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Ubiquitous Tourist System Based on Multicriteria Decision Making and Augmented Reality

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Abstract: Increasing global demand for travel has drawn public attention to the tourism industry. This industry needs the design of intelligent systems based on new concepts to facilitate better service delivery. To this end, this study proposes a ubiquitous tourist system based on context-awareness, multicriteria decision making (MCDM), and augmented reality (AR) using a geospatial information system (GIS). This system provides two services to the user. First, it recommends a hotel in the vicinity of the user based on their preferences. Subsequently, it modifies the information property to augment the information concerning the visited object using AR technology. This system offers the advantage of adapting its models based on the user and their environment using context-awareness, thereby facilitating increased system automation during service delivery. Furthermore, this system enables personalization based on user needs. Our system was evaluated via a usability test using a Likert scale based on two system aspects, namely, system design, and user acceptance of the result. The output of this test yielded an average score of 4.112. The proximity of this score to the highest level of the Likert scale indicates the acceptance of the system by users.

Keywords: ubiquitous system; smart tourism; geospatial information system (GIS); multicriteria decision making (MCDM); augmented reality (AR)

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1. Introduction

Tourism is considered to be an influential industry in the global economy. In particular, the increasing demand for travel in different parts of the world has propelled this industry into the global sector [1]. Moreover, tourism is an important tool for sustainability, as per the concept of circular economy. A circular economy proposes a business- and solution-oriented approach to sustainability issues to limit the use of resources (non-renewable) and reduce waste generation. Additionally, tourism plays an important role in resource consumption, and poor management may cause irreversible damage to the achievement of a circular economy [2,3].

Smart tourism is a new idea to increase the capability of the tourist industry to achieve the mentioned advantages. This idea refers to the convergence of tourists and information and communications technology to create an advanced tourism industry wherein better experiences are provided to tourists. Here, information can be extracted from various sources and combined using advanced technologies to provide a more enriched and efficient service for tourists [4]. The establishment of smart tourism is based on the design of intelligent applications applying new concepts. Designing an application applying multicriteria decision making (MCDM) [5] is one example for this purpose. This concept allows the entry of different items to better model user preferences, and combines these items to make decisions pertaining to delivering services to tourists. In this regard, different methods are used. For example, the analytical hierarchy process

(AHP) [5,6] involves the construction of a hierarchical structure of criteria and alternatives, and the use of pairwise comparisons based on quantitative numbers ranging from one to nine to identify the best alternative. The Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) [5,7] method is based on ranking the alternatives using the distance between negative and positive ideal solutions. This method calculates the proximity to the ideal solution (closeness index) for identifying the superior alternatives. This method is popular in decision making involving quantitative criteria, owing to its simplicity, comprehensibility, and simple formulation. Additionally, the Vise Kriterijumsa Optimizacija I Kompromisno Resenje (VIKOR) [5,7] method allows the selection of appropriate alternatives under conflicting criteria in complex systems. This method provides a quantitative indicator for decision making by measuring the closeness to the ideal solution [5,7]. Employing geospatial information systems (GISs) is also useful for this aim; the GIS collects, stores, and modifies data, analyzes information and its object through spatial analysis, and presents the results as a map for the tourist [8]. Ubiquitous computing is another concept applicable in tourist applications. Systems designed based on this concept enable tourists to access the service at any time and location without the need for interpretation. This is achieved via the use of context, which includes user- and environment-related information, and enables the system to adapt accordingly [9,10]. Furthermore, in tourism applications, new methods such as augmented reality (AR) can be used to enhance the visualization and display of information to users. AR combines real-world experience with computer-generated content to overlay imagery information on live, direct, or indirect real-world environments. Furthermore, it allows tourists to interact with virtual content [11,12]. By combining the proposed concepts, an intelligent system can be implemented to provide services to tourists. For example, such a system can be used as a recommender system for selecting the location of a point of interest (POI) [13]. Alternatively, it can be used to visualize the digital form of an artifact related to the visited object [14].

Owing to the importance of such systems, this study aims to develop a ubiquitous system for tourism involving a combination of context-awareness, MCDM, GIS, and AR. This system operates in two stages: In the first, it acts as a recommendation system that selects the hotel. In the next stage, it augments the information concerning visited objects by applying AR technology. In the hotel recommender model of our system, first, the position of the user is determined based on the context and used in spatial filtering (SF) to generate the list of candidate hotels in the vicinity of the user. Subsequently, the candidate hotels are compared using the MCDM method for final hotel selection. These steps are performed based on criteria such as the distances to the nearest transportation links, restaurants, historical attractions, cost, and the number of hotel stars. Notably, the type of transportation, restaurant, and historical attraction are obtained from the user preferences stored within the context. Finally, the location of the selected hotel is displayed to the user via Google Maps. It must be noted that a modified methodology based on MCDM and clustering is proposed here, and is used when the number of candidate hotels is large.

In the AR component of our system, first, the users and environmental conditions (e.g., the time of day at which the system is operated) are extracted from the context. This information is applied in conjunction with spatial information, such as the distance of the user from the visited object, to define rules in the system. Subsequently, our system applies these rules to determine the text size as well as the level of detail (LOD) of the information. Finally, this configuration is provided as an input to the AR technology for augmenting information concerning the visited object.

We developed a ubiquitous tourism system called UTS-mAR that operates in two phases: first, as a recommendation system, and subsequently as a functional engine. In the first phase, the system selects the hotel, and in the second, it adjusts the display features of information concerning the visited object, such as the LOD and text size, and displays the information using AR technology.

The proposed system offers the following contributions:

- We developed a dynamic model to build a ubiquitous tourism system based on a combination of MCDM, AR, and context-awareness of the environment. The parameters of this model are determined based on the user and their environment. For example, a suitable hotel is selected for the tourist (i.e., the user) based on their location and preferences pertaining to hotel selection criteria such as the type of transportation, restaurant, and/or historical attraction.
- Additionally, our system offers GIS capabilities, such as using geospatial vector data and analysis during the process of the system model. For example, the system visualizes the location of the hotel on Google Maps, and uses spatial functions such as distance analysis for generating hotel criteria.

The remainder of our study is organized as follows: Section 2 discusses existing research relevant to this study, and Section 3 introduces the details of the proposed system. Section 4 describes the implementation of the proposed system. Sections 5 and 6 present an experiment for testing the system in the real world and discuss the corresponding results, respectively. Section 7 provides the conclusion, and discusses the scope for future research. Finally, the pseudocode for the algorithms used in the proposed system is attached at the end.

2. Related Works

Intelligent tourist systems are widely used to recommend or select tourist locations and to display information concerning visited objects. The advancement of these systems using newer concepts and technologies is a fundamental goal. In this regard, we discuss existing research related to this study that is divided into the following categories: (1) MCDM-based systems, (2) GIS-based systems, (3) ubiquitous systems, and (4) AR-based systems.

2.1. MCDM-Based Systems

Bueno et al. (2021) integrated multiple decision-making techniques to rank hotels based on past clients. In this method, the value of users was determined based on a "recency, frequency, and helpfulness" model. User opinions on the social network were analyzed via the fuzzy linguistic approach involving a multigranular two-tuples model. This methodology was evaluated using data from Tripadvisor [15]. Effendy et al. (2021) applied the MCDM technique to model user preferences in a tourist recommendation system [16]. This technique, which is based on the VIKOR method, was applied to a web-based system that enabled tourists to enter certain criteria, and subsequently combined them to generate the highest-ranking advisor in a recommendation system. Forouzandeh et al. (2021) proposed a novel method for hotel recommendation based on a metaheuristic technique and MCDM [17]. This method was based on the artificial bee colony algorithm and the fuzzy Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) model to recommend a hotel based on user interests. Sezgin et al. (2016) employed a methodology based on MCDM methods such as the analytical hierarchical process (AHP) and the TOPSIS method for hotel selection [18]. In this method, AHP was used to determine the weights for the hotel criteria; subsequently, TOPSIS was applied to select the best hotel from among the candidate hotels based on these weights. In tourist scenarios involving large amounts of data, conventional MCDM models need to be improved using techniques such as clustering. In this regard, a methodology based on hierarchical clustering and TOPSIS was proposed by Masnadjam et al. (2015) for selecting suppliers under limited-supply conditions [19].

Although MCDM-based systems have demonstrated their significance in achieving objectives such as recommending or selecting hotels, the models constructed by these systems are static, and cannot adapt to the real-time conditions of the user. Therefore, in the field of tourism, MCDM-based systems that accept contextual information as inputs need to be developed. Contextual data enable the system to model real-time user status. Based on the mentioned studies, there is a lack of consideration of MCDM-based systems that accept context. These capabilities enable the system to change the model based on user context—such as preference and position—for tourist applications.

2.2. GIS-Based Systems

Noguera et al. (2012) applied a GIS to develop a novel mobile recommendation system for tourism [20]. The system contained a recommendation engine and a three-dimensional (3D) mobile GIS architecture. These capabilities provided the user with location-based recommendations and access to a 3D-map-based interface. Honarparvar et al. (2019) developed a location-aware recommender system using volunteered geographic information (VGI) [21]. This system consisted of two phases: VGI collection and filtering, and location-based recommendation. In this system, the VGI is collected and purified according to position accuracy and user contribution history. Subsequently, the system applies filtered VGI and a content-based filtering strategy to recommend the best restaurant based on user preferences. Jing et al. (2020) proposed a novel spatiotemporal analysis based on Flickr data to construct a fine-grained pattern for tourists [22]. First, a temporal variation analysis was performed. Second, the study employed kernel density estimation to analyze the seasonality of tourism. Third, the correlation between attraction grade and popularity was measured using both qualitative and quantitative methods. Finally, the space–time cube method was employed to visualize the identified pattern. Manoharan et al. (2020) employed a method to assess the emotions of visitors using social media messages about theme parks [23]. This was achieved using geospatial analysis and social media analytics. In addition, the place of emotion gathering was visualized. Different statistics were used in this study. The circumplex model of affect proposed by Russell was used to analyze tweets with one or more emotional words. Furthermore, GIS exploratory analysis and text mining were used to assess the emotions in each quadrant of tweets. In addition, based on significant clustering of emotions in quadrants, the areas of riding attraction in the theme park were determined. Kato et al. (2020) developed a recommendation system for sightseeing spots [24]. The system was based on recommended social networking services, a web-based GIS, and recommendation systems. The recommendation component was developed using two methods for selecting the POIs for a tourist: knowledge-based recommendation, and collaborative recommendation.

Notably, geospatial systems require personalization based on contextual information. Such systems can be incorporate analytical methods such as MCDM to perform functions such as recommending or selecting tourist POIs. This enables the system to consider multiple factors, which may increase user satisfaction during POI selection.

2.3. Ubiquitous Systems

Chen et al. (2020) constructed a ubiquitous recommender system for hotels involving fuzzy ubiquitous traveler-clustering and hotel recommendations [25]. In this system, travelers were initially clustered according to the decision mechanism based on user choice. Moreover, the system applied a fuzzy mixed binary nonlinear programming model for the recommendation section. Abbasi-Moud et al. (2021) incorporated context-awareness to create personalization in a recommender system based on sentiment analysis, sentiment clustering, and contextual data [26]. The system could filter inappropriate items to recommend the best result to the user. Barranco et al. (2012) implemented a context-aware system to identify personalized POIs [27]. The system applied user context, such as speed and trajectory, to create recommendations along the user's path based on the current position and driving speed of the user.

Kanmani et al. (2020) proposed a context-based social media recommendation system for travel. This system provided recommendations based on geotagged data to determine the similarity of users and POIs along travel routes [28]. This was achieved using collaborative filtering techniques and similarity computing, and by selecting neighborhoods via the k-nearest neighbors algorithm.

Owing to the unique capabilities of ubiquitous tourism systems, such as their ability to provide recommendations and their adaptability based on user conditions and environments, they can be combined with GISs and incorporate MCDM analysis. This provides a comprehensive system in which users can modify hotel selection items through a user-friendly interface and, subsequently, different factors for item selection are combined and displayed in the form of a map. This system can update results based on the user and their environment.

2.4. AR-Based Systems

Techasarntikul et al. (2019) used AR technology to develop a guidance system for AR museums [29]. This study applied embodied agents and allowed the user to observe a variety of information related to different pieces of art through interaction with an agent. Sasaki et al. (2019) combined location-based AR and object recognition to develop an intelligent system for tourism [30]. The system was used for navigation, and provided information about sightseeing spots. Blanco-Pons et al. (2019) proposed an immersive AR application for an outdoor environment [31]. This application merged simulated images with historical and current content. In addition, this study proposed a suitable framework for multi-image tracking for this purpose. The output of this application offered the opportunity to enrich the information concerning the rehabilitation of the visited object. Demir et al. (2018) developed an application that suggested tourist spots such as tourist centers, hotels, restaurants, and attractions [32]. This study employed image processing and used positioning based on the haversine formula to implement AR. The haversine formula [32] applies the geographical position of user, object, and Earth radius, and then uses the spherical law of cosines to estimate the distance between user and object. This application integrates image detection and social media, and visualizes different visited object features such as intensity, ratings, comments, current social media data, and price information using AR. Čejka et al. (2020) developed an innovative AR system to improve diver experience while visiting underwater cultural heritage sites [33]. The system employed a hybrid localization method based on markers and inertial sensors. This method first searched for the images of cultural heritage markers stored in the system. Subsequently, the Kalman filter was applied to fuse the position obtained from these markers with the sensor information. Finally, the obtained position was used to position the virtual object for viewing by the diver. Vert et al. (2016) conducted research-related data profiling of AR applications for tourism purposes. This study reviewed the literature to propose a methodology for integrating data, such as user-generated and governmental open datasets, for using mobile AR applications. This was achieved by assessing the structure and ontology of the data to manage the heterogeneous data structure [34]. Li et al. (2019) proposed research related to using situated visualization for AR based on context data. In this study, a distance-driven interface was applied with collaborative exhibit viewing. In this interface, the distance of the user obtained from user position context determined the information level, and provided detailed information for users in proximity using the AR technology. The system also allowed the user to come closer to explore more detailed information. Furthermore, interactions between users were modeled in the system, which enabled the users to observe other user comments related to a visiting object [35]. Seo et al. (2020) applied context data for virtual content visualization with AR technology. A good example in this study was the ride-sharing accommodation service. In this case, when the tourist approached the pickup location, a virtual sign was displayed at the interface for the pickup location [36].

Additionally, AR-based systems need customization based on contextual data. This enables the system to act as a rule-based engine to define information properties during visualization based on the user and their environment. Based on these studies, there is a great need for creating situated visualization for AR for tourism, which changes the property of visualization based on the application of contextual data.

3. Ubiquitous Tourist System Based on MCDM and AR

We developed a ubiquitous tourist system based on MCDM and AR using GIS data and analysis, which we called UTS-mAR. This system a hybrid system for tourism; it consists of two components: a hotel recommender, and AR visualization. The hotel recommender selects a hotel in the vicinity of the user based on their preferences. The AR visualization applies AR technology to visualize information related to visited objects. UTS-mAR offers significant capabilities, as follows: First, the system uses context data, which include information related to the user and their environment. This information is used to enable the system to manage different types of users and changes in the test environment. Second, the system operates based on the intelligent models at its core. These models facilitate adequate analysis of the context to deliver services.

The hotel recommender model applies SF and MCDM; it filters hotels in the vicinity of the user and recommends the final hotel based on user preferences. In addition, an improved version of this model with added clustering is available in the system. This version is useful when the amount of input data is large. The AR visualization model defines the information properties during visualization using the necessary rules, distance calculations, fuzzy functions, and AR technology. Furthermore, this system is a spatial system, which allows the use of geospatial data and spatial functions in intelligent models. In this regard, geospatial databases that contain hotels, hotel items, and spatial functions—such as the closest distance during SF—can be used.

3.1. UTS-mAR Framework

The proposed framework (UTS-mAR) comprises three main components: the context, intelligent model, and service. Figure 1 depicts these components in detail. The context component is defined in two categories that model the user and their environment. These categories contain various types of information. In the hotel recommender part, the user context stores the user position and preferences. The user preferences refer to the user's selection of restaurant, transportation, and attraction types. The environmental context is obtained from the geospatial data stored in the system. Geospatial data include spatial and non-spatial information. Spatial information includes the locations of hotels as well as hotel selection items, such as attractions, restaurants, and transportation. Non-spatial information refers to the cost and the number of hotel stars. In the AR visualization part, the user context includes general information on the user (such as their age), user health status (such as vision problems), and user position. The environmental context also contains information related to the test environment and the visited object. In our test system conditions, the environment was defined by the daytime parameter. In addition, the visited object information includes images, position, and general textual information related to the objects. The system process for preparing context information is explained in Section 4.1.

The intelligent model is a system-analysis model, and is used to analyze the context for service delivery. In our system, the hotel recommender model is based on SF and MCDM to select the final hotel. The AR visualization model in our system uses context and AR technology to display the properties of information such as LOD and text size. The detail of the models is discussed in Section 3.2.

The service component delivers the output of the system to the user. Thus, the proposed system provides services in the form of displaying the location of the selected hotel on Google Maps via the hotel recommender model and displaying the outputted textual information via AR using the AR visualization model.

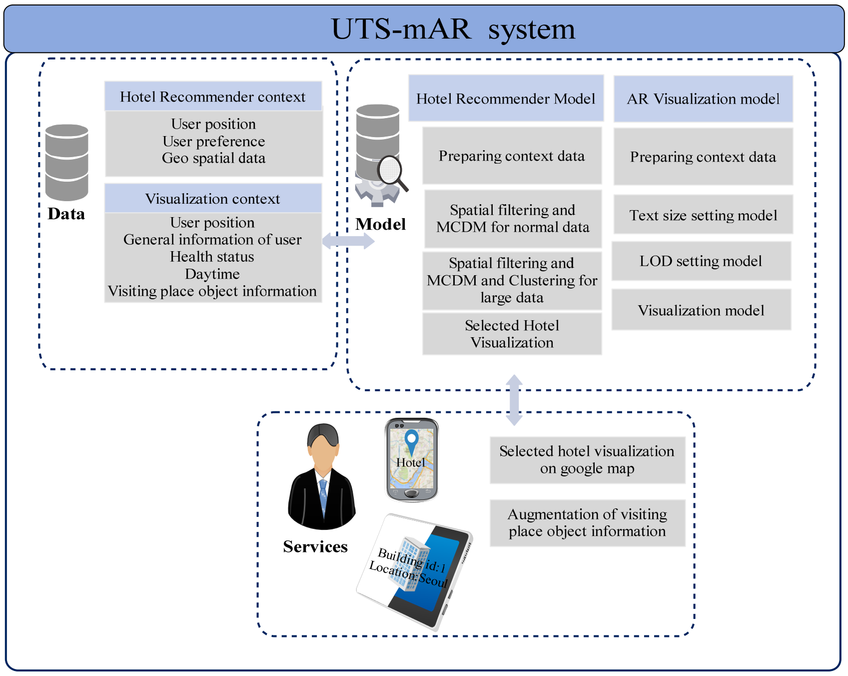


Figure 1. UTS-mAR components.

3.2. UTS-mAR Methodology

As shown in Figure 2, our system contains the following models:

The hotel recommender model of the proposed system is based on MCDM using context data. This algorithm applies SF to generate a list of candidate hotels near the user. Then, these candidate hotels are compared using the MCDM technique, based on different items, such as distance to transportation, restaurant, historical attraction, cost, and the number of hotel stars. This step selects the final hotel, and its position is displayed in Google Maps. To solve the problem of managing a large amount of data pertaining to candidate hotels, we propose an extended version of this algorithm, which simultaneously uses MCDM and clustering to select the final hotel. Additional detail about the proposed algorithm is provided in Appendix A.

The AR visualization model enables the system to visualize the information concerning the visited object using AR technology. This model applies context and, subsequently, adjusts the information properties for visualization using AR technology. This model involves three models: text-size setting, LOD setting, and the construction of the visualization model. These models apply various statistical methods, such as rule creation, distance calculation, and fuzzy functions, to adjust the information properties. Subsequently, these properties are used by the AR technology to augment information concerning the visited place. The details of the proposed model are described in Algorithm A2, and in the following subsections.

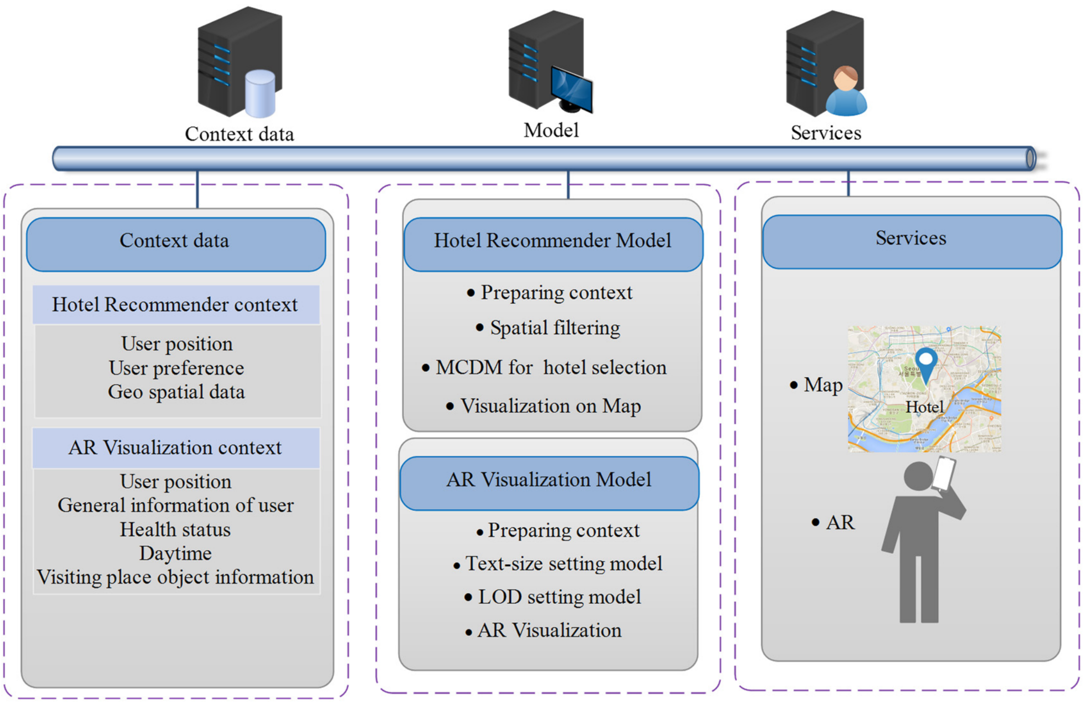


Figure 2. UTS-mAR methodology.

3.2.1. Hotel Recommender Model Based on SF and MCDM

In our system, the hotel recommender model is based on SF and MCDM. This model uses context information and performs SF to generate a list of candidate hotels in the vicinity of the user. Subsequently, the model compares the generated candidate hotels using the MCDM method with TOPSIS. This comparison is based on various criteria, such as cost, number of hotel stars, and distances from candidate hotels to transportation, attractions, and restaurants. The preferred types of transportation, attractions, and restaurants are previously selected by the user and stored in the context. The result of this process is the selection of the final hotel, which is displayed via Google Maps to facilitate easy navigation for the user. An extended version of the proposed model was considered for cases when the number of candidate hotels was too large to be processed via the MCDM method. To solve this problem, the extended model applies both clustering and MCDM after performing SF. The hotel recommender model is shown in Figure 3. This model involves various steps, as follows: (1) Context preparation, which provides data for the system model. This data model is related to the environment and users. (2) Application of SF for candidate hotel generation. In this step, a list of candidate hotels in the vicinity of the user is created. (3) Use of the hotel selection model to select the final hotel from the list of candidates. This step uses one of the following models:

(3-1) MCDM for final hotel selection in the case of a small number of candidate hotels. The candidate hotels are compared via the MCDM method based on TOPSIS, and the final hotel is selected based on the TOPSIS index.

(3-2) MCDM and clustering for final hotel selection in the case of large numbers of candidate hotels. Here, the candidate hotels are analyzed based on a combination of clustering and MCDM to determine the final hotel to be selected.

(4) Visualization model. This step displays the output of the selected model to the user. Here, the location of the selected hotel is displayed on the Google Maps interface to enable easy navigation for the user. These four steps are described in detail below.

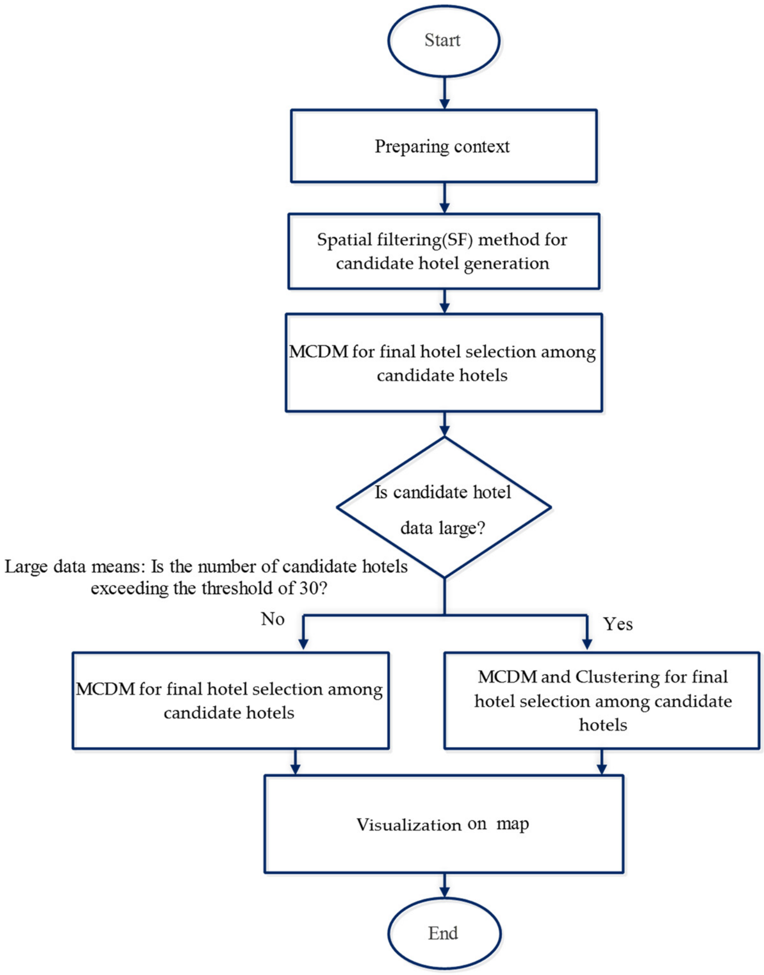


Figure 3. Hotel recommender model.

- **Preparing context**

As shown in Algorithm A1 (Appendix A), context preparation is the first step in the hotel recommender model. Table 1 lists the contexts necessary for achieving this aim. The context is obtained from different sources. The environmental context is obtained from geospatial data. These data are stored in the SpatiaLite database in the user's mobile phone, and include two types of information: spatial and non-spatial. Spatial information includes the location of the hotel and the hotel items, such as attractions, restaurants, and transportation. Non-spatial information also includes information related to hotels, such as the number of hotel stars and cost. The user context includes the user location and preferences. The user location was determined via fused tracking, which estimates the user position by combining information from different sources, such as Wi-Fi, telecommunication towers, and global positioning systems (GPSs). The user location is provided as an input to the spatial transformation method, which returns an estimation of the user position in metric units using the universal transverse Mercator projection system. This position is stored in the system. Defining user preferences involves the selection of hotel attributes through the system interface. The user selects the type of transportation system (e.g., bus, subway), type of restaurant (e.g., restaurant, fast food), and type of historical attraction (usual (here, parks), museum, or historical (here, castles)). Section 4.1 provides more details concerning the steps for context preparation. In the Table 1, some explanation detail related table items are shown with "*".

Table 1. Hotel recommender model context.

Parameters		Descriptions
User context	User position	Estimated by the system via user tracking
	User preference	Selection of hotel items, such as: Transportation type (bus, subway), Restaurant type (restaurant, fast food), Attraction type (usual (park), museum, historical (castle)) * These items are selected via the system interface
Environmental context	Spatial item	Access to transportation, attractions, and restaurants * Type of spatial items is entered by user. * Access to a spatial item is estimated by the system via spatial function (closest: minimum distance).
	Non-spatial item	Hotel cost and the number of stars (star rating) * Star number contains the number of stars in the star ratings of hotels. * Hotel cost is classified as follows: Class1: Cheap hotel: Defined with score equal to 1. Class2: Usual hotel: Defined with score equal to 2. Class3: Expensive hotel: Defined with score equal to 3.

- **SF method for candidate hotel generation**

Running SF is the next step in the hotel recommender model. This function creates a list of candidate hotels in the vicinity of the user based on the search radius. In this study, the search radius was set to 2000 m. SF estimates the minimum distance (closest distance) between the user and the candidate hotels using user and hotel locations, which are obtained from the user context and environment. The generated candidate hotels are provided as inputs to the MCDM method.

- **MCDM for final selection among candidate hotels**

In this step, the MCDM method applies the non-spatial and spatial criteria for candidate hotels. The spatial criteria include the calculation of the distance of the candidate hotels to the nearest transportation systems, historical attractions, and restaurants. This is achieved using the minimum distance function with the positions of candidate hotels and the facilities retrieved from the environmental context. The specific types of transportation, attractions, and restaurants are obtained from user context. While, the non-spatial criteria are retrieved from the environmental context. Spatial and non-spatial criteria create candidate hotel data, which are provided as inputs to the TOPSIS method with their weights. Different methods, such as the AHP [37], can be used to calculate the weights of these items. In this study, we consider 0.20 as the equal weight for all (five) items. Of course, our system is not sensitive to this value, and it can easily change for the optional user. To determine the final hotel, the TOPSIS [38] method calculates a closeness index (CI) for each candidate, and the hotel with the highest CI is selected.

The reason for choosing the TOPSIS method in this section is its popularity and efficiency in similar research involving hotel selection based on the evaluation criteria. This method offers several advantages, as follows: The performance of this method is minimally dependent on the number of criteria. It can be used easily in positive and negative criteria. The application of the TOPSIS is practical for both quantitative and qualitative data. This method provides a quantitative index for ranking alternatives and choosing the better one. The simplicity of this method, as well as the possibility of a simple formulation offered by it, has made this a popular method for evaluating options [7,18,39].

- **MCDM and Clustering for final hotel selection from among candidate hotels**

In addition to the method proposed in Appendix A (3.1), a modified method was developed for use in more complex situations, such as when the number of candidate hotels is large. One of the applications of this modified model is in a scenario where the user selects a search radius too large to use all of the candidate hotels. Section 3.2 shows the different stages of creating such a model. The model is based on a combination of hierarchical clustering and TOPSIS [19,40]. Here, the candidate hotel data are normalized, and the results of this operation are provided as inputs to the next step, wherein the candidate hotels are clustered using hierarchical clustering. Considering that in this method, the analysis is performed on all candidate hotels, and the number of candidate hotels in our experiment was 30, four clusters were used to perform the clustering operations. This cluster number is determined by checking dendrogram data and normal distribution of data for achieving a small number of candidates for comparison with TOPSIS. Subsequently, the agents of the clusters are determined using the clustering results. The agent of each cluster has a value for each criterion equal to the average of all members of that cluster for that criterion. In the next step, criteria values of the cluster agent are provided as inputs to the TOPSIS method to select the best cluster with the highest closeness index (CI). Finally, the candidate hotels within the best cluster are compared using the TOPSIS method to select the final hotel.

- **Visualization**

After this step, the location of the selected hotel is obtained from the environmental context and used for visualization. This method expresses the location of the hotel as geographic coordinates (longitude and latitude), which are subsequently displayed in Google Maps.

3.2.2. AR Visualization Model

The AR visualization model uses context and AR technology to display the properties of information for visualization, and involves three models: text-size setting, LOD setting, and visualization. These models employ various statistical techniques, such as rule definition, distance calculation, and the use of fuzzy functions. These statistical techniques result in the determination of the features of the displayed information, such as its text size and LOD, and these features are subsequently used in AR visualization. As shown in Figure 4, the AR visualization model contains several stages, as follows: First, the context that represents the user and environmental data is prepared. Next, a text-size-setting model is used to adjust the text size of the information based on the rules defined in the user context of the system. Subsequently, the LOD-setting model is used, which sets the LOD for the information based on distance, fuzzy function, or user preference. Because this model requires an estimation of the distance between the user and the visited object using the haversine formula, the corresponding distance is estimated. Finally, a visualization model is employed. At this stage, the LOD and text size, which are defined in the previous stage, are used for augmenting information on the visited object via AR technology. As discussed, our real-time system links the modules of the LOD-setting model and visualization with AR technology.

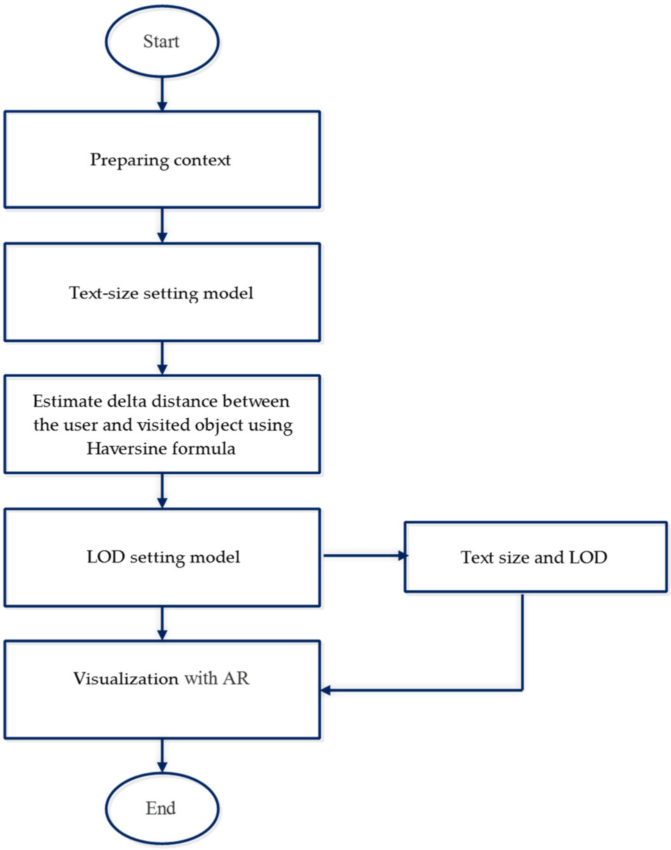


Figure 4. AR visualization model.

- **Preparing context**

As shown in Algorithm A2 (Appendix A), context preparation is the first step in creating the AR visualization model. The user context comprises a variety of information, including user position, general user information—such as age—and user health information (including vision problems). The positional information of the user is obtained using the fused tracking function in the system. Other user information, such as age and health status (e.g., presence of vision problems), is entered by the user through the system interface. Moreover, the environmental context includes two categories of information: the time of day during system execution, and visited-object information, such as images, location, and textual information. In this regard, time of day information is entered via the system interface, and the visited-object information for Sejong University as the test area is stored. Table 2 provides a description of the context. In the Table 2, some explanation detail related table items are shown with "*".

Table 2. AR visualization model context.

Parameters		Descriptions
User context	User position	Estimated by user tracking in the system.
	User characteristics	Age * This item is entered through the system interface.
	User health condition	Vision problems
Environmental context	Time of day(daytime)	* This item is entered through the system interface. Vision problems are classified into the

		following classes: Class 1: User with vision problems. Class 2: User without vision problems * Users enter the value Yes for Class 1 and No for Class 2.
		* This item is entered through the system interface. Users enter day or night regarding the time of day during system test
	Visited-object data	* Image dataset containing 46 images concerning the visited object. * Spatial data, such as the position of the visited object. * Non-spatial data, such as visited object information. These items are stored in the system for the test object, which is Sejong University

Context data are used by the system for defining information properties, which is achieved using the following three components of the AR visualization model: the text-size-setting model, which adjusts the text size of the information; the LOD-setting model, which adjusts the level of information detail; and the visualization model, which uses AR technology.

- **Text-size-setting model**

The text-size-setting model considers two general modes for adjusting the text size. The first is an automatic setting, which determines the text size based on the information provided by the system. The second is a manual setting, which determines the size based on the settings entered by the user. The automatic setting applies predefined rules to the system employing context information, such as age, status of vision problems, and time of day. This setting renders text in a small size for young users without vision problems, in a medium size for middle-aged users without vision problems, and in a large size for older users, users with vision problems, or when system execution occurs during nighttime.

- **LOD-setting model**

The LOD-setting model determines the LOD of the information. First, the distance between the user and the visited object is calculated using the haversine formula [41,42] on the corresponding locations.

The next step is the selection of the LOD-setting model by the user. The “LOD Model 1” setting determines the LOD of the information very sharply; if the distance between the user and the object is less than the search radius (here, 15 m), the LOD is set to “complete information”; otherwise, it includes general information, such as the name and ID. The “LOD Model 2” setting determines the LOD based on a fuzzy function using a descending linear fuzzy membership [43]; if the distance between the user and the object visited is less than the fuzzy lower band (here, 15 m), the LOD provided includes complete information. In addition, if the distance is between those of the lower and upper bands (here, 20 m), the LOD is determined based on the degree of membership of the fuzzy function. Furthermore, if the distance exceeds that of the upper band, the LOD is zero. Finally, the “LOD Model 3” setting allows the user to enter the LOD information through the system interface.

- **Visualization model**

The visualization model visualizes information based on the properties set by preceding models. This model applies the text size and LOD determined in the preceding steps. Subsequently, the visited object is recognized via the images stored in the system. Finally, the model augments the information related to this visited object.

4. UTS-mAR Implementation

UTS-mAR implementation refers to all of the necessary steps to create and develop the system. The preparation of context information and the development of the proposed system based on a standard programming language are introduced in this section.

4.1. UTS-mAR Context Preparation

The first stage of UTS-mAR is the preparation of the context data. The context related to the hotel recommendation service is obtained from different sources. The environmental context is obtained from geospatial data. This information contains both spatial and non-spatial information. Spatial information includes the position of candidate hotels, transportation, restaurants, and attractions. Non-spatial data also contain hotel information, such as the number of hotel stars and cost. Geospatial vector data were obtained from the free data available on the website [44], in shape file format. Subsequently, a portion of the data concerning Seoul was selected for the simulation. This information contained locations of candidate hotels, transportation (e.g., bus, subway), restaurants (e.g., restaurants, fast food), and historical attractions (usual (park), museum, historical (castle)). This information was inputted into the GIS software (ArcGIS 10.2) for completion. Several features in the layers of candidate hotels and historical attractions were added from the data obtained via Google Earth software. In addition, the candidate hotel information, such as the cost and the number of hotel stars, was determined using information available in Google Maps. Notably, hotel cost information varies at different times, and the data used herein were at the time of extracting this information. Finally, the geospatial data were entered into the SpatiaLite database for use in the system. Figure 5 shows geospatial vector data created with ArcGIS software. The user context is entered via the system interface developed in the Android Studio environment. This interface contains different textboxes to enter the transportation type (e.g., bus and subway), restaurant type (e.g., restaurant, fast food), and historical attraction type (usual (park), museum, historical (castle)). This interface also allows the user to track location data by pressing the tracking button to create user context.

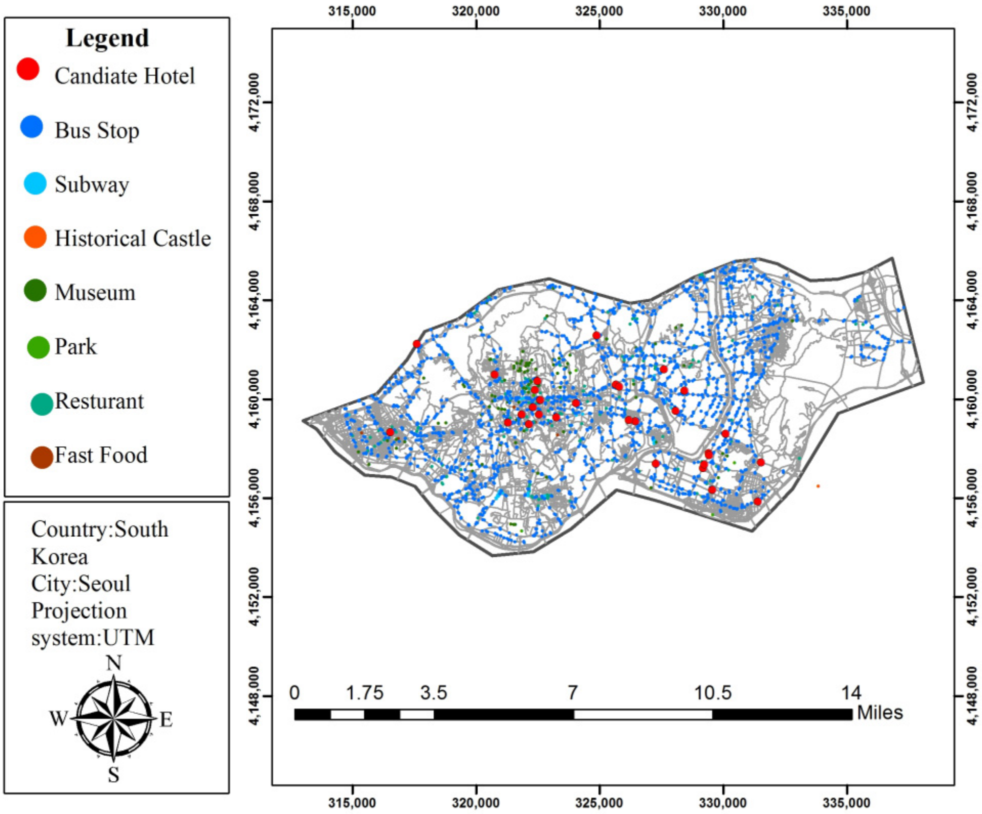


Figure 5. Seoul data created with ArcGIS software.

In addition, the context data related to the AR visualization section were extracted in different ways. Images related to the target object for visit were captured. In this study, the main gate of Sejong University was selected as the target object for visit. In addition, Wikipedia was used to prepare information related to Sejong University. The position of the Sejong main gate was defined in the system using a tracking method. The time of day for system testing, along with data such as age and the presence of vision problems, was entered via the system interface. These data were entered by the user using the list box. This interface also allows the storage of user position data based on the tracking model. These data were stored in the system and added to the context. The exact locations of the user and main gate are defined using GPS during the experiment.

4.2. UTS-mAR Development

The implementation of the analytical models used in UTS-mAR is based on a standard programming language, Java. In this study, the Android Studio environment was selected for developing the system because of its open-source nature and the possibility of creating a mobile service for tourists. In this regard, the hotel recommender model was developed in Android Studio using the Java programming language. In addition, supplementary application programming interfaces (APIs) were added to this environment to introduce different functions in the model. Google API (fused location provider) was used to track the user. SpatiaLite for Android was used to create the distance and transformation functions. The Google Maps API allowed the system to display the results on Google Maps for the user. In addition, the TOPSIS and MCDM functions were implemented using Native coding in Android Studio, which facilitates the creation of an interface to simplify user interaction. In addition, R was used to implement the improved version of the model proposed for large amounts of data using clustering (Section 3.2). Spatial libraries such as sp, rgeos, rgdal, and maptools were used to analyze geospatial data via R. Additionally, the hierarchical clustering library hclust was used for agglomerative hierarchical clustering analysis.

The AR visualization model was also developed in the Android Studio environment by adding two important APIs: Google API (fused location provider) was used to track the user, while Google Sceneform and an (YOLO; (version 5s) object-detection software development kit (SDK) were used to introduce the AR capability. These AR SDKs handles image based and markerless AR respectively. The output of our system is shown in term of markerless AR. In addition, Native coding in the Android Studio was used to develop the different functions used in the text-size-setting, LOD-setting, and visualization models. The interface designed in this section was flexible, allowing the user to enter the context data and select the type of model for defining the AR property.

5. Experiment and Results

The proposed system was developed in Android Studio and R, and was tested and evaluated by optional users. This test was performed at two levels: hotel recommendation service test, and AR visualization service test. The details of these tests are provided in the following sections.

5.1. Hotel Recommendation Service Test

The system test at this level was performed by a default user in the Gwangjin-gue area of Seoul. In this test, the user was asked to operate the system at their location by performing the following steps: (1) entering user position by pressing the TRACKING button, (2) entering hotel items using the list box defined in the system, (3) storage of information from steps 1 and 2 as context by pressing the SET button, and (4) executing The system result by pressing the show map button. Figure 6 depicts the system procedure for this test.

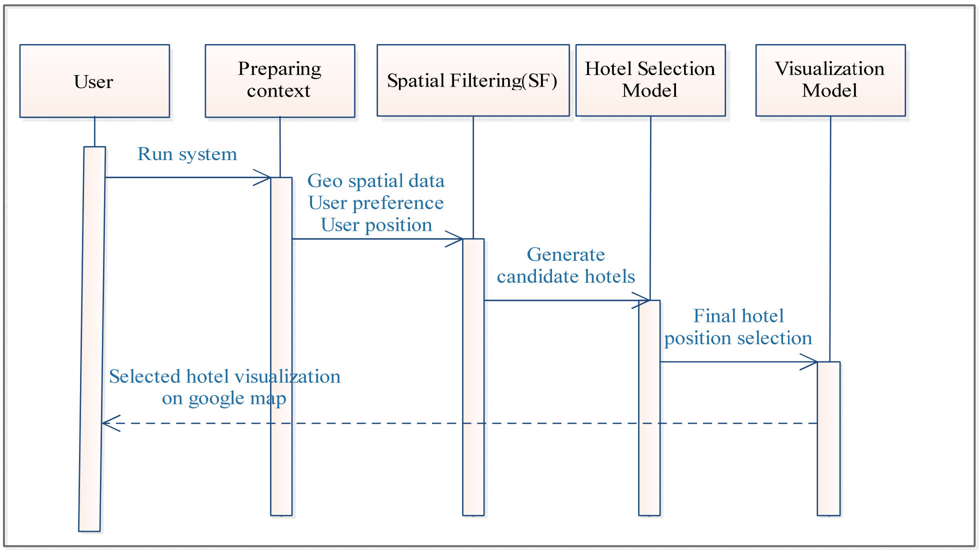


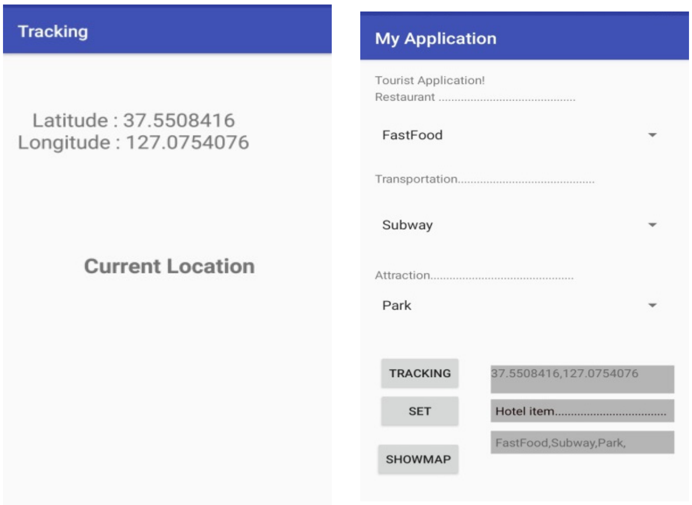
Figure 6. General procedure of the hotel recommendation service.

The results of the system test at this stage are shown in Figures 7 and 8. As shown in Figure 7, the user selected fast food, subways, and parks for the analysis. This information was stored in the system. Then, the system selected seven candidate hotels in the vicinity of the user using a 2000 m search radius. These candidate hotels were used by the TOPSIS model for the final hotel selection. The result of the system test at this stage is the selection of the hotel with the highest CI (in this case, 0.92) among all candidate hotels. The details of this comparison are presented in Table 3 and Figure 9.

Table 3 lists the following information concerning each candidate hotel: distances to the closest fast food restaurant, subway, and park as C1, C2, and C3, respectively; cost and number of hotel stars as C4 and C5, respectively, and the CI. Figure 9 depicts the CI for each candidate hotel (referred to as candidates in the figure).

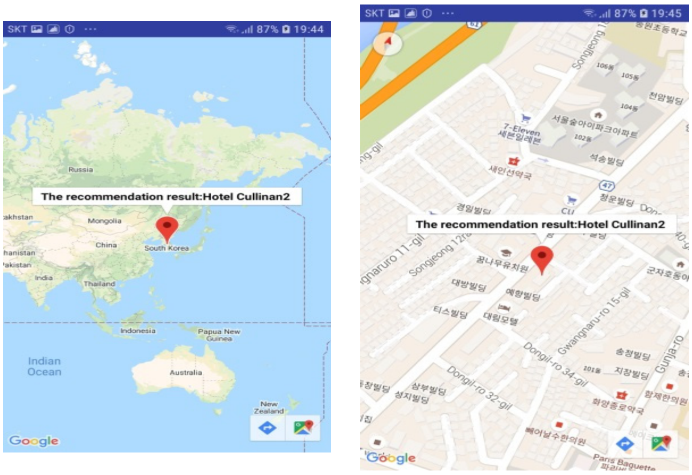
In the continuation of the system test in this step, the same step was repeated for all candidate hotels. Therefore, the system used clustering and TOPSIS models. Four clusters were created in this process, and the cluster agents were compared based on the five criteria C1, C2, C3, C4, and C5, as mentioned previously before using the TOPSIS method to select the best cluster. It must be noted that the five criteria for cluster agents are obtained by the average value of C1, C2, C3, C4, and C5 for each cluster's member, which are called C1average, C2average, C3average, C4average, and C5average. Subsequently, the candidate hotels within the best cluster were compared using the TOPSIS method to select the final hotel. The comparison results are shown in Tables 4 and 5.

Table 4 lists the average values of the C1, C2, C3, C4, and C5 criteria (defined in Table 3) of the candidate hotels within each cluster agent as C1average, C2average, C3average, C4average, and C5average, respectively; it also lists the corresponding CIs. Cluster 2 has the highest CI. As a result, the selection of the final hotel will be done based on a comparison of candidate hotels belonging to cluster2. Table 5 lists the C1, C2, C3, C4, C5, and CI values for the candidate hotels within Cluster 2. As discussed before, the closeness of CI to 1 (the higher value of CI) shows a greater chance for selection of candidate hotels. The hotel with the highest value of CI is selected as the final hotel. The mentioned result shows that the result of Figure 9 is the result of the system for a search radius (here, 2000 m) that generates a small number of candidate hotels but the results of Tables 4 and 5 are for managing the largedata set, which here is using all candidate hotels for the analysis.



(a) (b)

Figure 7. User item setting: (**a**) user position tracking and (**b**) hotel item selection.



(**a**) (**b**)

Figure 8. Selected hotel visualization: (**a**) position visualization and (**b**) detail of the selected hotel.

Table 3. Candidate hotel criteria matrix: C1, C2, and C3 represent distances to the closest fast food restaurant, subway, and park, respectively; C4 and C5 represent the cost and the number of hotel stars, respectively, while CI is the closeness index.

Candidate Hotel	C1	C2	C3	C4	C5	CI
H Avenue Hotel Kondae Seongsoo	4230.588	2221.525	1290.617	1	2	0.7501
Hotel The Designers Konkuk University	3154.782	2445.536	1214.613	1	3	0.909
Hotel The Designers Premier Kondae	4086.088	2201.338	1227.685	2	2	0.6207
Plein Hotel	3679.193	2257.693	1105.75	1	0	0.5249
W Hotel	4876.355	4247.521	1073.118	1	0	0.4429
The Classic 500	5153.299	3011.659	1008.67	3	3	0.5121
Hotel Cullinan2	3753.529	2284.855	1069.903	1	3	0.9278

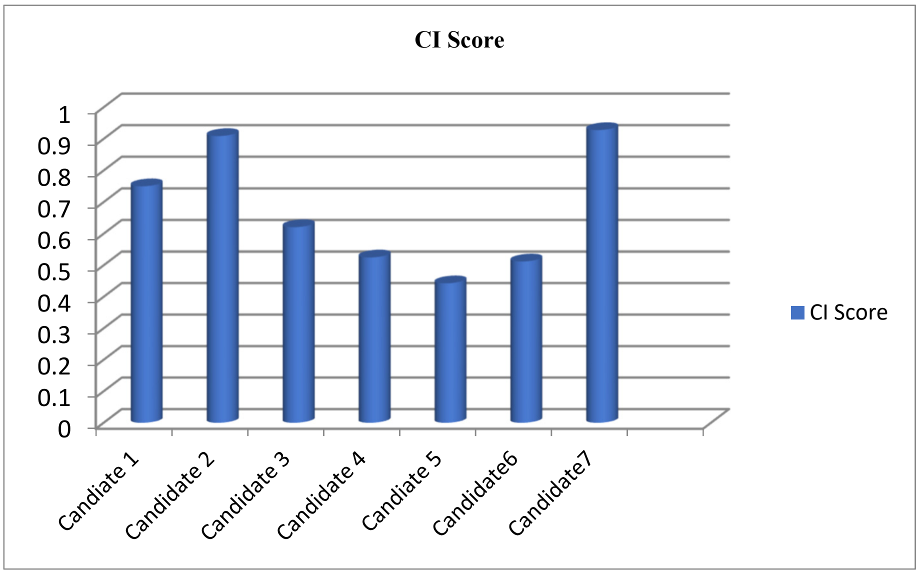


Figure 9. TOPSIS score results.

Table 4. Cluster agent comparison using TOPSIS: C1average, C2average, and C3average represent the average distances of hotels from the closest fast food restaurant, subway, and park in the metric

units for the cluster agents, respectively; C4average and C5average represent the average cost and number of stars for the cluster agents, respectively, while CI is the closeness index.

Cluster	C1 Average	C2 Average	C3 Average	C4 Average	C5 Average	CI
Cluster 1	4263.399	2660.783	1193.158	1.125	1.875	0.449633
Cluster 2	727.4722	963.8861	1344.764	2	3.3	0.767236
Cluster 3	1119.911	1038.127	2221.861	1	1.4	0.625212
Cluster 4	4384.46	2299.778	3088.15	3	4	0.326147

Table 5. Comparison of the candidate hotels of the best cluster (Cluster 2) using TOPSIS: C1, C2, and C3 represent the distances to the closest fast food restaurant, subway, and park respectively; C4 and C5 represent the cost and number of hotel stars, respectively, and CI represents the closeness index of the candidate hotels in Cluster 2.

Candidate Hotels in Cluster 2	C1	C2	C3	C4	C5	CI
LOTTE City Hotel Myeongdong	199.8618	501.4997	470.4098	2	4	0.968301
Hotel Prince Seoul	285.5777	1060.923	1148.291	2	3	0.76584
Best Western Arirang Hill Dongdaemun	988.36	2838.882	1640.39	2	4	0.38273
GRID INN	359.6967	657.8149	308.1377	2	2	0.827459
Hanok 24 Guesthouse Gyeongbokgung	1529.143	1149.351	1799.023	2	2	0.476285
Hotel Gracery Seoul	663.8276	966.0803	1509.317	2	4	0.697971
Hotel Skypark Kingstown Dongdaemun	1337.307	482.365	1324.931	2	4	0.631902
Hotel The Designers Cheongnyangni	1122.58	466.6121	3547.513	2	3	0.475993
Ibis Ambassador Seoul Myeong Dong	438.0678	631.4463	912.0501	2	3	0.831646
Nine Tree Premier Hotel Myeongdong II	350.2999	883.8861	787.5742	2	4	0.850426

5.2. AR Visualization Service Test

The main gate of Sejong University was selected as the target for testing the second service of the system. At this stage, the user was asked to operate the default system by performing the following steps: (1) entering user context such as age, presence of vision problems, and time of day in the first form of the system shown in Figure 10a; (2) opening the AR settings form by pressing the “AR service 1” button; (3) entering the AR setting parameters, such as type of text-size- and LOD-setting models (Figure 10b,c); (4) pointing the mobile camera toward the AR object—in this case, the main gate of Sejong University—and (5) pressing the AR service button (SET) to execute the AR scenario. The system procedure for this test is shown in Figure 11.

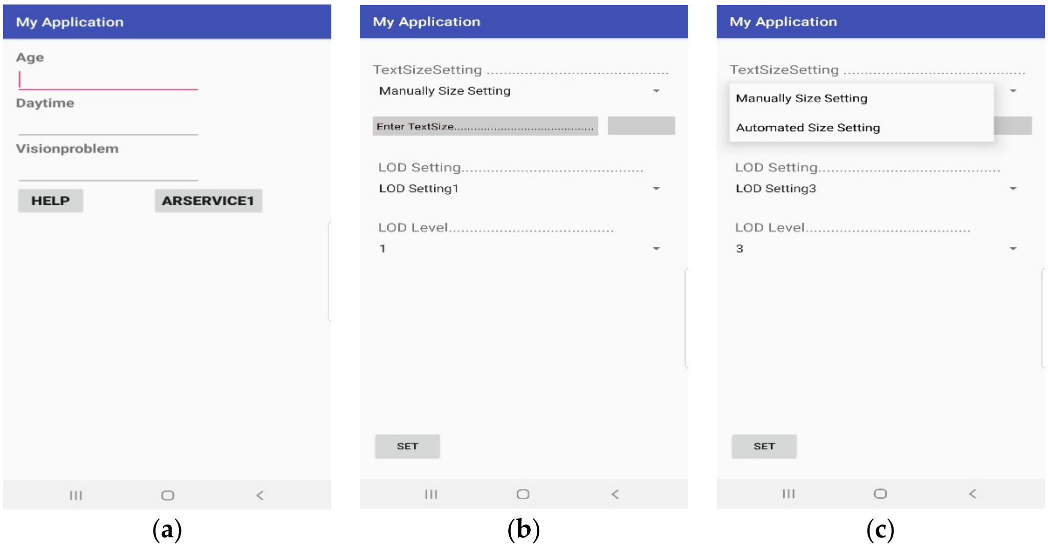


Figure 10. AR visualization using a mobile device: (**a**) user item setting, (**b**) AR parameter settings page, and (**c**) AR parameter settings.

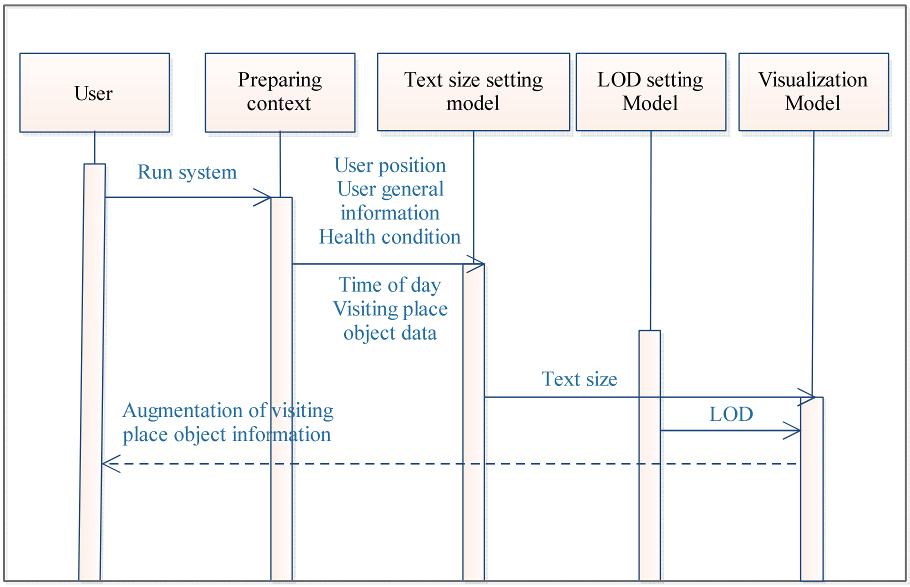


Figure 11. General system procedure for the AR visualization service.

The system test results of this step are shown for three different modes of the LOD model in Figure 12. Figure 12a shows the real object selected for the experiment herein. Figure 12b shows the output on running the LOD Model 1 setting, which displays all information (9 information fields) for the user located near the visited object. Notably, proximity (being near the visited object) is defined by the system via a threshold of 15 m. This implies that if the distance between the user and the visited object does not exceed this threshold, all of the information concerning the visited object is displayed. At this location, the "LOD Model 2" setting yields the same result. The result of this model is based on the membership function degree. In this test, the degree of membership was 1, which led to a display of 100% of the information. Notably, the font size of the experimental results is determined based on the user context shown in Table 6, which is entered via the system interface.

Finally, Figure 12c shows the output of executing the "LOD Model 3" setting. This model visualizes information based on the LOD specified by the user. In this test, the user selected an LOD of 3, which led to the visualization of three information fields in the display stage. In addition, in this experiment, the user selected a text size of 10 sp units for visualization. It should be noted that the maximum LOD differs between objects. The LOD defined for the test object of the experiment, which was the main gate of Sejong University, included nine information fields. These fields were Name, ID (identification), Type, Establish (date of establishment), History (explanation concerning the name or history of the place), Location (geographic coordinates), Urban (land use), Time (time of opening), and President (name of the president of the institution).

As the implementation shows, this study created an interface that is personalized based on the environment and context of the user. This interface adjusts the information properties (primarily, LOD and text size) using context data, and this is a significant innovation compared to other studies.

Table 6. User context for system test.

User Context	Value
Age	29
Time of day (daytime)	Day
Vision problem	No

(**a**)

(**b**)

(**c**)

Figure 12. Visualization via LOD Model: (**a**) real object, (**b**) information concerning the object displayed by the "LOD Model 1: Distance-based model" and "LOD Model 2: Fuzzy model" settings, and (**c**) information concerning the object displayed by the "LOD Model 3: user preference" setting.

5.3. System Evaluation

The proposed system was evaluated by users to obtain feedback on the system from their perspective. To this end, the following points were considered:

- Selection of users: Fifty-two random volunteer users participated in the evaluation. These users were selected from different age groups, such as young (63.46%), middle-aged, (26.92%), and old (9.62%), to obtain feedback on the system from a broad range of user categories. About 15.38% of these users had visual problems. Furthermore, a test was carried out on the location of the users in different parts of the city of Seoul.
- The evaluation was performed based on two aspects, namely, system design, and acceptance of the output based on user ideas. To achieve this, the design of the system interface was evaluated in terms of effectiveness, efficiency, and user satisfaction. In this regard, the usability was determined based on user responses to the questionnaire outlined in Table 7 [45,46]; users selected the desired score for each item (i.e., question) on a 5-point Likert scale. In this scale, 1 represents the worst case—i.e., complete user dissatisfaction—and 5 indicates complete user satisfaction. Notably, when a usability component consists of several items, the average of these item-scores is considered the output score.

Table 8 and Figure 13 show the averages of the usability item-scores entered by all users for each usability component. This evaluation revealed that efficiency was the most accepted component, with a score of 4.159 reported in the evaluation report. Additionally, the average overall score among the users, which indicates the overall user satisfaction with the system, was 4.112. Notably, the overall score was estimated by averaging the efficiency, effectiveness, and user satisfaction components of the usability test.

Table 7. Questionnaire for usability testing.

Usability Component	Question
Efficiency	Is the processing time adequately fast? (slow–fast) How many steps does the system require to achieve the result? (many–few) How quickly does the system provide the result? (slow–fast)
Effectiveness	Is data entry for tourists complex or easy? (complex–easy) Is the size of the screen reasonable, or is it difficult to interpret? (difficult–easy) How much interpretability does the presented information offer? (poor–high)
User satisfaction	What level of alignment with your expectations concerning the hotel recommendation and AR visualization services do the results of our application provide? (poor–high) How likely are you to use this application as a tourist? (poor–high)

Table 8. Usability testing results.

Usability Item	Average of All User Scores
Efficiency	4.159
Effectiveness	4.146
User satisfaction	4.028
Overall average score	4.112

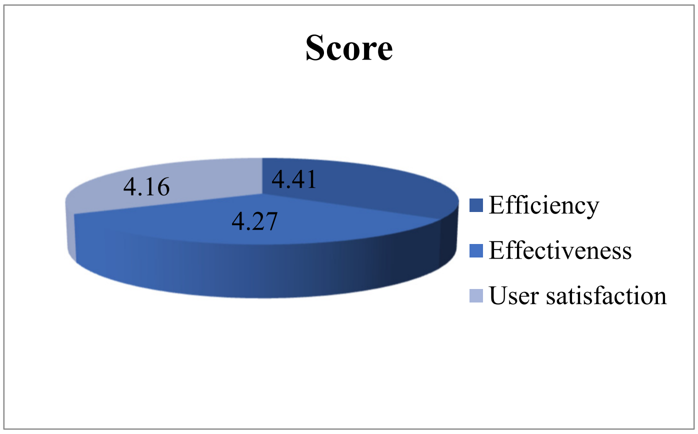


Figure 13. Usability testing results.

6. Discussion

The experimental implementation of the system demonstrates the several innovations offered by the system at the application level, which distinguish it from existing systems [18,30]. These innovations are as follows:

In the hotel recommendation service:

- The proposed system applies a combination of MCDM and context-awareness, which enables adaptiveness or dynamism of the models in the system. Based on this combination, the MCDM models configure their parameters based on context. As a result, in the MCDM model, the alternatives (i.e., candidate hotels) are generated based on the position of the user determined via the context using SF. Additionally, the MCDM model compares the generated candidate hotels based on predetermined criteria whose values are selected via user preferences. These criteria include the distances to the nearest transportation systems, historical attractions, and restaurants; notably, the types of transportation systems, historical attractions, and restaurants are selected by the user and stored in the context.

- Furthermore, the hotel selection model applies clustering to manage datasets involving a considerably large number of candidate hotels. This capability overcomes the limitation of MCDM-based models for handling many alternatives, such as candidate hotels for applications such as hotel selection. This also increases the performance of the system.

In the AR visualization service:

- The AR model incorporates context-awareness to define the rules necessary for adjusting the properties of the information to be displayed concerning the visited object, such as the text size and LOD. This analytical engine supports information from different context types, such as user and environmental contexts.
- This engine is a functional engine that offers two different modes, namely, automatic and manual. If the user selects the automatic mode, the information is configured based on the rules defined by the system; in the manual mode, the user enters their preferred text size and LOD.
- Furthermore, this engine employs spatial analysis methods, such as distance analysis. Such analysis is employed to adjust the LOD of information based on the distance between the user and the visited object. The ability of users closer to a point of interest (POI) to obtain more information is always a basic need that causes better management of the access level and reduces unnecessary information for the user and the system. Therefore, using the proposed engine and management of LOD based on distance leads to achievement of this aim.

Despite the importance of UTS-mAR and the advantages offered by it, there are some limitations that can be improved upon in future attempts to develop the system. First, UTS-mAR is designed for utilization by a single user, implying that the system displays the output based on the interactions of a single user with the hotel selection and visualization services. Therefore, for subsequent development, the system can be designed such that it can accommodate multiple users and match output results across sets of similar users. Second, the design and implementation of the models in the information visualization section focus on outdoor locations; consequently, most context information is related to outdoor spaces. Therefore, there is scope to include more contexts or define more rules that can improve the quality of the system models for indoor spaces.

7. Conclusions

This study presents a ubiquitous system for tourism that uses a combination of MCDM, AR, and context-awareness, called UTS-mAR, which can be adapted based on user and environmental contexts. The hotel recommendation component of this system generates several candidate hotels based on the user’s location, compares these candidates via MCDM using the TOPSIS method based on several criteria, and selects a final hotel. Subsequently, the selected hotel is displayed on Google Maps to facilitate navigation to the hotel for users. Additionally, an extended version of the hotel recommendation model, employing a combination of clustering and the TOPSIS method, was developed to manage the analysis of large datasets, such as those that include all candidate hotels. In the AR visualization component, UTS-mAR applies contextual information such as tourist age, presence of vision problems, and time of day during system operation to set the text size of outputted information. Next, this component uses the distance between the user and the visited object to adjust the LOD of information using the models available in the system. Finally, the AR model uses this text size and LOD of the information to augment information concerning the visited object. Additionally, the proposed system was evaluated via a usability test in terms of system design and user acceptance of output based on a five-point Likert scale. This evaluation yielded an overall average user score of 4.112, which indicates the acceptance of the system by users, owing to its proximity to the highest level of the Likert scale. However, the proposed system offers scope for future development. The criteria for hotel selection could be expanded to accommodate criteria based on temporal events, such as the distance of the hotels from COVID-19 hotspots, or the air pollution quality of the region where the hotels are located. Furthermore, the user's view of assessment-related hotels could be entered as criteria to the system. Moreover, criteria could be generated using smart methods; for example, machine learning could be used to select the attraction type for a user based on the user's characteristics and the type of tourists. In the visualization service, the accuracy of the tracking and object recognition methods could be increased by using novel tracking methods and deep learning models, respectively. Additionally, the visualization model based on AR technology could be completed by adding three-dimensional data, such as the three-dimensional model during application of the LOD setting. Finally, this model could be improved by adding more parameters for better flexibility of the model, such as adding screen size in the text-size-setting model. The results of the visualization model will be assessed using performance analysis during the evaluation analysis.

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Conflicts of Interest: The authors declare no conflict of interest

Appendix A. Algorithm Pseudocode

Algorithm A1. Hotel recommender model based on spatial filtering (SF) and multicriteria decision making (MCDM)

1. Preparing context

- ❖ **Preparing environmental context**
  - ▪ Spatial data include locations of hotels, transportation, restaurants, and features of tourist attractions, while non-spatial data include hotel features, namely, their cost and star ratings.
- ❖ **Preparing user context**
  - ▪ Prepare user position using fused tracking and transformation, and accept user preferences, including selection of transportation type, restaurant type, and attraction type through the system interface.

2. SF method for candidate hotel generation

- ▪ Use user position and hotel feature position from the user and environmental contexts.
- ▪ For each hotel:
  - ▪ Estimate distance between the user and hotel based on user and hotel locations.
  - ▪ If distance (hotel, user) ≤ search radius: 2000 m.
  - ▪ Save hotel location in the list as a candidate hotel location.

3. Hotel selection model

- ❖ Run Model 3.1 for final hotel selection from normal data and Model 3.2 for final hotel selection from large data, where large data means the number of candidate hotels exceeds the threshold of 30.

3.1. MCDM for selection of final hotel from among candidate hotels

- ❖ Preparing candidate hotel data
    - ▪ Use transportation, attraction, and restaurant feature locations, and candidate hotel locations obtained from the environmental context.
- ❖ For each candidate hotel:
- ❖ Estimate distance to the closest transportation, attraction, and restaurant features.
- ❖ Use candidate hotel cost and star rating from context.
- ❖ Save the above distance, cost, and star rating as candidate hotel data.
- ❖ Run TOPSIS using candidate hotel data.
- ❖ Estimate closeness coefficients for each candidate hotel ($\mathrm{CI_i}$) using the formula below:

$$\mathbf{CI_i} = \frac{\mathbf{d_i^-}}{\mathbf{d_i^+} + \mathbf{d_i^-}},$$

where:

$\mathbf{d_i^+}$ **is the distance from the positive ideal solution**;

$\mathbf{d_i^-}$ **is the distance from the negative ideal solution**;

Obtain the location of the hotel with the highest CI from environmental context.

Note: see [38] for details related to the TOPSIS formula.

3.2. MCDM and clustering for final hotel selection from among candidate hotels

- ❖ **Preparing candidate hotel data**
    - ▪ Use transportation, attraction, and restaurant feature locations, and candidate hotel location obtained from environmental context.
- ❖ For each candidate hotel:
- ❖ Estimate distance to the closest transportation, attraction, and restaurant features.
- ❖ Use candidate hotel costs and number of hotel stars from context.
- ❖ Save the above distance, cost, and number of hotel stars as candidate hotel data.
- ❖ Run normalization on candidate hotel data.
- ❖ For criteria values belonging to jth column ($\mathrm{C_i^N}$), perform the following normalization:

$$\mathrm{C_i^N} = \frac{\mathrm{C_i} - \min(\mathrm{C_i})}{\mathrm{Max}(\mathrm{C_i}) - \mathrm{Min}(\mathrm{C_i})},$$

where:

$\mathrm{i} = 1{:}\ldots,\mathrm{n};\ \mathrm{i} = \text{row number};\ \mathrm{n} = \text{number of hotels}.$

- ❖ Run hierarchical clustering using normalized candidate hotel data.
- ❖ Identify cluster numbers for candidate hotels.
- ❖ Generate cluster agents using the average of cluster-member criteria values.
- ❖ Use cluster agent data in TOPSIS to find the best cluster.
- ❖ Compare candidate hotels within the best cluster using the TOPSIS method.
- ❖ Select the hotel with the highest CI.
- ❖ Obtain the location of the selected hotel from environmental context.
- ❖ Note: see [19,40] for more details related to hierarchical clustering.

4. Visualization

- ▪ Use the location of the selected hotel.
- ▪ Transform this hotel location into geographic coordinates (longitude and latitude).
- ▪ Visualize the geographic coordinates in Google Maps

Algorithm A2: AR visualization model based on augmented reality.

1. Preparing context

- ❖ **Preparing user context**
    - ▪ Obtain user position using fused tracking, user age, and presence of vision problems entered via the system interface.

- **Prepare the environmental context**
    - Enter time of day through the system interface, and store visited object data comprising the location and information in the system.

2. Text-size-setting model

- **Select automatic or manual setting options from the system interface**
    - In the automatic setting, text size is set using the following rules:

If age ≤ 30, daytime = day, and vision problem = no,
text size is set to small (8sp).
Else if age ≤ 50, daytime = day, and vision problem = no,
text size is set to medium (10sp).
Else: #This means age > 50, daytime = night, or vision problem = yes,
text size is set to large (14sp).
End if.

- In the manual setting, the text size is entered into the system interface by the user.

3. LOD-setting model

- Use user and object locations and the radius of the Earth as per the following notations:

lat1 and lon1→The object's latitude and longitude.
lat2 and lon2→ The user's latitude and longitude.
R →The Earth's radius, which is set to 6,371,000 m.

3.1. Estimate distance between the user and the visited object using the haversine formula [41,42], as follows:

phi1 = (lat1 * PI)/180; // φ, λ in radians
phi2 = (lat2 * PI)/180;
dphi = (lat2-lat1)* PI/180;
dlanda = (lon2-lon1)* PI/180;
a = sin(dphi/2)*sin(dphi/2) +cos(phi1)*cos(phi2) *sin(dlanda/2)* sin(dlanda/2)
c = 2* atan2(sqrt(a),sqrt(1-a))
dist (user, object) = R*c; // in meters.

3.2. LOD-setting model

- Select the LOD-setting Model 1, 2, or 3 via the system interface.
    - Use Model 1 for sharp output determination using the following rule:
      If the distance (user, object) ≥ search radius: 15 m.
      LOD is general, and contains the ID and name of the visited object.
      Else#: This means distance (user, object) ≤ search radius: 15 m.
      LOD is complete.
      End if.
    - Use Model 2, which is based on fuzzy theory, to set LOD using the following rule:
      LOD = % (Fuzzy membership grade) *Information.
    - In Model 3, the LOD is entered into the system interface by the user.

4. Visualization model

- Use the text size and LOD determined in the previous steps.
- Identify the visited object using the image dataset.
- Augment the visited object information using text size and LOD.

References

1. Rocha, J. Smart Tourism and Smart Destinations for a Sustainable Future. In *Encyclopedia of the UN Sustainable Development Goals Decent Work and Economic Growth*; Springer: Cham, Switzerland, 2020; pp. 871–880.
2. Sørensen, F.; Bærenholdt, J.O. Tourist practices in the circular economy. *Ann. Tour. Res.* **2020**, *85*, 103027.
3. Falcone, P.M. Tourism-based circular economy in Salento (South Italy): A SWOT-ANP analysis. *Soc. Sci.* **2019**, *8*, 216.
4. Lee, P.; Hunter, W.C.; Chung, N. Smart tourism city: Developments and transformations. *Sustainability* **2020**, *12*, 3958.

5. Gülsün, B.; Yıldız, S.; Yılmaz, B. Multi-criteria decision making and the choice of hotels in tourism sector. *Int. J. Bus. Tour. Appl. Sci.* **2017**, *5*, 64–70. Available online: http://www.ijbts-journal.com/images/main_1366796758/IJBTS%205(2_7)%20BAHADIR%20G%C3%9CLS%C3%9CN%20MU17.pdf (accessed on 9 May 2022).
6. D'Adamo, I.; Falcone, P.M.; Gastaldi, M.; Morone, P. RES-T trajectories and an integrated SWOT-AHP analysis for biomethane. Policy implications to support a green revolution in European transport. *Energy Policy* **2020**, *138*, 111220.
7. Hezer, S.; Gelmez, E.; Özceylan, E. Comparative analysis of TOPSIS, VIKOR and COPRAS methods for the COVID-19 Regional Safety Assessment. *J. Infect. Public Health* **2021**, *14*, 775–786.
8. Sanjaya, M.R.; Kurniawan, D.; Saputra, A. GIS Android mobile based Software Development for Tourism Objects, Public Places list, Transportations list, and Culinary Places list Using Usability Measurement. *J. Phys. Conf. Ser.* **2020**, *1500*, 012117.
9. Hashemi, M.; Sadeghi-Niaraki, A. A theoretical framework for ubiquitous computing. *Int. J. Adv. Pervasive Ubiquitous Comput. (IJAPUC)* **2016**, *8*, 1–15.
10. Sun, J. Ubiquitous computing capabilities and user-system interaction readiness: An activity perspective. *Inf. Syst. Front.* **2020**, *22*, 259–271.
11. Rokhsaritalemi, S.; Sadeghi-Niaraki, A.; Choi, S.-M. A review on mixed reality: Current trends, challenges and prospects. *Appl. Sci.* **2020**, *10*, 636.
12. Giganti, P.; Falcone, P.M. Socio-technical transitions and innovation niches: The case of the virtual and augmented reality in Europe. *AIMS Energy* **2021**, *9*, 755–774.
13. Zhao, G.; Lou, P.; Qian, X.; Hou, X. Personalized location recommendation by fusing sentimental and spatial context. *Knowl. Based Syst.* **2020**, *196*, 105849.
14. Jung, K.; Nguyen, V.T.; Piscarac, D.; Yoo, S.-C. Meet the virtual jeju dol harubang—The mixed VR/Ar application for cultural immersion in Korea's main heritage. *ISPRS Int. J. Geo-Inf.* **2020**, *9*, 367.
15. Bueno, I.; Carrasco, R.A.; Porcel, C.; Kou, G.; Herrera-Viedma, E. A linguistic multi-criteria decision making methodology for the evaluation of tourist services considering customer opinion value. *Appl. Soft Comput.* **2021**, *101*, 107045.
16. Effendy, F. Developing web apps based on multi-criteria decision making and user preferences. *IOP Conf. Ser. Mater. Sci. Eng.* **2021**, *1088*, 012019.
17. Forouzandeh, S.; Berahmand, K.; Nasiri, E.; Rostami, M. A Hotel Recommender System for Tourists Using the Artificial Bee Colony Algorithm and Fuzzy TOPSIS Model: A Case Study of TripAdvisor. *Int. J. Inf. Technol. Decis. Mak.* **2021**, *20*, 399–429.
18. Sezgin, M.; Tokay, S. Determining the most appropriate hotel with multi-criteria decision making techniques: The example of Mersin Province. *Int. J. Sci. Res. Publ.* **2016**, *6*, 1–11.
19. Masnadjam, M.; Sadeghian, R. Utilization of Clustering and TOPSIS Method for Selecting Suppliers with Supply's Limitation. *J. Prod. Oper. Manag.* **2015**, *6*, 171–186.
20. Noguera, J.M.; Barranco, M.J.; Segura, R.J.; Martínez, L. A mobile 3D-GIS hybrid recommender system for tourism. *Inf. Sci.* **2012**, *215*, 37–52.
21. Honarparvar, S.; Forouzandeh Jonaghani, R.; Alesheikh, A.A.; Atazadeh, B. Improvement of a location-aware recommender system using volunteered geographic information. *Geocarto Int.* **2019**, *34*, 1496–1513.
22. Jing, C.; Dong, M.; Du, M.; Zhu, Y.; Fu, J. Fine-Grained Spatiotemporal Dynamics of Inbound Tourists Based on Geotagged Photos: A Case Study in Beijing, China. *IEEE Access* **2020**, *8*, 28735–28745.
23. Manoharan, S. Geospatial and social media analytics for emotion analysis of theme park visitors using text mining and gis. *J. Inf. Technol.* **2020**, *2*, 100–107.
24. Kato, Y.; Yamamoto, K. A sightseeing spot recommendation system that takes into account the visiting frequency of users. *ISPRS Int. J. Geo-Inf.* **2020**, *9*, 411.
25. Chen, T. A fuzzy ubiquitous traveler clustering and hotel recommendation system by differentiating travelers' decision-making behaviors. *Appl. Soft Comput.* **2020**, *96*, 106585.
26. Abbasi-Moud, Z.; Vahdat-Nejad, H.; Sadri, J. Tourism recommendation system based on semantic clustering and sentiment analysis. *Expert Syst. Appl.* **2021**, *167*, 114324.
27. Barranco, M.J.; Noguera, J.M.; Castro, J.; Martínez, L. A context-aware mobile recommender system based on location and trajectory. In *Management Intelligent Systems*; Springer: Cham, Switzerland, 2012; pp. 153–162.
28. Kanmani, R.S.; Surendiran, B. Context-Based Social Media Recommendation System. In *Recommender System with Machine Learning and Artificial Intelligence: Practical Tools and Applications in Medical, Agricultural and Other Industries*; Wiley: Hoboken, NJ, USA, 2020; pp. 237–249.
29. Techasarntikul, N.; Mashita, T.; Ratsamee, P.; Uranishi, Y.; Takemura, H.; Orlosky, J.; Kiyokawa, K. Evaluation of pointing interfaces with an ar agent for multi-section information guidance. In Proceedings of the 2019 IEEE Conference on Virtual Reality and 3D User Interfaces (VR), Osaka, Japan, 23–27 March 2019; IEEE: Piscataway, NJ, USA, 2019; pp. 1185–1186.
30. Sasaki, R.; Yamamoto, K. A Sightseeing Support System Using Augmented Reality and Pictograms within Urban Tourist Areas in Japan. *ISPRS Int. J. Geo-Inf.* **2019**, *8*, 381.
31. Blanco-Pons, S.; Carrión-Ruiz, B.; Duong, M.; Chartrand, J.; Fai, S.; Lerma, J.L. Augmented Reality markerless multi-image outdoor tracking system for the historical buildings on Parliament Hill. *Sustainability* **2019**, *11*, 4268.

32. Demir, Ö.F.; Karaarslan, E. Augmented reality application for smart tourism: GökovAR. In Proceedings of the 2018 6th International Istanbul Smart Grids and Cities Congress and Fair (ICSG), Istanbul, Turkey, 25–26 April 2018; IEEE: Piscataway, NJ, USA, 2018; pp. 164–167.
33. Čejka, J.; Zsíros, A.; Liarokapis, F. A hybrid augmented reality guide for underwater cultural heritage sites. *Pers. Ubiquitous Comput.* **2020**, *24*, 815–828.
34. Vert, S.; Vasiu, R. Data profiling in a mobile touristic augmented reality application for smart environments based on linked open data. *IxDA* **2016**, *31*, 43–58.
35. Li, X.; Chen, W.; Wu, Y. Distance-driven User Interface for Collaborative Exhibit Viewing in Augmented Reality Museum. In Proceedings of the UIST'19: The Adjunct Publication of the 32nd Annual ACM Symposium on User Interface Software and Technology, New Orleans, LA, USA, 20–23 October 2019; pp. 42–43.
36. Seo, D.; Yoo, B. Interoperable information model for geovisualization and interaction in XR environments. *Int. J. Geogr. Inf. Sci.* **2020**, *34*, 1323–1352.
37. Sadeghi-Niaraki, A.; Kim, K.; Varshosaz, M. Multi-criteria decision-based model for road network process. *Int. J. Environ. Res.* **2010**, *4*, 573–582.
38. Meshram, S.G.; Alvandi, E.; Meshram, C.; Kahya, E.; Al-Quraishi, A.M.F. Application of SAW and TOPSIS in prioritizing watersheds. *Water Resour. Manag.* **2020**, *34*, 715–732.
39. Zavadskas, E.K.; Mardani, A.; Turskis, Z.; Jusoh, A.; Nor, K.M. Development of TOPSIS method to solve complicated decision-making problems—An overview on developments from 2000 to 2015. *Int. J. Inf. Technol. Decis. Mak.* **2016**, *15*, 645–682.
40. Bhandari, N.; Pahwa, P. Evaluating performance of agglomerative clustering for extended NMF. *J. Stat. Manag. Syst.* **2020**, *23*, 1117–1128.
41. Available online: https://www.movable-type.co.uk/scripts/latlong.html (accessed on 9 May 2022).
42. Peña-Rios, A.; Hagras, H.; Gardner, M.; Owusu, G. A type-2 fuzzy logic based system for augmented reality visualisation of georeferenced data. In Proceedings of the 2018 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE), Rio de Janeiro, Brazil, 8–13 July 2018; IEEE: Piscataway, NJ, USA, 2018; pp. 1–8.
43. Borovička, A. Fuzzy weights estimation method based on the linguistic expression of criteria relevance. *Cent. Eur. Rev. Econ. Issues* **2014**, *17*, 13–23.
44. Available online: https://mapcruzin.com/free-south-korea-country-city-place-gis-shapefiles.htm (accessed on *9* May 2022).
45. Sánchez, J.M.; Carrera, Á.; Iglesias, C.Á.; Serrano, E. A participatory agent-based simulation for indoor evacuation supported by google glass. *Sensors* **2016**, *16*, 1360.
46. mHIMSS App Usability Work Group: Selecting a Mobile App: Evaluating the Usability of Medical Applications. 2012. Available online: https://vdocument.in/selecting-a-mobile-app-evaluating-the-usability-of-s3-a-mobile-app-evaluating.html?page=2 (accessed on 9 May 2022).