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Procedia Computer Science 225 (2023) 626–634

Procedia Computer Science

www.elsevier.com/locate/procedia

27th International Conference on Knowledge-Based and Intelligent Information & Engineering Systems (KES 2023)

Development of an expert system to overpass citizens technological barriers on smart home and living

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Abstract

Adopting new technologies can be overwhelming, even for people with experience in the field. For the general public, learning about new implementations, releases, brands, and enhancements can cause them to lose interest. There is a clear need to create point sources and platforms that provide helpful information about the novel and smart technologies, assisting users, technicians, and providers with products and technologies. The purpose of these platforms is twofold, as they can gather and share information on interests common to manufacturers and vendors. This paper presents the "Finde-Dein-SmartHome" tool. Developed in association with the Smart Home & Living competence center [5] to help users learn about, understand, and purchase available technologies that meet their home automation needs. This tool aims to lower the usability barrier and guide potential customers to clear their doubts about privacy and pricing. Communities can use the information provided by this tool to identify market trends that could eventually lower costs for providers and incentivize access to innovative home technologies and devices supporting long-term care.

Keywords: smart-home; long-term care; machine learning; expert systems; survey systems; smart-home & living

1. Introduction

Usual sources for information about Smart-Home products tend to inundate customers with technical details that are not relevant to everyone. This causes potential customers to lose interest in these products and fail to recognize their benefits. Against this backdrop, the Smart Home & Living competence center, in collaboration with several research institutes, has endeavored to develop a tool to educate and guide potential users of smart-Home solutions about their functionalities and provide them with intelligent recommendations tailored to their preferences. This Software was developed as part of the Project "Establishment and operation of a (virtual) marketplace competence center and

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10.1016/j.procs.2023.10.048

business processes for Smart-Home & Living in Baden-Württemberg" [5], to create synergies and business models between different actors (i.e., social and housing industry, craft companies, manufacturers, IT-companies, end customers) around the topic of smart-Home & Living (SHL).

This article describes the architecture and practical implementation of a recommendation system called "Finde dein Smart-Home" available in the Komzet SHL BW portal [5], built to sensitise, orient and inform customers (private or commercial) on the topic of Smart Home & Living in a needs-based and individual manner.

2. Intelligent Recommendation

Different strategies are used for recommendation systems, depending on their domain, source of information, and the algorithms employed [10]. For example, the "Content-based" recommendation system strategies rely on user interactions and feedback to make recommendations using the similarity between items and user profiles. Other approaches, such as "Collaborative Filtering", use user behavior and a utility matrix to compare similarities. Similarly, "Knowledge-based" systems use information collected from the users about their preferences to generate recommendations [10]. Thanks to the availability of data from social media and constant interaction via the World Wide Web, "knowledge graph" strategies are widespread among these systems [13], finding applications in e-commerce systems [16], but also in the health and medicine [15] sectors. Despite the strategy, common problems affect recommender systems when new unrated items are added (aka. cold start). Similarly, the lack of information about new users affects the accuracy of recommendations, but in counterpart, collecting too much personal data from users poses security and privacy risks.

2.1. Current approaches and implementations

To overcome the previously exposed challenges, several approaches in the literature implement recommendation systems with heuristics as part of the inference engine [4] and achieve valuable recommendations. More complex approaches tend to encapsulate inherent knowledge by combining machine learning techniques such as clustering, linear regression, and similarity algorithms [9] or novel approaches incorporating compensation strategies [2]. In some cases, human expert validation is included as part of the learning process [11]. Also, for knowledge representation, structures such as Petri-nets allow performing more complex approaches as linguistic reasoning in real applications [8] [6].

2.2. Expert Product Catalogue as Knowledge Base

The absence of datasets with generic SHL products drove the project's experts to seek alternatives to define a characterized list. At first, a list with 80 commercially available SHL products was created, including a general description and utility of each product. Then, a set of attributes related to the target population was defined, mainly focused on usability and accessibility. Finally, a group of SHL experts supplied a numeric assessment for each product and feature. The compendium of these assessments were used to create a utility matrix for the products and represent the experts' knowledge base. The rating scale used in the assessment for each feature is between one and five. The intelligent behavior of the system is based on this product catalog.

2.3. User Characterization

The users' first interaction with the system is to answer a survey to characterize their needs, preferences, and main interest regarding SHL products and services. Each inquiry is connected to one or more features from the catalog. Such a strategy allows the system to link users with characteristics at the same scale and criteria as the products and using the same values. When multiple questions target the same feature, an average of the punctuation is calculated that does not depend on the number of questions answered, thus increasing flexibility by allowing users to skip answers without affecting the final recommendation. Since users and products belong to the same value system, the similarity between both can be measured using distance metrics.

In order to simplify the number of features targeted by the survey and, therefore, the number of questions that a user should answer to get a recommendation, a further analysis was conducted measuring the (information) entropy for

each of the features of the SHL product catalog. Figure 1 shows the results obtained. Using this approach, a reduced set of questions/answers was formulated targeting only the criteria that better distinguish the products.

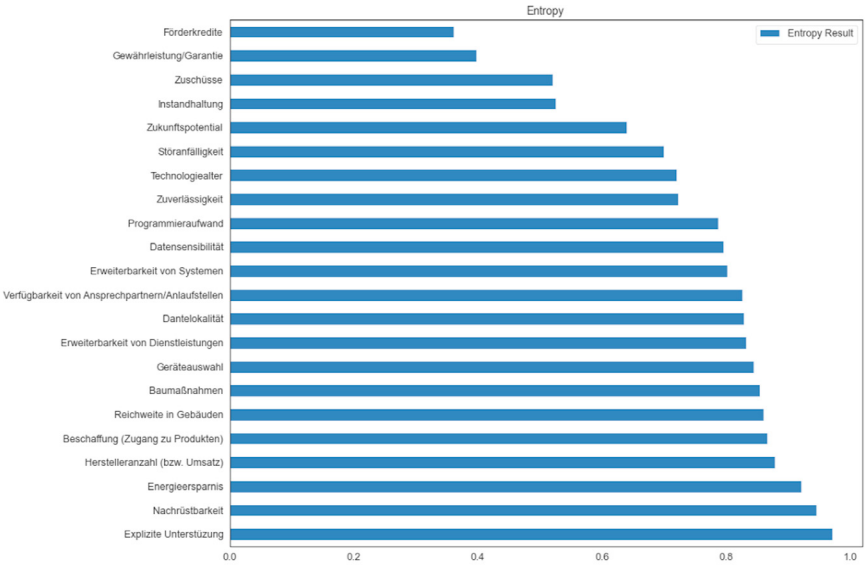

Fig. 1. Entropy distribution for all catalog products

The score assigned to each answer and the characteristics linked to them are customisable functionalities that can be changed through the administration module described in section 4.2.

Figure 2 describes the underlying behaviour of the system when creating a recommendation.

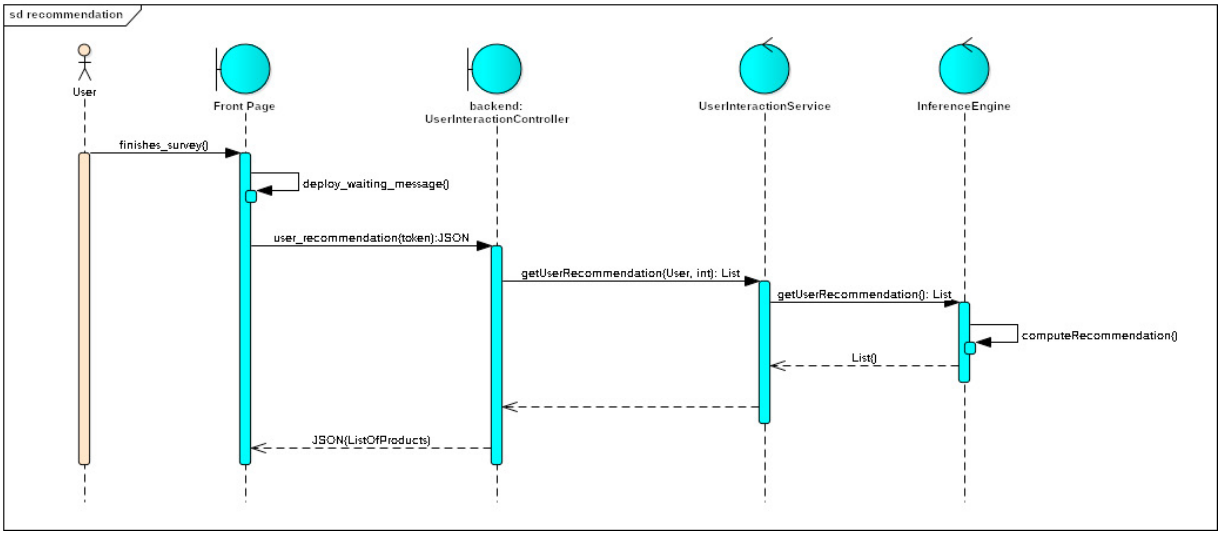

Fig. 2. Recommendation sequence diagram

2.4. Comparison Algorithms

The tool supports the inclusion of multiple comparison algorithms. System administrators can change the comparison algorithm used for recommendations via the administration panel. The first productive version had two algorithms: ”Cosine Similarity” and the ”Euclidean Distance”.

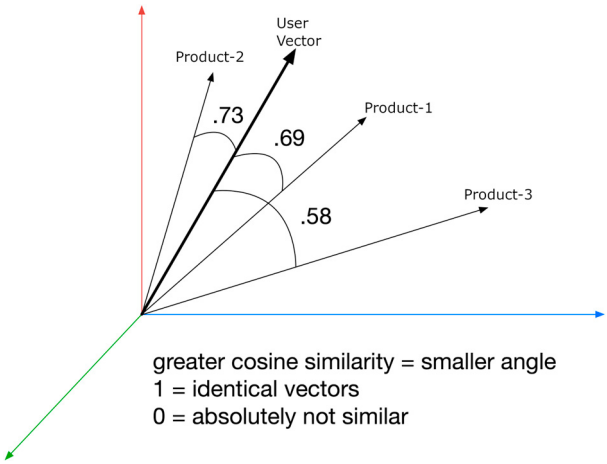

Fig. 3. Cosine Similarity interpretation

The "**Cosine similarity**" algorithm measures the similarity between two vectors projected into a multidimensional space and determines if they point approximately in the same direction. Figure 3 shows how the results of this measurement algorithm are interpreted. This algorithm is preferred because it considers the direction rather than the magnitude of the vector, which allows the comparison of samples with different lengths, meaning that users and products do not need to share the same complete set of features. Similar solutions have been implemented in recent reported productive solutions [14] [1].

$$d = \sqrt[2]{[(x_1 - Y_1)^2 + ... + (X_n - Y_n)^2]} \tag{1}$$

The "**Euclidean Distance**" or L2 norm calculates the shortest distance between two points in an N-dimensional (Euclidean) space. Equation 1 summarizes the calculation process. It is a common metric for measuring the similarity between two data points. Unlike the cosine similarity algorithm, the compared points must have the same dimensionality, so the missing features are replaced with zero when using this calculation. Products closer to the user representation are the first to be selected. Other recommendation systems reported include this algorithm with good results [12] [3].

3. Software Architecture

The "Finde dein Smart Home" recommendation system uses three main components in its architecture (Figure 4): A customized LimeSurvey application [7]; a backend component that provides a Web Restful API and runs an "inference engine" to compute recommendations; and a commercial open source database for data persistence. The technologies implemented in the backend server allow the user's interface to be embedded or deployed as a separate component. The user interface was developed using the Angular framework, which provides a scalable interface and makes the website accessible on multiple devices with different screen sizes. With Limesurvey as the survey tool of choice, the other system components work as wrappers that drive user interaction and retrieve information for product recommendations. The Java language and the Spring framework were used for the backend coding because of their stability and efficiency in production environments. At the database level, the MySQL database engine is used. This database is widely used for data storage in web services and thus provides all the necessary functions. Also, it is easy to use due to its open-source nature. The Limesurvey information structure and the parameters for performing the recommendations are stored in the same database.

4. User interface

The interface is accessible using modern web browsers via the URL: https://smarthome.etz-stuttgart.de. The navigation panel shown in Figure 5 shows the main control-actions available: A hyperlink at the top (1) redirects to the

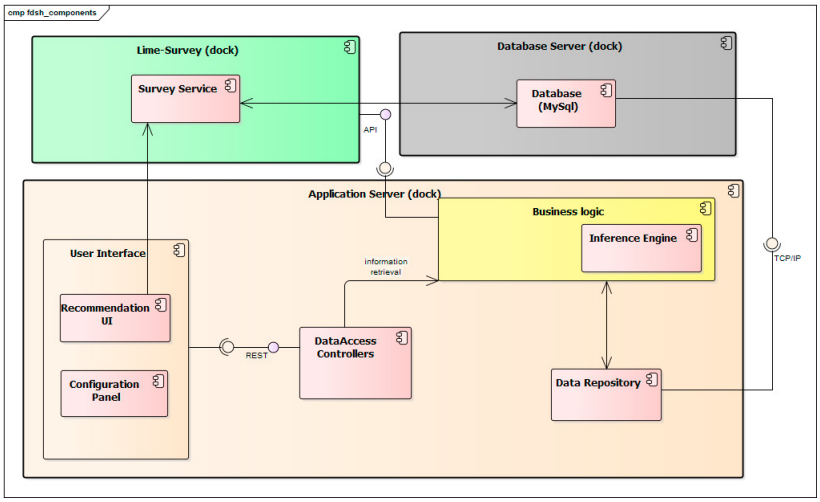

Fig. 4. Architectural components

landing home page and is present in all user views. A second hyperlink (2) displays a visual popup with the information of the user reference hex-code information (explained in the next section) and the copy, retrieve and withdraw utilities. A button (3) starts the survey for the user and displays the recommendation when the survey is complete. Another button (4) redirects to the ETZ portal page for further information.

Fig. 5. User's Interface: Landing Page

4.1. User privacy

This recommendation system uses an anonymous token strategy to recognize users to protect user privacy and avoid collecting personal data or referring to social media. The system creates a unique hex-code for each user that can be used to retrieve previous recommendations or surveys. Figure 6 shows the user interface for controlling this function. This hex-code becomes the user's reference to their preferences and can be shared with other interested parties such as vendors, IoT distributors, consultants, and other specialists so that they can rely on the information generated by the recommendation system to offer products and services. This can only happen when the user actively and consciously shares that information, and since no additional data is collected, external parties only will know about their SHL preferences.

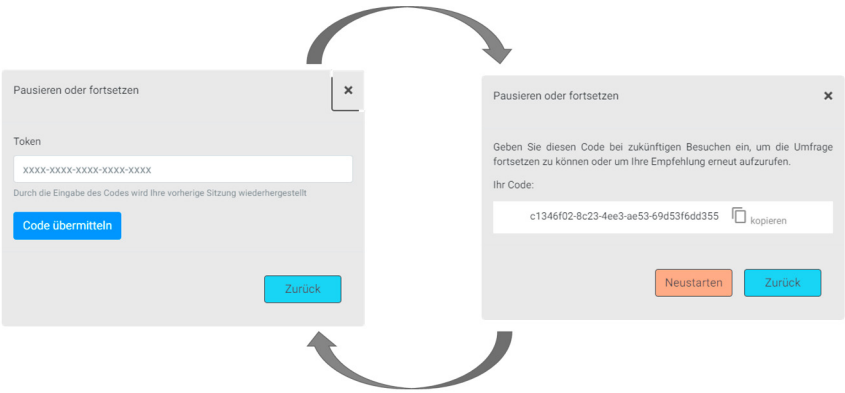

Fig. 6. User's Interface: Hex-code controls

4.2. System administration

To keep the information on SHL products and technologies updated, the tool includes an administration module that provides a web interface for modifying various configuration parameters and the product catalog included in the recommendations (Figure 7). The Original catalog in the first productive version included 80 generic products and their descriptions. With this management interface, it is possible to maintain such a catalog up to date with any new products and categories that may become available.

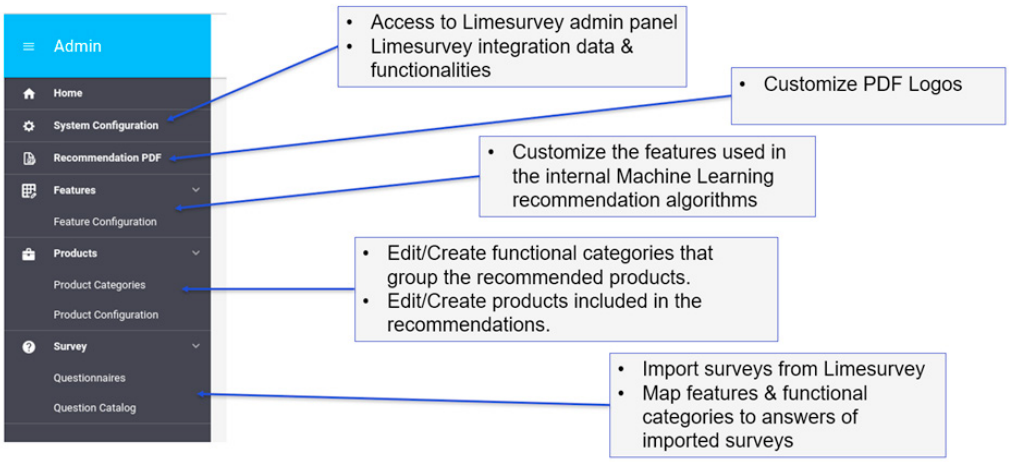

Fig. 7. User's Interface: Administration Page

5. Survey and Final Recommendation

This online tool aims to identify the user's primary interest and need for technical assistance to provide initial guidance. To achieve this, a survey was designed to characterize the respondent regarding products that may be of interest. A customized implementation of Limesurvey [7] is displayed into an embedded HTML frame component to improve navigation and grant the functionality of the active controls for users in all views. Figure 8 shows the layout for the survey.

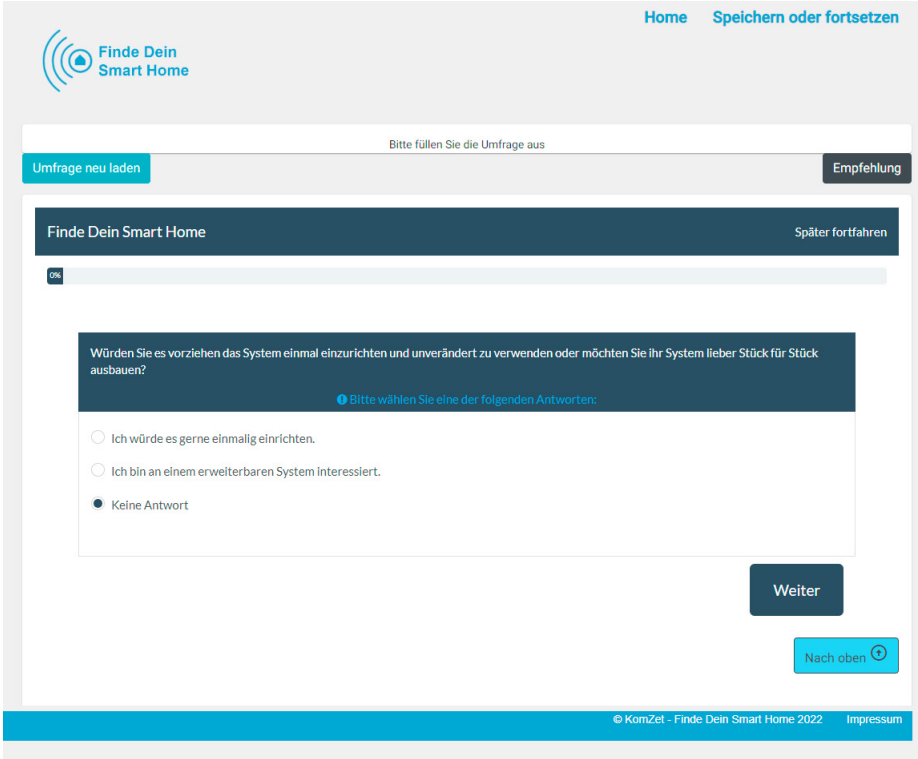

Fig. 8. User's Interface: Survey

After completing the survey, the user is redirected to the recommendation view (Figure 9), which contains a list of 10 products and their description. This list can be reviewed and modified by removing the products that are not of interest. Users can view a previously deleted item and add it to the list by activating a slider at the top right. A button at the top and bottom of the page allows exporting the product list in PDF format.

6. Conclusions and future work

Initial impressions of the system's features confirm the need for specialized sources of information designed to explain novel technologies to different audiences. The "Finde dein SmartHome" tool is a practical approach in this direction, creating a point of contact between potential customers and local sellers to foster the adoption of smart technologies. Future improvements should incorporate the feedback provided by platform's users to adapt and improve recommendations through clustering and more dynamic knowledge-base strategies, and with these, the incorporation of viable additional Artificial Intelligence approaches to generate useful recommendations.

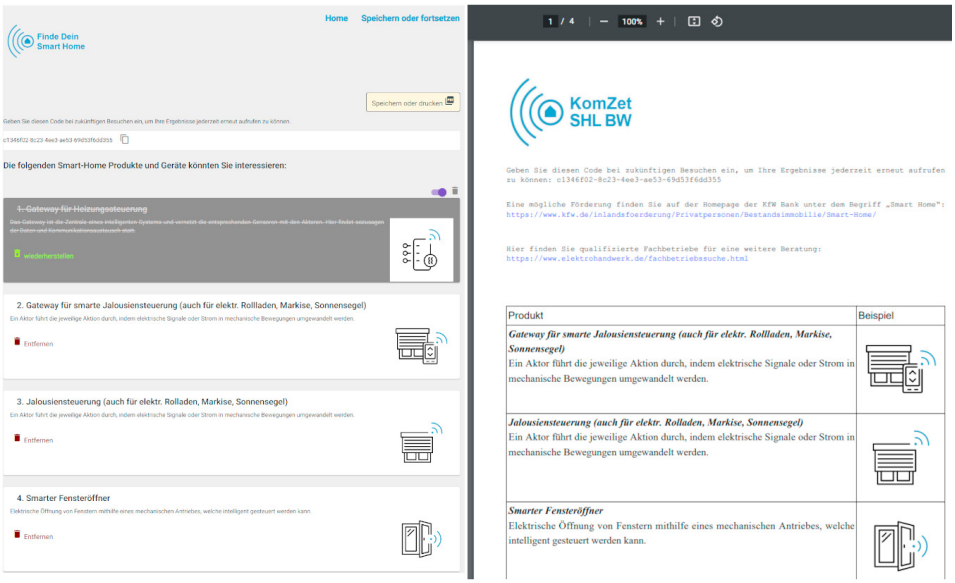

Fig. 9. User's Interface: Recommendation

Acknowledgment

This work has been supported by the Baden-Württemberg Ministry of Economics, Labor and Housing under the project title "Establishment and operation of a (virtual) competence center market and business process Smart Home & Living Baden-Württemberg" (KomZet).

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