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A Content Recommendation Platform for People with Intellectual Disability

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***Abstract*— People with Intellectual Disability (ID) encounter several problems in their daily living regarding their needs, activities, interrelationships, and communication. On this concept, an interactive web-based recommendation platform is proposed, aiming to provide personalized suggestions for information and entertainment, including creative and educational activities, tailored to the special users' needs of this population. The recommended items concern publicly available web-content, suggested according to the individual user interests, through a user-friendly environment.**

Keywords—Intellectual Disability, Support System, Web-based User Interface, User Profile, Information, Entertainment

I. INTRODUCTION

People with Intellectual Disability (ID) have certain limitations in cognitive functioning and skills including communication with other people, interaction with their environment, social, mental and self-care abilities, as well as core activities of daily living. The ID severity is categorized as mild, moderate, severe, and profound [1]. A major challenge is to offer people with ID opportunities for infotainment, education, specialized training and creative activities in order to maintain their morale at a high level. To this end, technological development can provide convenient interactive systems and services that can address their special needs and stimulate their interest and creativity.

According to a recent study [2], the use of digital devices has beneficial effects in children and adolescents with ID, as well as significant improvements in a) executive function, b) basic cognitive-linguistic skills, c) academic skills, and d) social and behavioral skills. Furthermore, an extensive analysis is included in [3], regarding the traits a content recommendation system targeted to individuals with ID could possess. Along this direction, in this paper, we present an under-development system, which aims to deliver an appropriate, interactive content recommendation platform for people with mild and moderate ID, in accordance to the analysis of [3]. The proposed system provides an easy-to-use solution, serving information and entertainment content, and suggesting educative and creative activities (Fig. 1). In order to generate recommendations, the semantically relevant content is identified, based on the information stored in the individuals' user profile and expresses their preferences, interests, and special skills. The user-friendly interface is designed for convenient use by people with ID, who encounter difficulties in efficiently handling Information Technology (IT) systems. The content's detailed thematic categories have been formed according to the general preferences and interests of people with ID, following the respective responses on interviews and questionnaires in a Greek association that supports people with such impairments. Additionally, the individual preferences in the user profile are automatically updated according to the actual user's web-activity (implicit feedback), which relieves people with ID from the manual adaptation, allowing to constantly receive suitable recommendations. Moreover, the proposed platform takes into consideration the crucial issue of exchanging information in a secure way, concerning the protection of personal data, but also the safety of the content that people with ID have access to. The latter is achieved by pre-filtering the candidate recommendations in order to exclude violent, or any kind of potentially harmful content.

The proposed system has been designed and being developed within the framework of QuaLiSID research project and its novelty lies in the fact that it combines all the above-mentioned characteristics to an integrated web-based platform tailored to the needs of people with ID, regarding the user-interface, but also the content recommendation services.

II. RELATED WORK

There is a number of initiatives, research projects, applications and platforms revolving around the use of digital technologies, that aim to help individuals with disabilities, including ID, in various ways [3], such as Inclusion International [4], DisabledBook [5], ELPIDA [6], and ENABLE [7] projects, Stomp interactive platform [8], KIDEA application [9], MAS [10] and IDPLIVING [11] platforms. Furthermore, several websites have been constructed in order to support people with ID and their families [3], such as Healthy Mind [12], the Puzzle [13] and epic [14] webpages, as well as the DEP project-site [15].

Regarding the recommendation services to people with ID, there is a limited number of projects dealing with the recommendation of multimedia content [3], such as in the case of interactive Internet Protocol (IP) television environments in [16].

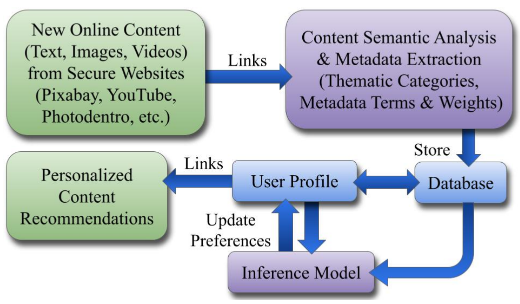

Fig. 1. Proposed platform architecture.

This work was prepared in the framework of the QuaLiSID project, which is co-financed by the European Union and Greek national funds through the Operational Program Competitiveness, Entrepreneurship and Innovation, under the call RESEARCH – CREATE – INNOVATE (project code: T2EDK-00306).

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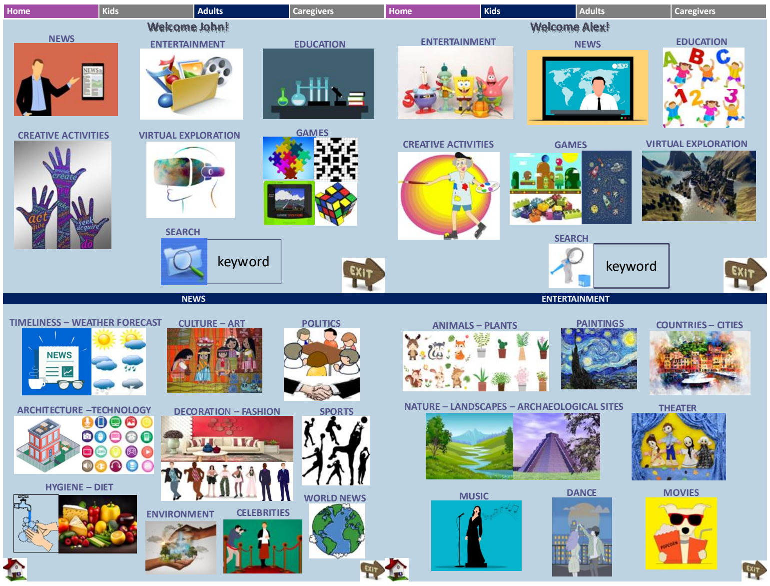

Fig. 2. English version of the User Interface: Homepage for adults (top left) and children (top right), sub-categories of "News" for adults (bottom left) and "Entertainment" for children (bottom right).

The delivery of personalized multimedia content in [16] is carried out by taking advantage of information gathered through the users' interaction with the system, while consequently adapting a group profile to each user's unique preferences. Moreover, the smartphone-based MUBS recommender system [17] introduced a personalized content-based activity recommendation model using a unique list of 384 enjoyable activities.

Content recommendation techniques can be distinguished to the two main approaches of collaborative and content-based filtering [18, 19]. In addition, there are other less common techniques, such as session-based [20] and knowledge-based recommendations [21]. Hybrid recommendation systems combine different techniques to overcome certain limitations of content-based and collaborative filtering [22]. Content-based filtering, which is utilized in the proposed system, analyzes the new content and calculates the similarity of items [23], aiming to recommend items similar to those that the user has selected / consumed in the past. In order to perform personalized recommendations, the user preferences, are stored in the profile and are constantly updated based on explicit or implicit user feedback. Similarity measures, such as cosine similarity, can be used to discover new content, relevant to the user's current preferences. Following this, the most relevant material is suggested and displayed in the priority order resulting from a ranking process based on the highest similarity between each element and the user profile [24].

III. Application Description

A. *Web-based User Interface*

The web-based user interface is being constructed in the Greek and English language (pilot version). The user enters the proposed platform through the login page that, apart from the search option, includes six different content categories (Table I). The general categories include sets of more specific subjects, such as Music, Movies, Theater, etc, as depicted in Fig. 2, through which people with ID can select and access the listed recommended internet items.

After the selection of a sub-category, the user is led to a list of titles that correspond to web-items, which are recommended based on the interests and special characteristics reflected in each user profile. In addition, the user interface allows the caregivers to access the data and preference profiles of the people with ID who are under their provision, through the corresponding page (tab), where they are automatically led after login. Additionally, for people with ID, the graphical environment varies, depending on the age-range, i.e., children interact with a slightly different interface, which leads to content that is suitable for children with ID, yet containing identical categories.

The development of the user interface is based on the WordPress tool version 6.2 combined with the WampServer web development platform that enables creating robust web-apps with MYSQL database and PHP Apache2 functionality.

TABLE I. Six Content Categories and Their Sub-Categories

Content	Content Sub-Categories
News	Timeliness & Weather-Forecast, Politics, Celebrities, Decoration & Fashion, Culture & Art, Sports, Environment, Architecture & Technology, Hygiene & Diet, World-News
Entertainment	Music, Movies, Dance, Theater, Paintings, Nature & Landscapes & Archaeological-Sites, Countries & Cities, Animals & Plants
Education	History & Archeology & Culture, Mathematics, Physics & Astronomy, People & Society & Ecology & Environment, Internet & IT, Biology, Chemistry, Vocational-Guidance, Geography & Geology, Language & Writing & Reading, Foreign-Languages, Literature, Theater & Art-History, Music-Theory
Creative Activities	Gymnastic & Dance, Pottery, Cooking & Pastry, Gardening, Knitting, Technology-Usage, Painting & Crafts, Musical-Instruments
Interactive Games	Assembling-Games & Puzzles, Number-Games, Crossword-Games, Riddles & Quizzes, Scientific-Fantasy, Adventure, Strategy, Sport-Games
Virtual Exploration	Museums & Temples & Archaeologies, City-Attractions, Natural-Landscapes, Art & Technology-Exhibitions

TABLE II. DATABASE TABLES

No	Table	Description
1	Users	User data, such as username, password, age, etc
2	Organization	Contact details of related organizations
3	Categories	Category name, description
4	Prototype	Keywords contained in the term
5	Content	Content title, format, link, date
6	Metadata	Descriptive terms contained in the item

Communication of front-end and back-end modules is achieved via REST service call in Python scripts (to handle back-end services and functionality) and JSON format communication to implement the 4 basic requests (GET, PUT, POST, DELETE) requests. The images that illustrate each category, as well as the functionality icons have all been downloaded from Pixabay [29], where they are freely available and are not subjected to license issues.

B. Content Items

Through the proposed system, people with ID have access to the pre-ingested online material falling under the six main categories. The corresponding items are published on a daily basis on secure websites and are of multiple formats, including text, image, video and multimedia.

Due to the limited number of websites that are especially addressed to people with ID, the recommended content is mainly selected from general purpose web-pages, where multiple items are available, such as Photodentro [25], Openbook [26], Travel All Over Greece [27], ΟΔΥΣΣΕΥΣ [28], Pixabay [29], Pexels [30], YouTube [31], Google Arts & Culture [32], Wikimedia Commons [33], Airpano [34], etc. Note that items presented to the user are not stored in the proposed system's server, but rather, the selection of a specific title directly leads to the web-source of the content, where it is publicly available.

C. Application Database

The relational system's database has been developed in MySQL, consisting of the following main units (Table II):

- System users: Apart from the system administrator, the users are distinguished by main roles of a) people with ID (adults and children), who are the key users of the recommendation system and may use it directly themselves, or with the aid of their relatives or/and caregivers and b) the caregivers who represent the professional carers - occupational therapists who have access to the data of the people with ID that they have under their provision.
- Content: The online content of multiple formats, which is recommended to the users is initially semantically analyzed and classified into one or more thematic categories. This analysis results in the extraction of metadata including the most descriptive and frequent terms contained in the item namely the *metadata terms* and the weights related to the terms' frequency of occurrence of the metadata terms in the items' content, i.e., the *metadata weights*.
- Categories: The web items are classified in one or more thematic categories, which consist of sets of particular descriptive human-interpretable terms (keywords), namely the *prototype terms* that actually represent more detailed categories' aspects. For instance, the category of "Movies" contains "film", "actor", "director", etc. Moreover, each prototype term is accompanied with a degree of relevance, namely the *prototype weight*, corresponding to its association with the current category.

The user profile consists of the entire set of the system's categories along with the corresponding degrees of preference, ranging between 0 and 1 and consists of three levels: Low [0–0.3], Medium (0.3–0.7) and High [0,7–1]. The detailed preferences in the user profile are initialized based on explicit user feedback, namely by the information gathered through questionnaires and interviews of the participating people with ID. Additionally, the prototype terms are also included in the user profile, along with the respective weights, which differ among users. The latter are initially calculated from the user-defined preference inherited by the parent category, multiplied with the respective prototype weight, expressing the intra-category and inter-user differentiation.

D. Content Semantic Analysis Methods

Aiming to support the matching of media items to the predefined categories of the platform, we designed methods for image, video, and text semantic analysis (Fig. 3). Concerning the image semantic analysis, we exploited three publicly available models pre-trained on the ImageNet [35], Places365 [36], and YouTube8M [37] datasets, as well as two new models that we trained on the TRECVID SIN [38] and Kaggle 100 Sports [39] datasets. These five models constitute model set *I* and can annotate images with more than 6000 unique semantic labels. In order to semantically analyze video items, we first segment the video into shots using the method of [40]. Then, leveraging the model set *I*, we analyze three key-frames per shot (selected by uniform sampling within the shot), annotating the shot with the most confident annotations of all key-frames. Additionally, we adopted the method of [41] and modified it for the annotation of each video shot with event/activity labels of the MiniKinetics [42], and ActivityNet [43] datasets with the two resulting models, constituting model set *V*. Our modifications on [41] concern dropping the object-level processing for the sake of computational efficiency. Regarding the text semantic analysis, we encode textual items in the joint feature space of [46] where we can compute the similarity to the - encoded in the same space - thematic categories' labels. Therefore, text can be directly annotated with the labels of the thematic categories.

Our semantic analysis methods extract metadata for media items in the form of semantic labels. We designed two methods to match a media item to a thematic category, leveraging such metadata. In the first one, *categories2concepts*, we initially use the Sentence-BERT text encoding method [44] to match each semantic label to a thematic category label.

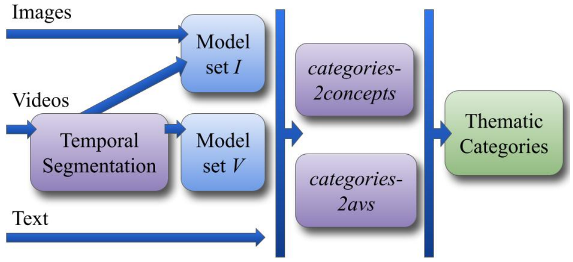

Fig. 3. Content Semantic Analysis

Through a manual filtering procedure, we selected the most relevant matches of semantic labels to each thematic category. When a media item is submitted for analysis, it is first annotated with semantic labels from the appropriate model set (i.e., *I* for images, *I* and *V* for videos). Then, the output semantic labels confidence scores of each model are ranked in ascending order and a ranking list is generated for each model. The relevance of an item to a thematic category is relative to the position of the matched semantic labels in the ranking list.

In our second approach, *categories2avs*, a pool of text sentences was first constructed, aggregating the textual part of the four video captioning datasets used in [45]. We measured the text similarity between the sentences of this pool and the thematic category labels, utilizing again the Sentence-BERT text encoding method, and finally, we manually selected the top 100 relevant sentences. When a media item is submitted for analysis, we calculate the cosine similarity between the item embedding and the relevant sentences embeddings in the joint feature space of [46]. The relevance of an item to a category is expressed as the maximum similarity of all relevant sentences. To evaluate the two approaches, we employed the V3C1 subset of the TRECVID AVS dataset [47] and treated each thematic category label as a query to retrieve related V3C1 videos. We performed a visual inspection of the top 50 videos returned by each approach, noting whether each video is relevant to the query. We used precision (i.e., correct answers against the number of examined videos, averaged over all categories) as the evaluation measure. We observed that late fusing the results of *categories2concepts* and *categories2avs* approaches (by considering the maximum confidence scores for each thematic category from the two approaches), yielded the best results (62.8% versus 54.4% and 58.8%, respectively), therefore this fusion of both approaches was employed for the thematic category matching. Therefore, the extracted metadata include the semantic description of items (i.e., semantic labels), and the categorization in one or more of the thematic categories (e.g., animals, music) with a respective weight term.

Moreover, the prototype terms of each content category were derived through the semantic analysis of large number of web-items. The human-interpretable stem-vectors, i.e., the set of prototype terms that semantically describe each thematic category were constructed, leveraging the matches of semantic labels to thematic category labels, computed for the *categories2concepts* approach. As reported in Section C, each category's prototype vector consists of a variable number of relevant semantic labels and the corresponding degree of relevance (i.e., a similarity value in [0,1]).

E. Inference Model

The inference model is responsible for a) the selection of personalized recommendations regarding each thematic category and ordering based on the preferences stored in the individual user profile, b) the update of the preference degrees of each category included in the profile, based on the user's current implicit feedback, i.e., the web-activity.

1) Personalized recommendations: In order to determine the particular online content for presentation to each individual user, the inference model takes as input: a) the metadata extracted from the semantic analysis of each web-item, i.e., the categories where the item has been classified, the metadata terms and the respective metadata weights as described in Section 4 and 5, b) the user's degrees of preference for each category and c) the prototype weights of each category stored in each user profile. Firstly, the new classified content and the respective metadata are specified. Following this, the common terms are detected between the current item (metadata terms) and the categories (where it belongs) in the user profile (prototype terms) and the Cosine Similarity measure is calculated according to the following formula:

$$CoSim(U_P, N_C) = \frac{\vec{U}_P * \vec{N}_C}{|\vec{U}_P| \cdot |\vec{N}_C|} \quad (1)$$

where *CoSim* is the Cosine Similarity measure, U_p stands for the vector of the user's prototype weights of the common terms and N_C represents the vector of the metadata weights extracted from the current content.

The results of the cosine similarity measure are used to rank the recommendations in an intra-category priority order. However, the user has the option of sorting the suggested content by its type (image, video, etc). Furthermore, depending on the user's degree of preference in each category, the most recent content is recommended according to the following rules: a) all the items for the high preference categories, b) up to 10 items for the medium preference categories and c) up to 5 items for the low preference categories.

2) User profile update: In order to dynamically update the categories' degrees of preference in the user profile based on the recent user online activity, all the user-determined prototype weights of the contained terms should be adapted. The prototype weights in the individual user profiles are constantly updated using the following input data: a) the metadata of the web items that were recently selected/consumed by the user, as reported in Section 4, b) the metadata of the suggested web items that were ignored by the user and c) the user prototype weights of the categories where the suggested content is classified. The updated prototype weights of each category in the user profile result from the mathematical formula of Eq. (2), which is based on the approach [24] and has been adapted to the particular characteristics of the proposed platform. More specifically, it has been modified taking into consideration the main differences and individual features of our system, compared with the system in [24], namely:

- The approach of [24] deals with a mobile-phone application, where the user is limited to a single screen.
- The content concerns textual news items in [24], as opposed to our system, where the content is multi-modal and derived from several different sources.
- The most important difference concerns the target users, which, in our case, constitute people with ID that are characterized by special behaviors, e.g., they might have opened a webpage, for a long time, without being concentrated on the content itself.

$$W_{new} = W_{old} \pm MW_f \cdot e^{-\beta \cdot U_b \cdot U_h} \quad (2)$$

where W_{new}, W_{old} are the new and the current prototype weight respectively in the user profile, MW_f corresponds to the average of the metadata weights of the specific term in the entire set of items presented to the user. The weights of a specific term in the user-ignored items are subtracted from

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those contained in the selected ones. Hence, the +or - sign is applied where the metadata weights of the term prevail concerning the consumed or ignored items respectively. Moreover, e^{-x} is used to follow the personalized nonlinear change of the prototype weight with respect to the usage term's history. The changing rate of the weight is inversely proportional to the value of the parameter x, where U_h stands for the number of the selected items, where the term exists and U_b represents the indicative mean number of the daily selected items, computed every week, i.e., the more items a user consumed per day, the more slowly the prototype weights increase in the profile. Furthermore, the β constant is used to differentiate between the changing rate of the weight if the update is performed concerning an interesting, or an ignored item, taking different values for positive and negative user feedback. More specifically, in the case of ignored items, the changing (decreasing) rate should be slower since a non-selected item does not constitute an explicit indication for non-interest. For instance, it can be interpreted as already read from another source, or as possible that the user had no time to spend on it.

Fig. 4. Content recommendations in "Animals – Plants" and "Paintings": Initial content for "High" (1st) and "Low" (2nd) degree of preference respectively and for "Medium" degree of preference in both categories, after the user activity (implicit feedback) during the week (3rd and 4th).

On the contrary, in the case of consumed items the changing (increasing) rate should be faster since a selected item demonstrates a strong indication for interest [24]. Based on the numerical values resulted by applying the formula, in Eq. (2), the indicative values for the β constant have been set to $\beta=0.01$ for selected items (positive feedback) and $\beta=0.02$ for non-selected items (negative feedback). Note that the weight adaptation concerns only the common terms between the user profile and the currently proposed items.

Finally, each new category's degree of preference is calculated as the average value of the included terms-weights, where each of them is divided with the respective initial prototype weight, i.e., the term's degree of relevance. Subsequently, the new preferences of the first-level categories result from the average of their subcategories. It should be noted that the categories' degrees of preference are not updated as regularly as the prototype weights (daily), but gradually, in a longer-term basis (e.g., once per week).

F. *Indicative Results*

Since the platform is currently under development, its functionality is demonstrated through an example of a registered user, who represents a person with mild intellectual disability. The user is assumed to have declared in his profile a "High" interest in "Animals – Plants" and "Low" interest in "Paintings" category. Based on the defined preferences the suggested content in those categories is illustrated in the first and second rows of Fig 4.

Subsequently, the user selects the first 5 items (about wild animals and cats) and ignores all the others. The next suggested items will be displayed according to the respective order. Assuming that the user is constantly interested in wild animals and cats, yet selecting only a few items per day from this category, after a few days, the degree of preference will be decreased to "Medium", resulting to the recommendation of fewer items. On the contrary, if the user is constantly interested in all the recommended items of the "Paintings" category, which has been initially defined with "Low" preference, its degree will be increased to "Medium", leading to the presentation of more articles, pictures, videos, etc, as illustrated in Fig. 4.

IV. Conclusion

In this paper the design of an under-development content recommendation platform for people with intellectual disability is presented. The proposed system is being constructed on a web-interface that constitutes a user-friendly environment, which, based on its initial evaluation, is fully handle-able and assisting for people with mild and moderate ID. It serves information and entertainment, while suggesting educative content and creative activities, according to the individual user preferences, interests, and skills, reflected in the personal profile. The latter is explicitly initialized, yet is dynamically updated through the inference model, taking into consideration the user's online activity concerning the web-items' selection. To match the new available content with the current user preferences, the inference model exploits certain metadata, extracted using advanced AI-based multi-modal semantic analysis.

The suggested items constitute freely available content of various formats such as text, image, video, for which the links to the source, rather than the files, are preserved to our database. The rationale behind building such a recommendation platform is the inability of people with ID to efficiently handle and make use of IT systems. Hence, the automatic adaptation of the profile-stored preferences, according to the web-interaction of those people, allows them to constantly receive suitable recommendations, without requiring to manually change their individual preferences. The proposed platform aspires of providing a personalized solution of multimodal-content suggestions from several thematic categories, offering people with ID the possibility of exploiting free time, favoring self-acting and the diverse creative employment, both in the environment of institutions (hospitality structures) and in their family homes.

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