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RESEARCH ARTICLE

Identifying and Evaluating Cyclist Points of Interest Using Ride Log Data and User Centered Evaluations

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ABSTRACT In cycle tourism, where cyclists can freely experience regional attractions, there exist Cyclist Points of Interest (CPoI) that cyclists prefer. However, these CPoIs are known only among cyclists and are not widely shared as general tourist information. This study proposes a semi-automated method for identifying and evaluating CPoIs using cyclist ride log data. The proposed method consists of three stages: automatic extraction using stop position estimation from GPS ride logs and Density-Based Spatial Clustering of Applications with Noise, facility identification using crowdsourcing, and evaluation using crowdsourcing. To evaluate the effectiveness of the proposed method, we collected ride data from 286 cyclists in Maebashi City, Gunma Prefecture, from April to December 2023, and successfully identified 48 CPoIs and assigned evaluation values to each CPoI. Expert validation of the identified CPoIs revealed high agreement rates: 89.6% for selection validity and 95.8% for the credibility of evaluation results. The detected CPoIs included many facilities often overlooked in conventional tourist destination selection, such as convenience stores, roadside stations, and cyclist-specialized cafes, demonstrating the practical utility of the proposed method.

INDEX TERMS Cycle tourism, cyclist points of interest (CPoI), crowdsourcing, DBSCAN clustering, point-of-interest identification.

I. INTRODUCTION

Cycle tourism has gained worldwide attention as a sustainable form of tourism, with continued market expansion in recent years [1], [2], [3]. This form of tourism contributes to regional economic revitalization and has the potential to utilize small-scale and diverse regional resources as tourist attractions, unlike conventional large-scale tourist destinations [2], [3]. In particular, the places where cyclists stop include rest facilities along main roads, scenic viewpoints, local specialty product stores, and public facilities with bicycle parking—locations often overlooked in conventional tourist destination selection [2].

In this study, we define locations where cyclists stop as Cyclist Points of Interest (CPoI). Conventional PoI research [4], [5], [6] has targeted general PoIs that refer to well-known tourist destinations and commercial facilities of interest to unspecified large numbers of tourists. Additionally, Hidden PoI research [7], [8] targets locations with high tourism value despite low popularity. In contrast, the CPoI proposed in this study differs in that it focuses on a user group utilizing a specific mode of transportation, cyclists, and refers to locations reflecting their stopping behavior characteristics. These facilities function as important stopping points for cyclists undertaking long-distance travel, and they simultaneously satisfying both tourism experiences and practical needs such as rest and supply.

However, systematic identification and evaluation of such CPoIs is challenging, and many depend on word-of-mouth

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among cyclists. This situation leads to underutilization of potential regional tourist resources and missed opportunities for cycle tourism promotion. In existing research on tourist destination detection, many general tourist destination extraction methods do not consider the characteristics of transportation modes [9], and research specialized in cyclist behavior patterns is limited [1]. Moreover, even in research considering bicycle use, the focus is primarily on route design and network optimization [2], and methods for identifying tourist spots based on actual stopping behavior remain unestablished.

Therefore, this study proposes a method for semi-automatically identifying and evaluating CPoIs using cyclist ride log data. The proposed method consists of three stages: automatic extraction using stop position estimation from GPS ride logs and DBSCAN clustering, facility identification using crowdsourcing, and evaluation using crowdsourcing. This method enables efficient CPoI identification by integrating large-scale data-driven pattern extraction with human judgment, eliminating the need for traditional expert-led field surveys. To evaluate the effectiveness of the proposed method, we collected ride data from 286 cyclists in Maebashi City, Gunma Prefecture, from April to December 2023, and conducted empirical experiments. As a result, the proposed method identified 48 CPoIs and assigned evaluation values to each CPoI. Practical evaluation by the local tourism association resulted in an 89.6% agreement rate for CPoI selection validity, and a 95.8% agreement rate for evaluation result credibility, and it was confirmed that places not conventionally considered tourist resources but actually useful for cyclists (such as rest points like convenience stores along main roads and scenic viewpoints) were effectively identified.

The novelty of this study lies in the definition of CPoI as a new tourist resource concept that explicitly incorporates transportation mode and user characteristics, the proposal of a method for extracting such resources based on GPS ride log data, and its application to real-world data. Furthermore, the social validity of the proposed approach is demonstrated through evaluation by practitioners with domain expertise.

The contributions of this research are as follows:

- **Proposal of a new tourist resource concept CPoI in cycle tourism**: Defining points of interest that cyclists are interested in as CPoIs.
- **Proposal of CPoI identification method based on cyclist-specific stopping behavior**: Proposing a CPoI identification method that combines cyclist log data analysis with crowdsourcing technology.
- **Effectiveness evaluation of the proposed CPoI identification method**: Demonstrating the effectiveness of the proposed method by applying it to actual ride data, identifying 48 CPoIs, and conducting expert validity evaluation.

The structure of this paper is as follows. Section II organizes related research and clarifies the positioning of this research. Section III details the proposed method. Section IV explains the experimental design and validation methods. Section V reports the experimental results. Section VI discusses the results and the significance of the proposed method. Section VII discusses the limitations and future challenges of this research. Finally, Section VIII summarizes the research achievements.

II. RELATED WORK

A. CYCLIST BEHAVIOR ANALYSIS

Numerous studies have been conducted on cyclist route selection by analyzing GPS data. As research on GPS and tourism, Prato et al. [10] proposed a bicycle route choice model in distance-value space from GPS data in the Copenhagen region.

In research using bike share system data, Khatri et al. [11] and Scott et al. [12] analyzed user behavior characteristics and preferences in Phoenix and Hamilton cities, respectively. Chen et al. [13] examined the impact of land use and road network characteristics on cyclist route preferences, and Zimmerman et al. [14] proposed an efficient route choice model using a recursive logit model. These studies reveal cyclist preferences for locations. Cyclists show preferences for cycling along scenic routes [10], tend to move quickly on low-traffic roads, and prefer bicycle-specific infrastructure [11], [13]. Some cyclists also prefer routes with street trees, lighting, and complex land use [13].

On the other hand, cyclists tend to avoid cycling on unpaved roads, hilly areas, and along major roads [10], [13]. Detour routes, turns, steep slopes, high-traffic roads, and one-way sections also negatively impact route selection [11], [12].

B. POI EXTRACTION USING LOCATION DATA

Numerous studies have been conducted on extracting PoIs from location data [4], [5], [6], [15], [16]. Research utilizing location-tagged user-generated content (UGC), such as Flickr includes Kuo et al. [4], who proposed a method for efficiently extracting PoIs and ROIs from geotagged photos, and Kozaki et al. [15], who conducted research on discovering hotspots from social media data.

In research identifying PoIs from GPS data, Krause et al. [16] proposed an automatic activity location identification method combining GPS data and land use data for short-term movement prediction, and Ashbrook et al. [5] developed a Markov model for learning important locations of multiple users and predicting movements. Zheng et al. [6] proposed a method for estimating user interest in locations from personal location history.

Research on finding unknown PoIs (Hidden PoIs) has also been conducted extensively [7], [8], [17], [18]. Kitayama et al. [7] proposed a method for extracting attractive hidden spots from user ratings and visitor numbers, and Zhuang et al. [8] developed a method for discovering hidden tourist spots by evaluating popularity and landscape quality based on photographer behavior analysis. In PoI evaluation research, Yang et al. [19] proposed a method for calculating popularity and user ratings using social media data, and Cui et al. [20] developed a method for ranking Hidden PoIs using crowdsourcing. However, these studies target general tourist behavior and do not consider cyclist-specific behavior patterns or stopping characteristics.

C. STOP LOCATION IDENTIFICATION USING GPS DATA

Research on stop location identification and activity analysis using GPS data has been actively conducted in recent years [21], [22], [23], [24], [25], [26]. Methods utilizing PoI data include Liu et al. [21], who automatically identified urban districts using OpenStreetMap and PoI data, and Huang et al. [22], who proposed a method for identifying activity locations from GPS data by defining spatial and temporal attractiveness of PoIs. Zhao et al. [23] achieved high-accuracy trip purpose prediction using gradient boosting decision trees by combining GPS data and PoI information.

As more advanced analysis methods, Lyu et al. [24] developed a destination prediction model based on understanding movement purposes by combining GPS and land use data. Tao et al. [25] achieved high-accuracy activity type detection (96.8%) using random forests by integrating spatial and temporal information. These studies provide technical foundations for stop location identification but do not consider applications in cycle tourism contexts or CPoI evaluation as tourist resources.

D. CHALLENGES IN EXISTING RESEARCH AND OUR APPROACH

Investigation of existing research revealed the challenge that PoI detection methods specialized for cyclist stopping points have not been established. Research on cyclist behavior analysis primarily focuses on route selection [10], [11], [13], with insufficient consideration of actual stopping point identification. Furthermore, while technical foundations for stop location identification using GPS data [21], [22], [23] are established, applications to CPoI detection and evaluation in cycle tourism contexts have not been considered.

The CPoI proposed in this study is not an extension of conventional PoI research, but rather a new tourist resource concept that explicitly considers transportation mode and user characteristics. As shown in Table 1, CPoI has different characteristics from existing PoI and Hidden PoI research in four aspects: target users, definition, characteristics of extracted locations, and extraction methods.

Conventional PoI research [4], [5], [6] targets general tourists and has primarily extracted large-scale tourist destinations and commercial facilities emphasizing popularity and scale through check-in record and SNS data analysis. Hidden PoI research [7], [8] focuses on discovering locations with high tourism value despite low popularity, extracting spots with particularly high scenic value using SNS image and rating data analysis.

In contrast, CPoI is fundamentally different in that it targets a user group specialized in a specific mode of transportation, cyclists, and integrates tourism value and practical value by combining GPS ride log analysis and crowdsourcing evaluation. Particularly in extraction methods, it adopts a different approach from conventional methods relying on voluntary information dissemination such as check-ins and SNS posts, by combining objective behavioral data in the form of GPS ride logs with crowdsourcing evaluation. This conceptual difference is not merely an expansion of targets, but compels reconsideration of the very definition of tourist resources.

Therefore, this study proposes a CPoI detection and evaluation method combining GPS ride log analysis and crowdsourcing evaluation to empirically validate this new concept.

III. PROPOSED METHOD

A. OVERVIEW OF THE PROPOSED METHOD

This study proposes a method for semi-automatically identifying and evaluating CPoIs using cyclist ride log data. The proposed method adopts a hybrid approach combining a data-driven automatic extraction stage with a verification and evaluation stage utilizing human knowledge. This design philosophy aims to balance the efficiency of objective pattern extraction from large-scale GPS log data with the accuracy of specialized judgment specific to cycle tourism contexts.

Conventional PoI detection methods often depend on single algorithms assuming general movement patterns, failing to adequately capture behavior characteristics unique to cycle tourism and the diversity of tourist resources. Therefore, this method first extracts stop points from spatiotemporal features of GPS data and identifies physically meaningful point groups through clustering based on geographical proximity. Next, by combining the advantages of geographic information systems and crowdsourcing, we clarify the actual facility content of each point and quantitatively evaluate attractiveness from cyclists' perspectives.

Specifically, we adopt an approach consisting of the following three stages:

1) **CPoI Extraction Stage**: Automatic extraction using stop position estimation from GPS ride logs and DBSCAN clustering
2) **CPoI Identification Stage**: Facility identification using crowdsourcing
3) **CPoI Evaluation Stage**: Attractiveness evaluation using crowdsourcing

Figure 1 shows the processing flow of the proposed method. In the first stage of CPoI extraction, stop positions are estimated from ride log data, and CPoI locations are identified by applying DBSCAN clustering to remove noise. In the second stage of CPoI identification, facility names and category information around each CPoI are obtained using geographic information APIs, and this information along with CPoI area maps are presented to crowdsourcing participants to select the most appropriate facility as the actual destination

TABLE 1. Conceptual comparison of PoI, hidden PoI, and CPoI.

Characteristics	PoI	Hidden PoI	CPoI (This Study)
Target Users	General tourists	General tourists (especially photography enthusiasts, etc.)	Cyclists
Definition	Well-known locations of interest to many tourists	Locations with high tourism value despite low popularity	Locations reflecting cyclist stopping behavior characteristics
Characteristics of Extracted Locations	Large-scale tourist destinations, commercial facilities	Low-profile spots with high scenic value	Tourist destinations + practical facilities (roadside stations, convenience stores along main roads, rest facilities)
Extraction Methods	Check-in records, SNS data analysis	SNS image and rating data analysis	GPS ride log analysis + crowdsourcing evaluation

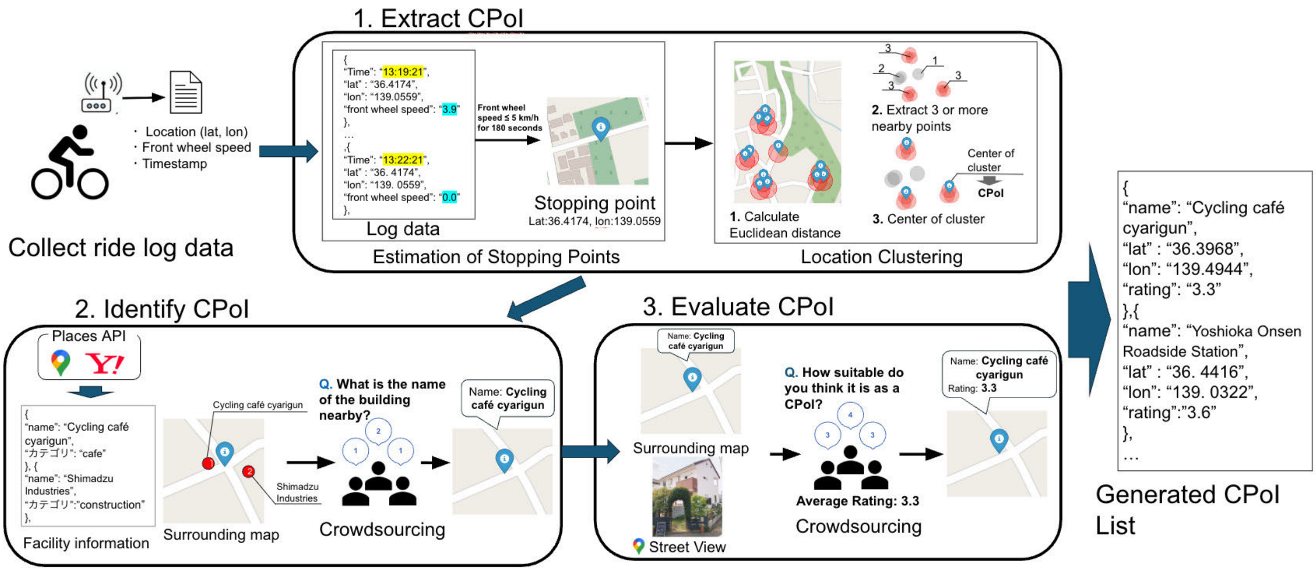

FIGURE 1. Overview of the proposed method.

cyclists stopped at from multiple candidate facilities. In the third stage of CPoI evaluation, the identified facilities are presented to crowdsourcing participants using area maps, facility information, and street view, and the attractiveness of the location for cyclists is evaluated on a 4-point Likert scale. Through this staged processing, the location, name, and evaluation of CPoIs can be obtained.

B. STOP POSITION ESTIMATION AND AUTOMATIC EXTRACTION BY CLUSTERING FROM GPS RIDE LOGS

1) STRUCTURE OF RIDE LOG DATA

Ride log data is recorded as time-series tracking data of each cyclist's movement. This data includes cyclist position information (latitude and longitude), bicycle speed information, and time information recorded at 1-second intervals.

2) STOP POSITION ESTIMATION

To extract meaningful CPoIs, it is necessary to first narrow down important points from ride log data. Since CPoIs are places for rest, sightseeing, and enjoying scenery, identifying cyclist stay locations is appropriate.

Stay locations are defined as GPS coordinates recorded when front wheel speed is below threshold v for t seconds or more.

Cich et al. [27], [28] adopted a time threshold of 180 seconds for stop detection from GPS traces and demonstrated its effectiveness. In this experiment, t was set to 180 seconds based on their research. Additionally, considering measurement errors, threshold v was set to 5 km/h. To verify the validity of these speed threshold v and settings of stay time threshold t, sensitivity analysis was conducted. Specifically, detection results were compared for a total of 12 combinations of $v \in \{3, 5, 10\}$ km/h and $t \in \{60, 120, 180, 240\}$ seconds.

Analysis results showed that the influence of speed threshold was limited, with no significant differences in final CPoI numbers observed in the range of v=3–10 km/h. In contrast, the influence of time threshold was prominent. At t=60 seconds, numerous stops that were not substantial rest or sightseeing activities, such as traffic light waiting and brief route confirmation, were detected, resulting in over-detection. At t=120 seconds, a tendency toward over-detection persisted, and numerous temporary stops at intersections and roadside locations without nearby facilities were detected. These do not qualify as attractive stopping points in the context of cycle tourism and constitute noise in CPoI extraction, warranting their elimination.

Conversely, at t=240 seconds, the risk of missing short but attractive stopping points was confirmed, and cases where convenience stores and roadside rest areas—locations where cyclists engage in brief rest and supply activities (3-4 *minutes*)—were excluded from detection were observed. At t=180 seconds, the balance between over-detection and missing detection was most favorable, enabling appropriate capture of stopping behavior in cycle tourism.

This result is also consistent with previous research on stop detection from GPS traces. Therefore, this study comprehensively considered sensitivity analysis results and findings from previous research, and adopted v=5 km/h and t=180 seconds as final parameters.

3) LOCATION CLUSTERING

Since GPS measurement can record the same location as different coordinates with several meters of error, clustering locations is necessary to determine CPoIs.

In selecting the clustering method, comparative experiments were conducted for hierarchical clustering, DBSCAN [29], OPTICS [30], and HDBSCAN [31]. Hierarchical clustering requires specifying the number of clusters in advance and lacks noise exclusion functionality, resulting in the problem of stop points at geographically distant different facilities being integrated into a single cluster. OPTICS is sensitive to minute changes in density, resulting in the problem of excessively dividing stop points at the same facility into separate clusters due to slight differences in parking positions. HDBSCAN emphasizes density continuity, resulting in the problem of integrating different facilities several hundred meters apart into the same cluster. In contrast, DBSCAN prevents excessive division and integration with clear distance constraints through radius ϵ, automatically excludes noise, and achieves both reproducibility of results and computational efficiency. Therefore, this study adopted DBSCAN.

DBSCAN is a method that forms clusters based on data point density. Specifically, first, Euclidean distances between each stop position are calculated, and points with minimum points *MinPts* or more neighbor points within set radius ϵ are identified as core points. Next, points directly density-reachable from core points are combined into the same cluster, and clusters are formed by repeating this process. Finally, points that do not belong to any cluster are excluded as noise, identifying final CPoIs.

In DBSCAN parameter setting, the values of ϵ and MinPts greatly affect cluster quality. This study conducted systematic preliminary experiments considering GPS measurement accuracy (within $\pm$10m) and bicycle parking range (approximately 50–100m from destination). For ϵ, multiple candidate values (30m, 50m, 75m, 100m) were validated, and while ϵ = 30m resulted in excessive division and ϵ = 100m resulted in excessive integration, ϵ = 50m achieved an appropriate balance. For *MinPts*, values of 2, 3, and 5 were validated, and while *MinPts* = 2 resulted in false detection of coincidental proximity and *MinPts* = 5 resulted in noise generation due to insufficient data, *MinPts* = 3 achieved appropriate balance. Based on these validation results, the combination of ϵ = 50m and *MinPts* = 3 was adopted.

C. CPoI IDENTIFICATION USING CROWDSOURCING

After narrowing down meaningful CPoIs from large amounts of ride log data, it is necessary to identify what buildings or facilities exist at each cluster. When there are multiple location candidates, it is necessary to select places that cyclists particularly prefer among them. This method uses Yahoo Crowdsourcing[1] for location identification. Crowdsourcing is excellent in that it enables inexpensive and objective evaluation by many participants and can efficiently collect judgments on geographical information [32], [33].

For evaluators to make appropriate judgments, not only place names but also specific category information is important. Therefore, this study adopts a hybrid strategy using both Yahoo! JAPAN Local Search API (Yahoo Local API)[2] and Google Places API.[3] Yahoo Local API provides detailed category information such as cuisine types and product categories of shops, enabling more accurate judgment of suitability as cyclist rest points. On the other hand, Google Places API covers a wide range of facilities and plays a complementary role for places that cannot be obtained with Yahoo Local API.

The specific identification procedure is as follows:

1) Calculate the center coordinates of each cluster.
2) Obtain area maps around the center coordinates.
3) Use Yahoo Local API to obtain lists of buildings and facilities near the center coordinates and their category information. When not obtainable with Yahoo Local API, supplement with Google Places API.
4) Through crowdsourcing platforms, present area maps to participants and have them select the most appropriate place from lists including facility names and category information.

The list of buildings and facilities selects the 5 closest ones within a 100m radius from the center coordinates. This considers that the bicycle parking position and destination may be separated, and that having more than 5 choices complicates judgment and may prevent appropriate responses.

[1] https://crowdsourcing.yahoo.co.jp/
[2] https://developer.yahoo.co.jp/webapi/map/openlocalplatform/v1/localsearch.html
[3] https://developers.google.com/maps/documentation/places/

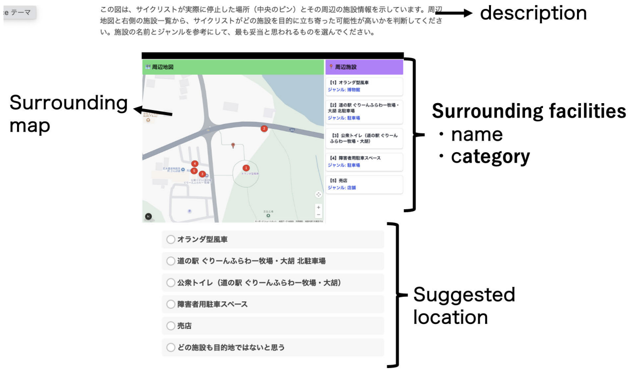

FIGURE 2. Sample Crowdsourcing Interface for CPoI identification.

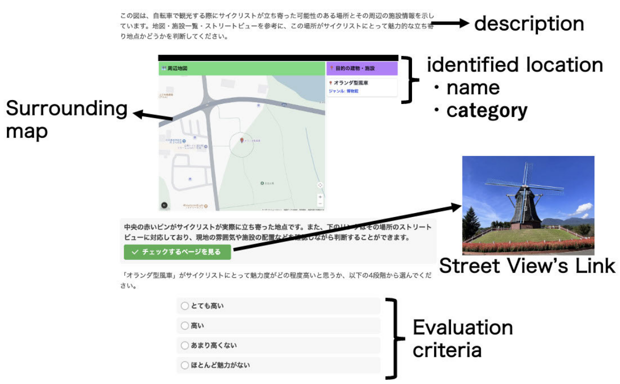

FIGURE 3. Sample crowdsourcing interface for CPoI evaluation.

1) DESIGN OF IDENTIFICATION CROWDSOURCING INTERFACE

To support facility identification by participants, we designed a crowdsourcing interface as shown in Figure 2. The screen consists of explanatory text at the top, images serving as judgment materials in the center, and choices at the bottom. The explanatory text at the top requests participants to infer cyclist stopping purposes based on stop point and surrounding facility information, providing contextual information for appropriate judgment. In the center image section, the left side displays a map around the stop point, with the actual cyclist stop point shown at the center of the map. Candidate facility positions are displayed with numbered markers. The right side lists facility names and category information, allowing participants to understand the surrounding situation in detail through correspondence with marker numbers. At the bottom of the screen, choices are presented, and participants select the facility they consider most appropriate as the cyclist's actual destination from the presented candidate facilities. When none of the presented candidates are judged appropriate, we provide the choice "I don't think any of these facilities are the destination", enabling flexible participant judgment.

D. CPoI EVALUATION USING CROWDSOURCING

It is necessary to evaluate whether identified CPoIs are actually attractive places for cyclists, but appropriate evaluation is difficult with conventional methods due to insufficient data such as check-in records and reviews commonly used as evaluation indicators.

Therefore, this study conducts CPoI evaluation using crowdsourcing. Crowdsourcing is widely used in situations such as evaluating hidden spots with little data [20] and efficiently collecting human judgments on geographical information in images [32], [33], and is considered an appropriate method for this study that requires objective evaluation from many users. Specifically, maps centered on places identified in Section III-C and facility category information are presented to participants, who evaluate the degree of attractiveness of the location for cyclists on a 4-point Likert scale (Table 2).

TABLE 2. CPoI evaluation criteria.

Rating	Attractiveness for Cyclists
4	Very high
3	High
2	Not very high
1	Almost no attraction

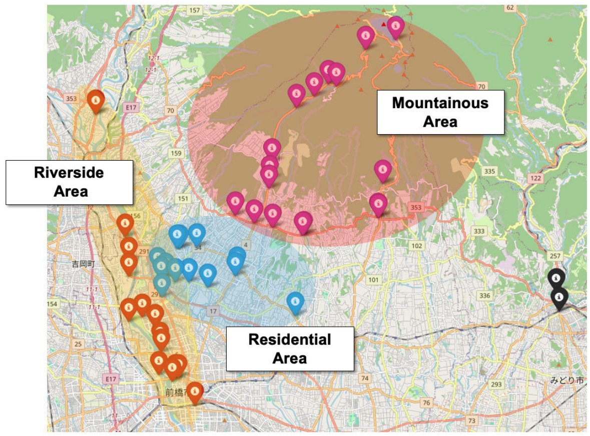

FIGURE 4. Distribution map of detected CPoIs.

1) DESIGN OF EVALUATION CROWDSOURCING INTERFACE

To support appropriate evaluation by participants, we designed an evaluation crowdsourcing interface as shown in Figure 3. The screen consists of explanatory text at the top, followed by images serving as judgment materials, links to street view, and evaluation choices at the bottom.

The explanatory text at the top requests participants to evaluate the attractiveness for cyclists of facilities identified in Section III-C, clearly indicating evaluation perspectives. In the image section, the left side displays an area map centered on the identified facility, and the right side displays the target facility's name and category information. This allows participants to understand facility positional relationships and basic information.

Furthermore, street view links are provided, allowing participants to view detailed scenery and surrounding environment of the target location by clicking. This enables visual understanding of local atmosphere and facility conditions that are difficult to grasp from map information alone. At the bottom, choices are configured for participants to evaluate the attractiveness of the location for cyclists on a 4-point Likert scale (Table 2).

IV. EVALUATION EXPERIMENT

A. EXPERIMENT OVERVIEW

The purpose of this experiment is to demonstrate that the proposed CPoI identification and evaluation method can provide practical and reliable results.

Specifically, we aim to clarify the following three points:

1) Whether CPoIs automatically extracted from GPS ride logs are valid as stopping points where cyclists actually feel value
2) Whether the crowdsourcing-based facility identification method can accurately identify specific facilities of CPoIs
3) Whether crowdsourcing-based attractiveness evaluation is consistent with expert judgment and actual cyclist needs

To verify these points, we designed an experiment consisting of large-scale data collection in Maebashi City, Gunma Prefecture, three-stage CPoI identification and evaluation experiments, and validation by regional tourism association experts.

B. EXPERIMENT TARGET

This study targets rental bicycles operated starting from Michi-no-Eki Maebashi Akagi in Maebashi City, Gunma Prefecture. As target data, we collected ride log data by having cyclists (participants) freely tour the surrounding area. Data collection was conducted from April to December 2023, and experimental cooperation was requested from all users who used rental bicycles at Michi-no-Eki Maebashi Akagi, targeting all users who provided consent. As a result, the total number of participants was 286, and participant age groups were widely distributed from their 20s to 60s.

Participants were limited to those who received explanations about research purposes and data use when using rental bicycles and gave written consent for GPS tracking ride data recording and research use. Participants were not given specific routes but were asked to freely cycle in the surrounding area starting from Michi-no-Eki Maebashi Akagi. Ride data was automatically recorded at 1-second intervals by GPS devices mounted on bicycles, including position information (latitude and longitude), front wheel speed, and time information, and data was collected after cycling completion.The collected data includes complete travel routes from departure to return.

C. CPOI IDENTIFICATION AND EVALUATION EXPERIMENT

We conducted the following three-stage experiment on the collected ride log data.

First, we applied the stop position estimation method described in Section III-B2 and the DBSCAN clustering method in Section III-B3 to automatically detect CPoI candidates.

Next, following the method described in Section III-C, we conducted facility identification using the Yahoo crowdsourcing platform. We assigned 10 participants to each CPoI, presented area maps and facility category information, and had them select the most appropriate place from presented candidates, determining final facilities by majority vote.

Finally, following the method described in Section III-D, we conducted attractiveness evaluation from cyclists' perspectives using crowdsourcing for identified CPoIs. We assigned 10 participants to each CPoI, presented maps centered on identified locations, facility information, and street view links, and had them evaluate on the 4-point Likert scale shown in Table 2. Evaluation results were averaged to obtain attractiveness scores for each CPoI.

These experiments were conducted in June 2025.

D. EXPERT VALIDATION

To further validate the practicality and validity of the proposed method, we conducted face-to-face interview surveys with three experts from the regional tourism association. The validation target was all 48 CPoIs identified and evaluated through the above experiments, and we requested binary evaluation (appropriate/inappropriate) from the following three perspectives:

- **Validity of CPoI selection**: Appropriateness of the location being selected as a cyclist stopping point
- **Accuracy of identification results**: Correctness of crowdsourcing facility identification results
- **Credibility of evaluation results**: Validity of crowdsourcing attractiveness evaluation

Validation was conducted in July 2025. The validation procedure was as follows. First, we confirmed the position of each CPoI on maps and had experts explain actual conditions based on their local knowledge. Next, we presented crowdsourcing identification and evaluation results and requested evaluation from the three perspectives by comparing with experts' experience. Final validity judgment considered cases where two or more of the three experts evaluated as "appropriate" as valid. We also collected detailed opinions and improvement suggestions for each CPoI.

V. EVALUATION RESULTS

This chapter describes results based on the three perspectives mentioned in Section IV-A and opinions obtained from experts.

A. RESULTS ON VALIDITY OF CPoI DETECTION

As a result of applying the proposed method, 977 CPoI candidates were extracted as stop positions where speed was 5km/h or below for 180 seconds or more. Applying density-based clustering using DBSCAN ($\epsilon = 50$m, $MinPts = 3$) to these candidates resulted in the detection of 48 CPoIs.

Figure 4 shows the positional relationships of detected CPoIs on a map. The distribution of CPoIs by distance from the starting point (Michi-no-Eki Maebashi Akagi) showed 16 locations (33.3%) within 0–3km, 7 locations (14.6%) within 3–5km, 13 locations (27.1%) within 5–10km, 8 locations (16.7%) within 10–15km, and 4 locations (8.3%) beyond 15km, distributed over a wide range from around the starting point to distant areas.

Examining location patterns, 13 locations (27.1%) were distributed in the Residential Area (approximately within 5km from the starting point), 15 locations (31.3%) in the Riverside Area (from along the Tone River toward the Maebashi urban area), 17 locations (35.4%) in the Mountainous Area (toward Mt. Akagi), and 3 locations (6.3%) in other distant areas. The concentration in the Mountainous Area and the Riverside Area indicates that natural scenery and comfortable riding environments are important stopping factors in cycle tourism.

Expert validity validation results showed that 43 out of 48 locations (89.6%) were evaluated as valid cyclist stopping points (Table 4). Questions were raised about the selection rationale for the remaining 5 locations.

B. RESULTS ON ACCURACY OF FACILITY IDENTIFICATION METHOD

As a result of crowdsourcing identification experiments, specific location names were identified for 45 out of 48 CPoIs (93.8%). Facilities determined by majority vote spanned a wide range including tourist spots, dining facilities, public facilities, and commercial facilities. The remaining three locations (6.3%) were confirmed to be road points where no specific buildings or facilities existed nearby.

Expert validation of identification result accuracy showed agreement with expert expectations for 34 out of 48 locations (70.8%) (Table 4). For the 14 locations with disagreement, it became clear that there were differences in facility selection perspectives between crowdsourcing participants and experts.

C. RESULTS ON RELIABILITY OF ATTRACTIVENESS EVALUATION

As a result of evaluation experiments on 45 identified CPoIs, evaluation values ranged from 1.4 to 3.7, with a mean evaluation of 2.73 and a standard deviation of 0.54.

As distribution characteristics, the most CPoIs (15 locations, 31.3%) were concentrated in the 2.7–3.0 evaluation range, followed by nine locations (18.8%) in the 2.4–2.7 range. CPoIs receiving high evaluations of 3.0 or above numbered 17 locations (35.4%), while CPoIs receiving low evaluations below 2.0 were limited to six locations (12.5%).

The mean value of 2.73 and median value of 2.75 were nearly identical, confirming no significant bias in evaluations. Furthermore, the standard deviation value of 0.54 indicates that relatively consistent evaluations were obtained among crowdsourcing participants. Facility analysis by evaluation band revealed that the high evaluation band (3.0 or above) contained a mixture of facilities leveraging regional characteristics (roadside stations, specialized cafes, etc.) and strategically located convenience stores. The medium evaluation band (2.4–3.0) was predominantly occupied by practical rest facilities, while the low evaluation band (below 2.0) included roadside locations where facilities could not be identified and places with limited attractiveness in surrounding environments.

Table 3 shows the top 10 highest-evaluated CPoIs.

Expert validation of evaluation result credibility confirmed consistency with expert field experience for 46 out of 48 locations (95.8%) (Table 4). Particularly for highly-evaluated CPoIs, they matched locations with high actual cyclist usage frequency and facilities with good reputation among local residents.

D. VERIFICATION OF INTER-RATER RELIABILITY

To verify the reliability of attractiveness evaluation through crowdsourcing, inter-rater consistency was quantitatively evaluated. This study collected evaluations from 10 raters for each of 48 CPoIs and conducted reliability analysis using ICC Consistency [34]. ICC Consistency is an index that measures the degree of agreement in relative patterns among raters and is suitable for analyzing subjective location evaluation in that it does not consider differences in individual rater strictness. This index has been shown to be effective in verifying the reliability of subjective evaluation through crowdsourcing [35].

This study calculated $ICC(C, k)$, which indicates the reliability of the average of 10 raters, based on a two-way random effects model. As a result of calculation, a value of $ICC(C, k) = 0.837$ was obtained. According to Cicchetti's [36] interpretation criteria (Poor: < 0.40, Fair: 0.40–0.59, Good: 0.60–0.74, Excellent: ≥ 0.75), the average of 10 raters showed excellent reliability.

This result demonstrates that in subjective evaluation through crowdsourcing, using the average of multiple raters offsets individual differences and can achieve high reliability. The excellent reliability of $ICC(C, k) = 0.837$ indicates that the design of 10 raters in this study was appropriate, and it was confirmed that CPoI evaluation using crowdsourcing can achieve high reliability.

E. EXPERT OPINIONS ON THE PROPOSED METHOD

Experts provided the following evaluations and improvement proposals for the proposed method.

Regarding method effectiveness:

- The extracted convenience stores were all locations that cyclists would naturally stop at when touring by bicycle
- Places with high demand for cyclists, such as cycling cafes and local light meal shops along main roads, were appropriately identified
- It was confirmed that there is demand even for small-scale cultural elements like roadside dosojin (guardian deities) not included in conventional tourist guides

TABLE 3. Top 10 highest rated CPoIs.

Rank	Place Name	Category	Rating
1	Umaimon-dokoro Rokusai Chaya	Cafe/Restaurant	3.7
2	Michi-no-Eki Yoshioka Onsen	Roadside Station	3.6
3	Food Corner	Restaurant	3.5
4	Michi-no-Eki Maebashi Akagi Tourist Information	Travel Agency	3.3
5	Seven-Eleven Maebashi Fujimi Tajima Store	Convenience Store	3.3
6	Cycling Cafe Charigun	Cafe/Restaurant	3.2
7	Seven-Eleven Maebashi Komagata Inter Store	Convenience Store	3.2
8	Kuwafuan Main Store	Japanese Food/Soba	3.2
9	Misai	Udon/Rice Bowl	3.1
10	Dutch Windmill	Museum	3.1

TABLE 4. Detailed expert validation results for 48 CPoIs.

Evaluation Item	Agreements	Disagreements	Agreement Rate(%)
Validity of CPoI Selection	43	5	89.6
Accuracy of Identification Results	34	14	70.8
Credibility of Evaluation Results	46	2	95.8

Suggestions for future improvement:

- Improving the accuracy of crowdsourcing facility identification is an important challenge, requiring construction of mechanisms to support more appropriate facility selection
- Building systems considering seasonality would enable information provision reflecting temporal attractions such as flower viewing seasons and autumn foliage periods
- For locations where many cyclists stop despite having no specific facilities, elucidating attraction factors other than facilities, such as scenic beauty and rest comfort, is expected to develop new tourist resource discovery methods

These results indicate that the proposed method can identify and evaluate CPoIs with high accuracy while having some room for improvement.

VI. DISCUSSION

A. CHARACTERISTICS AND VALIDITY OF IDENTIFIED CPoIs

The high level of 89.6% validity in CPoI selection demonstrated in expert validation proves that the proposed method appropriately captures actual cyclist stopping behavior.

Analysis of the 48 identified CPoIs revealed that many practical facilities such as convenience stores, roadside stations, public toilets, and rest areas were included. These facilities are often excluded from conventional tourist destination selection and general PoI research. However, tourism association experts evaluated that "not merely practical facilities, but strategically located places with high bicycle accessibility that cyclists want to stop at were effectively extracted".

As shown in Table 1, general PoI research and Hidden PoI research analyze locations where users intentionally check in or post photos. Since cyclists do not bother to post convenience store rest stops on SNS, even frequently used stopping points cannot be detected by conventional methods. This study discovered such "places that are not posted but actually used" through GPS automatic recording and crowdsourcing evaluation. As a result, practical facilities such as Seven-Eleven Maebashi Fujimi Tajima Store (evaluation 3.3/4.0) received high evaluations. Experts commented that "places where cyclists tend to stop when touring by bicycle were well extracted", confirming the effectiveness of the proposed method.

Additionally, cyclist-specialized facilities such as "Cycling Cafe Charigun" were also identified, successfully discovering facilities with specialized demands often overlooked in conventional PoI research.

These results indicate that valuable places for cyclists differ significantly from conventional tourist destination concepts. The bottom-up approach based on actual user behavior revealed that even places not recognized as commercial tourist resources can function as important stopping points in cycle tourism. This finding shows that CPoI is a new concept with essentially different characteristics from conventional PoIs, suggesting the need to redefine tourist resources in cycle tourism promotion.

On the other hand, identified CPoIs included road points and locations without specific facilities. These correspond to cases questioned in selection validity evaluation. However, reasons why cyclists stop at places without facilities could include scenic beauty, suitable rest environment, response to road condition changes, and route confirmation needs. This suggests that CPoIs may have environmental and situational value independent of physical facilities.

For addressing such "facility-less CPoIs", introducing evaluation criteria considering environmental factors (scenery, ventilation, safety, etc.) and multifaceted analysis combining GPS with other sensor data would be effective. Additionally, these locations may have large seasonal and weather variations, and accumulating time-series data is expected to enable more accurate CPoI identification.

B. DETAILED ANALYSIS AND IMPROVEMENT STRATEGIES FOR IDENTIFICATION ACCURACY

Regarding crowdsourcing facility identification where expert agreement rate remained at 70.8%, analysis during the experimental process revealed the following four main factors.

First, limitations in information acquisition due to API constraints existed. Cases where target locations were outside the scope of Google Maps or Yahoo Local API were confirmed. Particularly for small-scale regional facilities and privately-owned shops, cases where these APIs could not obtain information were observed. Moreover, for natural terrain with scenic value such as ponds and scenic viewpoints, problems arose where they could not be presented as candidates because they were not included in API search scope.

Second, insufficient granularity of position information in large-scale facilities had an impact. Cases occurred where facilities existed within the target range but did not appear as choices because they were not within 100m of center coordinates. This was prominent in large-scale facilities, where facility names were linked to only parts of facilities, causing problems where choices did not appear even when actually within facilities.

Third, qualitative inconsistency in information presentation in task design existed. Specifically, quality differences in street view, namely outdated image capture dates or inappropriate capture positions, were confirmed, which may have caused information bias. Moreover, insufficient granularity of facility name and category information suggests that structural understanding of complex facilities may have been difficult.

Fourth, inconsistency in facility selection due to differences in evaluation perspectives was confirmed. Participants tended to select restaurants or specific service locations within facilities rather than facility names. For example, strong tendencies were observed to select specific restaurants or cafes within roadside stations rather than the entire roadside station. Conversely, tourism association experts emphasized the tourism value of entire facilities and expected selection of more comprehensive facility names.

Multiple approaches can be considered as improvement strategies for these challenges. For facilities outside API scope, utilizing spatial crowdsourcing that can request tasks from participants who can actually visit locations would be effective [32]. For position information challenges in large-scale facilities, system design considering detailed position information within facilities through dynamic search radius adjustment and hierarchical facility information presentation is required. For qualitative challenges in information presentation in task design, standardized presentation of facility images from multiple perspectives and structuring hierarchical facility information would be effective. For participant selection tendencies, clarifying evaluation criteria in crowdsourcing tasks [33] and constructing multilayered evaluation frameworks integrating user perspectives and tourism promotion perspectives are important.

C. EFFECTIVENESS AND IMPROVEMENT POINTS OF CROWDSOURCING EVALUATION

Regarding attractiveness evaluation through crowdsourcing, credibility with experts showed a very high agreement rate of 95.8%. This result demonstrates that evaluations by unspecified multiple participants unfamiliar with regions can highly agree with judgments by experts familiar with local conditions. This suggests that attractiveness of places for cyclists tends to be judged based on universal convenience and scenic value rather than region-specific knowledge.

This finding supports that crowdsourcing advantages [20] are extremely suitable for CPoI evaluation. Particularly, it was demonstrated that collective intelligence can appropriately evaluate the value of practical facilities often overlooked in conventional tourist destination evaluation.

However, detailed analysis of evaluation results revealed challenges requiring improvement. Analysis of factors in CPoIs receiving low evaluations identified three patterns. First, in locations where no buildings existed nearby, participants could not recognize evaluation targets from only maps and street views, resulting in low evaluations. Second, cultural facilities with value only to specific groups, such as roadside monuments and churches, received low evaluations because they did not satisfy practical needs common to many cyclists. Third, cases were confirmed where facilities different from actual stopping purposes were evaluated due to facility identification errors. For example, in a case where a stop at a convenience store was misidentified as a nearby mailbox, it was evaluated as the attractiveness of the mailbox, resulting in a low evaluation.

To further enhance evaluation accuracy, the following improvement points are identified. First, cases where judgment was difficult based only on location names or street view were observed. Characteristics such as scenic beauty and rest comfort require detailed information presentation of surrounding environments and images from multiple perspectives.

Addressing various heuristics affecting human judgment is also important [37], [38]. Anchoring effects where participants are influenced by initially presented evaluation criteria, availability heuristics based on personal experience, and superficial judgments due to representativeness heuristics regarding "tourist-like appearance" may affect evaluations.

To address these challenges, clarifying evaluation criteria and introducing multifaceted evaluation would be effective. Specifically, setting evaluation criteria from multiple specific perspectives such as "ease of bicycle parking", "completeness of rest facilities", and "scenic attractiveness" would enable more objective and practical evaluation.

Additionally, for practical implementation of this research, ensuring privacy protection and data integrity in data collection is also an important challenge. Since GPS ride logs contain detailed individual behavior patterns [39], data must be collected with participant consent.

Moreover, technical constraints regarding data integrity exist, such as GPS measurement errors [40] and data loss due to communication errors. Furthermore, although this study adopts a method in which GPS data is collected after the completion of each ride, extending the system to one that collects and processes data from multiple GPS devices in real time would necessitate careful consideration of cybersecurity risks associated with network-based data collection. For instance, incorporating insights from studies on robust control against communication delays, packet loss, and false data injection attacks [41], adaptive control mechanisms for multiple devices under DoS attacks [42], and H_∞ fuzzy control against deception attacks on sensor data [43], such as event-triggered control and robust security control protocols, would provide a pathway toward developing a more resilient CPoI identification system capable of withstanding malicious data injection and communication disruptions. Addressing these limitations is positioned as an important future research challenge for social implementation of this method.

VII. LIMITATIONS AND FUTURE CHALLENGES

A. DATA GENERALIZABILITY AND GEOGRAPHICAL CONSTRAINTS

The main contribution and significance of this study lies not in establishing universal applicability, but in the formal definition of CPoI as a new concept representing cyclist-specific stopping behavior different from general tourism patterns, and the demonstration of a method for semi-automatically identifying and evaluating these CPoIs by combining actual GPS log data and crowdsourcing technology. This study provides the first systematic framework for CPoI identification and has been validated with high accuracy (89.6% for CPoI selection validity and 95.8% for evaluation result credibility) through expert validation in actual environments.

However, the experiments of this study depend only on data from 286 cyclists collected in Maebashi City, Gunma Prefecture, from April to December 2023. Due to these geographical and temporal constraints, there are limitations to the generalizability of this study's findings.

The proposed method was validated in the specific regional environment of Maebashi City, which is characterized by a temperate climate and well-developed cycling infrastructure, using data collected over a nine-month period from April to December 2023. Therefore, in regions with different climatic conditions, topography, or tourism resources, cyclist stopping behavior may differ substantially from that observed in this study, and there are limitations to directly applying these findings to other geographical, climatic, or cultural contexts.

Therefore, validating this method in multiple regions with various geographical, climatic, and cultural characteristics and adapting it as necessary is an important direction for future research. Such multi-regional research would establish broader applicability of this approach and clarify regional adaptations necessary for the CPoI identification and evaluation framework. This extension is expected to enhance the practical utility of this method for diverse cycle tourism promotion measures worldwide.

B. SCALE OF EXPERT EVALUATION AND FUTURE DEVELOPMENTS

In this study, validation by three experts from the regional tourism association was conducted. Although this sample size is small, the purpose of expert validation in this study was to evaluate the practical utility of the proposed system from actual user perspectives. The proposed system is intended for use by tourism promotion organizations such as regional tourism associations, and it was important to conduct evaluation from both the perspectives of tourism associations providing the system and crowdsourcing participants generating information.

In the future, it is necessary to more rigorously validate the versatility of the proposed method through large-scale evaluation targeting tourism association experts in multiple regions.

VIII. CONCLUSION

This study proposed a method for semi-automatically identifying and evaluating CPoIs from cyclist ride log data. The proposed method consists of three stages: automatic extraction using stop position estimation from GPS ride logs and DBSCAN clustering, facility identification using crowdsourcing, and evaluation using crowdsourcing.

As a result of applying the proposed method to ride data from 286 cyclists collected in Maebashi City, Gunma Prefecture, 48 CPoIs were identified and evaluated, and expert validation confirmed high agreement rates of 89.6% for CPoI selection validity and 95.8% for evaluation result credibility.

It was demonstrated that CPoIs defined in this study have essentially different characteristics from conventional PoIs. While conventional PoIs center on large-scale tourist destinations and commercial facilities emphasizing popularity and scale, CPoIs differ significantly by including practical facilities and cyclist-specialized facilities. These facilities are in strategic locations and have unique value simultaneously satisfying cyclist supply and rest needs and tourism experiences.

This CPoI concept holds important significance for cycle tourism promotion. First, it shows the possibility of utilizing small-scale and diverse regional resources often overlooked as tourist resources. Second, by balancing practicality and tourism value, it becomes possible to provide more attractive and practical tourism experiences for cyclists. Third, discovering new tourist resources independent of existing tourism infrastructure enables maximum utilization of regional potential tourism resources.

However, challenges to be addressed in the future were also clarified, such as improving crowdsourcing facility identification accuracy (70.8%) and confirming versatility limited to validation in a single region. For these challenges, effective improvement strategies are expected including utilizing spatial crowdsourcing, conducting multi-regional validation experiments, and constructing dynamic evaluation systems considering seasonality.

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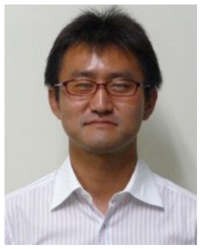

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