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WarehouseVis: A Visual Analytics Approach to Facilitating Warehouse Location Selection for Business Districts

Q. Li[1], Q. Q. Liu[1], C. F. Tang[1], Z. W. Li[1], S. C. Wei[1], X. R. Peng[1], M. H. Zheng[1], T. J. Chen[1], and Q. Yang[1,2]

[1]AI Group, WeBank, Shenzhen, Guangdong, China
[2]Department of Computer Science and Engineering, The Hong Kong University of Science and Technology, Hong Kong

Abstract

Selecting a proper warehouse location serving to satisfy the demands of the goods from a certain business area is important to a successful retail business. However, the large solution space, uncertain traffic conditions, and varying business preferences impose great challenges on warehouse location selection. Conventional approaches mainly summarize relevant evaluation criteria and compile them into an analysis report to facilitate rapid data absorption but fail to support a comprehensive and joint decision-making process in warehouse location selection. In this paper, we propose a visual analytics approach to facilitating warehouse location selection. We first visually centralize relevant information of warehouses and adapts a widely-used methodology to efficiently rank warehouse candidates. We then design a delivering estimation model based on massive logistics trajectories to resolve the uncertainty issue of traffic conditions of warehouses. Based on these techniques, an interactive framework is proposed to generate and explore the candidate warehouses. We conduct a case study and a within-subject study with baseline systems to assess the efficacy of our system. Experts' feedback also suggests that our approach indeed helps them better tackle the problem of finding an ideal warehouse in the field of retail logistics management.

CCS Concepts

• ***Human-centered computing*** → *Visualization; Visualization design and evaluation methods;*

1. Introduction

Warehouse placement serving to satisfy the demands of the goods of a certain business district has been of great significance to a successful retail business. Logistic administrators have to cautiously consider many factors, such as a good warehouse qualification that can avoid potential future conflicts, favorable policy laws and regulations, region functionality that may attract possible consumptions, good traffic conditions with effective reachability, as well as comparatively lower renting costs. Given the characteristics of the involved data, there is thus a pressing need for an approach that can provide effective representation of the relevant attributes from different sources, support interactive analysis of factors that impact an informed decision, and facilitate coordinated efforts of location selection among online and offline participating personnel.

Conventional approaches mainly involve manually summarizing the relevant evaluation criteria, conducting offline surveys, and employing different evaluation methods [Xio07, TKA*08, KYH08, ÖÇE11, DBSS16, DBSS17] to determine the desired warehouse location. Although these methods have demonstrated preliminary performance in warehouse location selection in previous cases [ÖÇE11], they still face several challenges in supporting a comprehensive and joint decision-making process in warehouse location selection. **(1) Large Solution Space.** The ideal way of warehouse location selection should integrate all sorts of relevant data and provide a comprehensive picture for logistical administrators to maintain awareness of all aspects of the candidate warehouses. However, organizing such heterogeneous data is expensive. The large candidate solution space and all the relevant information pose difficulties for domain experts to determine a proper warehouse location. Furthermore, due to limit budgets and constraints of human resources, only a small part of the information is used. Under this premise, failing to make a good sense of the available information may cause different warehouse location selection results, even jeopardizing future goods supply in the worst-case scenarios. **(2) Uncertain Traffic Conditions.** Among all the factors that may influence launching a successful warehouse, the geographical locations and traffic conditions of a warehouse location are considered the most critical due to that the demands from its covered business districts should be satisfied in a time-efficient manner [ÖÇE11, ŻW14, CSGP15, RPHB15]. A good criterion to measure the quality of the selection of a warehouse location is computing the distance from the candidate warehouse to its serving business districts and main supplier markets. However, only considering the distance of a road segment cannot well capture its traveling-time, i.e., it may cost a lot of time to traverse road segments even their distance is short due to the varying and uncertain traffic congestion over time. According to our collaboration experts, to handle such uncertain information, they have to manipulate various sources of data and organize comparable attributes before making an informed decision, which is quite labor-intensive and inflexible. It would save considerable efforts for them beforehand if such uncertainty can be streamlined by leveraging both the computational power of machines and their domain expertise. **(3) Varying Business Preferences.** Different retail businesses may have different requirements for their preferences. The requirement diversity demands good flexibility in expressing preferences, thus, an interactive mechanism is demanded to assist domain experts in specifying their requirements.

Prior studies have extensively analyzed the location selection problems in the context of selecting retail stores [KNS*13], billboards [LWL*16], rental housing [WZB*18], and ambulance stations [LZJ*15]. A number of location selection models have been proposed, including maximum coverage models [LBL*16, LWL*16], learning-to-rank model [FGZ*14], etc. Nonetheless, choosing an optimal warehouse location to serve a specified scope of business districts remains unexplored and challenging. First, unlike the billboard or retail store location that highly depends on the surrounding human traffic volumes, the selection of a warehouse location is mainly determined by the logistics and transportation costs to certain areas. Also different from the renting house reachability problem which compares the reachable scopes within a certain period of time starting from a single point of interest, the warehouse location selection maximizes the scope of reachable destinations within a certain period of time, satisfying the demands through time-efficient routes to multiple destinations.

In this paper, we characterize domain experts' requirements for finding an ideal warehouse and address the aforementioned challenges from three aspects. First, we propose a visualization-driven pipeline that centralizes relevant information of warehouses and adapts a widely-used methodology used by our collaboration experts to efficiently rank warehouse candidates. Second, we overcome the uncertainty of traffic conditions by a delivering estimation model based on massive logistics trajectories. Third, we propose a set of coupled visualizations, allowing users to inspect and compare candidate warehouses from multiple perspectives. The major contributions of this study are summarized as follows:

- A systematic characterization of domain experts' requirements in the context of locating an ideal warehouse.
- An interactive framework to generate and explore candidate warehouse with a back end engine and a visual analytics system.
- A set of new visualizations to empower experts in finding an idea warehouse based on multiple criteria and a within-subjects study to evaluate the performance of our system.

2. Related Work

Literature that overlaps this work can be divided into three categories, namely, facility location, multi-criteria decision-making, visual comparison and ranking.

2.1. Facility Location

Facility location selection is an integral part of organizational strategies, which involves organizations seeking to locate, relocate or expand their operations [Rao07]. The process of facility location decision process encompasses the identification, analysis, and evaluation of, and selection among alternatives. It has attracted researchers with diverse backgrounds such as economics, industrial engineering, and geography [GH93]. Prior studies have proposed many models and algorithms to address the facility location problems, including location selection of retail stores [KNS*13], ambulance stations [LZJ*15], plant [DV01], and charging stations [LBL*16]. However, most of them are based on several predefined criteria and work automatically, which tends to generate unsatisfactory results. Researchers have recently integrated human knowledges and expertise into the automatic models via visual analytics in making an informed location decision. For example, Liu et al. [LWL*16] leveraged the maximum coverage model and employed well-established visualizations enhanced with new features to facilitate advertising experts in evaluating and choosing billboard locations. Weng et al. [WZB*18] addressed the renting house location selection problem from the perspective of reachability of candidate houses. The difference between our work and the previous studies lies in that the warehouse location selection is mainly determined by the logistics and transportation costs instead of the surrounding human traffic volumes. Furthermore, instead of comparing the reachability scope starting from a certain point of interest, the warehouse location selection is subject to the delivery promise given several specified business districts, thereby, it should maximize the scope of reachable destinations within a certain period of time and satisfy the goods demands through time-efficient routes.

2.2. Multi-criteria Decision Making

In warehouse location selection, many criteria, e..g., investment cost, human resources, availability, traffic conditions, must be cautiously considered. Taking on this perspective, warehouse location selection can be viewed as a multiple-criteria decision-making (MCDM) problem [Yon06]. Techniques for ranking preference by similarity to an ideal solution are all well-known classical MCDM methods [TH11], which are based on the concept that the ideal candidate has the best level for all attributes considered, whereas the negative-ideal is the one with all the worst attribute values. In the studies dealing with this decision-making process, while at first solutions based on cost minimization is traditionally recommended [TH11]. After then, there are also studies concerning profit maximization [HK91]. Apart from the cost and profitability, indicators revealing customer service level and customer satisfaction are also demanded. For example, Korpela and Lehmusvaara [KLN07] developed a customer-oriented approach to evaluate alternative stocks and logistic services based on *AHP* and a mixed-integer programming model. In this study, we adapt *TOPSIS* model embedded with a visualization-driven pipeline to facilitate domain experts in obtaining the recommended warehouses.

2.3. Visual Comparison and Ranking

Warehouse location comparison belongs to the topic of visual comparison. Three categories of comparative visualization are proposed [GAW*11], i.e., juxtaposition (i.e., side-by-side), superposition, and explicit encoding (i.e., visual display of difference or correlation). For example, two juxtaposed identical objects are linked through VisLink [CC07]. EmbeddingVis [LNH*18] and Lineup [GLG*13] support sorting items based on multiple heterogeneous attributes. Forvizor [WXW*18] leverages a flow chart based on juxtaposition to show the formation changes of two soccer teams. AirVis [DWC*19] compares different propagation modes based on juxtaposition, and StreamExplorer [WCS*18] shows different topic maps with juxtaposition for comparing topics of events at different timestamps. Seo and Shneiderman [SS05] proposed a rank-by feature approach that consists of a ranked list and scores with ordered bars. RankExplorer [SCL*12] uses stacked graphs to visualize data trends and explicitly encodes the variation in rankings by using color bars and glyphs. Behrisch et al. [BDS*13] used small multiples and a radial node-link representation to demonstrate rankings with multiple attributes. WeightLifter [PSTW*16] allows users to investigate the sensitivity of the attribute weights. Weng et al. [WCD*18] proposed a spatial ranking visualization that supports efficient spatial multi-criteria decision-making processes by addressing challenges in terms of the presentation of spatial rankings and contexts, the scalability of rankings' visual representations, and the analysis of context-integrated spatial rankings. While in our work, we first leverage a back-end engine to filter out most of the candidates to alleviate manual power and then use juxtaposition to allow experts to conduct a comparative analysis.

3. Background and Observational Study

3.1. About Warehouse Location Selection in Retail Business

A reasonable warehouse location should maximize the economic benefit through a smooth collection, transition, and distribution of goods. Among all the selection factors, some of them are quite uncertain. For example, considering logistics costs, warehouses should be built close to the shops to shorten transportation distance and reduce freight and other logistics costs. Besides, the candidate warehouse should be located in a convenient traffic condition so that goods can be delivered on time, ensuring goods requirements from customers can be satisfied at any time. To sum up, a good warehouse location should fully consider the uncertain factors by aggregating comprehensive information to effectively resolve the distribution delay and high distribution costs.

3.2. About the Team and the Conventional Practice

To understand the existing practice of warehouse location selection in the retail business, we worked with the experts from *MeiCai*[†], a retail company, including a goods category planning specialist (E.1), a warehouse planning manager (E.2), and a logistics distribution personnel (E.3). The business operations in the retail sector indicate that it will be inadequate in performing the current warehouses parallel to the growth rate from the end of 2019. Thus, to cover the coming 5-year growing target (over 1,000 newly open warehouses), they plan to make a decision about the new storage area to provide the logistic operations completely and thoroughly.

To tackle this issue, the team launched an internal GIS system to facilitate observing the current business distribution by a heat map visualization. Based on this system, they can have a preliminary understanding of the current distribution of business districts and suppliers. They then looked for several geographical regions for warehouses by considering factors such as the delivery and transportation costs, surrounding functions, and the general traffic situation. After initially determining the approximate scope of the warehouse locations, they conducted offline visits to study the actual situation of the warehouses. They then identified a feasible location among all the recommended locations. Although these measures do capture some useful information, the human resource cost grows rapidly as the number of candidate warehouses increases. Meanwhile, it requires a large number of manual visits to collect relevant information, the overall efficiency is thus low, often with an unsatisfactory outcome. Besides, location selection is an experience-dependent process and cannot be easily generalizable to others.

3.3. Experts' Needs and Expectations

We interviewed the experts (E.1-3) in three separate sessions to identify their primary concerns about warehouse location selection, the potential obstacles in their path to efficient obtaining knowledge and making an informed decision, and the following four requirements were expressed across the board: **R.1 Overview of Business Districts and Warehouses.** Similar to their current practice, all the experts were interested in knowing the current distribution of the business districts and available warehouses. Such information can help them, especially E.1, obtain the overview picture of their business and identify the target areas judiciously. **R.2 Automatic Recommendation of Candidates.** During the interview, E.2 mentioned that when using their internal GIS system to review possible warehouse locations, he had to navigate to the corresponding area to inspect detailed information. Manually selecting warehouses without computational aids is time-consuming and may easily lead to suboptimal candidates. Therefore, an interactive visual exploration capability combining with automatic recommendation mechanisms is strongly required. **R.3 Filtering and Ranking Candidates.** The experts may have different preferences on the optimal, thereby an interactive filtering and ranking method should be provided, allowing them to rank candidates as desired based on relevant attributes. A reasonable ranking can help the experts quickly identify the desired candidate for further inspection **R.4 Delivery Time Assessment and Comparison.** E.3 maintained that the ideal warehouse should be located in a convenient traffic condition so that goods can be delivered in a timely manner, ensuring the customers who put forward goods requirements at any time can get satisfactory services. Therefore, the expert expressed a desire to assess and compare the estimated traveling time from the main suppliers to the candidate warehouse, as well as from the candidate warehouse to the business districts.

4. System Overview

We drew inspiration from the observational study of domain experts' conventional practices to inform the system design, such as providing an overview of business districts and warehouses. Based on the above requirements, we propose *WarehouseVis* to support logistics practitioners to select an appropriate warehouse. Fig. 1

[†] https://www.meicai.cn

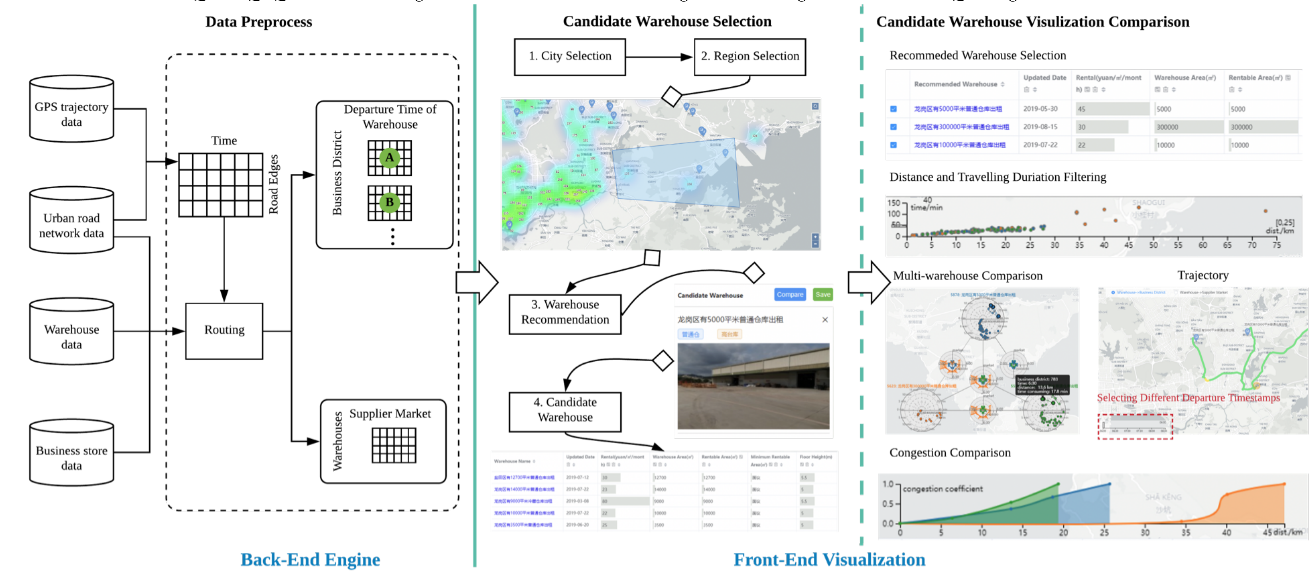

Figure 1: *System architecture and interaction pipeline.*

illustrates the system architecture and interaction pipeline, which consists of the back-end engine and the front-end visualization.

5. Back-End Engine

5.1. Data Description

The internal GIS system provides us with a dataset, which records four types of information: **(1) Urban road network data** comprises a directed graph of a city, where the vertices represent road intersections and the edges represent roads. This graph has $253,890$ vertices and $314,234$ edges; **(2) GPS trajectory data** includes $183,250,600$ snapshots of trunk status collected from a collaboration local logistics company of a one-month period. These snapshots were reported every 30 seconds on average by the GPS installed on the vehicles. Each trunk snapshot contains an id, GPS coordinates, current speed, direction, and timestamp; **(3) Warehouse data** includes the attributes of a warehouse such as the geographical location, images, area size, rental area, rent, floors, with a variety of formats, e.g., numerical values, plain texts, pictures, etc. This dataset has a total of 515 warehouses distributed in the local city; **(4) Business store data** consists of the basic properties of local business stores, including the geographical location, the shop title, the cuisine style, etc. This dataset has in total $29,980$ records.

5.2. Travel-time Estimation

To effectively evaluate the delivery time from a selected warehouse to a business district, we first use the road network matching algorithm [LZZ*09] and divide the trunk trajectories to estimate the traveling time on each road segment (Figure 1). For warehouse logistics and goods delivery, the best delivery time from the warehouse to the business districts is from 6 to 9 AM according to our experts, and there is no strict time limit for the goods delivery from the main suppliers to the warehouses. Therefore, we evenly divide a whole day into 48-time slices and then count the traveling time on each half-hour road segments. However, we encounter two issues when estimating the traveling time on each road segment. First, due to the data sparsity, we cannot guarantee to cover all the road segments. To tackle this issue, we leverage a matrix-factorization approach [SZT*14, Zhe15] to calculate the traveling time on the missing segments. Second, due to a large amount of data, directly calculating the traveling time is time-consuming. To speed up the process, we calculate the path with the shortest duration from one place to another starting at a specific timestamp [WDL*17].

5.3. Recommending Candidate Warehouses

In this section, we introduce the warehouse recommendation method used in this work. Based on the interviews with our experts, we identify the following evaluation criteria in the decision for warehouse location selection: *(1) Unit price.* One fundamental determiner for warehouse location selection is the unit price per m^2, and the domain experts tend to place high choice priority to a warehouse location alternative with a lower unit price. *(2) Stock holding capacity.* According to our experts, in a business structure with a high product variety, a stock holding capacity accords with the growth rate and it is quite important. For example, a high stock holding capacity would cause a formation of the inactive area and an increase in the cost of the warehouse area. *(3) Average distance to shops.* A shorter presentation period of products to customers and supply chain cycle time presents an important and competitive advantage for retail business [ÖÇE11], especially getting ahead of rival business when there is stock out of products with high sale volume and preventing the cost of sales and prestige loss. Therefore, minimizing the average distance of the candidate warehouses to the business districts is one of the fundamental objectives of the decision-maker. *(4) Average distance to main suppliers.* Another important factor that can reduce supply chain cycle time is the distance of the warehouse location to the main supplier markets. Minimizing this criterion also reduces the presentation time of products and logistics transportation costs. *(5) The Number of nearby main suppliers.* Similarly, warehouse alternatives with more main suppliers nearby may be considered with a top priority. *(6) The Number of nearby freeway entrances.* Candidate warehouse with more free-

Table 1: *Weighting of criteria by using Simos procedure.*

Subsets	Number	Positions	Weights	Normalized	Total
{NFE}	1	1	1	4	4
{DS, DMS}	2	2,3	2.5	11	22
{NMS}	1	4	4	17	17
White Card	1	(5)	...		
{UP}	1	6	6	26	26
{SHC}	1	7	7	31	31
Total	7	23			100

way entrances may have more options when choosing a reasonable route for goods delivering to the business districts. This situation also has vital importance to get ahead of a rival business.

5.3.1. Weighting Procedure of Criteria

Conventionally, our collaboration experts introduce some specific ways for weighting criteria. In this study, we leverage *Simos* procedure to weight criteria because that *Simos* is a method commonly used in the field of logistics. It also considers the criteria order of importance which can be determined by the experts. In *Simos*, every criteria is matched with a gaming card. In other words, for a decision making problem with *n* criteria, *n* card is picked. The detailed process of this method is as follows [FR02]:

- We arrange the criteria order from the least to the most importance. If some criteria share the same importance based on the decision-maker's view, a subset of these criteria is established.
- We consider the importance of two consecutive criteria, which may be closer or less close. In other words, when determining weightings, the difference between two consecutive criteria can be very small or very big. To deal with this situation, we put white cards between two consecutive criteria, and a bigger difference between criteria weighting means more white cards.

Based on the *Simos* procedure, the weighting of unit price (UP), stock holding capacity (*SHC*), average distance to shops (*DS*), average distance to main suppliers (*DMS*), the number of nearby main suppliers (*NMS*), and the number of nearby freeway entrance (NFE) criteria can be calculated as follows:

- Build criteria set $F = \{UP, SHC, DS, DMS, NMS, NFE\}$. Regarding the potential null values in the original data, we fulfill *DS*, *DMS*, *NMS*, and *NFE* by calculating the POI features of the corresponding warehouse, and *UP* and *SHC* through manual work such as using the average unit price and default values.
- The experts determine the increasing order of importance among the above criteria as NFS, DS, DMS, NMS, UP, and SHC.
- The experts further evaluate the average distance to main suppliers (*DMS*) and average distance to shops (*DS*) as equally important and the difference of importance between unit price (UP) and *NMS* is determined to be in a high level according to the difference between other two consecutive criteria.

We summarize the calculation steps of weighting criteria using *Simos* procedure in Table. 1. To be specific, criteria subset are first formed with same important criteria and in the parallel of this relation order and counting number for each criterion are appointed. Second, we calculate the average weighting value for each criteria subset. Finally, the classification value for criteria is proportioned to the sum of consecutive numbers and weighting values are calculated. Through these steps, we obtain the importance weights of criteria as follows: $\{W_{NFE}, W_{DMS}, W_{DS}, W_{NMS}, W_{UP}, W_{SHC}\} = \{0.04, 0.22, 0.17, 0.26, 0.31\}$.

5.3.2. Ranking Candidate Warehouses

After attaining the weightings of criteria, we then apply a widely-used multiple criteria decision making methodology, *TOPSIS*, which "*determines solution alternatives from a finite set based on maximizing the distance from the negative ideal point and minimizing the distance from the positive ideal point*" [SIG15]. We briefly describe the steps and its practice in our scenario as follows: **(1)** We collect m alternatives for n criteria performance data. Raw values x_{ij} are normalized as: $r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \quad i = 1, 2, ..., m;\ j = 1, 2, ..., n$. **(2)** We attain the importance weights w_j for each criterion and calculate the weighted normalized values as $v_{ij} = w_j * x_{ij} \quad i = 1, 2, ..., m;\ j = 1, 2, ..., n$. **(3)** We determine the ideal candidate with the best performance s^+ and the worst performance s^-. To be specific, if j is the benefit criteria: $s^+ = v_{1j}, v_{2j}, ..., v_{mj} = max\ v_{1j}\ for\ \forall j \in n$. If j is the cost criteria: $s^- = v_{1j}, v_{2j}, ..., v_{mj} = min\ v_{1j}\ for\ \forall j \in n$. **(4)** We calculate the distance to the best candidate D_i^+ and the worst candidate D_i^- for all candidate warehouses for all criteria as follows: $D_i^+ = \sqrt{\sum_{j=1}^{n} (v_{ij} - s_j^+)^2} \quad for\ i = 1, 2, ..., m$, and $D_i^- = \sqrt{\sum_{j=1}^{n} (v_{ij} - s_j^-)^2} \quad for\ i = 1, 2, ..., m$. **(5)** We divide the distance to the negative solution by the sum of distance to the positive and negative solution for every candidate and C_i is obtained, which exhibits the similarity to the positive ideal solution. The biggest C_i value is selected. Based on the attained values C_i for all candidates, we can rank all the candidate warehouse. $C_i = \frac{D_i^-}{D_i^- + D_i^+} \quad i = 1, 2, ..., m\ and\ 0 \leq C_i \leq 1$.

6. Front-End Visualization

Based on the preceding requirements, we develop five visualizations that allow the output of warehouse recommendation and the detailed information of warehouses to be easily inspected. Specially, we design a map view to assist users in selecting desired business districts in the spatial context; a ranking view to display all recommended candidates and support users to rank the candidates based on attributes; a candidate list view to save desired warehouses, as well as a warehouse inspection and comparison view to study the traffic conditions among several candidate warehouses.

6.1. Map View

To intuitively represent the density of the business district distribution, we use the K-Means clustering algorithm to calculate the business districts based on the store density. We determine the K value by finding the inflection point in the relationship between the cluster number and the average distance among the generated clusters. In our case, we determine that 220 is the cluster number for business districts. To assist domain experts in making decisions in the spatial context effectively, we adopt a map-centered exploratory approach [JAA01] by placing a map with three additional layers, namely, *business district*, *warehouse*, and *area drawing* layers (**R.1**). The area drawing layer supports drawing polygons on the map, enabling users to specify the target business district area. For the available warehouses, we directly use icons and render them on the map. We explore two alternative methods to plot the distribution of business districts and warehouses. One alternative is to directly draw circles to explicitly indicate the clustering results of business districts. However, this approach brings much visual clutter, thus obscuring users' observations. We thereby combine the heat map with the warehouse icons for visualization (Figure 1 (heat map)).

6.2. Ranking and Candidate List View

After recommending appropriate warehouses, the domain experts require a flexible ranking mechanism to help them quickly locate and identify good candidate warehouses they desire. Particularly, all performance-relevant indicators including the ranking order and the associated attributes should be displayed on demand. Furthermore, the system should enable the domain experts to freely adjust the range of each indicator due to that they may have different personal preferences and opinions on the performance indicators, thereby updating the orders accordingly and instantly (**R.2, R.3**). Figure 1 shows a matrix-based ranking view, which is inspired by lineup [GLG*13]. The first column lists all the recommended candidates with links that redirect to the source information. Other columns display the attribute values, which are normalized and encoded by the length of bars. Users can click over the header of a column to rank the candidates by the associated attribute. The header of the column also supports users to adjust the range of the associated attribute for quick filtering and updating. After initially exploring and ranking the warehouse candidates with different preferences, our experts required a candidate list for storing the interested candidates they found when using the system, which prompts us to add the candidate list view to store the candidate warehouses. Meanwhile, the subsequent warehouse inspection and comparison view also needs the desired warehouses as the input for further analysis of the delivery efficiency and traffic conditions among the selected candidates.

6.3. Warehouse Inspection View

Apart from some simple but rigid indicators that must be followed, logistics and delivery costs are key considerations of warehouse location selection. In other words, the deliverability of a certain warehouse to the surrounding goods suppliers and business districts is significantly affected by the traffic conditions of the delivery routes.

Ranking the candidate warehouses without considering the traffic efficiency is insufficient and may lead to poor decisions, especially when involving many uncertainties in the decision process and no clear cues of the traffic conditions are available. We convert the ranking to a pairwise comparison, which helps visually analyze the delivery duration and commuting distance that may be affected by different traffic conditions from the candidate warehouse

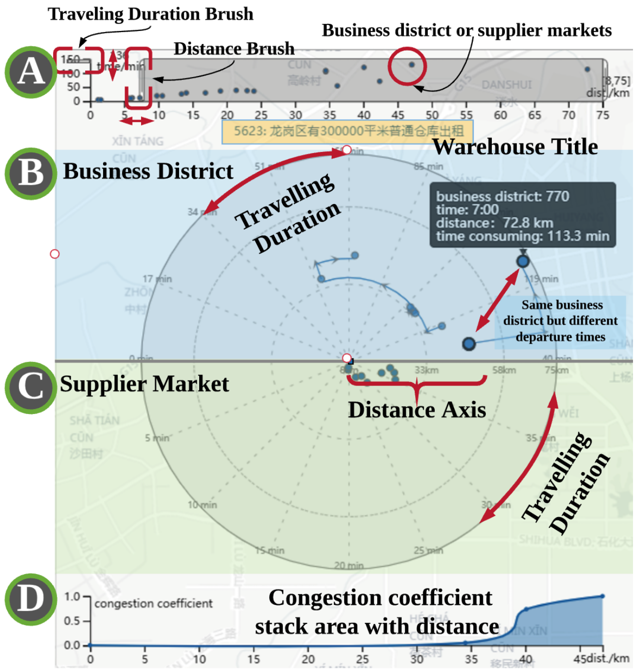

Figure 2: *Visual design of the warehouse inspection view. Ⓐ provides interactive mechanism for users to filter business districts or supplier markets. Ⓑ and Ⓒ show the distribution of business districts and supplier markets, respectively, and Ⓓ shows the cumulative congestion coefficient over distance for the warehouse.*

to the business districts and the suppliers from a spatiotemporal perspective (**R.4**). To achieve this target, the design should meet the following criteria: *(1) Support Observation at different departure timestamps.* The goods delivery departure time is from 6 AM to 9 AM with an interval of 30 minutes, and the traffic conditions may vary depending on the specific departure timestamp. Therefore, our design should facilitate the experts in observing the traffic conditions brought by the choice of different departure timestamps. *(2) Encode suppliers and warehouses.* Finding a way to encode the spatiotemporal information of both the suppliers and business districts is helpful to evaluate the delivery time efficiency of a candidate warehouse. *(3) Interactive operations.* Plotting a large number of business districts and comparing their delivery time efficiency simultaneously would inevitably cause severe visual clutter, i.e., they may be well separated or may be distributed close to each other. Therefore, an interactive mechanism should be provided to enable domain experts to focus on their areas of interest.

We leverage a circular polar coordinate design to demonstrate the road information from the main suppliers to the selected warehouse and from the selected warehouse to its serving business districts, respectively. The upper part of the circular (Figure 2Ⓑ) shows the distribution of the business districts while the below part (Figure 2Ⓒ) shows the distribution of the main supplier markets. The radius of the circles represents the distance from the selected warehouse (i.e., center point) to the business districts or the suppliers (Figure 2 (Distance Axis)). Each dot indicates a business district but with different departure timestamps. The position of a business district or a market is jointly determined by the distance and traveling duration between the selected warehouse and the business district or the market, e.g. if the whole concentric circle corresponds to an hour traveling duration, and if it takes half an hour for the goods to be delivered from the warehouse to a 10km away business district at the departure time of 6 AM, the dot that represents this business district would lie on the 10km distance ring with 90 degree. However, if it takes 40 minutes to deliver goods from the warehouse to the 10km away business district at the departure time of 7 AM, dot that represents this business district would lie on the 10km distance ring with 120 degrees. This design also applies to the market positions in the below part of the circular.

To avoid potential visual clutter, we only show three timestamps preceded or followed by the selected departure time (Figure 1 (Selecting Different Departure Timestamps)) and use arrows to connect the identical business district at different departure timestamps. When hovering over each dot, the corresponding business district id, departure timestamp, and the delivery time duration, as well as the distance from the warehouse to the corresponding business district will be displayed (Figure 2 (Tooltip)). For the same business district, since the recommended route from the warehouse to the business district may be different at different departure timestamps, the distance may also vary. For example, if the recommended route is always the same regardless of departing at different timestamps, all the dots that represent the same business districts would lie on the same concentric circle. On the other hand, if the routes starting at 6:30 AM and 7 AM are different, the dots would lie on different concentric circles. That is, when connecting the two departure timestamps, we first link the dot at 6:30 AM to the position of another different distance concentric circle and then link it to the actual position of 7 AM along the direction of the circle.

To further reducing the potential visual clutter introduced by too many business districts, we show the distribution of all business districts and main suppliers on the traveling duration (y-axis) and distance (x-axis) in Figure 2Ⓐ. Users can brush on both axes to filter out dots that are displayed in Figure 2ⒷⒸ and thus adjust the scale of the concentric circles. In Figure 2Ⓓ, we derive a term called the *congestion coefficient* with a stack area representing the cumulative congestion coefficient over the distance from the warehouse to the business districts. We calculate the total areas of the pies formed by the same business district but with different departure timestamps. The color of the areas indicates one specific warehouse.

Although the literature indicates that radial layouts do not significantly improve the understandability of daily periodical data [WDG*19], in our scenario, we only focus on limited time of period to depict the total delivery duration, e.g., one hour. Furthermore, the candidate warehouse should be placed into the context, which is also in accordance with the classic central place theory in facility location [Chr64]. Taken together, we choose the radial layout as our basic visualization. We also present a series of alternative designs based on the radial layout that have been evaluated by our experts. Initially, we use a pie chart to link all the identical business districts starting at different departure timestamps Figure 3ⓐ. Although the effects of traffic conditions across different departure timestamps can be reflected by the pie area (i.e., the larger the pie area, the greater the effect of the traffic condition), it is rather difficult to tell the sequential order since we need to know whether the traffic condition gets better or worse over time (e.g., taking 20 minutes starting at 6 AM and 10 minutes starting at 6:30 AM indicates that the traffic condition gets better, and vice versa). Therefore, one solution to tackle this issue is to use the gradient ramp ranging from the light to dark colors to indicate the time direction (Figure 3ⓑ). Nevertheless, the experts reported that this visualization causes severe visual clutter, especially when involving a large number of business districts. Therefore, we use arrows to link dots that represent the same business district/market starting at different departure timestamps, which can present a more concise and clear distribution, as well as the effects of traffic conditions by different departure timestamps from the warehouse (Figure 3ⓒ).

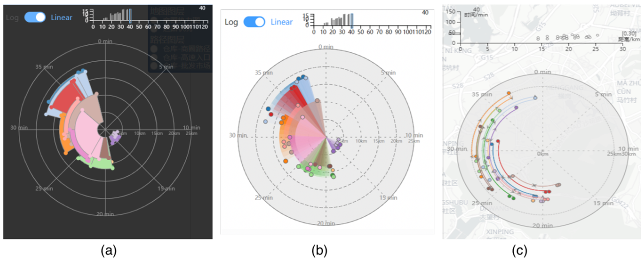

Figure 3: *Design alternatives for the warehouse inspection view.*

6.4. Warehouse Comparison View

The previous inspection view provides an overview of a certain warehouse and the associated traffic conditions to the supplier markets and business districts, as well as to what extent the delivery duration and distance can be affected by traffic conditions. While evaluating the details of each warehouse's properties on traffic conditions and delivery efficiency is important, experts should also understand why a certain candidate is better than another. That is, multiple candidates should be placed into context with one another, thereby allowing to compare the relevant information and differences among multiple candidates simultaneously and thoroughly.

When users find several desirable candidate warehouses through the warehouse inspection view, they can add them and form a warehouse comparison view for detailed comparison. Factors such as different departure timestamps, traveling duration, and congestion index, etc. are all important aspects for comparison. Inspired by *skylens* [ZWC*17], we design a warehouse comparison view to allow users to closely investigate the differences among a few candidate warehouses from these aspects (Figure 4ⓑ). Specially, a radar chart-based design (Figure 4ⓐ) is leveraged to perceive the factor values of different candidate warehouses (differentiated by categorical colors). We enhance the traditional radar charts in several ways for our specific scenario. First, we arrange the distance concentric circles with each circle representing 20km (Figure 4ⓐ). In the radar chart, three axes represent the delivery distance to the business districts at three departure timestamps from the warehouse (e.g., Leaving for business districts at 6AM, 6:30AM, and 7AM) and the fourth axis represents the delivery distance to the supplier markets (Figure 4ⓐ: Departure from market). The height of the curve areas that cover the concentric circles represents the normalized delivery duration from the warehouse to the business districts or the markets (Figure 4ⓐ: Traveling duration), with solid lines indicating the median values of the traveling duration on the corresponding axis.

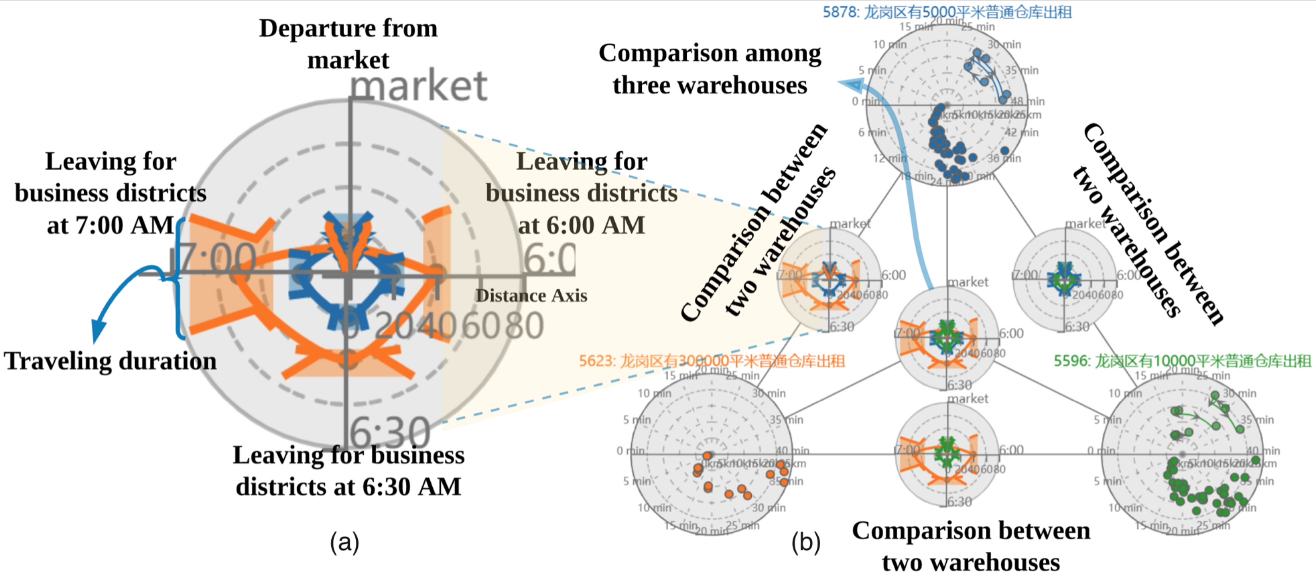

Figure 4: *Visual design of the warehouse comparison view. (a) A radar chart-based is used to show the factor values of selected candidate warehouses. Each distance concentric circle represents 20km. Three axes represent the delivery distance to the business districts at three departure timestamps from the warehouse (e.g., Leaving for business districts at 6AM, 6:30AM, and 7AM) and the fourth axis represents the delivery distance to the supplier markets. The height of the curve areas that cover the concentric circles represents the normalized delivery duration from the warehouse to the business districts or the markets, with the solid lines indicating the median values of the traveling duration on the corresponding axis. (b) At most three warehouses can be compared simultaneously.*

6.5. Interactions

Rich interactions are integrated to catalyze an efficient in-depth analysis. *(1) Filtering and Highlighting.* Users can interactively select areas of interest in the map view and the system automatically highlights the corresponding information in other views. *(2) Linking.* Views are linked through id correspondence. The coordinated interactions among the candidates facilitate the examination of a variety of information at different granularities and in different contexts. *(3) Hovering and Brushing.* Users can hover on the dots such as the business districts at different timestamps and the relevant information would be displayed. Brushing is also supported to facilitate selecting different departure timestamps for further inspection.

7. Evaluation

7.1. Case Study

We first demonstrate a real-world case and then evaluate the system efficacy instead of the accuracy of the recommended warehouses since it usually takes a much longer time and more data to evaluate the correctness of a final selected warehouse. We introduce a real case conducted by Jack (E.2), whose requirement is that the warehouse should have a high delivery efficiency and a low cost since the goods are mainly vegetables and fruits.

E.2 firstly selected a region in *Jiading District*, Shanghai. The system automatically retrieved the candidate warehouses from the pool within 40 km (a preset threshold according to the domain expert) away from each business district. A total of 198 warehouses are extracted and input to the back-end engine and the system recommended the top 20 candidates as the output. To evaluate the recommendation result, we compared the value distribution of three metrics, i.e., unit price, stock holding capacity and average distance

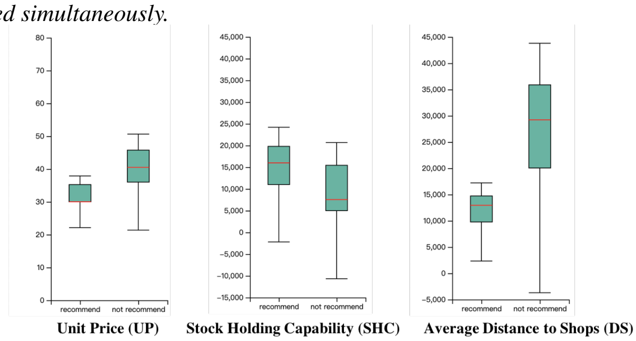

Figure 5: *Comparing the value distribution of UP, SHC, and DS between the set of recommended warehouses and the rest.*

to shops of the set of recommended warehouses and the rest. As shown in Figure 5, from the three groups of box plots, we identified that the value distribution of all metrics from the recommended warehouses is generally more stable than the other set, indicating the reliability of the back-end recommendation method.

After the system's recommendation and ranking, E.2 filtered out five candidates for further inspection. As shown in Fig. 6(left), the 2^{nd} warehouse is close to the business district but far away from the supplier markets, while the opposite is true for the 1^{st} warehouse. From the warehouse comparison view, he could witness that the warehouse represented by the orange color has a better performance at 6AM, 6:30AM and 7AM departure timestamps. The warehouse distributions (the top view in Fig. 6(left)) also indicate that the orange warehouse takes less time and shorter distance to the business districts. From the ranking view, the experts observed that the 2^{nd} warehouse is more expensive than the 1^{st}. However, the difference in price is small (Fig. 6(Price 1 vs 2)), while the deliv-

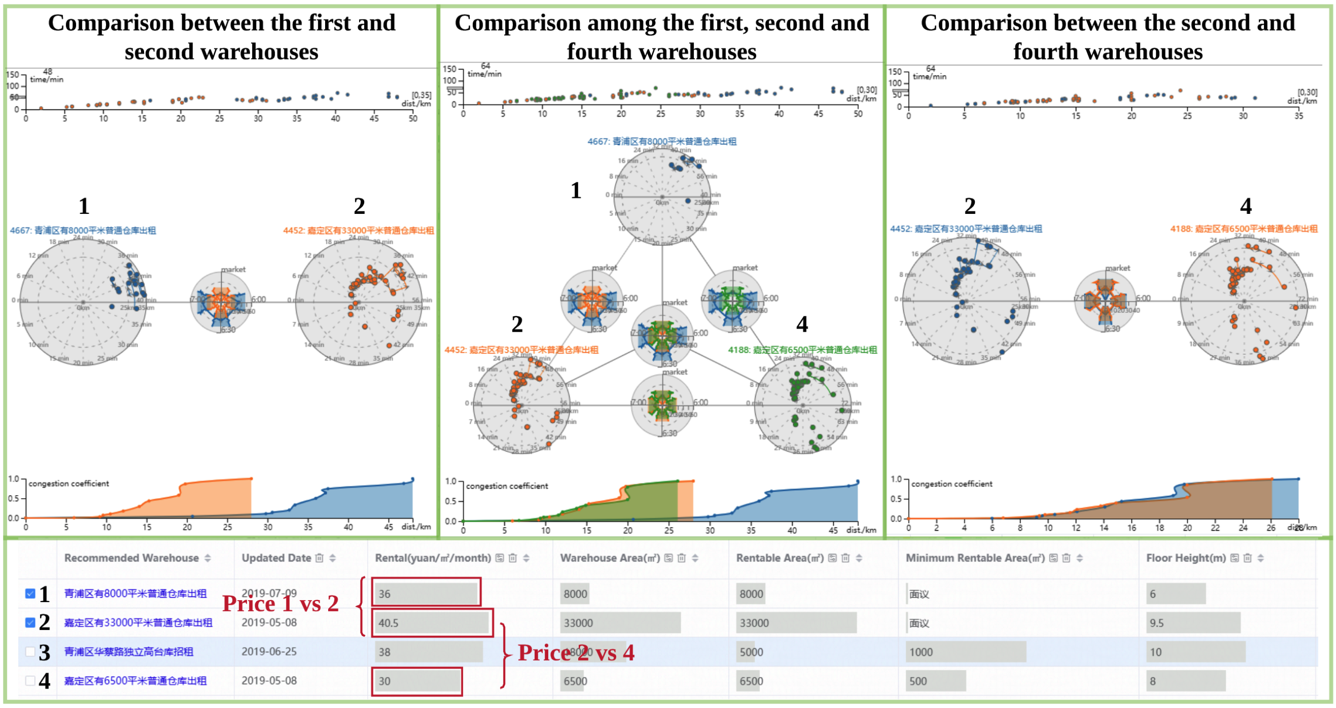

Figure 6: *The comparative exploration process among three candidate warehouses.*

ery time of the 2^{nd} warehouse is much shorter. Less delivery time can significantly decrease logistics costs. Therefore, he tended to select the 2^{nd} warehouse which is in *Jiading District*. However, he witnessed another warehouse in *Jiading District* and he then added the 4^{th} warehouse for comparison. He found that the 2^{nd} and the 4^{th} warehouse are similar through the comparison view (Fig. 6(right)). Therefore, he just compared the 2^{nd} and the 4^{th} warehouse. Again, he identified that almost every aspect of the two warehouses is similar regarding the traffic conditions. He then turned to the ranking view for more details. He found that although the area of the 4^{th} warehouse is less than the 2^{nd} one, the price is much cheaper, which also satisfies his requirement. He then changed his mind and chose the 4^{th} one as the best candidate.

E.2 then moved to examine the deliver stability from the 4^{th} warehouse to the business districts at different timestamps for departure. After interacting with the warehouse inspection view, he identified that the traffic condition from the 4^{th} warehouse to one business district is greatly affected by the departure time. After he scaled the distance range from 12km to 22km, he observed the detailed information of the business district named 499. He compared the delivery routes starting at different timestamps (Figure 7). From the left subfigure of Figure 7, E.2 observed that if goods were delivered at 6 AM and 7 AM, the average distances are similar, i.e., 14km. However, the distance increases to 20.2km when departing at 6:30 AM (the middle subfigure of Figure 7). Particularly, E.2 observed three different delivery routes due to different departure timestamps, i.e., route 1 at 6 AM, 7 AM, and 7:30 AM, route 2 at 6:30 AM, and route 3 at 8:30 AM. E.2 was quite sure that the traffic condition around the 4^{th} warehouse is not stable and can be greatly affected by different departure timestamps. Therefore, considering the delivery efficacy, E.2 commented that he would pay special attention to business district 499 when making future delivery plan.

7.2. User Study

We conduct a within-subjects study to systematically assess the informativeness, effectiveness in decision-making, usability and visual design [Wei01, QHX*20]. We recruit 18 volunteers (9 females, 9 males, age: 28 ± 3.03) from the collaborated retail company. They all have a knowledge of retail business. In particular, we choose the participants with logistics transportation experiences, for which they could provide us more comprehensive insights.

We compare *WarehouseVis* with two alternative systems. One is the GIS system used by our collaboration experts (namely the baseline). The other one is a primitive version of *WarehouseVis*. We compare our systems with the GIS system for a more objective and comprehensive comparison due to the following reasons. First, our designs cover functions provided by the GIS system such as providing an overview of business districts and existing warehouses and observing the surroundings around the planned location. Second, our recruited volunteers are already familiar with the GIS system and directly comparing our systems with the GIS system can help us further judge our design alternatives. Third, few warehouse location selection tools exist in the literature. The primitive system shares the same candidate warehouse ranking function with *WarehouseVis*. The differences between the primitive and full version lie in: (1) The full version inspects the traffic conditions from the suppliers to the warehouse and from the warehouse to the business districts while the primitive version only inspects the traffic conditions from the warehouse to the business district (i.e., using the entire circle to represent the distribution of business districts); (2) The full version supports simultaneous comparison of multiple candidates at different departure timestamps while the primitive version only inspects one by one at only one departure timestamp; (3) The full version embeds the warehouse comparison into a radar chart, thus

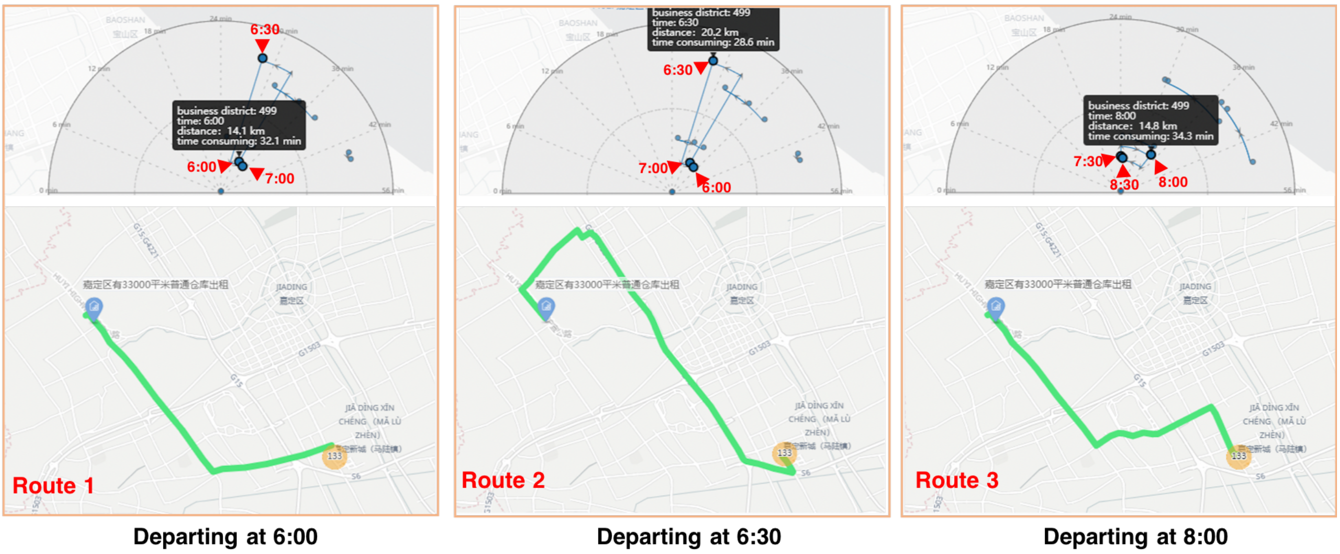

Figure 7: *Different goods delivery routes when departing at different timestamps: (left) departing at 6, 7, and 7:30 AM; (middle) departing at 6:30 AM; and (right) departing at 8:30 AM.*

forming a complete design while the primitive version uses line charts (Fig. 8 (b)) to compare the factor values of multiple warehouses by employing more visual cues and hints. To minimize the ordering and learning effect, we counterbalance the three systems.

We conduct the experiment in four sessions. In the first session, participants are briefed about the background, purpose and procedure of the experiment. Each following session lasts around 10 minutes and one of the three systems is presented, briefed, and tested. Each participant is required to conduct two tasks with the provided system. The first task is to observe the relevant information of a certain candidate warehouse. The second task is to evaluate the traffic conditions for the selected warehouse. Participants are allowed to think aloud their ideas when performing all the tasks. After finishing all the tasks with a particular system, they are required to complete a questionnaire with 7-point Likert scale questions [OCH18].

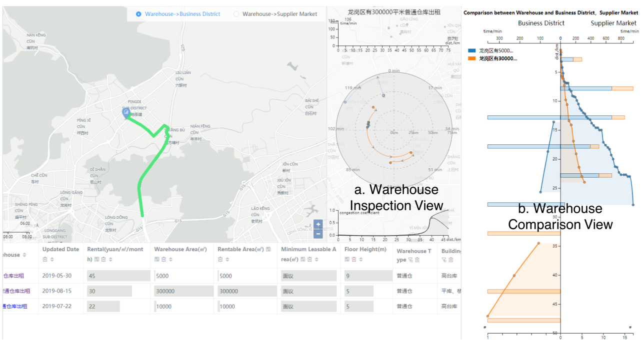

Figure 8: *The primitive WarehouseVis differs from the full one in terms of (a) the warehouse inspection and (b) comparison view.*

We propose the following hypotheses: ***H1.*** The primitive and full systems perform better than the baseline in terms of informativeness. Specifically, *WarehouseVis* systems enjoy their advantages on information accessibility (*H1a*), richness (*H1b*), and sufficiency (*H1c*) compared with the baseline. ***H2.*** The primitive and full *WarehouseVis* are better than the baseline in facilitating decision-making. In particular, *WarehouseVis* systems provide more confidence (*H2a*) and assistance (*H2b*) compared with the baseline. ***H3.*** The full version is more informative than the primitive version. Specifically, the information accessibility (*H3a*), richness (*H3b*), and sufficiency (*H3c*) of the full version is better than that of the primitive one. ***H4.*** The full version performs better than the primitive version in facilitating decision-making in terms of confidence (*H4a*), and assistance (*H4b*). ***H5.*** The primitive version is preferred over the full one, i.e., more intuitive (*H5a*), easier to comprehend (*H5b*), learn (*H5c*), and use (*H5d*), and thus is better recommended (*H5e*) than the full one. We report the participants' quantitative ratings and verbal feedback on *informativeness*, *decision-making efficacy*, *visual designs* and usability, and run repeated measures ANOVA on each questionnaire item, as well as the Bonferroni post-hoc test on measures with statistically significant differences.

Informativeness and Decision-Making Efficacy. The primitive and full versions of *WarehouseVis* receive significantly higher scores in all the studied metrics of informativeness than the baseline (Fig. 9). Participants find assessing information is significantly easier in the full and the primitive version than the baseline (**H1a supported**), as well as richer information than the baseline (**H1b supported**). In addition, we observe a significant difference between the full and the primitive version with $p < .01$, **H3b supported**. "*The full version complies more data at different departure timestamps than the primitive version*" (P12, male, age: 33). The information offered by the full and the primitive version are shown to be sufficient in measuring a candidate warehouse, compared with the baseline (**H1c supported**). No significant difference is found between the full and primitive version ($p = .32$, **H3c rejected**). Participants report significantly higher confidence in warehouse location selection using the two versions compared with the baseline (**H2a supported**). No significant difference is identified between the full and primitive version ($p = 1.0$, **H4a rejected**). Participants also report that the full and primitive version provide significantly more assistance than the baseline (**H2b supported**). No significant difference has been found between the full and primitive version

(**H4b rejected**). When asking the participants whether *WarehouseVis* helps make informed decisions, results show that both versions are significantly better than the baseline (**H2c supported**). However, no significant difference exists between the two versions ($p = .72$, **H4c rejected**). In summary, the results on informativeness and decision-making efficacy demonstrate that *WarehouseVis* provides more accessible, rich, and sufficient information. Particularly, the full version largely enhances information richness while still maintaining a good accessibility. However, the two systems do not differ significantly to facilitate decision-making. Participants comment that they lack ground-truth feedback to confirm the systems' ability, although they said that the full version is more comprehensive". "*I tend to trust all systems because they summarize all needed information*" (P3, male, age: 25).

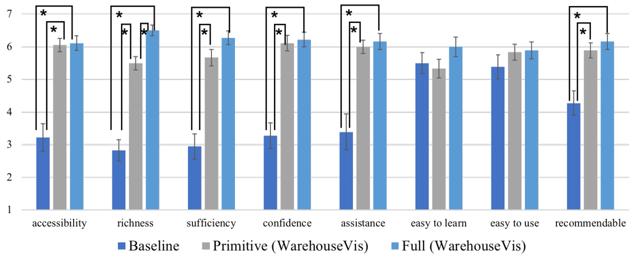

Figure 9: *Metric means and standard errors of Baseline, Primitive, and Full on a 7-point Likert scale (*: $p < .01$).*

Intuitiveness and Comprehension. Different from our hypothesis, the design of warehouse inspection view is not significantly more intuitive or more comprehensible than that in the full version. However, the design of the warehouse comparison view in the full version is more intuitive, although there is no significant difference regarding the comprehension (**H5a and H5b rejected**). Participants report that they can easily compare the attributes of different warehouses since it is similar to the radar charts. "*The warehouse comparison view centralizes the information at different departure timestamps*" (P6, male, age: 26).

Learn, Use and Recommendable. We do not notice a significant difference regarding easy to learn and use among the three systems, and also no significant difference between the full and primitive version, $p = .15$ and 1.00, respectively (**H5c, H5d rejected**). However, participants are more willing to recommend the two versions than the baseline to other scenarios. "*WarehouseVis is very useful because it provides a novel and highly interactive way*" (P2, male, age: 28). "*WarehouseVis significantly expands from a single-page heat map to a system with multiple features*" (P15, female, age: 27). However, no significant difference is found regarding recommendation between the two systems ($p = .35$, **H5e rejected**).

8. Discussion and Limitation

We conducted a half-hour semi-structured interview with E.1-3 to evaluate whether our approach helps warehouse location selection.

System and Visual Designs. All experts appreciated the ability of our system to support interactive exploration of the candidate warehouses. E.2 commented that our system would greatly boost their work efficiency. Conventionally, E.2 had to manually compile information from different sources and summarize the pros and cons for pairwise comparison. Now he could easily compare candidates and their relevant information in one single page. The experts were also satisfied with the system's customized visual design and interactions. We deliberately selected familiar visual metaphors to help them quickly familiarize with our visual encodings. What's more, we conducted a user-centric design process. After introducing the system, they developed a customized path for exploration.

Generalizability and Scalability. When discussing with the experts about which components of *WarehouseVis* can be directly deployed to other scenarios and which one needs further customization, two insights are identified: *(1) Design.* The experts commented that our designs are quite generic and can fit other application scenarios without much modification. For example, the map and ranking view can be applied to almost every facility location scenario and the inspection and comparison view can be leveraged to analyze multiple candidates simultaneously. *(2) Algorithms. WarehouseVis* has well-defined APIs and can easily integrate other multi-criteria decision-making models. Regarding the scalability, when involving many business districts, the amount of trajectories would largely increase that may delay the performance. One solution is to control the size of user-specific business districts.

Communication Tactics. When considering the output of the back-end model, the domain experts need more explanation of the recommended results. Considering that the back-end model and domain experts treat data quite differently, a preliminary version of *WarehouseVis* that imitates the conventional approaches taken by the experts may be a good start. Thus, they would not be overwhelmed and intimidated by working with something unknown to them. Meanwhile, we can take the chance to test the initial designs.

Limitation. First, we do not distinguish different types of warehouses. For example, requirements of warehouses for fresh products and supermarket products are different in terms of goods delivery frequency. Second, we only consider one warehouse as a solution, instead of taking multiple warehouses as a solution. In some cases, renting two warehouses may be better than only renting one.

9. Conclusion and Future Work

In this paper, we introduce an exploratory visual analytics system to support a comparative analysis of recommended candidate warehouses. It adapts a widely-used multi-criteria decision-making model and embeds with a delivering estimation method to assist domain experts in finding an ideal warehouse. We further propose a novel visual design to facilitate them in inspecting and comparing multiple candidates simultaneously. A case study and a user study, as well as feedback collected from the experts confirm the efficacy of our system. In the future, we plan to include the special characters of different warehouses and consider the cases in which multiple warehouses are a better solution than a single one.

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