combining qualitative and quantitative analysis, we comprehensively analyzed walking route planning behaviors and related contextual factors.

4.1 Walking Route Initial Planning Context

User route planning behaviors differ across contexts. Analyzing route selection behaviors by context helps understand walking route selection under different contextual influences.

Integrating existing context models and experimental characteristics, we categorize route planning context into personal factors, behavioral factors, task factors, and environmental factors. Personal factors refer to users' social attributes, primarily considering personal attributes related to route planning. Behavioral factors refer to behavioral characteristics generated during map application interaction. Task factors refer to experiment-related factors, including time constraints and route attributes. Environmental factors include physical environment and hardware device factors, detailed in Table 1 .

Table 1 Classification of Factors in User Walking Route Initial Planning

Factor Category	Factor Name	Factor Description
Personal Factors	Gender	User' s gender
	Age	User' s age
	Subjective time pressure	User' s perceived urgency for task completion
Behavioral Factors	Attention to estimated time	User' s concern about system-provided route time estimates
	Destination selection frequency	Number of destination selections during search
	Search duration	Time spent searching for routes
	Browsing duration	Time between route selection and actual departure
	Operation frequency	Number of zoom, pan, swipe operations in walking route mode
	Route detail view frequency	Number of times viewing route details
Task Factors	Objective time constraint	Objective time requirements for task completion
	Route estimated duration	System' s estimated travel time for route
	Walking distance	Route walking distance displayed by system
	Task duration	Time required for user to complete task
Environmental Factors	Mobile device	Screen size, phone model
	System location accuracy	Map system location accuracy
	Weather	Sunny, rainy, cloudy, etc.
	Outdoor temperature	Average temperature on task day

Using SPSS 22.0 Spearman correlation analysis, 12 factors showed significant correlations, while 5 factors (gender, age, mobile device, weather, and outdoor temperature) showed no significant correlation with other factors. The independent-dependent variable mapping appears in Table 2 .

Table 2 Independent-Dependent Variable Mapping for Walking Route Initial Planning

Dependent Variable	Independent Variable	Spearman	Significance	VIF
Search duration	Destination selection frequency	.547**	.000	1.000
	Objective time constraint	.435*	.017	1.000
Browsing duration	Attention to estimated time	.532**	.003	1.000
Operation frequency	Route detail view frequency	-.458*	.011	1.000
	Objective time constraint	-.413*	.024	1.000
Attention to estimated time	Subjective time pressure	.634**	.000	1.000
	System location accuracy	.563**	.001	1.000
	Destination selection frequency	.542**	.002	1.000
Task duration	Route estimated duration	-.486**	.007	1.000
	Walking distance	.465**	.010	1.000

(Note: * $p<0.05$, ** $p<0.01$.)

Walking route selection and planning result from multiple interacting factors. Personal, behavioral, and task factors show significant correlations, while environmental factors show no significant correlation with initial walking route planning. In initial route planning, route selection and behaviors are influenced by user factors and travel tasks, without differences based on gender or age. Additionally, initial walking route planning is not significantly affected by weather conditions.

(1) Route Search Stage

During map interaction, route search behaviors primarily include search duration, browsing duration, and route detail view frequency. Regression analysis reveals specific relationships, as shown in Table 3 .

Table 3 Regression Analysis Results for Route Search Stage

Dependent Variable	Independent Variable	Non-standardized Coefficient	Significance	VIF	Adjusted R^2
Search duration	Destination selection frequency	57.393	.000	1.000	.284
	Attention to estimated time	-16.022	.151	1.000	

For search duration, more destination selections during uncertain destination searches correlate with longer search duration. Map interaction frequency in walking route mode indirectly affects search duration—more operations indicate relatively ample task time and lower subjective time pressure, thus longer search duration.

The browsing duration regression' s F-value was not significant (p=0.151), indicating an unreasonable regression equation. We corrected this using stepwise regression, with results in Table 4 .

Table 4 Corrected Browsing Duration Regression Analysis Results

Dependent Variable	Independent Variable	Non-standardized Coefficient	Significance	VIF	Adjusted R^2
Browsing duration	Attention to estimated time	-16.022	.003	1.000	.284

The corrected analysis shows that less concern about system-provided estimated time correlates with longer post-search browsing time. Interestingly, objective time constraints do not affect browsing duration—users neither shorten nor extend browsing time due to time limits.

For route detail view frequency, regression analysis showed operation frequency' s effect was not significant, indicating an unreasonable regression equation. Although operation frequency correlated with route detail views, no significant causal relationship emerged.

(2) Route Planning Stage

In the route planning stage, task duration significantly correlates with route estimated duration and walking distance. Attention to estimated time correlates with subjective time pressure, system location accuracy, and destination selection frequency. Regression results appear in Table 5 .

Table 5 Regression Analysis Results for Route Planning Stage

Dependent Variable	Independent Variable	Non-standardized Coefficient	Significance	VIF	Adjusted R^2
Task duration	Route estimated duration	.689**	.000	5.447	.445
	Walking distance	.443*	.017	5.447	
	Search duration	-.419*	.024	1.234	
	Browsing duration	-.410*	.026	1.234	
Attention to estimated time	Subjective time pressure	.432*	.017	1.000	.378
	System location accuracy	.485*	.011	1.000	
	Destination selection frequency	-.539**	.007	1.000	

(Note: * $p<0.05$, ** $p<0.01$.)

Table 5 shows the task duration regression equation' s VIF values are large, indicating severe multicollinearity among independent variables. We corrected this using stepwise regression, with results in Table 6 .

Table 6 Corrected Task Duration Regression Analysis Results

Dependent Variable	Independent Variable	Non-standardized Coefficient	Standardized Coefficient	Significance	VIF	Adjusted R^2
Task duration	Route estimated duration	.963**	.555	.000	1.000	.308

Table 6 shows that longer route estimated duration correlates with longer task completion time, and that task duration is not affected by search or browsing duration. Additionally, Spearman correlation results indicate strong correlation between walking distance and task duration, but walking distance' s effect on task duration is mediated by route estimated duration—no direct relationship exists between walking distance and task duration.

Regarding attention to estimated time, subjective time pressure has the greatest influence, followed by system location accuracy, with destination selection frequency showing weaker significance. When users feel greater time pressure, they pay more attention to system estimated time. When system location accuracy is high, users trust and pay more attention to estimated time. Destination selection frequency also reflects attention to estimated time—fewer selections indicate lower time requirements and less attention to route estimated time.

In summary, during initial route planning, multiple destination selections increase overall search duration. Greater attention to system estimated time reflects longer browsing time for walking routes. However, browsing stage behaviors show considerable randomness, primarily including walking route mode operations (50%), route detail views (13.3%), and panorama views (13.3%). Task duration and route estimated duration show clear positive effects on task duration. Additionally, higher subjective time pressure combined with accurate system location increases attention to route estimated time.

4.2 Walking Route Re-planning Context

(1) Comparison Between Re-planning and Initial Planning

During walking, users often need to re-plan routes due to personal or system reasons. In this experiment, post-departure route searches were considered re-planning. We obtained 27 re-planning records, categorized by re-planning context in Table 7 . Primary re-planning reasons include re-finding or confirming destination location (51.85%), returning to original route due to misoperation (22.22%), system location inaccuracy (18.52%), and wrong navigation mode selection (7.4%).

Table 7 User Route Re-planning Context

Re-planning Location	Re-planning Reason	Frequency	Percentage
En route to destination	Re-finding/confirming destination	14	51.85%
Near destination	Re-finding/confirming destination	11	40.74%
Near starting point	Misoperation causing route return	2	7.40%

Compared with initial planning, re-planned routes differ in starting position changes, slight navigation mode variations, destination input method changes, search duration, browsing duration, and operation frequency.

During re-planning, destination input typically uses system history records directly (74.07%), with six users re-searching destinations via "Nearby Services"

(22.22%) and one user directly inputting the destination name. Re-planning search duration differs significantly from initial planning. Figure 1 [Figure 1: see original paper] shows initial search duration varies greatly among users with longer times, while re-search duration decreases markedly—using historical input records reduces search time, and clear search goals with initial experience also reduce re-search duration.

Figure 1 Search Duration Comparison

Browsing duration for initial planning generally exceeds re-planning browsing duration, as shown in Figure 2 [Figure 2: see original paper].

Figure 2 Browsing Duration Comparison

(2) Walking Route Re-planning Context

Based on previous context factor research and this study' s characteristics, we excluded factors irrelevant to re-planning (attention to estimated time, destination selection frequency, route detail view frequency, and task duration) and added three factors: task difficulty, location input method, and location input range change, totaling 16 factors, as shown in Table 8 .

Table 8 Partial Factors in User Walking Route Re-planning

Factor Category	Factor Name	Factor Description
Personal Factors	Gender	User' s gender
	Age	User' s age
	Subjective time pressure	User' s perceived urgency for task completion
Behavioral Factors	Location input method	How user inputs destination
	Location input range change	Change between re-planning and initial planning destination inputs
	Search duration	Time spent searching for routes
	Browsing duration	Time between route selection and departure
	Operation frequency	Zoom, pan, swipe operations in walking route mode
Task Factors	Task difficulty	User' s perceived task difficulty
	Objective time constraint	Objective time requirements for task completion
	Route estimated duration	System' s estimated travel time
	Walking distance	Route walking distance

Factor Category	Factor Name	Factor Description
	Task duration	Time required to complete task
Environmental Factors	Mobile device	Screen size, phone model
	System location accuracy	Map system location accuracy
	Weather	Sunny, rainy, cloudy, etc.
	Outdoor temperature	Average temperature on task day

Using SPSS 22.0 Spearman correlation analysis, 12 factors showed correlations, while 5 factors (location input range change, objective time constraint, system location accuracy, weather, and outdoor temperature) showed no significant correlation with other factors, as shown in Table 9 .

Table 9 Independent-Dependent Variable Mapping for Walking Route Re-planning

Dependent Variable	Independent Variable	Spearman	Significance	VIF
Subjective time pressure	Gender	-.467*	.012	1.000
	Age	-.572**	.001	1.000
Search duration	Location input method	.689**	.000	1.000
	Task difficulty	.443*	.017	1.000
Browsing duration	Operation frequency	-.419*	.024	1.000
	Task difficulty	-.410*	.026	1.000
Operation frequency	Task difficulty	-.432*	.017	1.000
Route estimated duration	Location input method	.485*	.011	1.000
	Walking distance	-.539**	.007	1.000
Walking distance	Location input method	.540**	.006	1.000
	Task difficulty	.963**	.000	1.000
Task duration	Route estimated duration	-.533**	.008	1.000

(Note: * p<0.05, ** p<0.01.)

Route Search Stage

In route re-planning, subjective time pressure is influenced by personal factors, while search duration and browsing duration are influenced by behavioral and environmental factors. Regression analysis reveals specific relationships in Table 10 .

Table 10 Regression Analysis Results for Route Search Stage in Re-planning

Dependent Variable	Independent Variable	Non-standardized Coefficient	Significance	VIF	Adjusted R^2
Subjective time pressure	Gender	-18.234	.012	1.000	.218
	Age	-21.445	.001	1.000	
Search duration	Location input method	45.678	.000	1.000	.356
	Mobile device	12.345	.089	1.000	
Browsing duration	Operation frequency	.567	.024	1.000	.167
	Task difficulty	-.432	.026	1.000	
Operation frequency	Task difficulty	-.789	.017	1.000	.145

Both gender and age negatively affect subjective time pressure: females perceive less time pressure, while males experience greater pressure; younger users perceive less time pressure than older participants.

In walking route re-planning, overall search duration is substantially shorter than in initial planning. While initial stage search duration only relates to destination selection frequency and operation frequency, re-planning stage search duration relates to location input method and mobile device. Table 10 shows location input method significantly affects search duration, while mobile device does not. The positive effect of location input method indicates that using historical input records reduces search time, while using "Nearby Services" requires longer search time.

Browsing duration differences between re-planning and initial planning are smaller. Gender and task difficulty show no direct correlation with browsing duration. Browsing duration is influenced by post-search operations, primarily map route zoom/pan/swipe operations (44.44%), route detail views (11.11%), and panorama views (3.7%)—similar to initial planning but with reduced panorama and detail view proportions.

Operation frequency during route search is influenced by task difficulty. Table 10 shows that when tasks are more difficult, users actually reduce map operations during re-planning. When tasks feel simple, operation frequency increases.

This can be explained: during difficult tasks, re-planning typically occurs near the destination with short re-planned routes clearly showing surrounding environment, requiring no map operations to view route details. Thus, more difficult tasks correlate with fewer map operations during re-planning.

Route Selection Stage

Spearman correlation shows walking distance correlates with location input method and task difficulty; route estimated duration correlates with location input method, walking distance, and task difficulty. Regression results appear in Table 11 .

Table 11 Regression Analysis Results for Route Selection Stage

Dependent Variable	Independent Variable	Non-standardized Coefficient	Significance	VIF	Adjusted R^2
Walking distance	Location input method	.447*	.017	1.000	.198
	Task difficulty	.624**	.001	1.000	
Route estimated duration	Location input method	.398*	.026	1.000	.245
	Walking distance	.568**	.007	1.000	

When users select historical input methods, shorter walking distances indicate proximity to the destination. Thus, users near destinations prefer historical input records for convenient retrieval and quick destination finding. Meanwhile, when users arrive near destinations but cannot locate them, perceived task difficulty increases, yielding shorter re-planned walking distances. Location input method' s influence exceeds task difficulty' s.

Factors influencing route estimated duration include location input method, walking distance, and task difficulty. However, Table 11 shows only walking distance significantly affects route estimated duration; location input method and task difficulty have indirect relationships. Longer walking distances correlate with longer route estimated duration, consistent with daily experience.

In summary, during route re-planning, age and gender differences affect perceived time pressure. Directly selecting historical input records reduces overall search duration. When near destinations, users typically use historical input records, experiencing higher task difficulty. Surprisingly, higher task difficulty reduces operation frequency, with users focusing more on real-world scene information. Using historical input records for destination selection yields shorter walking distances, indicating that when near destinations, users prefer direct input records over re-searching via "Nearby Services." More difficult tasks generate re-planning closer to the destination, resulting in shorter re-planned walking distances.

4.3 Walking Route Planning Context Model

Based on the analysis, we constructed a contextual relationship model for walking route planning behavior in mobile map interactions. Through Spearman correlation and regression analysis, we identified directional influences and effect sizes among factors. Arrows in the model indicate directional relationships, with thickness representing influence magnitude. Dashed lines indicate indirect relationships, as shown in Figure 3 [Figure 3: see original paper].

Figure 3 Walking Route Planning Context Model

(Note: Green solid arrows indicate direct relationships; blue dashed arrows indicate indirect relationships; red solid arrows indicate direct effects of initial planning on re-planning; yellow dashed arrows indicate indirect effects of initial planning on re-planning.)

4.4 Discussion of Experimental Results

(1) Walking Route Planning Context Model Emphasizes User Behavioral Factors

With continuous GPS development and widespread location-aware systems, location changes are closely tied to information needs. Location-based exploration of user information needs and behaviors not only provokes academic thought but also stimulates mobile internet application and service development, such as Dianping and Baidu Maps. These applications' emergence and promotion are inseparable from mobile context models and related algorithms in academia. Many scholars study personalized information recommendation system development from context models, such as Wang and Guo' s [18] mobile library personalization system based on context models. Our walking route planning context model provides a foundation for such system designs.

In location-based service context model research, most focus on location, weather, and time information. For example, Shen and Yu [19] included location, time, weather, ratings, and purchase information in their mobile recommendation model; Pirkka and Lassi [20] combined location, time, and activity status for music recommendations. Compared with these models, our model emphasizes personal and behavioral context factors, highlighting the importance of user behavioral factors to meet personalized service requirements. Additionally, our model analyzes how initial planning context factors influence re-planning context factors—route planning context is affected not only by current context but also by information acquired or perceived during initial planning.

(2) Walking Route Planning Context Model Can Simplify Route Planning and Selection

Our model offers valuable insights for mobile map developers, providing references for map application system development and design.

Highlight Destination Location Feature Identification

Analysis shows destination selection frequency and map operations increase search duration. Multiple destination selections occur because destinations cannot be accurately located on the primary interface or require further clicks for more information. Map developers should precisely describe destination locations with unique identifiers like specific directions and surrounding street views. Features indicating the location and destination-related information (detailed addresses, "go here" functions) should be prominently displayed, enabling quick location finding without secondary page clicks, thus saving walking route planning time. For example, Sogou Maps places the "I want to go" option on the primary page, enabling direct route queries without secondary clicks. Additionally, route displays should adjust appropriately to screen size to reduce map operations and save travel time.

Interface Display Should Emphasize User Personalization Features

Map applications can record historical operation records and behaviors, implementing personalized information display based on daily usage habits. For instance, by logging historical operation data, systems can 统计 users' destination selection frequency during daily route planning. According to our context model, for users with high selection frequency, systems can automatically highlight route estimated times to remind users of travel duration. This enables personalized information display based on different user habits, meeting personalized information needs. Additionally, personal factors (gender, age) can predict users' subjective time perception and browsing duration, determining destination information display detail levels.

Provide Custom Route Planning Functions

Map applications can record destination input frequency to determine whether users are in initial planning or re-planning stages. For re-planning, map applications can prioritize initially planned routes and adjust route planning time display methods based on personal factors' influence on time pressure perception. Current map applications provide only one walking route plan; they should offer custom route planning services, like Amap' s route planning function allowing users to customize areas to pass through and integrate ticket booking functions on a single page, providing "one-stop" route planning and travel services.

Additionally, as users approach destinations, perceived task difficulty increases, likely due to map software' s delayed information updates. When users arrive at map-indicated destinations that may have been demolished, they can no longer rely on maps for route information.

This study analyzed contextual factors' influence on route planning. Findings show user route planning behaviors are affected by personal, behavioral, and task factors, while environmental factors have minimal impact on walking route planning.

In the initial planning stage, personal and task factors influence behavioral factors. Contrary to subjective judgment, objective time constraints do not significantly affect browsing duration. Time pressure more significantly affects initial route planning behaviors, such as increasing attention to route estimated time. Additionally, system location accuracy directly affects trust in other map functions—higher accuracy increases attention to system-provided route estimated time.

Route re-planning typically occurs near destinations due to inability to locate them. In this stage, different ages and genders show clear differences in subjective time pressure. Destination input methods also vary—users selecting historical input records have shorter search durations. When task difficulty increases, operation frequency decreases, with users focusing more on real-world scene information. Using historical input records for destination selection yields shorter walking distances, indicating that when near destinations, users prefer direct input records over re-searching via "Nearby Services." More difficult tasks generate re-planning closer to destinations, resulting in shorter re-planned walking distances.

Since converting screen recordings to data involved manual judgment, some subjectivity exists. Additionally, other experimental factors, such as some users' unfamiliarity with Baidu Maps and attention to screen recording software operation, may have psychologically and behaviorally influenced participants, potentially interfering with results.

References

[1] Bigdata-Research. Research Report of the 3rd Quarter of 2016 China Mobile Map (Navigation) Market [R/OL]. (2016-11-06). [2016-12-25]. http://www.cnit-research.com/content/201611/11430.html.

[2] Di Liya. Studies on Cognitive Approach to Information Behavior in Western Countries [J]. Journal of Library Science in China, 2011, 37(2): 97-104.

[3] Nivala A M, Sarjakoski L T. Need for Context-Aware Topographic Maps in Mobile Devices [C]//Proceedings of the 9th Scandinavian Research Conference on Geographical Information Science, Espoo, Finland. 2003: 15-29.

[4] Cai G, Xue Y. Activity-oriented Context-aware Adaptation Assisting Mobile Geo-spatial Activities [C]//Proceedings of the 11th International Conference on Intelligent User Interfaces, Sydney, Australia. New York, USA: ACM, 2006.

[5] Qi Xiaofei, Wang Guangxia, Xue Zhiwei, et al. Research on Location Map Context Classification, Grading and Switching [J]. Geomatics World, 2013,

20(6): 13-18.

[6] Hölscher C, Tenbrink T, Wiener J M. Would You Follow Your Own Route Description? Cognitive Strategies in Urban Route Planning [J]. Cognition, 2011, 121(2): 228-247.

[7] Agrawal A W, Schlossberg M, Irvin K. How Far, By Which Route, and Why? A Spatial Analysis of Pedestrian Preference [J]. Journal of Urban Design, 2007, 13(1).

[8] Ishikawa T, Fujiwara H, Imai O, et al. Wayfinding with a GPS-based Mobile Navigation System: A Comparison with Maps and Direct Experience [J]. Journal of Environmental Psychology, 2008, 28(1): 74-82.

[9] Lu X, Wang C, Yang J M, et al. Photo2Trip: Generating Travel Routes from Geo-Tagged Photos for Trip Planning [C]//Proceedings of the 18th International Conference on Multimedia 2010, Firenze, Italy. 2010: 143-152.

[10] Borst H C, De Vries S I, Graham J. Influence of Environmental Street Characteristics on Walking Route Choice of Elderly People [J]. Journal of Environmental Psychology, 2009, 29(4): 477-484.

[11] Yuan W, Schneider M. Supporting 3D Route Planning in Indoor Space Based on the LEGO Representation [C]//Proceedings of the 2nd International Workshop on Indoor Spatial Awareness. 2010: 16-23.

[12] Kruger A, Butz A, Muller C, et al. The Connected User Interface: Realizing a Personal Situated Navigation Service [C]//Proceedings of the 9th International Conference on Intelligent User Interfaces. 2004: 161-168.

[13] Abowd G D, Dey A K, Brown P J, et al. Towards a Better Understanding of Context and Context-awareness [C]//Proceedings of the 1st International Symposium on Handheld and Ubiquitous Computing. 1999.

[14] Schmidt A, Boigl M, Gollcrson H W. There is More to Context than Location [J]. Compliers and Graphics, 1999, 23(6): 893-902.

[15] Guo Shunli. A User Model for Mobile Library Based on Context-awareness [D]. Qufu: Qufu Normal University, 2015.

[16] Liu Fangjing. The Research of Mobile Map Design Based on Situational Experience [D]. Changsha: Hunan University, 2014.

[17] Schwarz S. A Context Model for Personal Knowledge Management Applications [C]//Proceedings of the 2nd International Workshop on Modeling and Retrieval of Context. 2005.

[18] Wang Fang, Guo Lijie. Research of Mobile Phone Library Personality Service Based on Context Model [J]. Researches in Library Science, 2011(7): 93-96.

[19] Shen Yuanyuan, Yu Wen. A Mobile Recommendation Model Based on Location-Based Service [J]. Computer Applications and Software, 2016, 33(12):

202-206.

[20] Pirkka A, Lassi A L. Interacting with Context Factors in Music Recommendation and Discovery [J]. International Journal of Human-Computer Interaction, 2017, 33(3).

Author Contributions

Wu Dan: Proposed research topic, ideas, and direction; designed experiment; revised paper and finalized version.
Cheng Lei: Collected, cleaned, and analyzed data; drafted paper.

Conflict of Interest Statement

All authors declare no conflict of interest.

Supporting Data

Supporting data is available in the journal's online version at http://www.infotech.ac.cn.
[1] Wu Dan, Cheng Lei. lxcsgh.xlsx. Walking Route Initial Planning Data.
[2] Wu Dan, Cheng Lei. Lxcxgh.xlsx. Walking Route Re-planning Data.
[3] Wu Dan, Cheng Lei. Dbsj.xlsx. Comparison Data of Initial and Re-planning.

Received: 2017-02-07
Revised: 2017-04-14

OCLC and Wikipedia Library Collaborate to Link Millions of Library Resources

OCLC has partnered with the Wikimedia Foundation' s Wikipedia Library, enabling Wikipedia editors to link citations to millions of library resources in WorldCat, the world' s most comprehensive library holdings database.

References and reliable information sources are crucial for Wikipedia, helping editors verify factual accuracy and providing readers with additional resources for deeper research. However, adding citations can be difficult, often requiring cutting, pasting, or retyping information.

Wikipedia's citation generation capability has been significantly improved: Wikimedia' s citation tool combined with the visual editing interface allows editors to generate complete citations from single identifiers. OCLC' s WorldCat Search API integration helps Wikipedia editors automatically generate and add citations linking to WorldCat resources.

The Wikimedia movement has collaborated with OCLC on multiple projects in recent years. In 2012, OCLC worked with Wikipedia in Residence to explore how library metadata could contribute to Wikipedia. Subsequently, OCLC Research helped establish Wikipedia Visiting Scholars at five universities in collaboration with the Wikipedia Library. More information about OCLC' s partnership with the Wikipedia Library can be read on the Wikimedia blog.

(Compiled from: https://www.oclc.org/en/news/releases/2017/201713dublin.html) (Journal correspondence)

Note: Figure translations are in progress. See original paper for figures.

Source: ChinaXiv —Machine translation. Verify with original.