Capstone Project
Mapxus

POI Collection and Brand Identification Enhancement in Indoor Map Production

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Background

Situation and Problem Statement

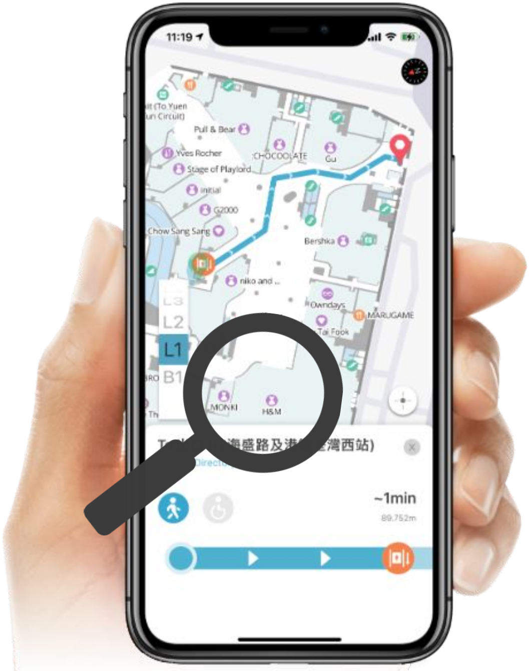
Mapxus specializes in making indoor mapping smart and simple

DIGITAL MAPS

require ‘Point-of-Interest’ (POI) information.

POI INFORMATION

help users to navigate and find specific locations.



Collecting POI information can be a challenging task

Procedures to collect POI information should be

- Accurate
- Resource-efficient
- Up-to-date
- Matching business model requirements

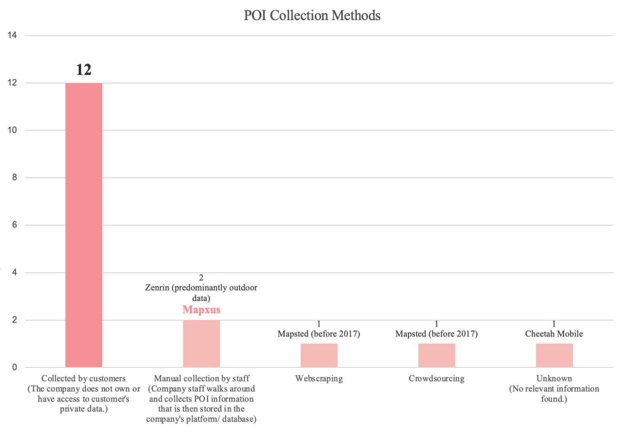
Background

Market Investigation and Overview

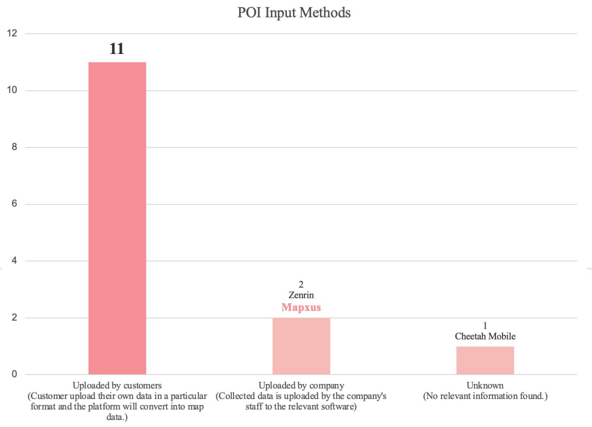
Current market practice for POI methods requires customers' own effort unlike Mapxus' approach

To better cater customers' needs and provide highly customized services to customers, companies would prefer having POI information collected, inputted and maintained by customers as customers own the most comprehensive and accurate information.

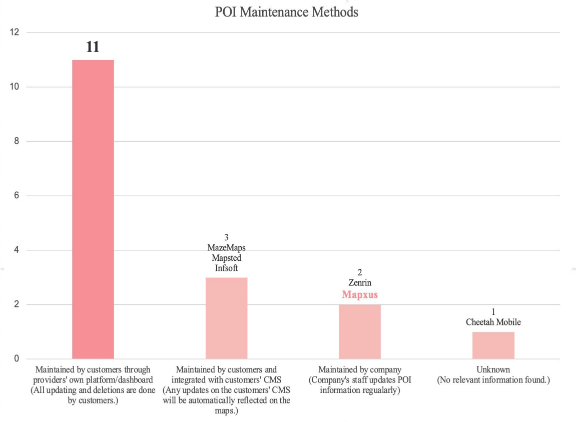
Majority of companies would have POIs collected by customers and companies do not own customers' data.



Almost 80% of companies would have POIs inputted by customers onto companies' platforms.



Most companies would have POIs maintained by customers, majorly through companies' platforms/ dashboards.



Mapxus, on the other hand, adopts a proactive approach to look for potential business opportunities.

Mapxus could work collaboratively with customers to get the most comprehensive and accurate information efficiently

Challenge

Lots of human effort is needed to capture, maintain and validate the POI information.

Standardize POI information from customers

List a clear set of requirements from customers on floor plan format and size, POI excel format etc.

Create CMS as Dashboard format

Utilize CMS as an efficient tool to monitor mall information, events, maintenance tasks and store updates.

Real time POI validation through brand name change detection

Based on Naver Labs' research on detecting store name changes in malls, attempt to integrate a cloud database to perform real-time updates for POI maintenance.

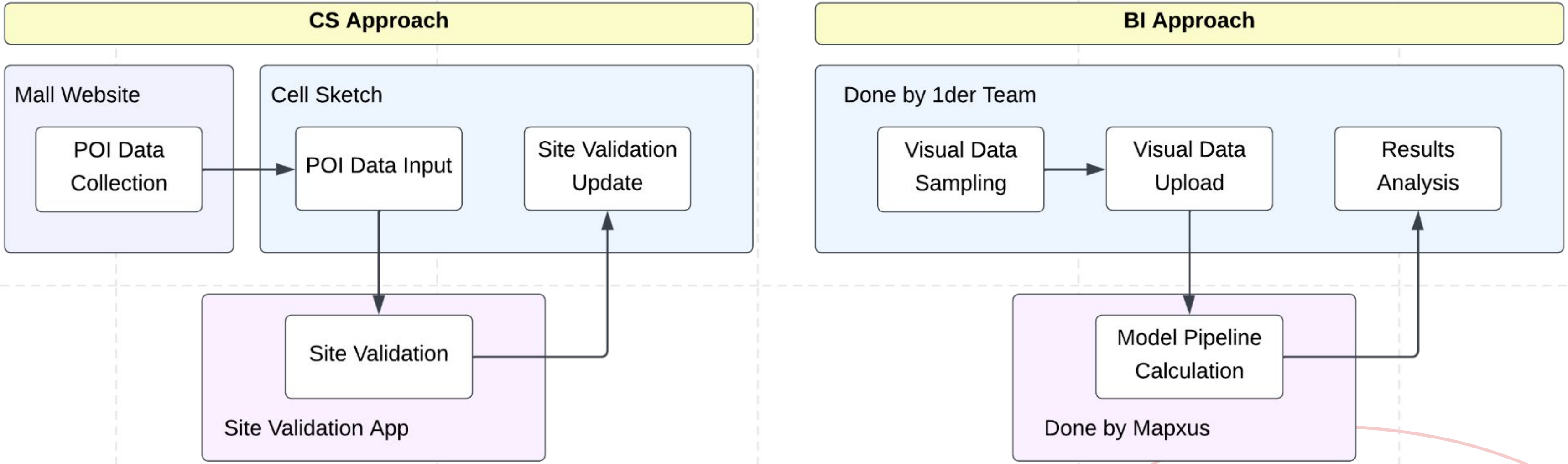
Analysis

Mapxus' Current Practice

Mapxus currently uses the Cell Sketch (CS) Approach and tests the Brand Identification (B.I.) AI Approach for POI data production

Plaza Hollywood (2F, 3F)

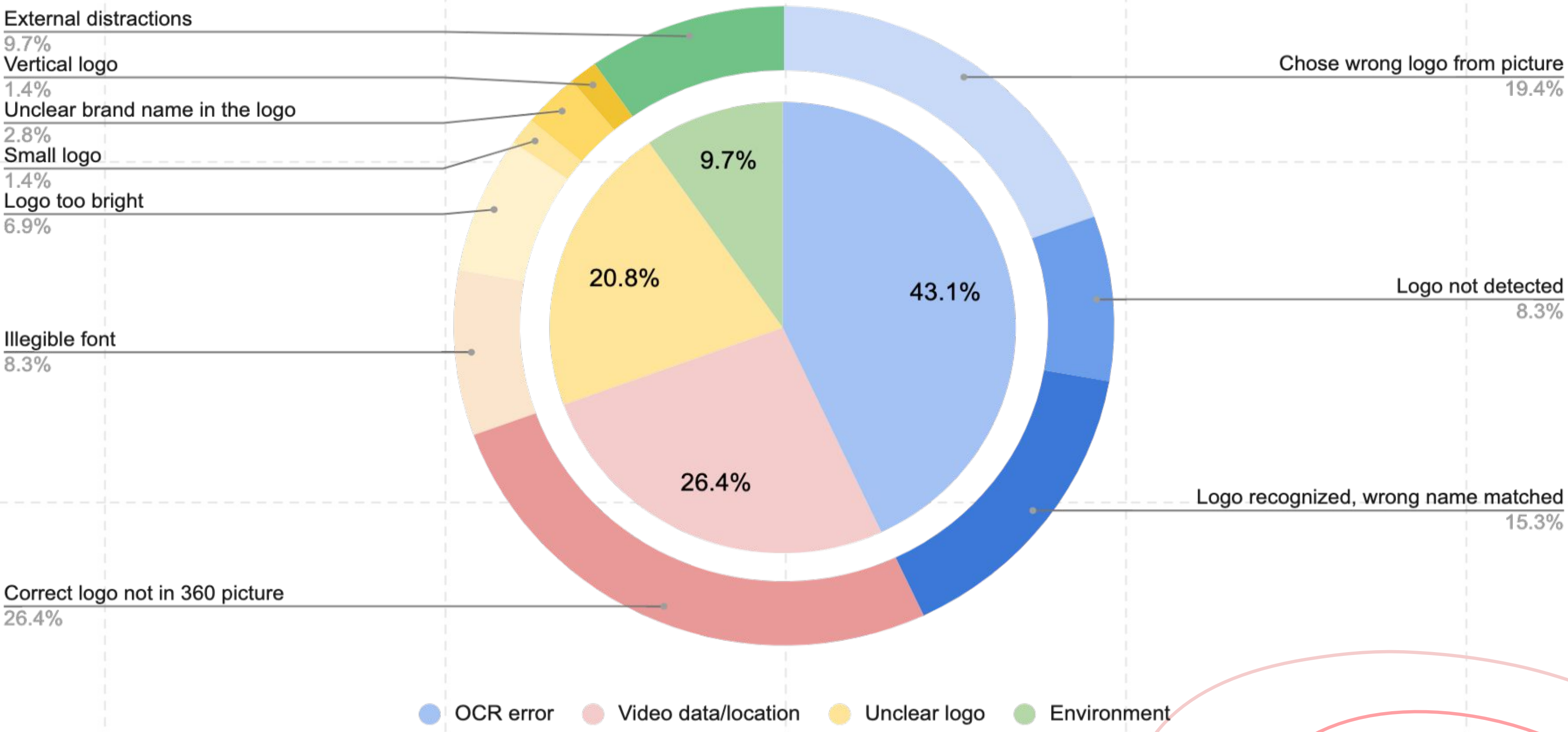
Temple Mall South (UG, L1).



Both approaches have strengths and weaknesses

	CS Approach	B.I. AI Approach
Average Accuracy	96 % without site validation, 100 % with site validation	61.5 %
Time for Manual Work	16 hours	6.21 hours
Efficiency	Low: avg. 4 hours/floor	High: avg. 1.5 hours/floor
Information Completeness	Additional information available, including POI category	360° street view available
Feasibility	Low: only applicable to big shopping malls with official websites	High
Extensibility	Low: only applicable to locations that provide public POI information	High
Learning Difficulty	Low: learning the use of Cell Sketch and Site Validation app	Low: learning the use of 360 cameras and Visual Map Editor
	Accuracy, Information Completeness	**Efficiency, Feasibility, Extensibility**

Errors in the B.I. AI Approach are due to both internal and external factors



Exploration

‘Pick out’ Algorithm and Jaro-Winkler Threshold Analysis

The 'pick out' algorithm is based on the output data from the B.I. AI algorithm

- The raw dataset consists of 4 csv files (Temple Mall South UG, L1; Plaza Hollywood 2F, 3F) with the same structure.
- There are 5,424 observations in total, the target variable is `BrandId`/ `Eng`, and the attributes used in the threshold analysis are `Winner`, `ModelConfidenceScore`, and `JWScore_ModelResult_MatchResult`.

Attribute Name	Description
`Winner`	The ID for a specific unit.
`ModelConfidenceScore`	The likelihood that the output of the machine learning model is correct and will satisfy user requests.
`JWScore_ModelResult_MatchResult`	A measurement on the similarity between two texts.

The following 'pick out' algorithm optimization and threshold analysis are based on the whole dataset.

The optimized algorithm picks the brand name with the largest JWScore instead of a random brand name

Current 'pick out' algorithm

a. Filter out the predictions with JWScores that are smaller than threshold *(ModelConfidenceScore > 0.1 and JWScore > 0.85)*

b. Pick the most frequently predicted brand name to determine the `Winner`

c. Pick one brand name **randomly** out of all brand names with the same count

Our optimized approach

a. Filter out the predictions with JWScores that are smaller than threshold

b. Pick the most frequently predicted brand name to determine the `Winner`

c. Out of all brand names with the same count, pick the prediction with the **largest JWScore**

Precision increases and recall rate drops as JW-threshold improves

Calculating Rule

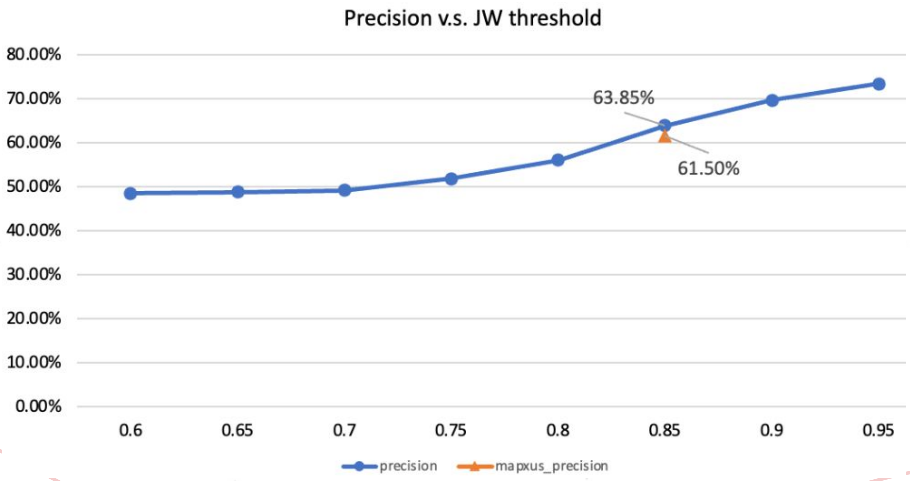
1. Three metrics to measure the accuracy:
   1) Precision = #correct predictions / #filtered POI
   2) Recall Rate = #correct predictions / #total POI
   3) F1 Score = 2 * Precision * Recall Rate / (Precision + Recall Rate)

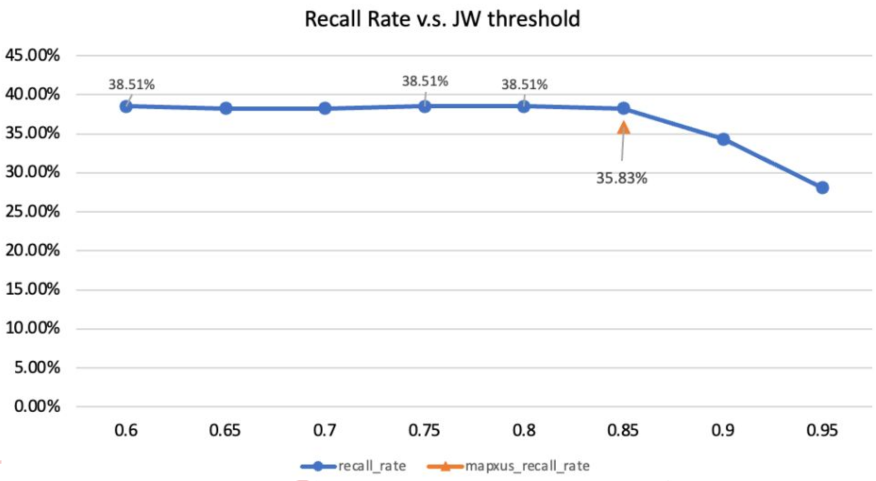
We use the F1 Score as the metric to decide on an optimal JW-threshold.

2. Precision, Recall Rate, and F1 Score are all calculated for the whole dataset.

3. To tune the JW-threshold, the *ModelConfidenceScore* threshold is set to 0.1.

4. POI data with unknown ground truth is dropped when calculating the accuracy.





The F1 Score has a maximum at a JW-threshold of 0.85

Calculating Rule

1. Three metrics to measure the accuracy:
   1) Precision = #correct predictions / #filtered POI
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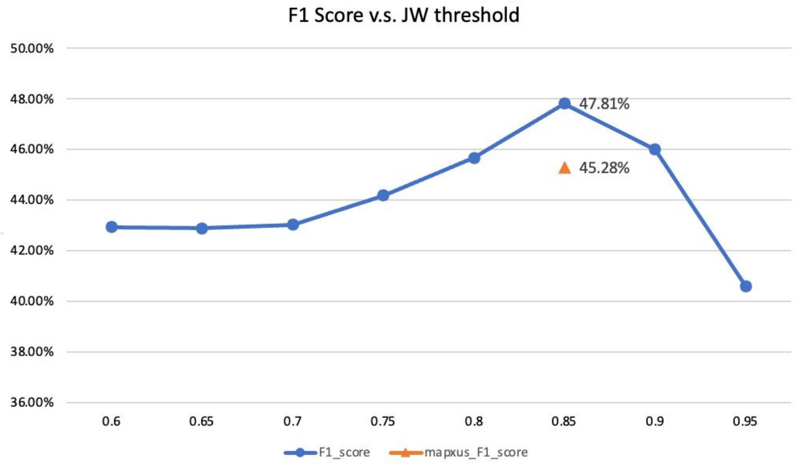

Optimal JW-threshold:

0.85

Accuracy gain with optimized algorithm:

2.52%

Exploration

Expanded Brand List and Brand Name Prediction

Expanded reference brand list and yielded prediction accuracy of ~90% for pure English OCR text and ~30% for text containing Chinese

Challenge

Prediction performance in the current process (besides OCR) relies on the completeness of the reference brand list, but there are always unseen or less popular brands not included in the list.

Expanding the brand list

Expand the existing reference brand list using web scraping

Web scraped from Google Maps shop names from a list of ~1,000 malls in Hong Kong.

- Retrieved 33,731 shop names.
- After a complete data cleaning process, approx. 27,000 unique brand names are expected to be obtained.

Brand name prediction

Predict a most likely brand from raw OCR text

Takes in a raw OCR text, we have written a function called `brand_autocorrect` that will output 5 suggested results for the most likely brand[1] based on Jaro-Winkler distance measures.

Accuracy analysis

Analyze how accurate the function predicts the most likely brand

The function along with the expanded brand list predicts the most likely brand on a set of simulated OCR data with overall accuracy[2] of:

- 91% for raw OCR text with English letters only (88% of filtered OCR text[3]); and
- 29% for raw OCR text containing Chinese characters (12% of filtered OCR text[3]).

[1] Most likely brand was the result from the 'Pick out' algorithm defined in the threshold analysis.
[2] 'Overall accuracy': for how many OCR texts in the simulated data does the correct brand name appear in one of the five corrections suggested by the brand_autocorrect function.
[3] Raw OCR text from Mapxus raw results for Temple Mall South and Plaza Hollywood with Jaro-Winkler distance greater than 0.85 and model confidence score greater than 0.1.

Expanded reference brand list and yielded prediction accuracy of ~90% for pure English OCR text and ~30% for text containing Chinese

Challenge

Prediction performance in the current process (besides OCR) relies on the completeness of the reference brand list, but there are always unseen or less popular brands not included in the list.

Expanding the brand list

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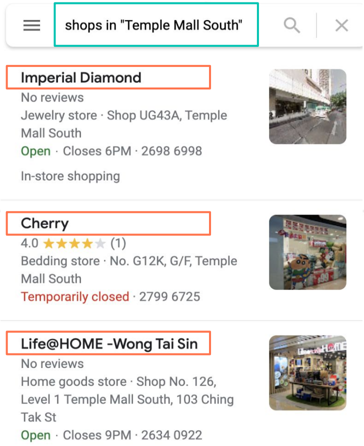
Web scraped from Google Maps shop names from a list of ~1,000 malls in Hong Kong.

- Retrieved 33,731 shop names.
- After a complete data cleaning process, approx. 27,000 unique brand names are expected to be obtained.

1. Query for shops in a specific mall
2. Scrape all the **shop names** in the results



3. Clean out **non-shop names** and **branch and mall information** in the shop name list.

Expanded reference brand list and yielded prediction accuracy of ~90% for pure English OCR text and ~30% for text containing Chinese

Challenge

Prediction performance in the current process (besides OCR) relies on the completeness of the reference brand list, but there are always unseen or less popular brands not included in the list.

Demonstration

OCR text as function input

```
brand_autocorrect("choiq- fungr")
```

	Correction	Input	JW_Similarity
6988	Choi Fung Hong	choiq- fungr	0.878788
6210	Choi Yun Kee	choiq- fungr	0.829091
3523	Choi Ming Market	choiq- fungr	0.827273
6201	Chao Inn	choiq- fungr	0.778355
2313	Cha Long	choiq- fungr	0.778355

Correct result

Outputs 5 suggested correct brand names

Ranked by Jaro-Winkler distance

Brand name prediction

Predict a most likely brand from raw OCR text

Takes in a raw OCR text, we have written a function called `brand_autocorrect` that will output **5** suggested results for the most likely brand[1] based on Jaro-Winkler distance measures.

Note 1: 'Most likely brand' was the final predicted brand name from the 'Pick out' algorithm defined in the 'Final Prediction Optimization' section.

Expanded reference brand list and yielded prediction accuracy of ~90% for pure English OCR text and ~30% for text containing Chinese

Challenge

Prediction performance in the current process (besides OCR) relies on the completeness of the reference brand list, but there are always unseen or less popular brands not included in the list.

Note 2: 'Overall accuracy' refers to **'One of the 5 suggested results' row** of the result.

Note 3: 'Filtered OCR text' refers to raw OCR text from Mapxus raw results for Temple Mall South and Plaza Hollywood in the 'raw results' files, after filtering for Jaro-Winkler distance greater than 0.85 and model confidence score greater than 0.1. This would include 567 (88%) pure English raw OCR text and 75 (12%) raw OCR text containing Chinese characters. For more information, please see 'Notes on OCR data simulation' slide in the Appendix.

Correct brand name appearing in	Input with English letters only	Input containing Chinese characters
One of the 5 suggested results	**90.59%**	**29.33%**
1st suggested result	85.22%	22.67%
2nd suggested result	41.60%	8.00%
3rd suggested result	18.93%	6.67%
4th suggested result	7.84%	8.00%
5th suggested result	2.05%	1.33%
Size of data (incl. simulated and original data)	11,792	75

Accuracy analysis

Analyze how accurate the function predicts the most likely brand

The function along with the expanded brand list predicts the most likely brand on a set of simulated OCR data with overall accuracy[2] of:

- **91%** for raw OCR text with **English** letters only (**88%** of filtered OCR text[3]); and
- **29%** for raw OCR text containing **Chinese** characters (**12%** of filtered OCR text[3]).

Web scraping is fast and extensible; data cleaning and validation would be the next step

Strengths

- Using web scraping to retrieve shop names is fast, and it is not limited to shops in malls (e.g. MTR stations)
- We can also scrape on other websites (e.g. yelp.com or openrice.com) for these shop informations to further expand the reference brand list

Weakness

- Data cleaning takes a long time due to the large variety of name formats in the scraped results
- Formatting the scraped brand list into the reference brand list (i.e. having both the English and Chinese names) will also take a large amount of time

Next steps

- Optimize algorithm for automating data cleaning and processing
- Data validation - checking the completeness and accuracy of the scraped information in greater detail

Extensions

Explore the possibility of combining the optimized 'pick out' algorithm, threshold analysis, and brand name prediction.

Exploration

Alternative POI Information Collection Method

Using web scraping to retrieve shop numbers and floors for faster Cell Sketch POI input is achievable

Context & Ideas

We suggested using web scraping to obtain an csv file of shop names and shop positions which can be imported directly into Cell Sketch for POI input.

Information Retrieval

Using the expanded brand list, we scraped the shops' addresses from openrice.com and Google Maps, and then obtained the shop number and shop floor for each shop.

Robustness

This method is robust and can be used for any shop name and any mall as long as they are listed on the internet.

Results

- Due to time constraints we were only able to finish 32% of all the scraping.
- After cleaning all the scraped results, 72% retrieved valid addresses, from which 73% were able to retrieve shop numbers or shop floors.

Next Steps

- Improve algorithm in extracting shop position information.
- Perform validation on scraped results.
- Perform scraping on other websites (e.g. yelp.com) to improve completeness of results.
- Adjust code to scrape other information, e.g. categories and opening times.

Recommendations

Summary and Recommendations

Mapxus can improve its current POI collection process

Improve B.I. AI accuracy

- Use **expanded brand list** for a better matching performance
- Apply **new 'Pick out' algorithm** for an immediate accuracy improvement

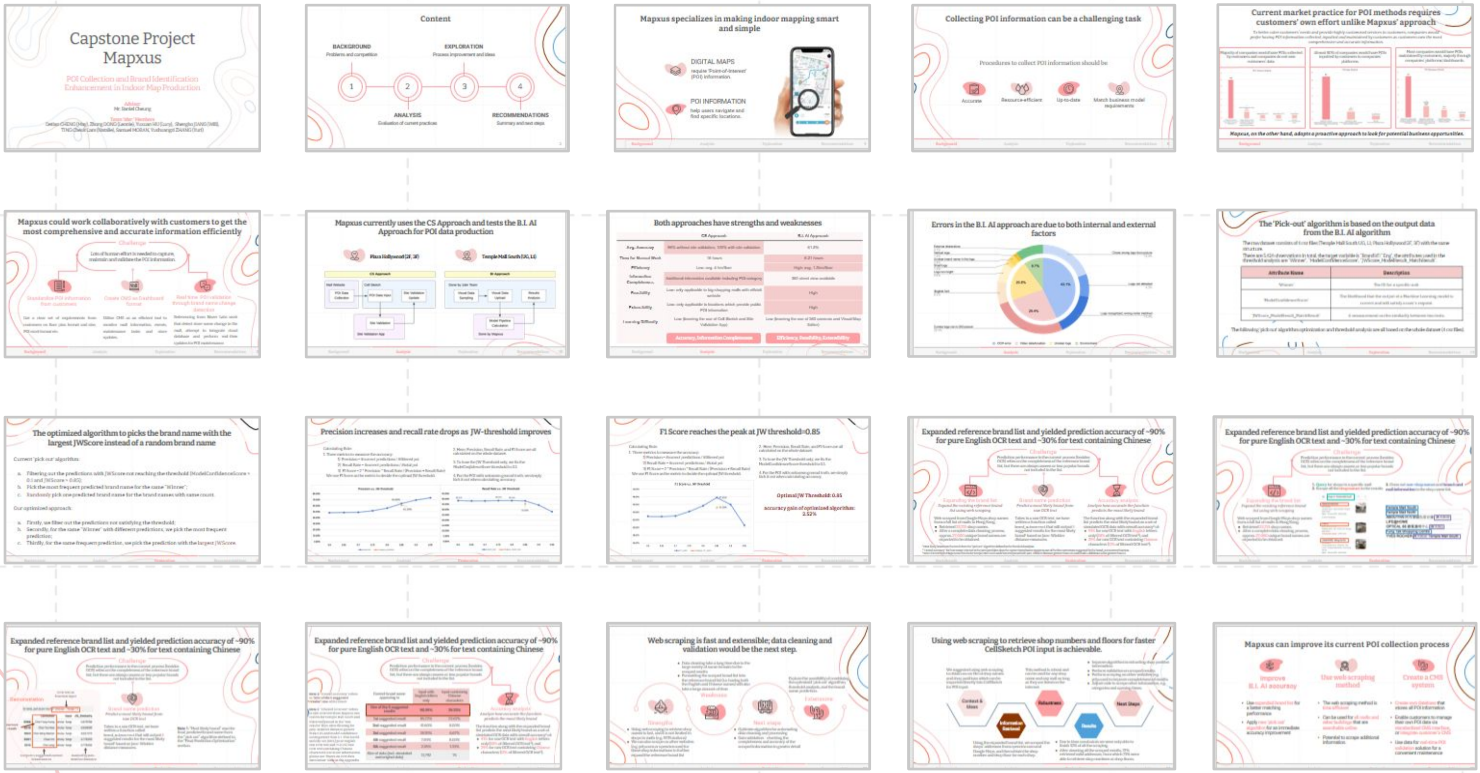
Use web scraping method

- The web scraping method is **time efficient**
- Can be used for **all malls and buildings** that are **searchable online**
- Potential to scrape additional information

Create a CMS system

- **Create own database** that stores all POI information
- Enable customers to manage their own POI data via **standardized CMS interface**, or **integrate customer's CMS**
- Use data for **real-time POI validation** solution for a convenient maintenance

Thanks for you attention!



Appendix

Summary

Section	Content
Background	• Identified 2 challenges of Mapxus: efficiency of POI collection procedures and accuracy of B.I.; • Investigated 13 competitors and offered a market overview on their POI collection, input and maintenance methods.
Analysis	• Conducted experiments on producing POI data in both CS approach and B.I. AI approach; • Analyzed and compared current CS and B.I. AI approach in 7 aspects.
Exploration	• Optimized the 'pick out' algorithm and performed threshold analysis; • Explored using web scraping to expand the brand list and tested the accuracy of using these results for brand name prediction; • Explored using web scraping to collect POI information for Cell Sketch input.
Recommendation	• Improve B.I. accuracy by using expanded brand list or the optimized 'pick out' algorithm; • Utilize web scraping algorithm for time efficient solution that works for all malls with an online presence; • Create a POI database and co-manager it with customers.

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Web scraping - Shop/restaurant names

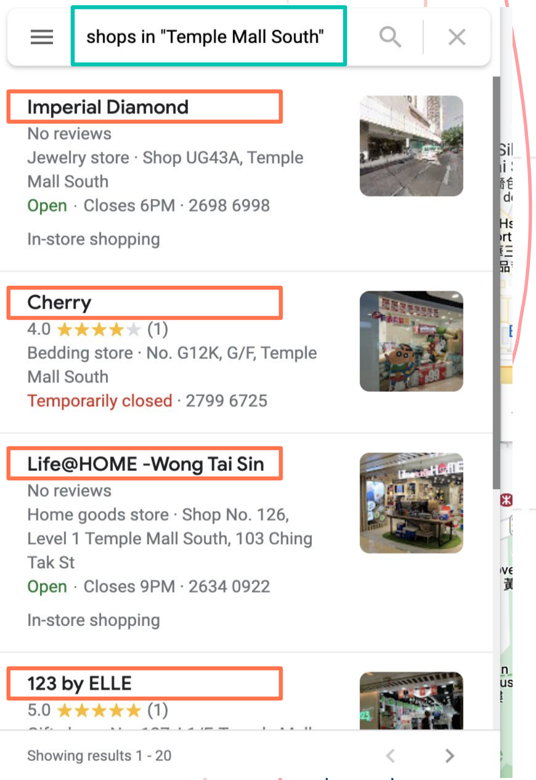
Shop/restaurant names in all malls in Hong Kong

- We retrieved a list of malls in English (131 malls) and in Chinese (853 malls) from Wikipedia.
- For all the malls on the two lists, we searched on Google map using queries either *shops in "<mall>"* or *restaurants in "<mall>"*, and scraped the names of all the results.
- In the end we retrieved 33,731 shop names.

Data cleaning (in progress)

- We will clean out non-shop names in the shop name list (e.g. names of malls, shopping centers, hotels, description of shops).
- We will also clean out branch and mall information included in the scraped shop names.
- Due to time limits we were not able to fully clean all the scraped data. For the purpose of exploration, we used a half-preprocessed list of 7,962 brand names, and these are used and fed into the `brand_autocorrect` function.

Temple Mall South
Temple Mall North
ABOUTHAI 阿布泰國生活百貨- 黃大仙店
LIFE@HOME
OPTICAL 88 聽覺護理中心 (黃大仙)
Fung Tak Shopping Centre
YVES ROCHER 黃大仙店 Temple Mall South



Next step: Brand name prediction

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Brand name prediction

`brand_autocorrect` function

This function takes in the raw OCR text (`Input` column), and will output 5 suggestions for the correct brand name (`Correction` column) ranked from the highest to lowest Jaro-Winkler distance between the OCR text input and the brand name (`JW_Similarity` column).

Demonstrations

```
input_word = "choi fo|} poyal can:ue$"
brand_autocorrect(input_word)
```

	Correction	Input	JW_Similarity
2277	Choi Fook Royal Banquet	choi fo|} poyal can:ue$	0.880000
2647	Chinyan	choi fo|} poyal can:ue$	0.775238
1874	Chap Lan Cafe	choi fo|} poyal can:ue$	0.762424
1007	:CHOCOOLATE	choi fo|} poyal can:ue$	0.719024
4319	:CHOCOOLATE	choi fo|} poyal can:ue$	0.719024

Correct result

Repeated result due to half-preprocessed expanded brand list not entirely cleaned

Example 1: output for simulated OCR text input in English (Correct brand name not in the reference brand list previously)

Chinese OCR text - not working so well

```
input_word = "屈&&"
brand_autocorrect(input_word)
```

	Correction	Input	JW_Similarity
2244	Mint & Basil Thai Vietnamese & Indian Cuisine...	屈&&	0.569444
2843	K & L	屈&&	0.555556
4096	K&Y	屈&&	0.555556
3785	屈臣氏	屈&&	0.555556
6955	H&M	屈&&	0.555556

Correct result

Example 2: output for simulated OCR text input in Chinese

Next step: accuracy analysis of this function's outputs on an simulated set of OCR input

Back to Summary

Accuracy of `brand_autocorrect` function on simulated data

How well do the outputs of the brand_autocorrect function match the most likely brand (result from "pick out" algorithm)?

Correct brand name appearing in	Input with English letters only	Input containing Chinese characters
One of the 5 suggested results	**90.59%**	**29.33%**
1st suggested result	85.22%	22.67%
2nd suggested result	41.60%	8.00%
3rd suggested result	18.93%	6.67%
4th suggested result	7.84%	8.00%
5th suggested result	2.05%	1.33%
Size of data	11,792	75

Note 1: the correct result might appear in multiple suggested results (see example below).

Note 2: if this function outputs only one prediction for the most counted brand, then it would be the **1st suggested result** (`Correction1` column in the example below).

This column is retrieved from the threshold analysis for the most counted branded with JWScore > 0.85. Each Correction is compared with this column to calculate its accuracy.

Illustration on calculation

Winner	Input	brand_id	Correction1	JWSim1	Correction2	JWSim2	Correction3	JWSim3	Correction4	JWSim4	Correction5	JWSim5	Most_counted_brand
540272	jurliqe	AA0530	Jurlique	0.975	Jurlique	0.975	Juice	0.832381	Juice Lab	0.770476	joli	0.753571	Jurlique

Correction1: Correct brand name in the 1st suggested result: ✔

Correction2: Correct brand name in the 2nd suggested result: ✔

Correction3: Correct brand name in the 3rd suggested result: ✗

Correction4: Correct brand name in the 4th suggested result: ✗

Correction5: Correct brand name in the 5th suggested result: ✗

Most_counted_brand: Correct brand name in one of the 5 suggested results: ✔

Back to Summary

Notes on OCR data simulation

Why we need to simulate data

- To test our brand_autocorrect function defined on the previous slide, we need data of the raw OCR text and their corresponding matched correct brand names.
- We first took in all the `ModelResult` and `MatchResult` from the 4 raw results files provided by Mapxus.
- After filtering for `ModelConfidenceScore` > 0.1 and `JWScore` > 0.85, it has 567 pure English raw OCR text and 75 raw OCR text containing Chinese characters, which we felt are not enough.

How we simulate data

- Three types of edit actions are performed on the English OCR text:
    1) Randomly deleting 1~10 characters
    2) Randomly inserting 1~10 characters
    3) Randomly replacing 1~10 characters
- Filtering for rows with `JWScore` > 0.85 and removing duplicated items, we have 11,792 records to test the accuracy of the function.
- No edits are performed on the remaining 75 raw OCR text that contains Chinese characters.

Next step: accuracy analysis

Cell Sketch POI Input from Web Scraping

- We explored the possibility to use web scraping to obtain a table of shop name as well as shop positions. We decided to use web scraping again to scrape the addresses of shops in malls.
- Using the expanded brand list we scraped previously, we will search all the restaurants from openrice.com and shops from Google Maps (we use these two websites because they can be used for every mall and they are considered to be containing relatively up-to-date and complete information), retrieve their addresses, then obtain the shop number and shop floor for each shop.

Restaurant information - from openrice (in progress)

Shop_name	Mall_name	Address	Shop_no	Shop_floor
Pho le	apm	Shop 19, 4/F, apm Millennium City 5, Kwun Tong...	Shop 19	4/F
E-pai	apm	Shop 20-21, 4/F, apm Millennium City 5, 418 Kw...	Shop 20-21	4/F
Italian Tomato Cafe	apm	Shop L5-6, 5/F, apm Millennium City 5, 418 Kwu...	Shop L5-6	5/F
Honjin	apm	Shop 23, 4/F, apm Millennium City 5, 418 Kwun ...	Shop 23	4/F

Example: restaurants in apm and their shop positions

Shop information - from google search (in progress)

Shop_name	Mall_name	Address	Shop_no	Shop_floor
THE ONE JEWELLERY	Amoy Plaza	Shop S118A, 2/F, Amoy Plaza Phase I, 77 Ngau T...	Shop S118A	2/F
CD warehouse	Amoy Plaza	Shop S57-58, 2/F, Amoy Plaza Phase I, 77 Ngau ...	Shop S57-58	2/F
Mannings	Amoy Plaza	Shop G183-185, G/F, Amoy Plaza Phase II, 77 Ng...	Shop G183-185	G/F
百惠	Amoy Plaza	Shop G112, G/F, Amoy Plaza Phase I, 77 Ngau Ta...	Shop G112	G/F

Example: shops in Amoy Plaza and their shop positions

Industry Overview

Investigation on 13 competitors in the indoor positioning and indoor navigation industry

1) POI-related Information
2) Technology
3) Business-related Information

Industry Size

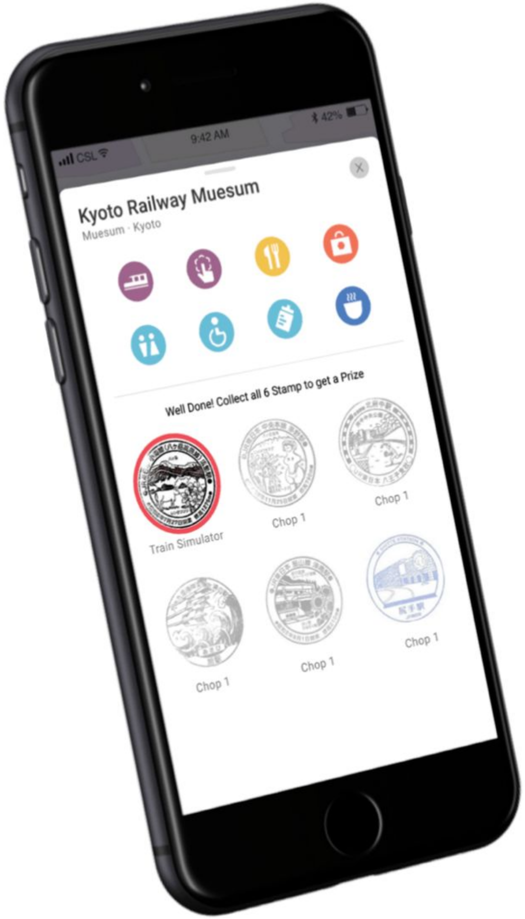
In 2017, the global indoor positioning and indoor navigation market was valued at $2642 million with the **expected growth to $43,511 million by 2025**, growing at a 42% compound annual growth rate from 2018 to 2025.

—Allied Market Research (2018)

Market CAGR increased by 42% (expected)

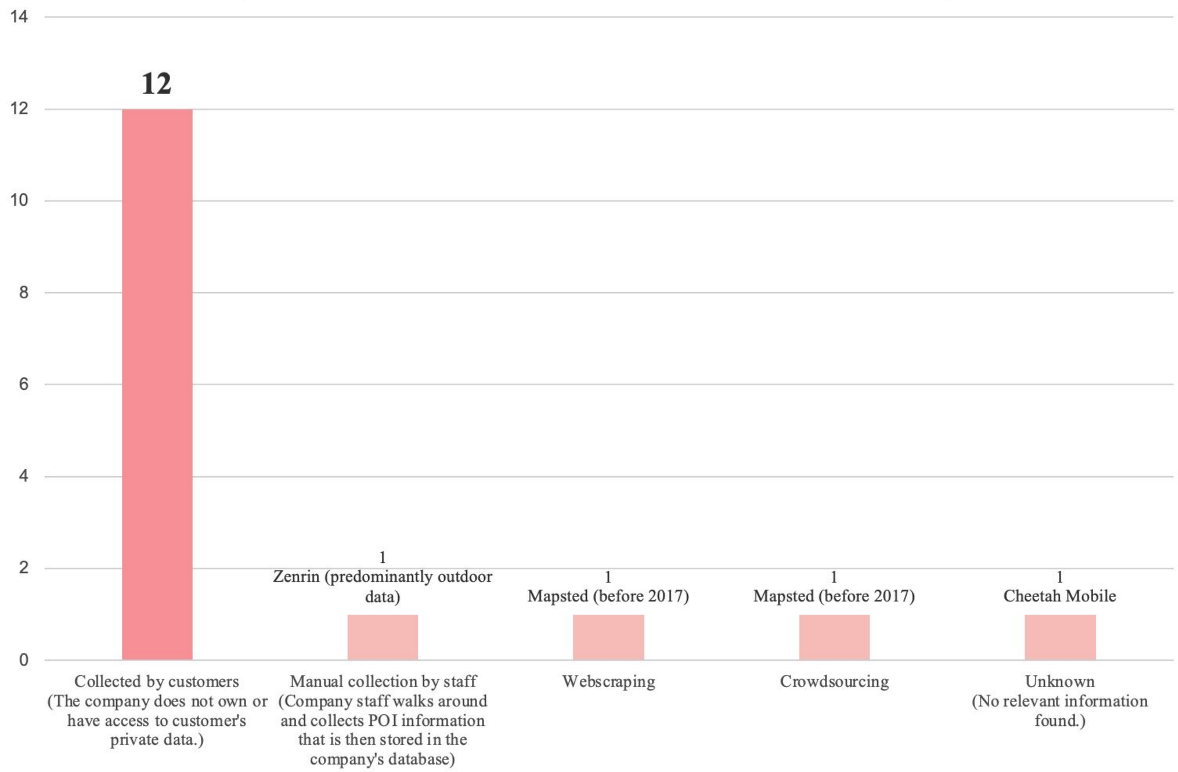
POI-related Information

Next 2) Technology 3) Business-related Information



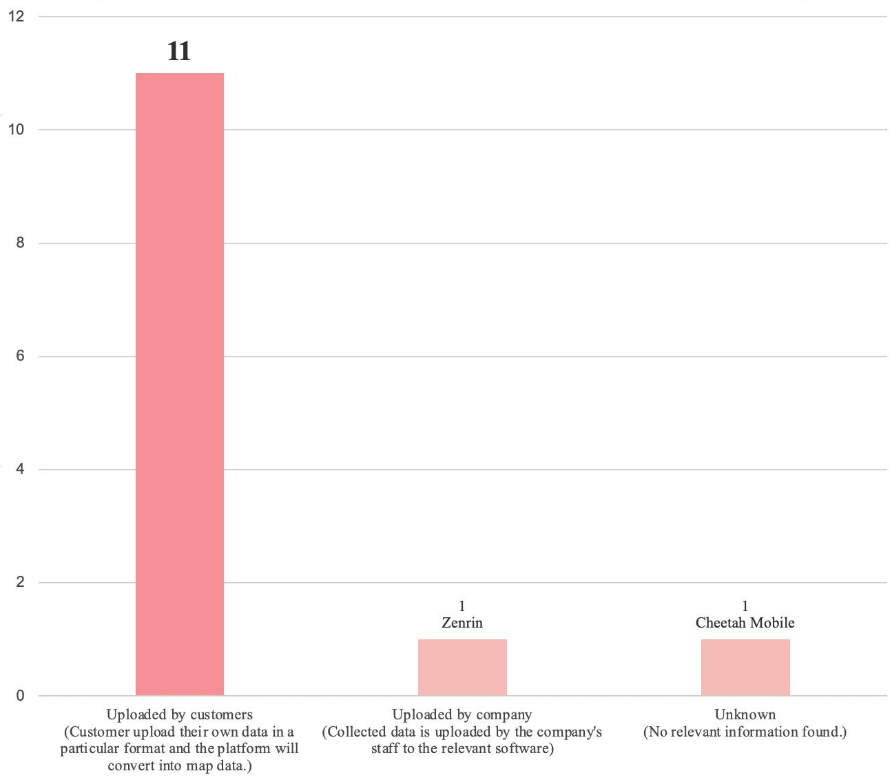
POI Collection

POI collection are mainly done by customers and companies do not have access to customers' private data unless upon request



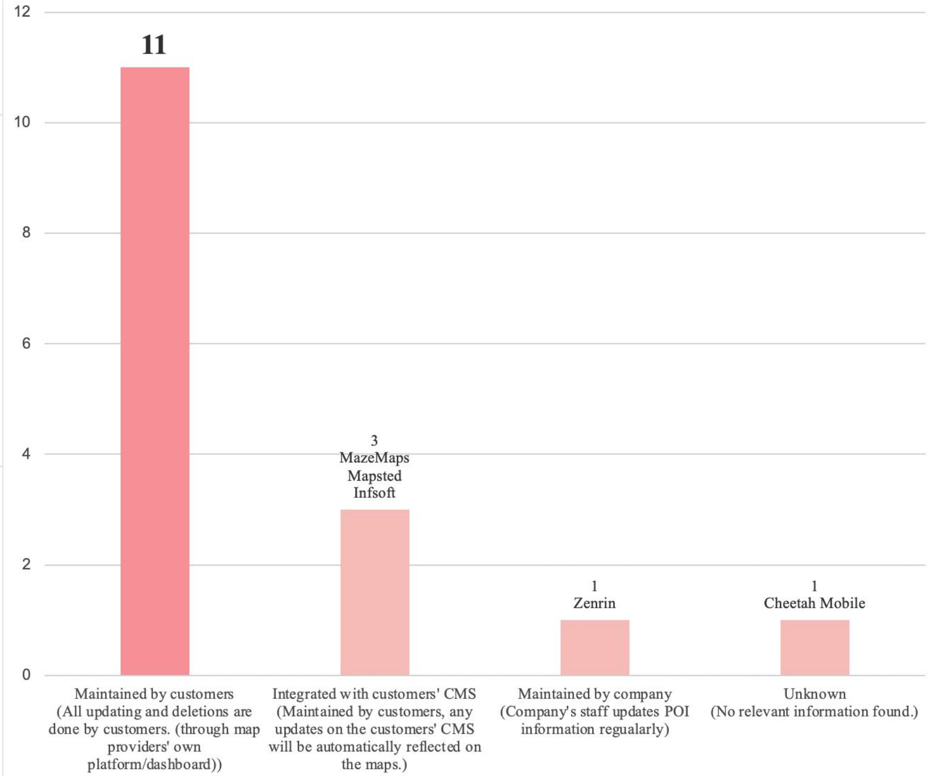
POI Input

POI collection are mainly done by customers, accounting for more than 80% among the methods



POI Maintenance

POI information are mainly maintained by customers through providers' own content management system (CMS) either in backend platform or dashboard

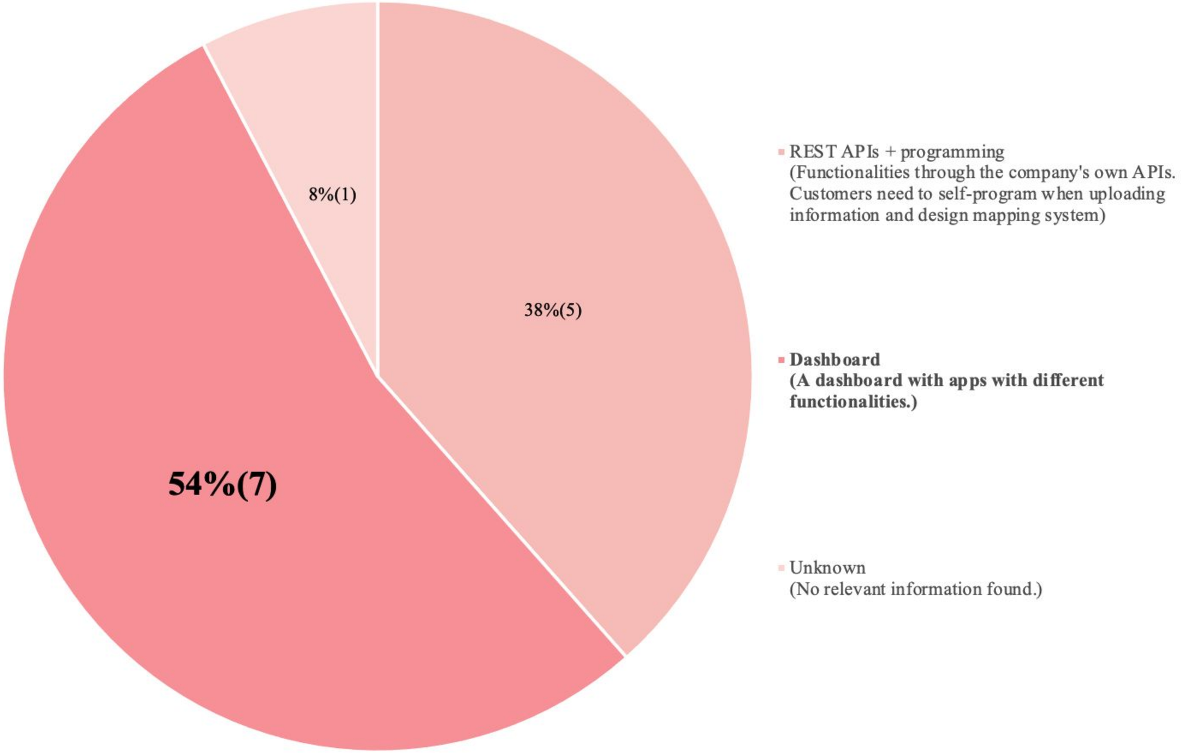


Technology

Next 3) Business-related Information

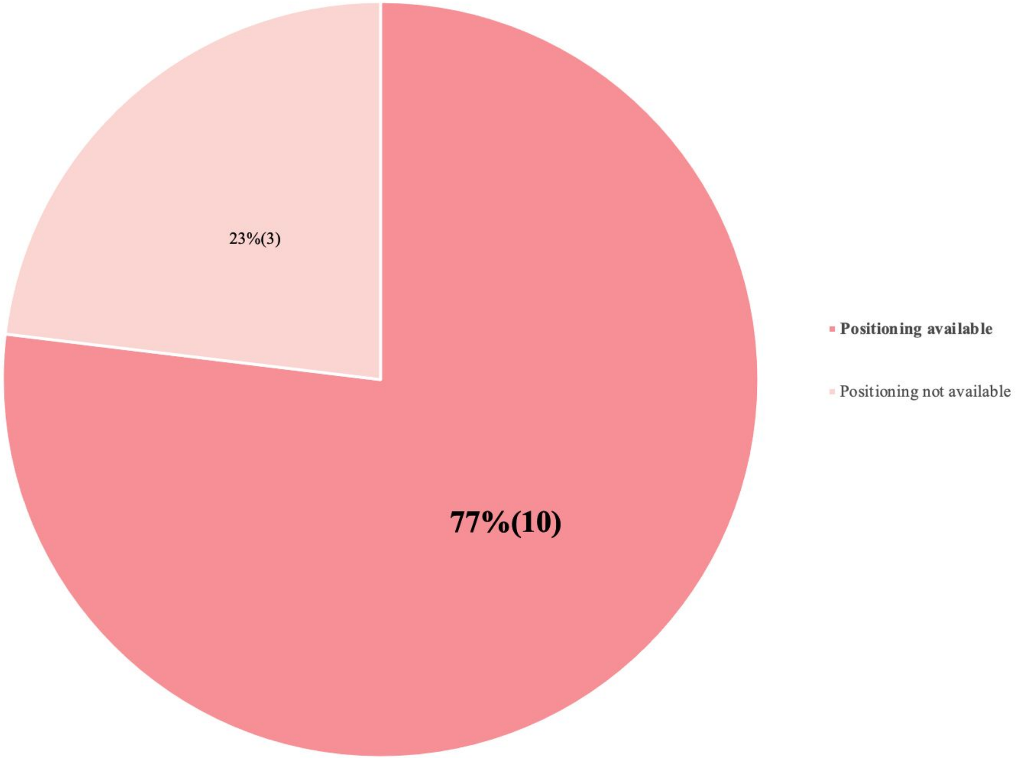
Technology Platform/Interface

Companies normally provide a dashboard for POI input and other functionalities,
API would be the second most common option



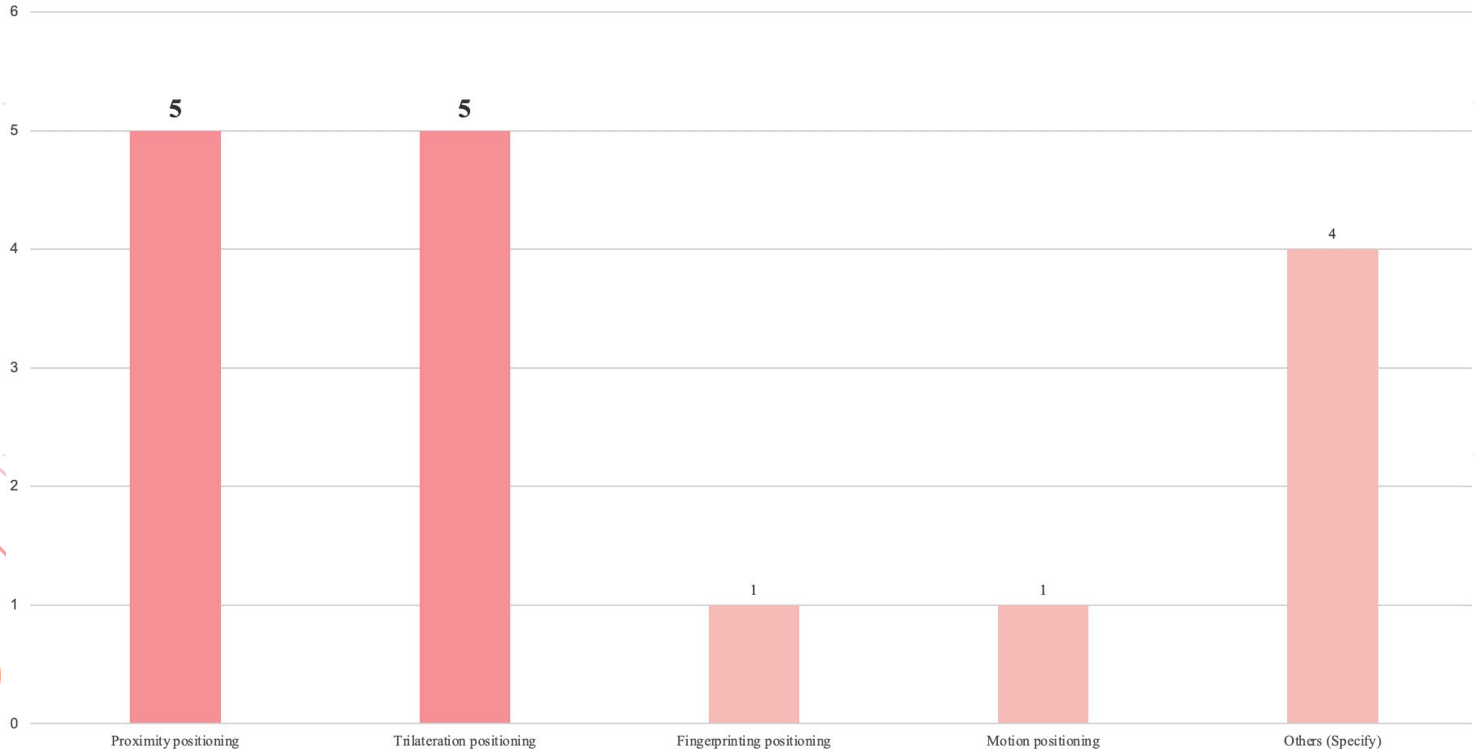
Positioning Technology Availability

Among all 13 companies, 10 companies include indoor positioning technology as their services



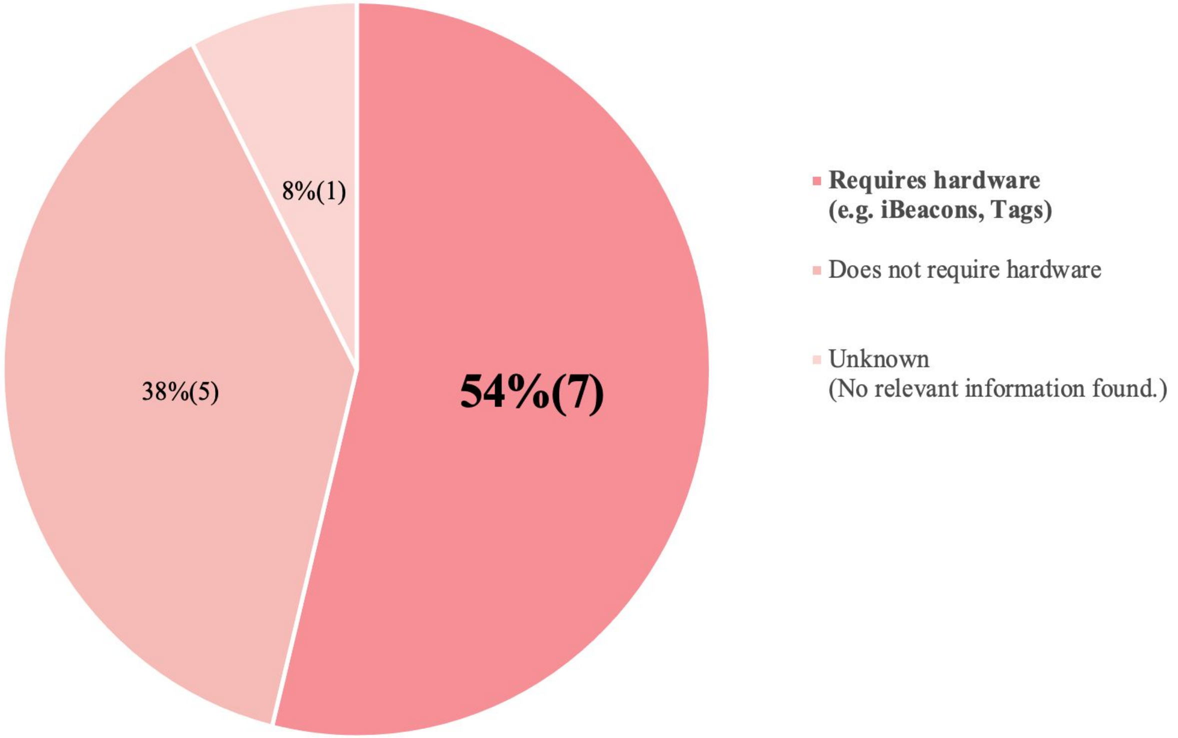
Positioning Technology

Companies with positioning technology usually utilise proximity and trilateration positioning technology. To highlight, for "Others" section, geomagnetic field, Robotics and AI, and a mix of technologies are utilized by specific companies like IndoorAtlas and Mapsted.



Technology Requirements

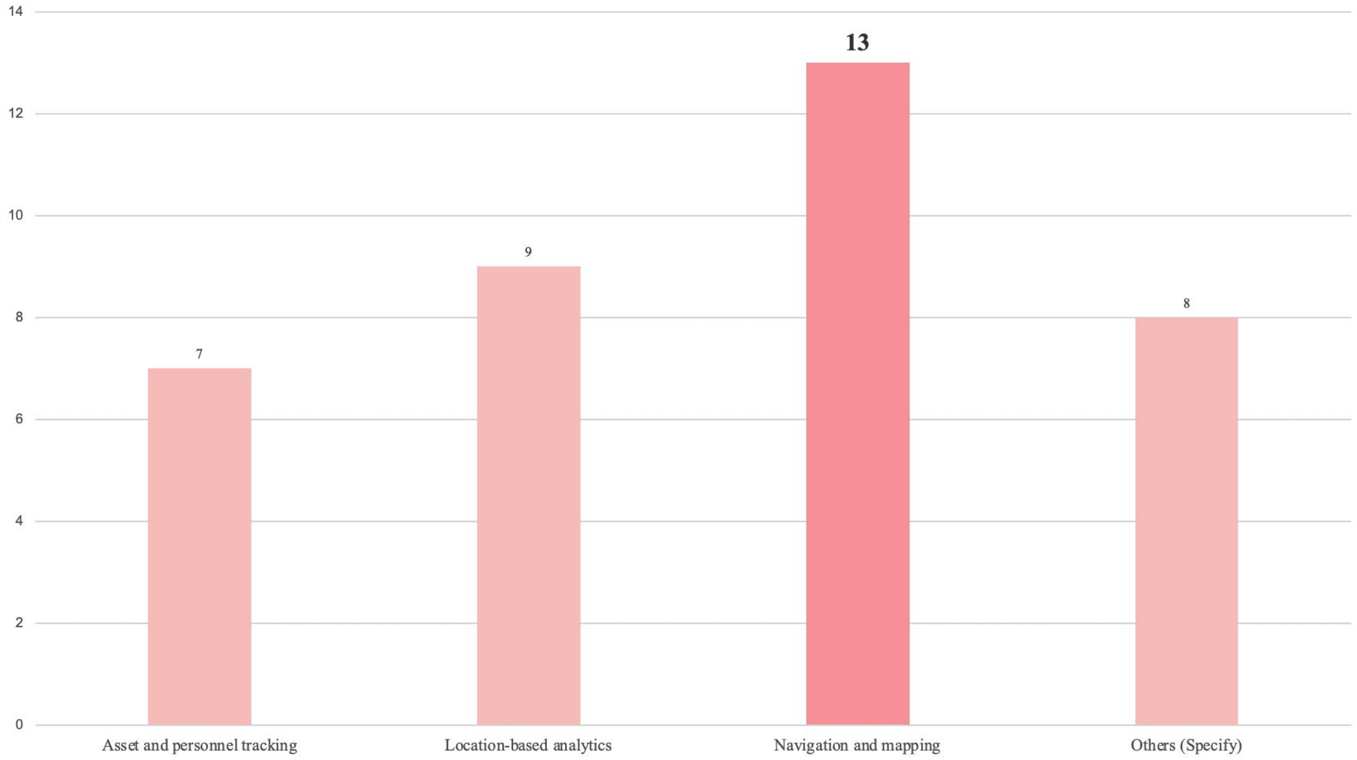
Companies utilising proximity and/or trilateration positioning technology would usually requires hardware and anchors, especially the commonly used BLE beacons



Business-related Information

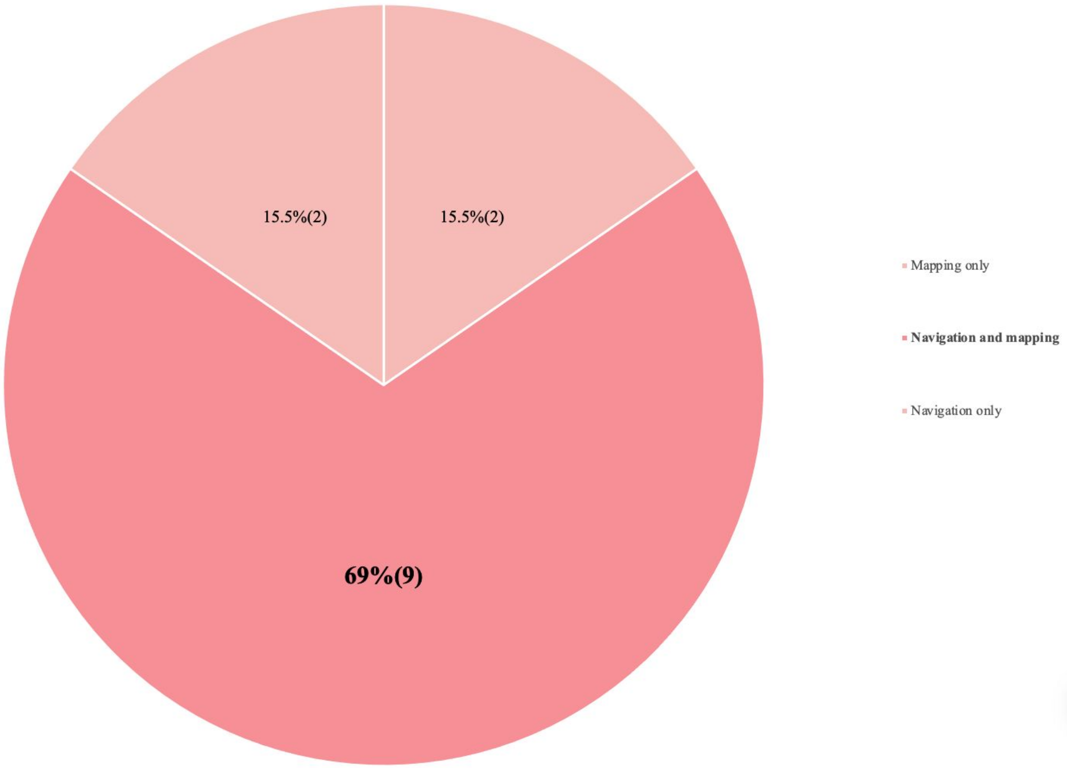
Applications

All companies provide navigation and mapping services. Both iOFFICE and Ubitrack focus on asset and personnel tracking solely. Specifically, for "Others" section, a majority of companies use geofencing for 1) marketing, and 2) manage crowd control.



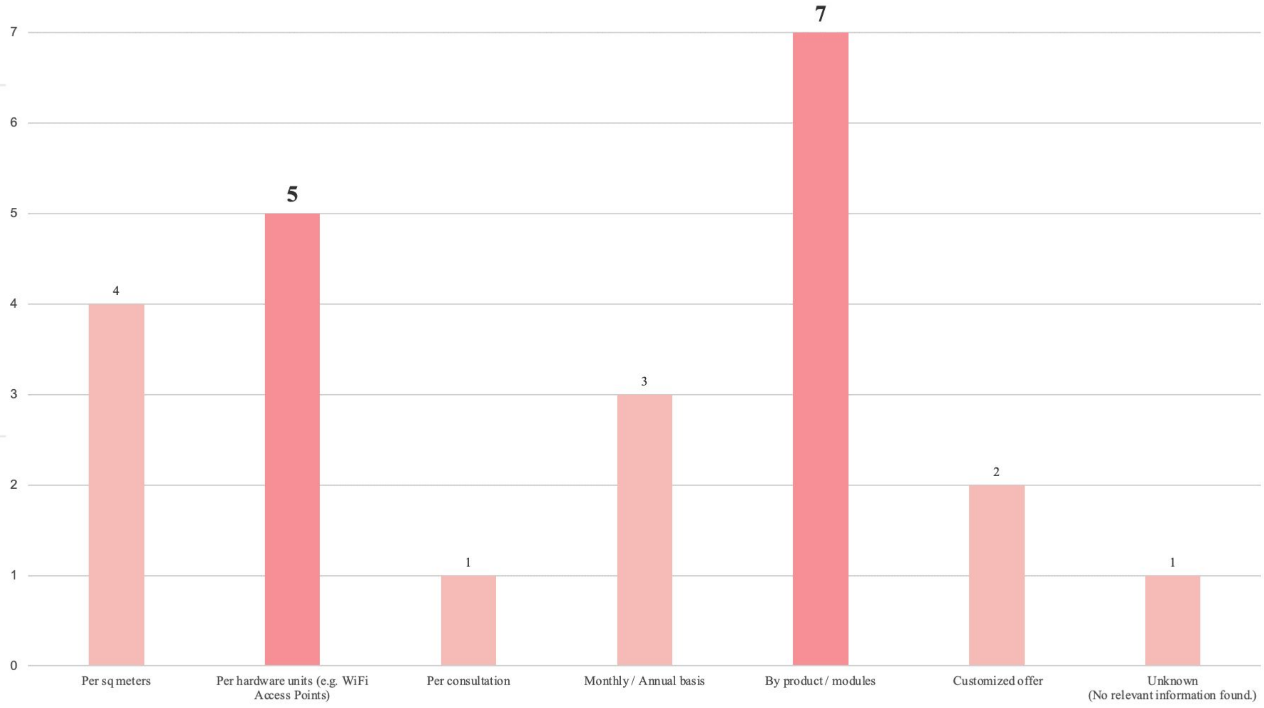
Within navigation and mapping

Around 70% of companies would provide both navigation and mapping. Zenrin and Cheetah Mobile only focus on navigation whereas Azure Maps and Esri ArcGIS Indoors only focus on mapping.



Monetization

Companies mainly charge customers by product or by module or per hardware units. It is also a common practice that companies charge customers with a combination of two or three components.



Business Model

We determine their business model based on how they generate value from customers.

Mapping service provider and SDK provider could not be totally separable as companies target different customer segments.

Mapping service provider	SDK provider	Middleman	Workplace management service provider	Robotics and AIoT
➢ MappedIn ➢ Mapsted ➢ Navigine ➢ Zenrin ➢ Ubitrack ➢ Cisco DNA Spaces + MazeMap ➢ Infsoft ➢ Cheetah Mobile	➢ MappedIn ➢ Mapsted ➢ Navigine ➢ Infsoft ➢ IndoorAtlas ➢ Azure Maps ➢ Esri ArcGIS Indoors	➢ Proximi	➢ iOFFICE ➢ Ubitrack	➢ Cheetah Mobile

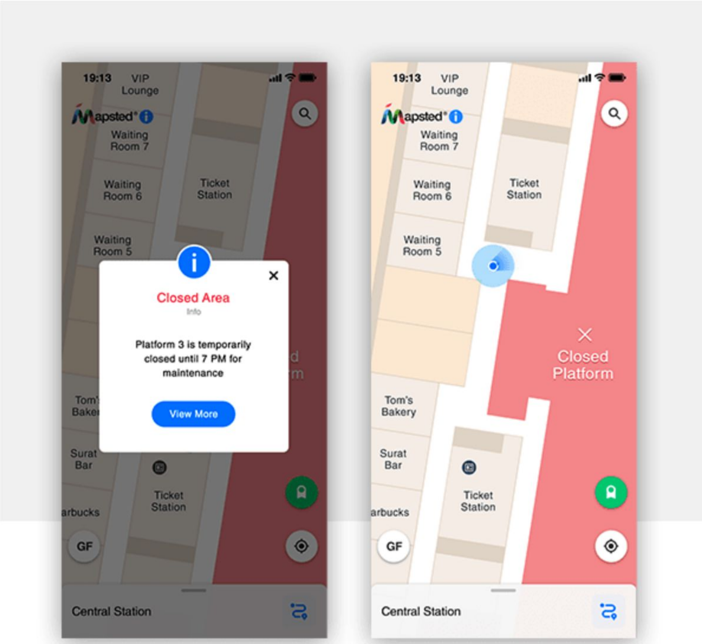
Target clients

60% of companies cover both private indoor spaces and public indoor spaces, It can be seen that most of the indoor spaces require indoor mapping, positioning and navigation services nowadays.

Private indoor spaces	Public indoor spaces	Outdoor spaces
➢ Navigine ➢ Proximi ➢ Cisco DNA Spaces + MazeMap ➢ iOFFICE ➢ IndoorAtlas ➢ Infsoft ➢ Zenrin ➢ MappedIn ➢ Azure Maps ➢ Esri ArcGIS Indoors ➢ Ubitrack	➢ Navigine ➢ Proximi ➢ Cisco DNA Spaces + MazeMap ➢ iOFFICE ➢ IndoorAtlas ➢ Infsoft ➢ Zenrin ➢ MappedIn ➢ Mapsted ➢ Cheetah Mobile	➢ Azure Maps ➢ Zenrin ➢ Ubitrack

POI Collection, Input and Maintenance

1) Standardised POI information from customers
2) Creating Content Management System (CMS) as Dashboard
3) Exploration to proceed B.I. AI Approach from POI collection to POI maintenance



Mapsted emergency maintenance example

Example for POI collection standardisation (Proximi)

1. Architectural floor plans (PDF or CAD) for all the buildings and floors of the venue
2. Information on ceiling height. If the architecture is very complex, it is suggested to include a section drawing
3. An Excel list of all the rooms/areas that should be included in the wayfinding setup as Points of Interests detailing their name (as it should be shown in the application, separately in all the languages), area type (e.g. office/restaurant) and the identification code on the floor plans.
4. An Excel list of all the other Points of Interests that should be shown in the application, such as first aid kits, detailing their name, POI type and exact location on the floor plans.
5. Any photos, descriptions, links, or other materials that should be displayed on the application about the Points of Interests. Photos should be sized between 480p (480x800px) to 720p (720x1280px), and they should be in JPG or PNG format.
6. UI design or information on customer's brand and wishes

Example of CMS features (Mapsted)

Mapsted utilises the CMS to let customers themselves to quickly add properties, upload floor plans, and customise interactive maps. Customers are allowed to make changes in real-time with Manage-Dashboard, Manage-Branding and Manage - Maintenance.

Manage-Dashboard	Manage-Branding	Manage-Maintenance
1. Add and customise new properties 2. Upload and organise floor plans 3. Set working and holiday hours for properties 4. Select authentication permissions for visitors and staff	1. Colours, logos, and fonts 2. Property layers, including parking, accessibility and dining options 3. Layers including parks, pathways and washrooms 4. Map style including classic, light mode and dark mode	1. POI asset tags 2. Authentication permissions 3. Emergency response planning Allows property management teams to mark points of interest, like elevators as closed for maintenance, and set desired levels of property access for contract workers and help keep visitors safe during emergencies which allows customers to control

Naver Labs POI change detection

Naver Labs concept: https://www.youtube.com/watch?v=UWna1WRoVcU

Naver Labs POI change detection demo:

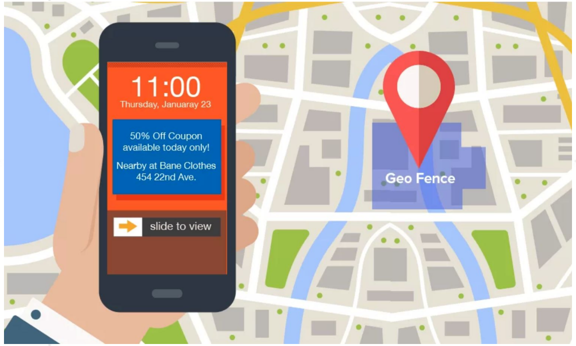
https://www.youtube.com/watch?v=496hNzgk4kU

Naver Labs self-updating map demo:

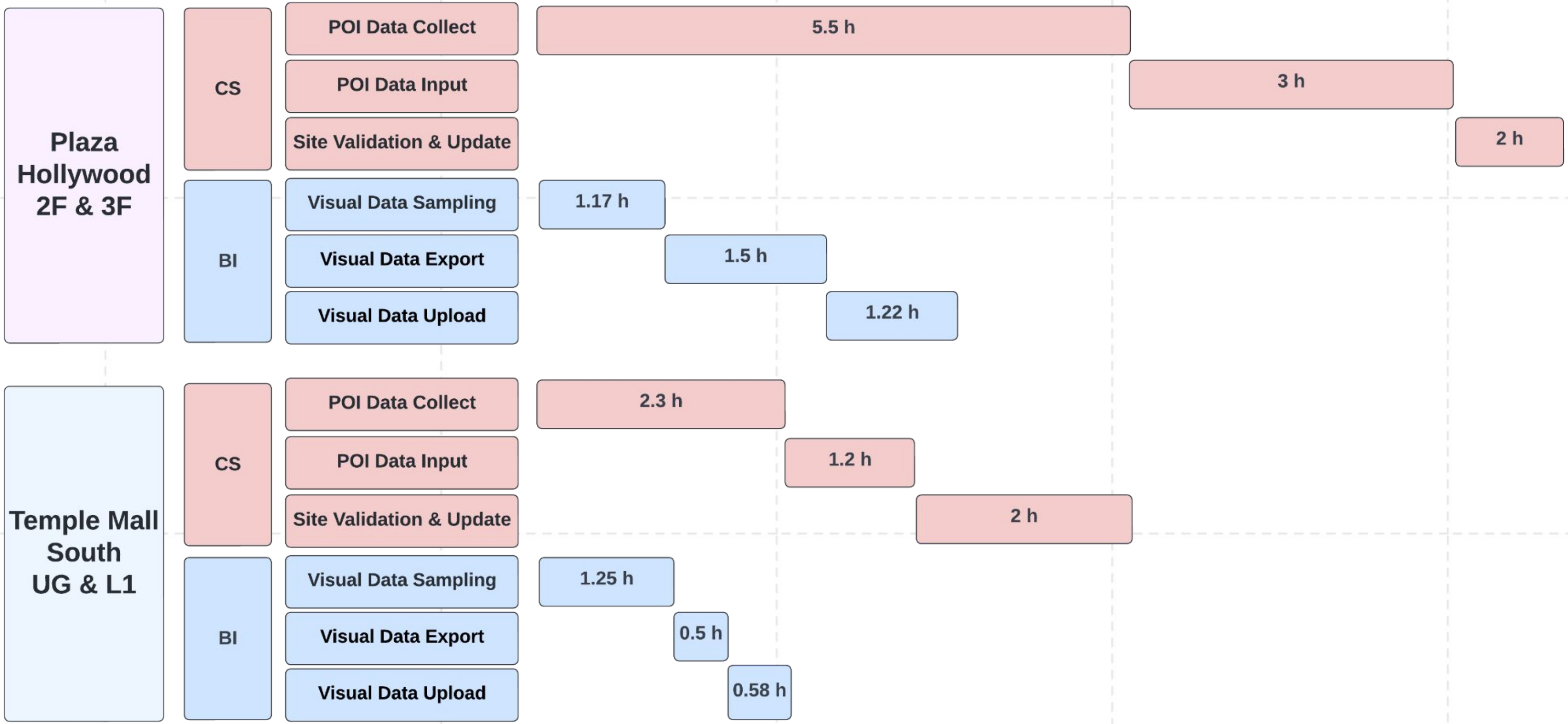
https://www.youtube.com/watch?v=QK_YV65OOnw

Positioning

1) Filtered layer and integrate customer request for different targeted users
2) Geofencing
3) Setting up an API that integrate hardware and software



Time Consumed for Manual Work



Time Consumed for Manual Work

Overall, for the two test buildings, the B.I. approach has about 9.8 hours (588 minutes) less time consumed for manual work and improved the efficiency by 61%.

Unit: hours	Plaza Hollywood	Temple Mall South	Total	Avg hours/floor
CS	10.5	5.5	16	4
B.I.	3.88	2.33	6.21	1.5
Total	14.38	7.83		