Estimating and Leveraging Latent Social Demand Based on IoT sensors: An Empirical Study in a Large Public Park

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***Abstract*—The continuously changing conditions of cities are now technically understandable in the information space through real-world sensing methods and analytical methods such as big data analysis and machine learning. On the other hand, it is currently difficult to estimate and present what the people in the city need (latent demand). This paper aims to solve latent demand by developing *Latent Demand Resolver* (LD-Resolver), the new latent demand estimation and exchanging system. LD-Resolver has two components, *Latent Demand Extractor* (LD-Extractor) and *Latent Demand Exchanger* (LD-Exchanger). LD-Extractor extracts a latent demand from various social conditions using IoT sensors, Web, and SNS. LD-Exchanger has a new structure to exchange a latent demand with an appropriate service supply. Finally, we developed the LD-Resolver and conducted a demonstration experiment at the Higashiyama Zoo and Botanical Garden to verify the method. As a result of the two-week experiment, the proposed method can be effectively used in actual facility operations.**

***Index Terms*—IoT, Smart City, Social Demand Estimation, Demand-Supply Exchange**

I. Introduction

Today, urban cities face serious social issues in many fields, such as traffic congestion, health care, and worker shortage. We should efficiently allocate limited human, physical, and computational resources to meet the demands of these issues. For this purpose, it is essential to identify social demands and to provide appropriate services to meet those demands.

It is necessary to develop IoT technologies that enable detailed sensing of people's situations and advanced analysis of the obtained data. Crowdsensing and participatory sensing can understand the situation and collect their opinions [1]–[4]. However, what we need for providing service is not the people's situation but the people's demand. We can currently only grasp the people's situation from the information space, and service providers' insight determines the demand.

For example, if many people who want to go to the station are waiting for cabs, there are many demands "I want to go to the station". It is very inefficient to meet these demands one by one with cabs in terms of human and physical resources. If a bus company provides a temporary bus, many demands will be satisfied simultaneously. No framework currently can identify and satisfy demands in this way. However, such a framework can be used in various social situations.

In an upcoming society, it is necessary to predict not only an apparent demand but also a latent demand buried in society. It is also needed to realize a system that can provide appropriate services to consumers. Therefore, we aim to develop *Latent Demand Resolver* (LD-Resolver) to understand and solve a wide variety of demands as shown in Fig. 1.

LD-Resolver has two components, *Latent Demand Extractor* (LD-Extractor) and *Latent Demand Exchanger* (LD-Exchanger). LD-Extractor extracts a latent demand from various social conditions. In demand extraction, we organize the types of demands into several domains and formalize the demands to make them easily processable by computers. We can easily perform the flexible division, aggregation, exchange, and classification on formalized demands. Also, we can use the same program for many service providers, leading to cost reduction in the future. In order to extract latent demand, it is necessary to capture minute changes in the real-world environment. We can do this by installing many IoT sensors in a city. In addition, we incorporate information from the information space, such as the Web and SNS. Therefore, LD-Extractor estimates a latent demand based on the data from real and information space.

LD-Exchanger is the demand exchange system for latent demand. In direct demand and supply exchange, service users and providers act as a pair to exchange demand and supply. However, since service users are not unaware of latent demand, LD-Exchanger conveys a demand from LD-Extractor to service providers. LD-Exchanger should also offer flexibility to add or remove service providers at any time.

Finally, we developed and deployed LD-Resolver in Higashiyama Zoo and Botanical Garden to verify the effectiveness of the proposed method. We extracted latent demand from person flow estimated from the Wi-Fi packet sensors' data and social information from Web and SNS. We also exchange

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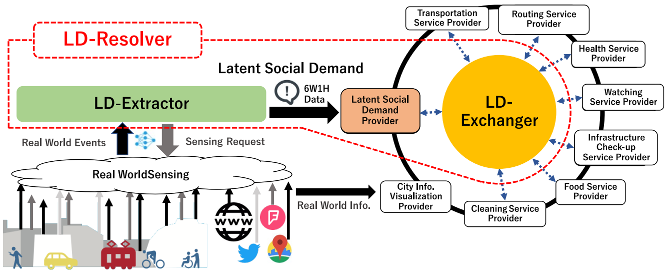

Fig. 1. Overview of the LD-Resolver

TABLE I
DOMAINS OF LATENT DEMAND

No.	Domain
D1.	Electricity, gas, water, steam and air conditioning supply
D2.	Waste management and remediation activities
D3.	Wholesale and retail trade
D4.	Transportation and storage
D5.	Accommodation and food service activities
D6.	Information and communication
D7.	Public administration and defence; compulsory social security
D8.	Human health and social work activities
D9.	Arts, entertainment and recreation

latent demand and service supply using Synerex [5], [6], which is designed to support flexible demand-supply exchange for Society 5.0, and provide services through signage displays. As a result of the demonstration experiment of the proposed method over two weeks, it was shown that the proposed method could be effectively used in actual facility operations.

The contributions of this paper are as follows.

- We present a method to extract latent social demands with a unified format by analyzing IoT data.
- We design and implement a process model that fulfills latent demands by exchanging extracted demands and services that solve the demand.
- We deployed the proposed system in Higashiyama Zoo and Botanical Garden, a large public park in Japan, and verified its effectiveness.

The rest of this paper is as follows. We will explain the detail of LD-Resolver in Section II, and show our field deployment in a large public park in Section III. We also show the experimental result from our deployment in Section IV, and introduce related work in Section V. Finally, we conclude our contribution and future work in Section VI.

II. LD-RESOLVER

We propose *Latent Demand Resolver* (LD-Resolver) to understand and solve latent demand. LD-Resolver has two components, *Latent Demand Extractor* (LD-Extractor) and *Latent Demand Exchanger* (LD-Exchanger), and we will explain them in this section.

A. LD-Extractor

LD-Extractor extracts a latent demand from various social conditions. First of all, to make it possible to process a wide variety of demands on a computer, we classify the demands into several domains and formalize them so that they can describe the contents, such as 6W1H. LD-Extractor collects the data from IoT sensors, Web, and SNS to capture minute changes in social conditions. Then, LD-Extractor predicts a latent demand based on the collected information and extracts the formalized latent demand.

1) Formalization of Demand: We formalize demand to represent various kinds of demand in a unified manner and enable flexible processing by computers. The formalization of demand facilitates the exchange of supply and demand in the information space. There are also several benefits such as:

- We can easily "classify" demands to a certain domain.
- When many people have the same demand, we can "aggregate" those demands and provide a service supply that solves them at all once.
- We can also "divide" the demand and solve it by multiple service providers.

First of all, to organize the various demands and make it easier to connect them with service providers, we categorized the demands into several domains, as shown in Table I. Considering the future international deployment of the proposed system, we classified the demands into nine domains based on the 21 industry classifications of the International Standard Industrial Classification [7].

Next, below is the explanation of the format for describing demand. Demand can be expressed in terms of 5W1H information such as "when," "where," "who," "what," "whom," and "how." In addition, it will be more helpful for service providers if the information on "why" this demand arises is included. Furthermore, since each demand has various levels of granularity (e.g., individual or group, and city or prefectural level), it is thought that the granularity should be included as well. Therefore, we formalize the demand in a format that can describe this 6W1H, granularity, and domain information.

Although there are various methods for formalizing data, we will use the JSON-LD format in this paper. This format provides encoding and decoding functions as standard libraries in many programming languages. Fig. 2 is an example of the demand formalized in JSON-LD format. In Fig. 2, 'name' and 'description' represent "What," "Whom," and "How," 'date' represents "When," 'location' represents "Where" and granularity, 'demandFrom' represents "Who," 'evidence' represents "Why," and 'domain' represents the domain.

2) Information sensing and demand extraction: In order to extract the latent demand for services, it is essential to capture minute changes in the real-world environment. For this purpose, we develop an efficient and low-cost method for sensing the real world. It is possible to obtain real-world information by placing IoT sensors in the real world and directly sensing it. However, this requires a large amount of installation and operation costs. Therefore, in addition to IoT sensors, we also incorporate information from the information space, such as the Web and social network services (SNS), to perform information sensing in real space and the information

```
{
  "@context": "https://schema.org",
  "@type":"LatentDemand",
  "name":"need weather info",
  "date":"2021-05-01T12:34:56.000Z",
  "location":{
    "@type":"Place",
    "latitude":"35.159090",
    "longitude":"136.973958",
    "name":"Seimon",
    "address":{
      "@type": "PostalAddress",
      "addressLocality": "Chikusa, Nagoya",
      "addressRegion": "Aichi",
      "streetAddress": "3-70 Higashiyama Motomachi"
    }
  },
  "domain":{
    "@type":"LatentDemandDomain",
    "domainID":"6",
  },
  "description":"weather information is needed",
  "demandFrom":"visitor",
  "evidence":"unstable weather of today"
}
```

Fig. 2. Example for JSON-LD message format

space. Based on the obtained sensing data, we extract the latent social demand (e.g., when the temperature becomes high, the demand for cold drinks and cool places may increase) and output it in the form described in the previous section. We can use various methods for extracting latent demand, including rule-based methods and ML-based methods. We can define a rule which assumes that a particular demand has occurred when a certain sensor value (e.g., temperature, brightness, or population) exceeds or falls below a pre-defined level. ML-based methods such as LSTM [8], [9], CNN, RNN [10] are seemed to be able to estimate more accurate occurrences of demands as described in related work. We can also analyze the feeling of people in society in real-time from information on SNS and Web using text mining and search word analysis [11], [12]. Applying these methods on IoT sensor data, SNS, and numerous open data on the Web, we have a possibility to uncover accurate latent demand. However, this paper focuses on the latent demand and supply exchange method described below and adopts a simple rule-based approach for latent demand extraction.

B. LD-Exchanger

We develop LD-Exchanger that exchanges a latent demand with an appropriate service supply. To satisfy the latent demand obtained in the previous section, service users should receive service supply from service suppliers. In the direct demand-supply exchange, the service user is the source of the demand, as shown on the left side of Fig. 3. On the other hand, since service users themselves are not aware of latent demand, the source of it cannot be service users. Therefore, LD-Exchanger receives a latent demand from LD-Extractor and exchanges service supply between users and suppliers, as shown on the right side of Fig. 3.

LD-Exchanger is connected to the followings:

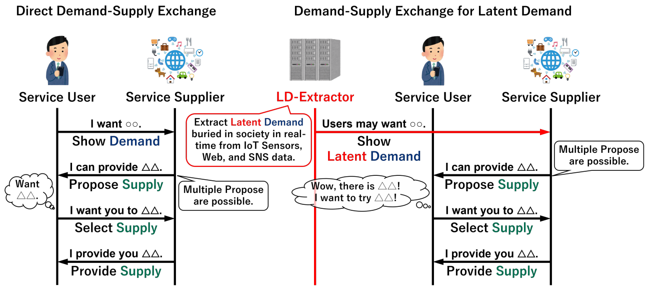

Fig. 3. Demand and supply exchange mechanism

- LD-Extractor
- Websites or smartphone applications for service users
- Systems of service providers

In this network, they communicate in a Pub/Sub format. First, when a latent demand is extracted to have occurred by LD-Extractor, LD-Extractor publishes the formalized demand to LD-Exchanger. Next, service providers receive the published demand and determine whether each service provider can supply the service for the demand. The systems of service providers that are deemed to be capable of providing the service will suggest the service supply to the users via websites and smartphone applications. Using them, the service user can select the service they feel necessary from the proposed service supply. Suppose a service user selects a particular service here. In that case, we build a communication channel that allows the user to exchange more detailed information (e.g., the user's precise location) with the system of the selected service supplier directly.

To make LD-Exchanger flexible, LD-Exchanger should allow LD-Extractor, the website and smartphone applications for service users, and the service provider's system to be added to or removed at any time. In this way, when a new service provider is added in the future, the provider's systems and websites can be added without stopping LD-Exchanger. Furthermore, when one of the connected providers stops due to its failure, we can continue using LD-Exchanger.

III. Field Deployment

We deployed LD-Resolver in the Higashiyama Zoo and Botanical Garden and conducted a demonstration experiment.

A. Purpose of experiment

The purpose of this experiment is as follows.

- To develop and operate LD-Extractor based on information from IoT sensors and the Web and evaluate the feasibility of extracting latent demand.
- To develop and operate LD-Exchanger to satisfy latent demand and evaluate whether demand and supply can be exchanged between service providers and users.

In this experiment, we define in advance the latent demands that can be estimated from the limited social conditions that can be obtained from the target area, and estimate the occurrence of these demands from the real-time social conditions.

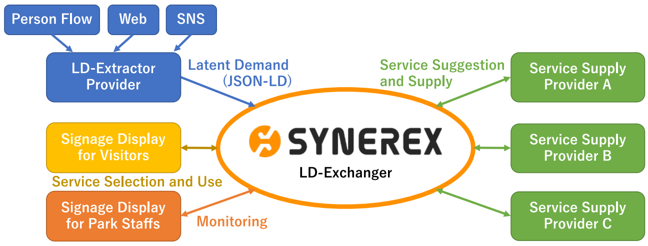

Fig. 4. The schematic of the developed LD-Resolver

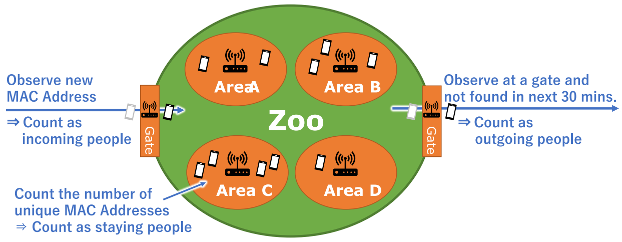

Fig. 5. Estimating the number of people entering, leaving, and staying

Then, we will evaluate whether the latent demand estimated from the limited area and social conditions can be used as a reference for providing better services, and evaluate the possibility of providing better services if we can obtain various social conditions in a wider area in the future.

B. Target Field

We deployed LD-Resolver in the Higashiyama Zoo and Botanical Garden, one of the largest public parks in Japan. About 2.5 million people visit this park yearly, and it is about 59.6 hectares in size. Also, it has about 500 species of animals and 7,000 kinds of botanicals. Therefore, citizens and tourists of all ages can enjoy this park.

C. Implementation

We explain the overview of the system and then describe the detail of implemented LD-Resolver.

1) System Overview: An overview of the implementation is shown in Fig. 4. Our LD-Extractor extracts latent demand from person flow data and information from the Web and SNS. We developed LD-Exchanger using Synerex [5], [6] and also created several Synerex providers to connect LD-Extractor, signage displays for visitors and park staff, and service supply systems. Visitors can receive services from the service supply system through the displays, which show the contents provided by the service supply system.

2) LD-Extractor: In this experiment, to extract latent demand, we used Wi-Fi packet sensors installed in the Higashiyama Zoo and Botanical Garden to estimate the number of visitors entering and exiting from specific gates and the number of visitors staying in a particular area, as shown in Fig. 5. First, we estimate the number of entering people by examining the Wi-Fi packets observed at multiple gates and measuring the number of MAC addresses observed for the first time that day for each period. To estimate the number of leaving people, we determined that a user of the terminal left the park when the MAC address contained in the Wi-Fi packet observed at the entrance/exit gate was not observed for a certain period by the packet sensor at another location, and measured the number of users for each period. The number of users in each area is measured by the number of unique MAC addresses observed in the area during a specific period. However, in relatively new smartphones, the MAC addresses in Wi-Fi packets may be anonymized. Therefore, these packets cannot be used to estimate the number of people entering and

Fig. 6. Location of the Wi-Fi packet sensors

staying in the area. To solve this, we compared the number of visitors with the actual number of people who entered and stayed in the area in advance and defined a scaling factor for weekdays, weekends, and holidays. Then, we multiply the scaling factor to estimate the number of visitors. The locations of the Wi-Fi packet sensors installed in this experiment are shown in Fig. 6.

Finally, the latent demand shown in Table II is extracted by analyzing the social conditions obtained from weather forecasts and parking lot congestion in addition to the data on the number of visitors entering, exiting, and staying. The demand domains in Table II correspond to those in Table I. We perform the demand extraction every 30 minutes. Then, the demand considered to be occurring is extracted based on the data collected in the past 30 minutes. The extracted demand is output in the format shown in Fig. 2.

3) LD-Exchanger: In this experiment, as shown in Fig. 4, we developed LD-Exchanger using Synerex. We also developed the LD-Extractor, signage displays for visitors and park staff, and service supply system as Synerex providers to connect to LD-Exchanger.

In Synerex, each provider publishes a message to a specific Synerex channel and subscribes to the channel to exchange data. Therefore, we created a channel for exchanging latent demands among the providers. Also, the flexibility required for LD-Exchanger can be realized because each Synerex provider can be added or removed at any time. Furthermore, the Mbus

TABLE II
LIST OF EXTRACTED LATENT DEMAND AND SERVICE SUPPLY TO MEET IT

No.	Latent Demand (Visitors want to...)	Demand Domain	Service Supply (Supplier provide...)
0	Know how crowded the parking lot is	D4	Real-time parking status
1	Take the train and go home	D4	Information of the nearest train station
2	Have a meal	D5	Information on crowded places to eat
3	Eat around the park	D5	Information on restaurants (menus) in the area
4	Have something to drink	D5	*
5	Know the weather	D6	Information on the weather at the arboretum
6	Buy a souvenir	D3	A list of souvenir information
7	Take a ride	D4	*
8	Know today's recommended animals and plants	D9	*
9	Be healed	D8	*
10	Take a good picture	D9	Information on official Twitter
11	Get around without getting tired	D8	Information on available areas
12	Know the real-time crowd status	D4	Relative crowd status compared to the past
13	Know the most popular areas	D9	Information on the most visited areas

*···the demand which was difficult to supply a service, therefore a service supply for it was not provided in this experiment.

Fig. 7. Installed display for real-time monitoring at Higashiyama Zoo and Botanical Garden

communication function of Synerex makes it easy to secure the communication path between service providers and service users.

In addition, we installed signage displays as shown in Fig. 7 at two locations in the park (one for visitors and the other for staff) to display the services that are estimated to be needed by visitors. For the experiment purpose, both displays show the supply service selected by the signage display provider automatically through the communication path to the service provider as described in the previous section. (That is, visitors can receive the supply services, and park staff can check what supply services are estimated to be needed.) In addition, as shown in Fig. 8, information on the estimated number of visitors entering, exiting, and staying and information from SNS are alternately displayed to improve convenience for visitors and to allow comparison with extracted latent demand.

IV. Experimental Result

We conducted a demonstration experiment of the proposed method for two weeks using the developed system. The following are the statistics of the extracted latent demand during the experiment and the questionnaire results to the park staff.

TABLE III
NUMBER OF TIMES EACH DEMAND IS EXTRACTED TO HAVE OCCURRED PER DAY (EVERY 30 MINUTES)

Date	Total	Demand No.									
		0	1	2	3	5	6	10	11	12	13
3/22	0										
3/23	20	10	3				7				
3/24	16	10	1				5				
3/25	33	5	7	2	2	1	8	2	2	2	2
3/26	32	10	4	2	2		6	2	2	2	2
3/27	25	14	5				6				
3/28	4		3				1				
3/29	0										
3/30	38	11	3	1	1	6	12	1	1	1	1
3/31	27	11	4	1	1		6	1	1	1	1
4/1	21	11	5				5				
4/2	21	10	4				7				
4/3	20	18	2								
4/4	6	1	5								
Total	263	111	46	6	6	7	63	6	6	6	6

A. Statistics of the Extracted Latent Demand

Table. III shows the number of times each demand was extracted to have been generated by the system developed during this experiment. Note that since Higashiyama Zoo and Botanical Garden is closed on Mondays, the number of times all demands were generated was determined to be zero. Demand No. 05 shows that the demand to know the weather was extracted to have occurred on a day when it was generally rainy or cloudy in Nagoya in the past weather data of the Japan Meteorological Agency (JMA) [13].

In addition, as shown in Figure 9, if we focus on demand No. 00, 01, and 06:

- Demand for parking lot congestion from mid-morning to early afternoon
- Demand for souvenir information from around noon to evening
- Demand for train schedule information as closing time approaches

is extracted to be enhanced, respectively.

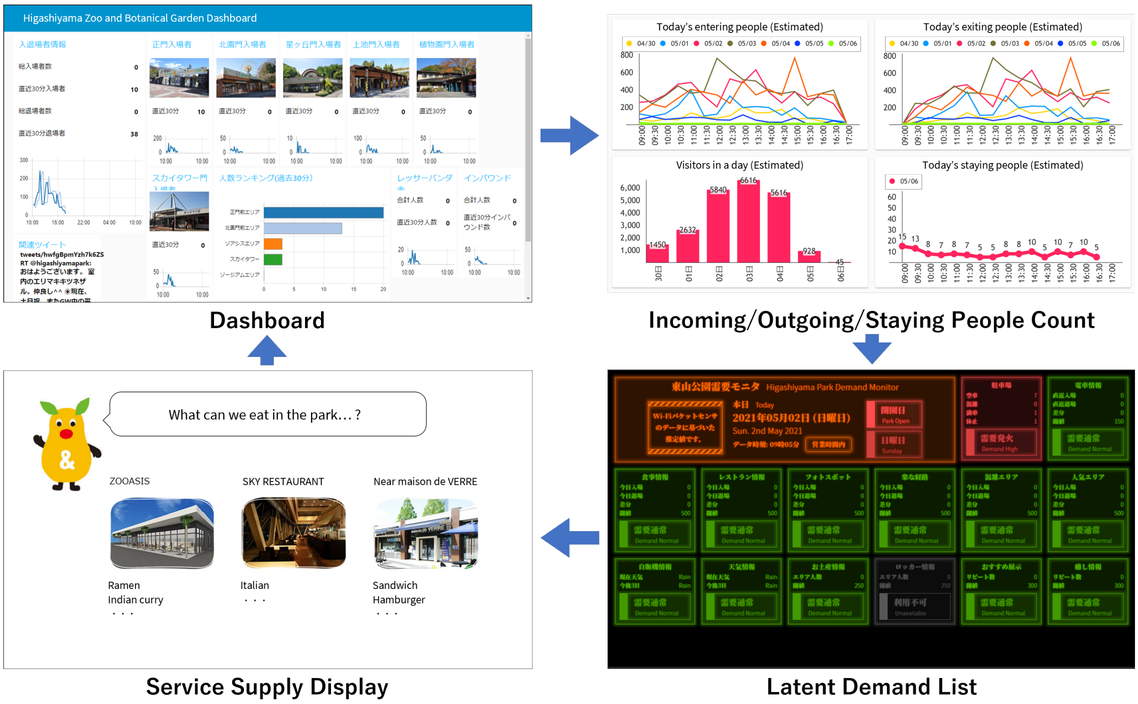

Fig. 8. Real-time data shown by the signage display

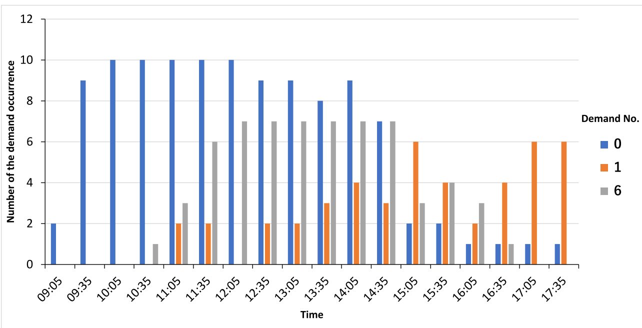

Fig. 9. Time-based distribution for the frequently occured demands

B. Results of questionnaire to park staff

In this experiment, we conducted a questionnaire survey among the Higashiyama Zoo and Botanical Garden staff to evaluate the effect of the system. In the questionnaire, we investigated the accuracy of person flow estimation by Wi-Fi packet sensor, the necessity of supply and demand exchange infrastructure, and the future system development.

First, we describe the results of the accuracy of person flow estimation using Wi-Fi packet sensors. In the questionnaire, we asked them to rate the accuracy of the estimated number of people entering and exiting in three levels (error of about $\pm 25\%$, $\pm 50\%$, or higher) in three time periods (morning, 12:00 to 15:00, and 15:00 to 18:00) on weekdays and weekends. The questionnaire results indicated that the error was about $\pm 25\%$ in all periods, which means that the results of the person flow estimation using Wi-Fi packet sensors are generally reliable and helpful to extract latent demand.

Next, the survey results on the necessity and future development of the LD-Resolver are shown in Table. IV. From the results, it can be evaluated that it is easier for the staff (i.e., service providers) to grasp the trend of visitors (i.e., consumers) by presenting the latent demand. However, the evaluation of the signage display for visitors is a little lower than that for the staff, and it is thought that a better way of presenting the supply other than the signage display is required to achieve better demand-supply exchange.

Finally, we asked the respondents to rate the degree to which the extracted occurrence of each latent demand was consistent with their senses, and if so, to rate it on a four-point scale (1: not consistent to 4: very consistent). The results are shown in Table V. From the results, it can be concluded that the demand was extracted approximately correctly for most of the demands. However, it was challenging to make an accurate evaluation because they said their answers were based on their senses except for the weather (Demand No.5).

From the results of the experiments, we can conclude that:

- We were able to extract the occurrence of many latent demands accurately.
- We were able to present latent demand to the service provider and provide useful information for service supply.

Therefore, the possibility is shown that the proposed method can be effectively used in actual facility operations.

TABLE IV
ASSESSMENT OF THE NEED FOR AND FUTURE DEVELOPMENT OF LD-RESOLVER

Questionnaire	Result
Do you understand the demand easier if sensor data is converted into demand?	5
Would you like to continue to put the display in your office?	5
Would you like to put a display to encourage visitors to change their behavior?	3
If the appearance of the display is elaborate, is it likely to get a good response from visitors?	4

TABLE V
ASSESSMENT OF THE ADEQUACY OF THE OCCURRENCE OF EACH LATENT DEMAND

No.	Latent Demand (Visitors want to...)	Result
0	Know how crowded the parking lot is	3
1	Take the train and go home	3
2	Have a meal	4
3	Eat around the park	Not evaluable
5	Know the weather	4
6	Buy a souvenir	3
10	Take a good picture	3
11	Get around without getting tired	Not evaluable
12	Know the real-time crowd status	3
13	Know the most popular areas	3

V. RELATED WORK

This section describes previous studies on real-world sensing methods related to the proposed method, demand extraction, and urban platforms related to demand and supply exchange.

A. Real world sensing methods

Although there is a wide range of information collected from the real world, this section discusses sensing methods considered helpful for demand extraction.

First, person flow data, representing the movement and stay of people, helps estimate the degree of congestion in a specific place and the number of people who have a particular demand. Such flow data can be obtained by various methods such as GPS, mobile networks, Wi-Fi, Bluetooth, and transit sensors. In the case of GPS, a smartphone application can be used to acquire the location of an individual. However, the user must install the application and allow it to acquire location information, which is a higher hurdle than other methods. In addition, mobile network-based methods have been studied to obtain location information mainly by using which base station the mobile terminal is connected to and the signal strength during transmission and reception [14]–[16]. However, mobile network information is challenging to be obtained by anyone other than cell phone companies. On the other hand, a Wi-Fi-based method that collects Probe Requests sent from smartphones by multiple Wi-Fi packet sensors and uses MAC addresses as anonymized IDs for person flow estimation has been actively studied [17]–[19]. In addition, a method using Bluetooth has been proposed in which packets emitted by multiple Bluetooth beacons installed in the target area are collected by the user's Bluetooth terminal, or the beacons and terminal are installed and distributed in reverse order to estimate the position of the user [20]. In this paper, we used Wi-Fi packet sensors to acquire person flow data from the perspective of reducing the burden on the sensing target and concerns about privacy.

Sensing the detailed urban environment is also crucial for understanding what people need in that environment. In the study by Chen et al. [21], it is shown that environmental sensors can be mounted on garbage trucks to collect detailed and efficient information about the conditions of the city since garbage trucks generally make detailed patrols of the city regularly.

B. Demand Estimation

There are many studies about demand estimation in various situations. In Law et al.'s research [8], they used a deep network based on LSTM to estimate tourist arrival volumes in Macau and achieved a better outcome than support vector regression and artificial neural network models. Abbasimehr et al. also compared LSTM with some other time series forecasting techniques on estimating demands for furniture products [9]. On the other hand, Geng et al. et al. proposed CNN and RNN based models to forecasting ride-hailing demand and improved accuracy more than 10% than baselines. In the study by Hopken et al. [11], they can estimate tourism demand more accurately using Google web search data. Li et al. explored study trends on predicting tourism forecasting and mentioned the possibility of acquiring more accurate predictions by combining various data from the Internet [12].

C. Urban Platform

Many IT companies provide urban platforms these days, and there are also many studies about collecting, exchanging, and utilizing urban information better. FIWARE, developed under the EU's FI-PPP program, is a platform for cross-sectoral public data utilization from various sectors. FIWARE has about 40 modules that exchange data with NGSI and can be used in any combination. Many European countries have already introduced FIWARE to share their public data. In Yonezawa et al.'s research [22], SOXFire has been developed as a distribution platform for urban sensor information based on XMPP, and several social implementation experiments have been conducted in the Shonan area of Kanagawa Prefecture. On the other hand, Lea et al.'s research [23] introduced the cloud-based IoT data hub to deal with the growing quantity and quality of smart city data. Also, Kawaguchi et al.'s research group has developed a platform called Synerex [5], [6], which focuses on demand and supply exchange. They have confirmed its effectiveness in a demonstration experiment in Kota Town, Aichi Prefecture. Furthermore, it is also used as a platform for various information exchanges, such as person flow estimation and collaboration with robots [24], [25]. In this paper, we developed LD-Exchanger using Synerex because of its structure and flexibility.

VI. Conclusion

In this paper, we proposed LD-Resolver to understand and resolve latent social demand. LD-Resolver has two components, LD-Extractor, which extracts latent demand from social information, and LD-Exchanger, which exchanges demand with an appropriate supply. Also, we implemented and deployed LD-Resolver in the Higashiyama Zoo and Botanical Garden. Then, we conducted a demonstration experiment to show that the proposed method can be effectively used in actual facility operations.

We have mainly two directions as the future works. Firstly, we would like to expand the range of latent demand that can be estimated by collecting more information from the real world at a lower cost. Secondly, Since most of the latent demand extracted in the demonstration experiment in this paper was relatively easy to extract, we would like to use ML methods and text mining to estimate more advanced latent demand from more social situations.

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