

## From Fingerprint to Footprint: Using Point of Interest (POI) Recommendation System in Marketing Applications

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**Abstract.** *Companies should be willing to adopt new technologies and business models to be able to stay competitive in the changing world, both regionally and globally. However, the US forest sector industry, including wood furniture sector seems to be lagging when it comes to implementing digital technologies. This study proposes a design of Point of Interest (POI) recommendation system to enhance the marketing practices to promote wood furniture stores. We produced a personal recommendation design utilising K-Means+ clustering, a combination between K-Means algorithm for spatial data clustering and Davies-Bouldin Index (DBI) methods to determine the optimal K value. This design can assist mobile users who are potential customers to find wood furniture store locations based on other users' preferences.*

**Keywords:** *Digitalisation; location-based social networks; user-based collaborative filtering; K-Means+ clustering; DBI method*

### 1. Introduction

Through digitalisation and more advanced Information Technology (IT), business has undergone dramatic changes. Nowadays, physical markets and stores are perceived to be no longer necessary (Arano and Spong 2012), taking the business competition to another level, entering a new era of e-business and e-commerce. Companies that control the interface between the provider of the goods or services and the consumers are believed to be in a dominant position (Goodwin 2015).

Amazon, eBay, and Alibaba that were unknown of two decades ago, have emerged as key players in modern economy.

There is a lot of pressure for companies to go online and do e-commerce as the old ways of doing business may rapidly become obsolete (Zander et al. 2015). Companies should be

prepared for the emerging changes and willing to adopt new technologies and business models to be able to stay competitive in a changing world, both regionally and globally. The world has entered “Digital Darwinism” phenomenon where technology and society evolve faster than an organisation can naturally adapt, setting a new generation of “adapt or die” business (Solis 2014). A senior consultant specialised in digital transformation predicts that “by 2025 about 40% of Fortune-500 companies are likely to vanish due to megatrends like digitalisation” (Zander et al. 2015).

The manufacturing industry is heading towards a digitalised and interconnected industrial production or “Industry 4.0”. This transformation will impact the ecological dimension such as resource efficiency and renewable energy and will disrupt business models (Beier et al. 2017). However, although

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digitalisation has become a buzzword in modern business and even is claimed as the core of the next industrial revolution, many manufacturing companies struggle to understand its real potential (Parviainen et al. 2017). Therefore, more research is needed regarding the impact of digitalisation in business development and business models that integrate products, business processes, sales channels, and value chains (Matt, Hess and Benlian 2015).

In general, the U.S. forest sector seems to be lagging when it comes to implementing digital technologies (Vlosky and Westbrook 2002; Vlosky, Westbrook and Poku 2002). This leads to a big question of maintaining business sustainability considering the importance of the forest sector in the U.S. economy. The industry accounts for approximately four per cent of the total U.S. manufacturing GDP and manufactures over \$200 billion in products (AF&PA 2018). By employing approximately 950,000 workers with a payroll of approximately \$50 billion, the industry is among the top 10 manufacturing sector employers in 45 states (AF&PA 2018).

Recently, there is a forest sector study investigating Geographical Information Systems (GIS), a growing technology that is mostly used in biomass mapping and logistics domains, in the application of a company's 4P marketing mix: product, place, price, and promotion (Quesada-Pineda, Brenes-Bastos and Smith 2017). Although there is a considerable potential to use GIS in the marketing applications, it would require some level of creativity by the interested stakeholders. This study's finding of the slow adoption of digital system in the forest sector industry is similar with a Finnish study about the use of IT in marketing of the forest sector companies, even though the two studies focus on different technology advancement and have twenty years gap of time. The Finnish study finds that IT can be used as a competitive advantage in order to emphasise customer relationships and service (Toivonen 1999).

However, IT planning has not been integrated into the marketing strategy and has not been used to its full potential (Toivonen 1999). Both studies showing that, despite a fast-growing digital technology in a rapidly changing world, the forest sector industry is still in the slow pace of digital adoption, specifically in the marketing system.

In this study, we propose an application of digital technology to boost the marketing of forest sector. The application is called Point of Interest (POI) recommendation system that is based on recent developments in mobile device technology that enables geographical data application for social networks. This location-based social network has been used to endorse items according to different user preferences, as has been applied by giant tech companies such as Amazon, Google, and Netflix. Specifically, we utilise wood furniture store as POI because of data accessibility and feasibility. We chose wood furniture because the industry is considered as a low-technology, resource- and labour-intensive sector facing globalisation (Larasatie 2018). Therefore, there is a need to boost the industry ability to adapt with competitive digital era.

The objective of this study is to investigate the application of Point of Interest (POI) recommendation system to assist potential customers in finding wood furniture store locations based on other users' preferences history. We aim to produce a design of a wood furniture store recommendation system based on POI. This paper is organized as follows. First, we provide a contextual background discussing existing digitalisation and IT research in the forest sector, and a theoretical background discussing POI recommendation system, K-Means + clustering, collaborative filtering, and contextual information. This is followed by a description of the study design. Findings are then discussed from academic and practical perspectives. Finally, conclusions and future research are offered.

## 2. Literature Review

### 2.1. Related research in the forest sector

There has been considerable research investigating digitalisation and the use of IT in the forest sector (Table 1). Looking at the research methods, most studies utilised mail and phone survey to both primary and secondary forest sector industry with

subsequent analyses ranged from simple descriptive statistics to multivariate statistical analyses. Those studies revealed that there is a lack of using advanced digital technologies in the forest sector business. Apart from pulp and paper companies, the North American forest sector companies have been slow in integrating IT into their business (Hewitt, Sowlati and Paradi 2011).

Table 1.

*Digitalisation and IT Research in The Forest Sector (from the most recent year)*

<b>AUTHORS</b>	<b>TITLE</b>	<b>BUSINESS CONTEXT</b>	<b>RESEARCH OBJECTIVES</b>
Gazal, Montague and Wiedenbeck 2019	Factors Affecting Social Media Adoption Among Wood Products Consumers	Social media adoption	To investigate the factors affecting social media adoption among wood products consumers in the U.S. within the B2C marketing context
Montague, Gazal and Wiedenbeck 2019	Social Media Use in the Wood Products Industry: Impact on the Consumer Purchasing Process	The use of social media	To provide an overview of consumer use of social media when making wood product purchasing decisions
Makkonen 2018	Stakeholder Perspectives on the Business Potential of Digitalization in the Wood Products Industry	Business potential of digitalisation	To understand how wood products industry could utilize digitalisation to apply customer-oriented business strategies, and what development will be needed to achieve this goal
Gazal et al. 2016	Forest Products Industry in a Digital Age: Factors Affecting Social Media Adoption	Social media adoption	To examine the factors affecting social media adoption among the US forest products companies
Montague et al. 2016	Forest Products Industry in a Digital Age: A Look at e-Commerce and Social Media	The use of e-commerce and social media	(1) to identify the type(s) of e-commerce and social media tools forest products companies use, (2) to identify and describe the reasons a company chooses to use or not use social media as a marketing tool, (3) to identify and describe perceptions held about social media as a marketing tool

Table 1. (continued)  
*Digitalisation and IT Research in The Forest Sector (from the most recent year)*

<b>AUTHORS</b>	<b>TITLE</b>	<b>BUSINESS CONTEXT</b>	<b>RESEARCH OBJECTIVES</b>
Trang et al. 2016	Towards an Importance–performance Analysis of Factors Affecting E-Business Diffusion in the Wood Industry	e-business adoption	To investigate factors of e-business adoption to derive recommendations for improving e-business diffusion in the wood industry
Zander et al. 2015	Integrating Industry Characteristics in Inter-Organizational IS Adoption Models: A Mixed Method Approach	Inter-organizational system adoption in the industry	To explain how industry characteristics can contribute to the explanation of inter-organizational system low adoption phenomenon
Hewitt, Sowlati and Paradi 2013	Analysis of Available Software Products in the North American Cabinet Industry	Software product functionalities in the industry	To evaluate the functionalities of software products currently available in the North American cabinet industry
Hewitt, Sowlati and Paradi 2012	Evaluation of Strategic Software Investments for the Canadian Cabinet Industry	Software contribution in the industry	To determine the types of software that could contribute the most to the future competitiveness of the Canadian cabinet industry using industry and IT expert input into an Analytic Network Process model
Hewitt, Sowlati and Paradi 2011	Information Technology Adoption in US and Canadian Forest Products Industries	IT adoption in the industry	To review key studies on IT adoption in US and Canadian forest products industries, summarizes their common findings, gives insights on these commonalities, and recommends future areas of research.
Montague 2011	Social Network Media in the Forest Products Industry: A Look at a New Way of Marketing	The use of social media	To collect preliminary data on social media use in the hardwood forest products industry and determine manufacturers' attitudes towards social media networking
Martin 2009	Opportunities for an Online GIS-Based Wood Supply Management System	Online GIS for optimizing supply chain management system	To develop the concept of using an Internet-based, Geographic Information System (GIS)-supported, optimized wood supply chain management system to overcome some of the current inefficiency problems

Table 1. (continued)  
*Digitalisation and IT Research in The Forest Sector (from the most recent year)*

AUTHORS	TITLE	BUSINESS CONTEXT	RESEARCH OBJECTIVES
Vlosky and Smith 2003	eBusiness in the US Hardwood Lumber Industry	e-business adoption and use	To examine e-business adoption and use in the U.S. hardwood lumber industry
Vlosky and Youn 2002	A Cross-National Study of Internet Adoption in the Forest Products Industry in the United States and South Korea	The use of Internet for e-business	To examine the current and future uses of e-business in the industry and identify how the forest products industry is investing in and leveraging e-business
Vlosky and Westbrook 2002	eBusiness Exchange between Homecenter Buyers and Wood Products Suppliers	The use of e-business	To examine e-business exchanges between homecenter retailers and wood products suppliers in the United States from the homecenter perspective
Vlosky, Westbrook and Poku 2002	An Exploratory Study of Internet Adoption by Primary Wood Products Manufacturers in the Western United States	The use of Internet for e-business	To examine current and potential use of internet-based technologies to conduct business by solid wood products manufacturers in the western United States
Pitis and Vlosky 2000	Forest Products Exporting and the Internet: Current Use Figures and Implementation Issues	The use of Internet in the export activities	To examine internet use by U.S. primary wood products exporters

IT adoption is positively correlated with company size (Stennes et al. 2006; Shook et al. 2002; Dupuy and Vlosky 2000) and export sales (Stennes et al. 2006; Pitis and Vlosky 2000), and is determined by the quality of IT staff (Poku 2003) and the degree of value-added in the products (Kozak 2002). Another finding is companies with more marketing orientation are found have higher IT adoption level than companies that are categorised have lower marketing orientation (Poku 2003; Hewitt, Sowlati and Paradi 2011).

Despite these significant findings, there are very few forest-related studies looking on the application of digital technology in forest sector marketing. Those few studies including a study investigating GIS in application of a company's 4P marketing mix (Quesada-Pineda, Brenes-Bastos and Smith 2017) and a

study of the use of IT in marketing of Finnish forest industry (Toivonen 1999).

*2.2. Point of interest (POI) recommendation system*  
 POI recommendation system is a subclass of information filtering system, seeking to predict a "rating" or "preference" that a user will possibly assign to items or locations (Ricci, Rokach and Shapira 2011). The basic computation concepts of this recommendation system are user, item, and transaction. User is a subject in the POI recommendation system, the item is a recommended object, and transaction is a rating given to the item in the system.

There is a considerable amount of research investigating the application of the recommendation system on business areas such as entertainment, tourism, and clothing

(Table 2). Collaborative filtering in recommendation system can handle problems such as low accuracy, data sparsity, and scalability (Isinkaye, Folajimi, and Ojokoh 2015). However, despite its advantages,

collaborative filtering has a weakness. The increase of the users over time may lead to an increase in the computational complexity of the system (Tuan, Hung and Wu 2016).

Table 2.

*Recommendation System Research on Business Areas (from the most recent year)*

AUTHORS	TITLE	BUSINESS AREAS	BUSINESS CONTEXT/ OBJECTIVE	DATA ANALYTIC TECHNIQUES
Katarya and Verma 2017	An Effective Collaborative Movie Recommender System with Cuckoo Search	Entertainment	Movie Recommender System	K-means cuckoo and collaborative filtering
Kesorn, Juraphanthong and Salaiwarakul 2017	Personalized Attraction Recommendation System for Tourists Through Check-in Data	Tourism	Knowing what kind of attractions tourists are interested in	PTIS framework is combination between collaborative filtering, content based filtering convolutional neural network combined with the support vector machine (mCNN-SVM)
Zhang et al. 2017	Trip Outfits Advisor: Location-Oriented Clothing Recommendation	Clothing	Trip outfits for travel destinations	Recommend a personalized travel sequence
Jiang et al. 2016	Personalized Travel Sequence Recommendation on Multi-Source Big Social Media	Tourism	Ubiquitous Shopping Recommendation system	collaborative-filtering-based recommender system
Kim, Kim and Ryu 2009	Personalized Recommendation over a Customer Network for Ubiquitous Shopping	Clothing	Making music recommendation system based on music and user grouping	The content-based, collaborative filtering
Chen and Chen 2005	A Music Recommendation System Based on Music and User Grouping	Entertainment		

### 2.3. K-Means+ Clustering

In this study, we utilized K-Means+, a combination between the K-Means algorithm

for spatial data clustering and Davies-Bouldin Index (DBI) methods to determine the optimal K value (the number of clusters). K-

means is an unsupervised learning algorithm that is relatively not complicated but can solve the well-known clustering problem such as low accuracy, time consumed and scalability (Zahra et al. 2015). K-Means has been used to solve recommendation system problems in some fields such as movies (Katarya and Verma 2017), books (Zhang 2016), and music (Chen and Chen 2005). However, the K-Means algorithm has a weakness in which the result of clustering has a high dependency on the value of defined K (Zahra et al. 2015). Therefore, the K-Means algorithm is combined with DBI method to determine the K value.

The combination between DBI and K-means algorithm aims to generate the most optimal K value of the dataset, producing more optimal clustering results (Sitompul 2018). As a cluster validation method, DBI can optimise the clustering results of K-means by maximising inter-cluster distance and minimising intra-cluster distance. The smaller the DBI value (non-negative  $\geq 0$ ), the better cluster results.

#### 2.4. Collaborative filtering

The most frequently used technique in the location-based recommendation system is collaborative filtering due to its high accuracy and its ability to handle data sparsity (Isinkaye, Folijimi, and Ojokoh 2015; Tuan, Hung and Wu 2016). Collaborative filtering considers the similarity between users to generate recommendation on items. The system will first look for users who share the same rating patterns with the active user. Then, the ratings from those like-minded users will be used to calculate a prediction for the other active users.

#### 2.5. Contextual information

Contextual information (e.g. location, time, or social network activities) is beneficial to build a personalised recommendation system since the relevant contextual information will improve the accuracy of consumer preference prediction (Odić et al. 2013; Adomavicius et al. 2011). Contextual information can be acquired automatically by the system (e.g.

location, season (Fall/ Spring/ Winter/ Summer), and daytime (morning/ afternoon/ night)) or optionally added by the users (e.g. budget and feeling (sad/happy)) (Achmad et al. 2017).

### 3. Methodological

#### Step 1. Applying K-Means+ Clustering

K-Means+ is applied by combining the K-Means algorithm and DBI method. K-Means algorithm is an unsupervised algorithm that is grouping the data based on central point (centroid) of the cluster that is the closest to the data. K-Means is used to avoid unlabeled data (i.e. data without defined categories or groups). The goal of this algorithm is to find groups in the data, with several groups represented by K variable. Each centroid defines one of the clusters, and each data point is assigned to its nearest centroid iteratively based on the Euclidean distance squared. Data points are clustered based on the feature similarities.

The Euclidean distance is defined by equation #1 (Maulik and Bandyopadhyay 2012):

$$D(x, y) = \sum_{i=1}^c \sum_{j=1}^{c_i} (\|x_i - y_j\|)^2$$

Where  $\|x_i - y_j\|$  is the Euclidean distance between  $x_i$  and  $y_j$ ,  $c_i$  is the number of data points in  $i^{th}$  cluster, and  $c$  is the number of cluster centres (centroid).

The next centroid is calculated by equation #2 (Jahiruzzaman and Hossain 2015):

$$v_i = (1/c_i) \sum_{j=1}^{c_i} x_i$$

Where  $c_i$  is the number of data points in  $i^{th}$  cluster. Iteration is conducted in a clustering process to the specific threshold that was previously determined.

DBI is an internal evaluation method that measures a cluster based on cohesion value and separation value (Davies and Bouldin 1979). In the grouping process, cohesion is defined as the sum of data closeness/

proximity with centroid from following cluster (inter-cluster), while the separation is based on the distance between the centroid and its cluster (intra-cluster).

DBI is calculated by equation #3 (Davies and Bouldin 1979):

$$DBI = \frac{1}{K} \sum_{i=1}^K R_{i,qt}$$

Where K is the number of clusters, and  $R_{i,qt} = \max_{j, j \neq i} \left\{ \frac{S_{iq} + S_{jq}}{d_{i,jt}} \right\}$ . The lowest DBI value, (non-negative  $\geq 0$ ), is the

cluster obtained from the given value of K (Sundar, Chitradevi and Geetharamani 2012).

*Step 2. Location (POI) Based Collaborative Filtering*

There are three recommendation system steps (Figure 1). First, the similarity between a user and another user is calculated. Cosine similarity is used because it is more appropriate in calculating binary data (Elavarasi and Akilandeswari 2014).

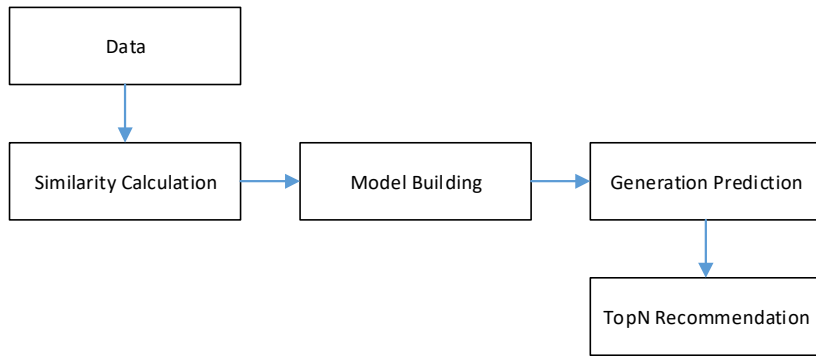


Figure 1. Recommendation System Steps

Cosine similarity is calculated by equation #4 (Elavarasi and Akilandeswari 2014):

$$sim(a, b) = \frac{n(A \cap B)}{\sqrt{n(A)n(B)}}$$

With  $n(A)$  is the number of items selected by user A,  $n(B)$  is the number of items selected by user B, and  $n(A \cap B)$  is the number of items selected by both A and B users.

Second step is model building, derived from the similarity calculation of the entire users who participate as models in the resting process. During the process, system seeks the similarities among active users taken from the models that have been created. Once the similarity of active users is found, it proceeds to generating prediction to build a recommendation system.

Location recommendations to active users are done in the third step, generation prediction.

In the user-based collaborative filtering, the nearest neighbours of an active user are selected based on similarity to the user. There are two steps in building recommendations for active users:

- (1) Find the N nearest neighbour with the most exceptional similarity value and
- (2) Calculate the predicted value of items selected by the nearest users but has never been selected by the active users, with equation #5 (Aggarwal 2016):

$$Pred(a, p) = \sum_{r \in U} sim(a, u) \times r_u$$

**4. Findings and Discussion**

Since this study is exploratory by nature, we utilized literature reviews such as purchase intention variables (e.g. Yaacob and Baroto 2019) to determine the taxonomy of



contextual information. For the wood furniture store recommendation system, we used store rating, product price, location (spatial information), and wood products as contextual information of the recommendation system (Figure 2). In the

future, we will survey to determine the contextual information. Then, we will test the independence between the contextual information on the users' ratings for items. This method is expected to increase the effectiveness of the system.

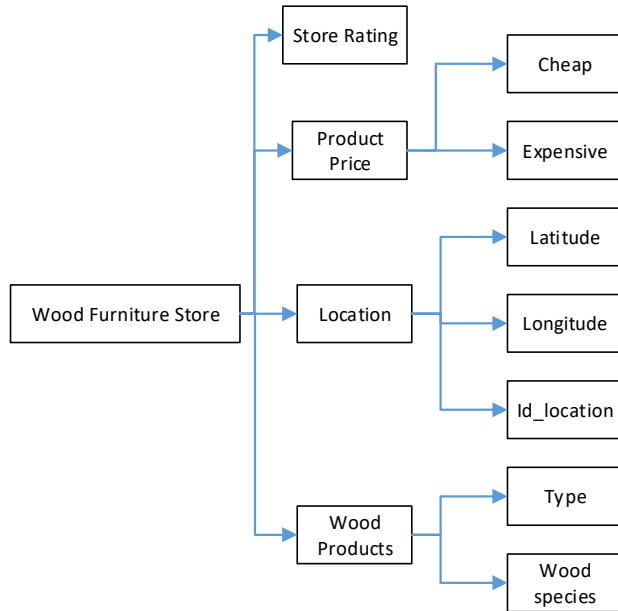


Figure 2. Contextual Information of Wood Furniture Store Recommendation System Based on POI

Contextual information of rating (R) consists of a scale of 1-5 in which 5 is the highest rating. Rating represents the value of item recommendation by users. The higher the rating, the more recommended the items. Contextual information of location (L) is broadly divided into the user location (buyer) and wood furniture store location based on geographical, address, place, or coverage (Aggarwal 2016; Hu et al. 2014). This contextual information can be used to recommend the wood furniture store and suggest the location of the nearest destinations.

The wood furniture store recommendation system based on POI (Figure 3) starts to work when users or potential customers input furniture specification that they are looking for, such as product type (e.g. tables/chairs) and wood species (e.g. Pine/Oak). The system will do data processing and then, clustering the data based on K values determined by DBI method. The clustering will result in grouping the users based on locations with user similarity levels. In this stage, collaborative filtering techniques are used to filter the clustering results to be only top five recommended wood furniture stores.

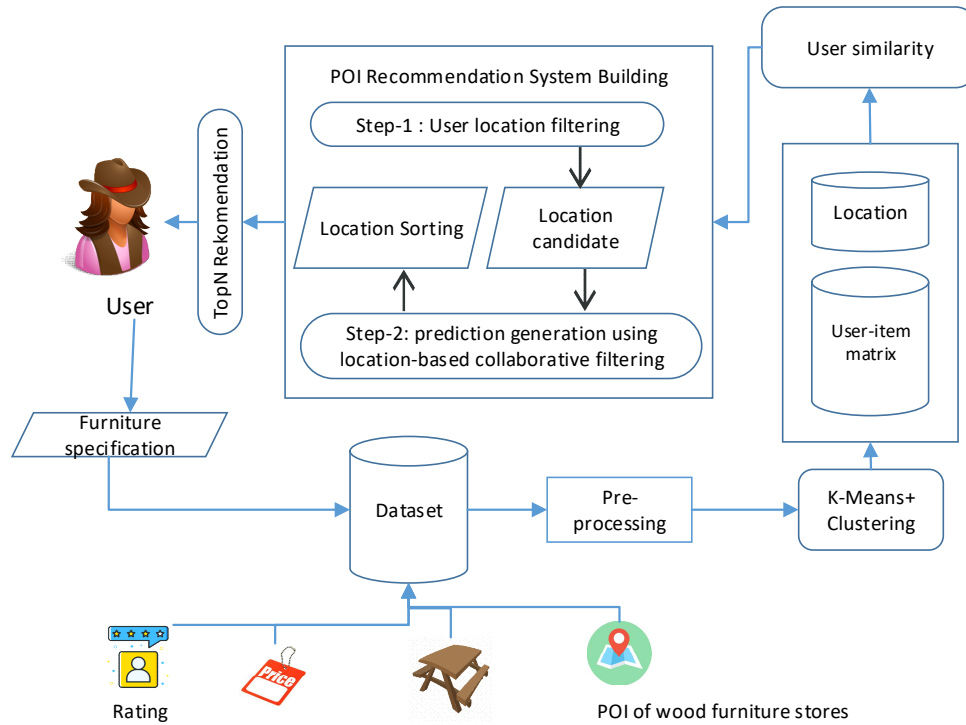


Figure 3. Research Design of Wood Furniture Store Recommendation System Based on POI

Based on our design, the POI recommendation system can be applied to enhance the marketing practices in forest sector industry. Mobile users that are also potential customers will have a new experience of wood furniture shopping. With up to date marketing applications, wood furniture industry is expected to be able to maintain their business sustainability.

## 5. Conclusion

Wood furniture store recommendation based on POI is a digital innovation that can be implemented to answer the challenges of increasing number of mobile users. Our design can be an alternative for improving the mobile business model in the mobile marketing environment.

For the next step, we will do a survey for analysing our contextual information design. We will also collect data from real-world mobile users and conduct an empirical

experiment to validate the usefulness of our design. The real-world data will be pre-processed to eliminate noise before being clustered. Then, we will apply our study design to evaluate the recommendation system. The process to build the wood furniture store recommendation system based on POI will consist of these sequence steps: clustering and optimisation process, recommendation process utilising collaborative filtering and method analysis and evaluation.

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