# Exploring User Feedbacks: The Basis of a Recommender System of Informative Videos for the Elderly

David Campelo(✉), Telmo Silva, and Jorge Abreu

Digimedia (CIC.DIGITAL), Aveiro University, Campus Universitário Santiago, Aveiro, Portugal
{david.campelo,tsilva,jfa}@ua.pt

**Abstract.** Given the popularity of television among older people, technologies based on this device represent a valuable alternative to promote info-inclusion of the senior population, enhancing well-being, autonomy and consequent improving their quality of life. However, to provide a better viewing experience, it is vital to use a personalized approach, which privileges the individual by dynamically learning users' preferences and interests. In the scope of +TV4E project an Interactive TV (iTV) platform is being developed to provide these citizens with personalized information about public and social services from which they could benefit. This research aims to assess seniors' preferences by identifying possible explicit and implicit feedbacks, such as up/down voting and amount of video viewed, retrieved from interactions performed within the iTV application. This paper describes the methodology used to define an adequate interaction scheme to learn seniors' preferences based on these feedbacks, in a participatory and iterative design process, with 14 seniors. Such scheme will support the +TV4E content recommender system in selecting and matching the informative contents with the users' interests more accurately.

**Keywords:** Interactive TV · Personalization · Recommender systems · Seniors Feedbacks · Preferences

## 1 Introduction

Increasing human longevity is, by many reasons, an achievement to be celebrated, but it can be very problematic both for the individuals themselves and for those around them if no proper conditions for being independent, active, and healthy for a longer time are made available [1]. To promote greater levels of participation and autonomy in old age, a set of technological solutions to support seniors' daily activities in a more reliable and secure manner have been developed, in areas ranging from health, mobility and leisure to communication and work [2]. In this context, given the popularity of television among seniors in a daily basis [3–6], some of these technological solutions have used this device to improve wellbeing and quality of life by adding interactive features to the traditional television experience [7].


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Particularly in Portugal, seniors often face recurrent scenarios of info-exclusion [8], low literacy levels [9] and digital divide [10], which makes them unaware of information regarding public and social services from which they could benefit (e.g. health campaigns, income taxes notifications, and laws changing alerts). Thus, in order to follow the European Commission orientations for sustainable development and active ageing [11], Portuguese public authorities have been investing strongly in new communication channels to disseminate information about public and social services [12]. These channels have been playing a vital role for Portuguese citizens to obtain valuable information on various governmental assignments. In this context, the +TV4E project comes up with a platform to which proposes an iTV platform to deliver informative videos about public and social services tailored for Portuguese seniors [13].

The +TV4E platform aims to take advantage of the proximity and familiarity seniors have with the television to enable an enriched viewing experience, featuring the integration of informative videos automatically generated from a set of predefined news and institutional Web feeds [14, 15]. Then, these generated videos are pushed to the end-users through an iTV application, which in turn, is in charge of interleaving them with the linear TV broadcasted presentation, according to short interruptions [13]. To achieve a more personalized approach, this study aims to assess the preferences of seniors as end-users of +TV4E platform. To this end, the present research sets out to identify and classify implicit and explicit data, retrieved from interactions performed within the iTV application, which may somehow infer users' interests. Such interactions are on the basis of an interaction scheme, which will support the construction of the user preferences on the informative videos. Therefore, this study plays a major role in the conceptual phase of the recommender system.

The remainder of this paper is structured as follows: The next section presents some related works on recommender systems of TV and video as well as user feedbacks and user profile construction. The third section describes the methodology used to define the interaction scheme, including a literature review, exploratory interviews with users which took part in the preliminary tests of the +TV4E platform, and finally tests with high-fidelity prototypes conducted with seniors recruited from an adult day care centre. The forth section is dedicated to discussions and practical challenges, while the fifth and last section highlights the main conclusions and future works arising from this study, especially with respect to the context of +TV4E platform.

## 2 Related Work

### 2.1 Recommender Systems of TV and Video Contents

The advent of Smart TVs, the expansion of TV program/contents and the popularization of VOD (Video on Demand) platforms have contributed to an exponential growth of video contents available. Most of these contents are accessible through many different screen devices (e.g. smartphones, tablets, TVs) and transmitted using broadband (e.g. Internet) and broadcasted TV (e.g. terrestrial, satellite, and cable) networks [14]. On the one hand, there are obvious advantages and, as such, benefits to viewers in having a wide range of reachable contents. However on the other hand, such a huge amount of video contents has enforced TV/set-top box manufacturers, broadcasters, content producers and streaming providers to search for automatic tools to support users in decisions about what to watch next, and thus, offer a more personalized viewing experience [14]. These tools are composed by algorithms and data collection schemes that predict and recommend contents (or items) matching users' interests and/or needs, in the so-called recommender systems [15]. Therefore, in order to provide an enhanced experience for these viewers during the discovery of new content, several pay-TV services providers and research projects have benefited from recommender systems to cope with this scenario of information overload [16].

With the expansion of digital networks and the increase of the number of channels, TV program recommender systems turned into the most popular application of personalized recommender systems for video contents [17]. These systems "assist TV watchers by recommending interesting TV programmes to watch more comfortably and avoiding the traditional way of channel surfing" [18]. First implementations of TV program recommender systems emerged in the 1990s and aimed at suggesting programs from the Electronic Programming Guide (EPG) [19]. Nowadays, some of the most complex and renowned recommender systems are implemented by online streaming services [16], such as Netflix [19] and Youtube [20].

As reported by Kumar and Sharma [17], there has been a significant increase in the movie recommender systems in the scientific literature, like MovieLens [21], a platform which recommends movies based on user past preferences; and Hulu [22], an VOD service which suggests movies and TV shows streamed to internet-connected devices at any time. Véras and his colleagues [16] conducted a broad literature review to analyse and classify scientific works according to different aspects of recommender systems in the TV domain, such as the recommended item types, algorithms, architectural models, output devices, user profiling, and evaluation. These authors reviewed techniques, methods, and applications of 282 studies published between 2003 and 2015 and among the main findings, it is worth to mention the growing focus on recommender systems of video contents beyond the traditional TV programs accessible through an EPG. It was noticed an increasing amount of studies using Web (browser) and mobile platforms as output devices for TV and TV-related contents, creating relevant opportunities for research on new types of video contents in multiple sources of information (e.g. cross-domain recommendation).

The main task of a recommender system for video services is to provide viewers with content suggestions they will most probably be interested in watching. To achieve this, these systems essentially estimate how much a user will like a given content, predicting how relevant it will be for the viewer using one or more prediction (or filtering) techniques [15]. Common examples of prediction techniques are collaborative filtering and content-based filtering. In the classical collaborative filtering technique, suggestions for a specific user are calculated based on the similarity between their interactions in the system, since individuals of similar interactions should have similar tastes [15]. Thus, in this technique users are clustered according to their behaviours in the past to predict potentially interesting items using similarity between clusters. On the other hand, content-based filtering prediction technique is based on descriptive data of recommended items to find items similar to those ones consumed previously, since past interests and tendencies are indicators of future preferences [15].

Barneveld and Setten [23] presented a generic prediction model for a TV recommender system (see Fig. 1). In this model, the prediction technique process calculates a probable interest value of a TV program for a given user, which consists in the item prediction (or suggestion). This process has as input all knowledge stored in the user profile, on items' data and metadata information, and on profiles of other users. Prediction techniques learn the interests and preferences of users from their feedbacks, which are basically constituted by direct and indirect interactions with the system. Some techniques may also provide users with explanations about their reasoning for providing a given item suggestion (e.g. "Because you enjoyed that one, you may like that also"). Optionally, a set of internal validity indicators may be employed to improve predictions when multiple prediction techniques are combined [23].

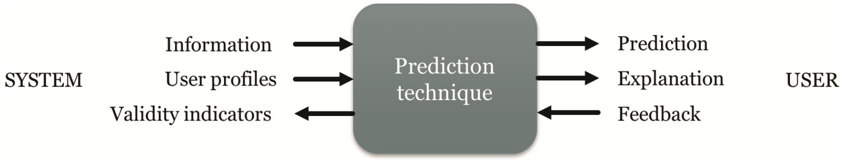


**Fig. 1.** Generic prediction model [23].

In order to create an intuitive, easy-to-use iTV application, tailored for seniors, to present informative videos along with regular TV broadcasted contents, this study particularly focuses on the possible feedbacks and interactions viewers would perform to support +TV4E recommender system in learning their preferences and interests with respect to these videos.

### 2.2 User Profile and Feedbacks in Recommender Systems of TV and Video Contents

According to Iglesias and his colleagues [24], the user profile concept can be defined as "a description of the user interests, characteristics, behaviours, and preferences". In general, user profiles can be constructed in a lot of different ways [14]. Many of the very earliest systems used to ask users to build their own profiles by actively providing information in the terms of items or characteristics they would be interested in. However, sometimes this turns out to be rather confusing and time-consuming for users. Hence, for more compelling and acceptable process of eliciting preferences, a user profile should also consider regular user actions and parameters (e.g. watching time, subscriptions, keywords used in search). Moreover, apart from the prediction technique or algorithm chosen to generate personalized item suggestions, data concerning relationships between users and these items must be collected by the recommender system. These interactions support the recommender system in learning the interest of a given user regarding the items that were somehow consumed.

In the particular case of TV and video services, there are two ways to obtain user interaction data to compose a user profile [14]: by analysing their behaviour during the viewing experience, which is called *implicit feedback*; and by requesting *explicit feedbacks*, which is when the user provides their opinions on a given content. So, user profiles can be built upon direct requests to users, which are clearly defining their positions in relation to the video contents; or by monitoring the system usage and user behaviour, based on interactions that may be indirectly linked to viewers' interests [14].

The main difference between implicit and explicit feedbacks is the main purpose of the associated interaction. In the implicit feedback, user is just following the normal system flow and performing interactions whose main purposes are not to inform a preference or an interest. Implicit feedback interactions range from global actions, such as the amount of time spent watching a video, to detailed actions (e.g. buttons pressed on remote control) [20, 23]. Though at the first place, these actions were envisioned by the system developers to perform a functional task, they may also infer how interested the user is in a content. In explicit feedback, in contrast, users evaluate the relevance and utility of a video, which is generally done by rating it.

According to [25], the simplest and most straightforward approach to elicit users' interest on a certain item is by actively asking them. However, explicit requests for feedback may also be annoying to and inefficient, since user's perceptions regarding the options presented may be quite subjective and divergent. For example, what does it really mean to give 4 out of 5 in star rating? More demanding users might have a very different judgment from less demanding users. In addition, users may be not interested in giving their opinions as it usually breaks their normal experience [25]. In addition, as providing explicit feedbacks usually distracts users from the TV and video viewing experience, requesting them should be as discreet and simple as possible [23, 25].

User feedbacks collected by recommender systems are intrinsically related to contents (or items) and the graphic interface. Some of the most common interfaces used for requesting explicit feedbacks are [25]: (i) scale ratings, where the user evaluates an item based on a scale, from the least to the most interesting/relevant; and (ii) up-down voting, where only two values are used to indicate the user's opinion.

As using explicit ratings is not enough to generate reliable recommendations [26], considering implicit interaction data is crucial to generate recommendations more accurately. However, for many applications it may be very challenging to relate or even quantify these interactions with respect to user preferences, specially to infer negative preferences. For example, considering the example of recommending online texts, what would it mean to spend only half of the average reading time on an electronic article? Several additional components would have to be analysed (e.g. average user read time, subject and word quantity of the article). Additionally, it is worth noticing that often the collection of implicit data is done asynchronously. Thus, in case of momentary network breakdowns, the precision of the implicit feedback may be affected.

Netflix is one of the most popular TV and video streaming services, with almost 100 million subscribers worldwide. In this service, both explicit and implicit feedbacks are used to compose user profiles [19]. Implicit feedbacks include information about partially or completely viewed content and content searching; while explicit feedbacks mainly include user voting data, which used to be implemented in a 5-star rating approach (see Fig. 2). Recently, however, this approach has changed to a thumbs up-down voting system in order to avoid subjectivities of scale ratings as well as to create a simpler approach to viewers [28].


**Fig. 2.** Netflix Daredevil details screen [28].

Considering that user interaction data is just a fraction of the viewing experience, Youtube recommender system [20] also uses both data retrieved implicitly and explicitly from users as input for its recommender system. Explicit data include favoriting, sharing or liking (thumbs up-down voting) a video, and subscribing to a channel; while implicit data is extracted from users' watching time and interacting with videos history (e.g. viewer started to watch a video, viewer watched a large portion of the video, viewer saved a video to a playlist).

## 3 Methods

The present study aims to enhance the +TV4E platform by providing an individual approach to the suggested informative videos. Particularly, the present study was part of the conceptual phase of the +TV4E recommender system development [28] and aimed to find adequate answers for the following research questions:

[RQ1] What implicit and explicit data gathered from interactions performed within the +TV4E iTV application could represent seniors' preferences on informative videos?

[RQ2] What associated weights each of these interactions should have to provide more accurate content suggestions to seniors?

The process of identifying and weighting interactive actions seniors may perform within +TV4E iTV application was a spiral and evolutionary process, where the outputs of a given phase served as input for the subsequent step to evolve, improve and validate the interaction scheme proposed by this study.

The initial part of this research consisted in an exploratory approach, a literature review to gather information about commonly used implicit and explicit feedbacks in TV and video services. Table 1 lists feedbacks used by recommender systems of TV and video contents. It is worth noting that, though many scientific studies clearly define the interactions used as input for their respective recommender system, no metrics or weights are associated to any of them.

**Table 1.** Feedbacks commonly used by recommender systems of TV and video.

| Implicit | Explicit |
|---|---|
| Amount of watching time [16, 20, 21, 23, 24] | 5-star rating scale [16, 20, 22] |
| Favorited contents [16, 21] | Up-down voting [16, 21] |
| Subscribed content channel [21] | Questionnaires [22] |
| Search history [20, 23] | Content tagging [22] |
| Remote control general key logging [24] | |

Considering the interactions listed on Table 1, a draft interaction scheme was designed. To enable a less annoying experience for seniors as consumers of +TV4E informative videos, this scheme counted with two feedback approaches only: an up-down voting request to explicitly get seniors' opinions presented by the end of the video exhibition only and the implicitly collected amount of watched time. Thus, data would be collected according to five possible interaction scenarios and their respective weights (Fig. 3): Video not started (weight 0); Exhibition interrupted before 50% of video time (weight −1); Exhibition interrupted between 50% and 100% of video time (weight +1); Exhibition completed and user voted up (like) (weight +2); and Exhibition completed and user voted down (dislike) (weight −2). In this scheme integer values would be used to weight the interaction scenarios (see Fig. 3), which is a simpler and easily implemented solution.

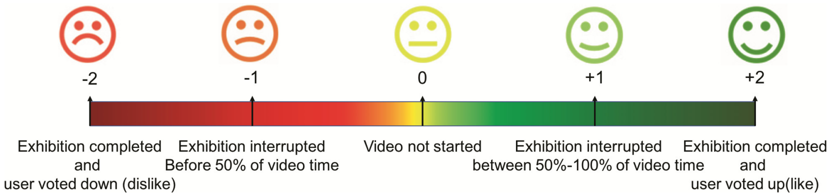


**Fig. 3.** First interaction scheme.

An evolution of this scheme would consist of a more elaborate and complex approach to calculate the implicit score associated to the viewing experience. Instead of using integer values in a small set of possible scenarios only, and moving from a negative value to a positive value abruptly at 50% of video watched, it would be assigned a proportional weight per percentage of the video watched (see Fig. 4).

Figure 4 shows how this interaction scheme works, with fractional weight values ranging from −1 to 1. If the user interrupts the video exhibition before a given time, a negative value will be assigned to that viewing experience, otherwise a positive value would be assigned. Additionally, in the same way as the first scheme an up-down voting explicit request could be used to collect users' opinions, which would assign maximum and minimum values to the viewing experience: +2 (up) and −2 (down).

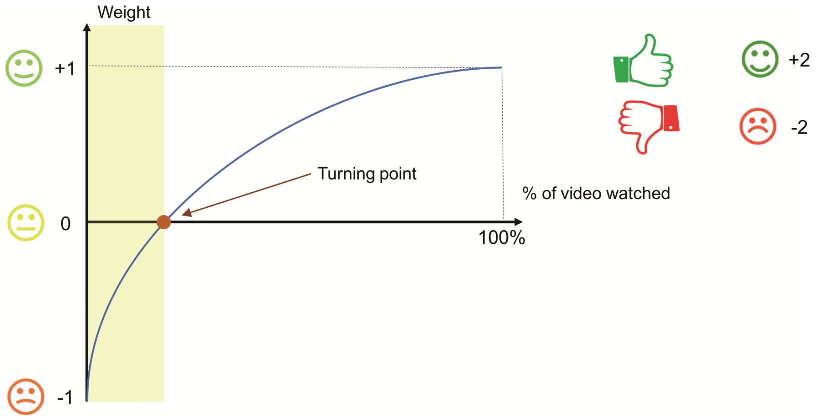


**Fig. 4.** Second interaction scheme.

In order to assess preferences of seniors, it was set out a participatory and iterative design process. Firstly, a minor set of users which had took part in the preliminary tests of the +TV4E platform were called to an exploratory interview. Afterwards, a larger group of seniors was recruited to provide their opinions on the implicit and explicit feedbacks selected to build up the platform profile.

**Phase I – Exploratory interviews with seniors**

The first step in the participatory process with seniors consisted of validating the interaction schemes with a random set of users which took part in the +TV4E platform preliminary tests. So, before implementing any high-fidelity prototype, three seniors who had used this platform during its preliminary tests were selected to provide their opinions on the explicit and implicit feedbacks used to assess their preferences on video contents.

The approach selected to this phase included a semi-structured interview guide (see questions in Table 2) to be applied at the participants' homes. This approach enabled higher levels of flexibility in the interviewing process and created a more casual environment in the interviews [32]. All interviews were conducted in September 2017, and participants were one male and two females, aged over 59 years. Questions addressed in the interviews are stated in Table 2 and were defined considering the context of +TV4E platform.

Answers from all three interviews were mostly similar. On Question 1, seniors stated that the remote control should have a special button to tell their impressions on the videos. Regarding questions 2 and 3, all of them agreed that interrupting a given video could be used as an indicative of lack of interest, and the amount of watched time would be proportional to the interest. Thus, the more compelling is the video content, the more they would watch it, having the initial part of the video a larger role in determining the video viewing experience, like in the second interaction scheme (see Fig. 4). Question 4, which aimed at assessing the explicit feedbacks, had divergent answers. One interviewee felt more comfortable with the five-star rating approach, since this concept, which also has been used in hotel ratings, would be more familiar. On the other hand,

**Table 2.** Exploratory questions on explicit and implicit feedbacks.

| | |
|---|---|
| 1 | Suppose that a given video content was not of your interest, how do you imagine this preference could be notified to the platform? |
| 2 | If you interrupt the video exhibition, should this interaction be considered as an indicative of a lack of interest on the respective content? |
| 3 | Considering that the initial part of the video may contain an overview of the informative content, should interrupting the video exhibition during this overview be considered as an indicative of even less interest on the respective content? |
| 4 | How about the system explicitly request your opinion after the video exhibition? How many options seems to be appropriate? Two options (I like it/I do not like it)? Or a five star rating scale? |
| 5 | How often should the system request your opinion? |

the other two interviewees said that having two or three different options (e.g. I like it, I do not like, I don't like or dislike it) would be more adequate and easier to use. Finally, on question 5 all interviewees said that explicit requests should be optional, and the system should ask their opinion a few times a day only, otherwise it would be very disturbing.

Findings from these exploratory interviews helped to confirm some assumptions as well as introduced some new perceptions on video consumption with +TV4E platform usage. Except for the requests of special buttons on the remote control to explicitly rate video contents, no new implicit or explicit feedbacks were identified. Finally, considering the conflicting answers given to Question 4 it was decided to implement two different rating screen prototypes to support the next phase of this study.

**Phase II – Tests with high-fidelity prototypes of explicit rating screens**

The second and final step of this study consisted of implementing and testing high-fidelity prototypes of explicit rating screens with collaboration of a broader set of potential users. This phase aimed to gather more substantial insights on the explicit and implicit feedbacks to be implemented by the +TV4E platform. The prototypes consisted of two different types of explicit inputs: 5-star rating (see Fig. 5a) and up-down voting (see Fig. 5b).

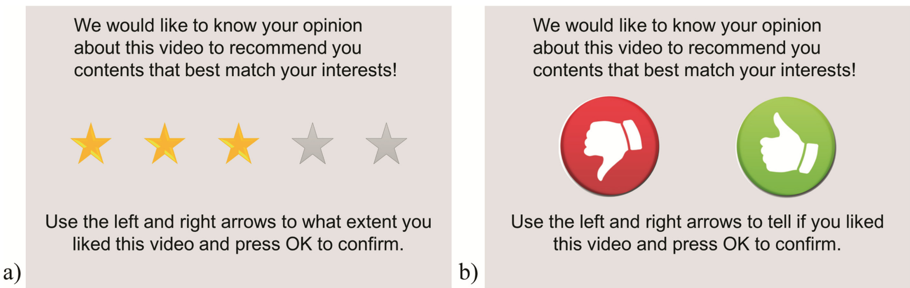


**Fig. 5.** High-fidelity prototype of rating screens: (a) 5-star rating and (b) up-down voting.

Participants recruited to this phase were selected by convenience among seniors enrolled in an adult day care centre of Aveiro, Portugal. The tests were conducted in September, 2017, and for the sample selection, the inclusion criteria were ageing over 64 years old, watching television regularly and being able to read. The group of interviewees (n = 11) included seven females (63.6%) and four males (36.4%), aged over 69 years. All invited participants demonstrated their willingness to help and collaborate.

Unlike in the first phase of exploratory interviews, data collected in this phase was not gathered at participants' homes, but in a controlled environment set up, at the adult day care centre (Fig. 6). Nevertheless, it was attempted to create a relaxed environment, making clear that it was not intended to assess participants' technical skills, but the utility and relevance of the +TV4E platform itself. In addition, in order to keep participants motivated and tuned to the tests, whenever possible conversations about the participant's daily life was held, such as TV shows they watch and hobbies. According to [29], this is an important strategy to be followed due to a recurring "reluctance of older people in talking about technologies".

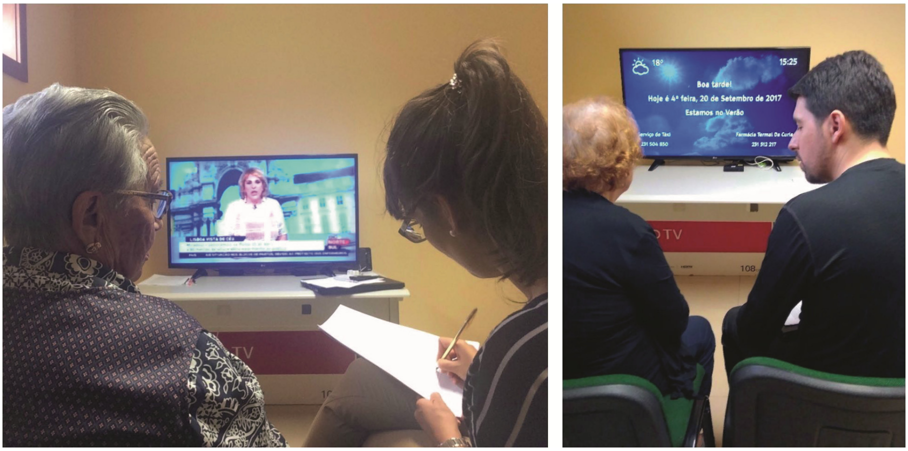


**Fig. 6.** Tests in controlled environment, at the adult day care centre.

As none of the participants had any previous contact with the +TV4E platform, it was adopted a cognitive walkthrough [30] approach to make them comfortable with the platform purposes and usage in a short time. By using this technique, participants were asked to perform a sequence of common TV and video consumption tasks, such as watching linear TV and +TV4E informative videos, changing channels, and so on. After getting minimally used to the platform usage, the same exploratory questions defined for the Phase I (see Table 2) were addressed, and along with the Question 4, both explicit rating screens (see Fig. 5) were presented. Due to time and resource constraints, the rating screens were not fully integrated into the +TV4E platform, but were accessible through a special key on the remote only.

During the tests, it was clear that being supported by a high-fidelity prototype is crucial to provide interviewees with a more solid and tangible idea of the research aims.

In addition, using the same semi-structured interview guide in both participatory design phases ensured that the same kind of information would be collected, and thus, helped to build more comparable results.

Like in Phase I, answers were mostly similar. On Questions 1 and 2, all participants said they would interrupt the video exhibition somehow if the content was not interesting at any time (e.g. turn off the TV, change channel, stop video exhibition). On Question 3, all participants said that the amount of video watched could be considered as an indicative of interest, with the initial part having a greater weight. There was no unanimity on Question 4 again, the large majority of participants (81.9%) considered that the up-down voting screen was more usable. In addition, the concept of like/dislike hands was easier to understand and, sometimes, considered more joyful by the participants. Regarding Question 5, six participants (54.5%) agreed to give their opinions after every video exhibition, while others (45.5%) said it would be very annoying and recommended to request for their opinions a few times a day only.

Findings from this phase helped to find the most suitable explicit rating screen to elicit seniors' preferences on informative videos. Using a simpler and less obtrusive approach, such as a like/dislike rating screen, should be more adequate, though such screen should be shown occasionally only.

## 4 Discussion

Identifying proper data driving content suggestions plays an essential role in the development process of any recommender system, and independently from the prediction or filtering technique strategy implemented, the system must learn users' interests by collecting feedbacks in order to provide more personalized recommendations [31].

Recommender systems of TV and video contents often rely on implicit feedbacks to build up user profiles, which deal with incremental updates on user's viewing history. Though implicit feedbacks may be noisier than explicit feedbacks, they are so ubiquitous that using them effectively can lead to more accurate suggestions [20]. This implicit nature of profiling enables a less disturbing experience, but also represents a challenge for system developers, as implicit data is less obvious to identify and to interpret. If a user has watched a video for only a couple of seconds, probably it's a negative sign, but what if the user has watched half the video? To what extent this experience was more positive than the previous one? It seems rather inefficient and arbitrary to require a minimum amount of video to achieve a positive score.

It is essential to consider the context of the +TV4E platform to define an adequate interaction scheme to assess seniors' preferences on informative videos and to build a proper user profile. Videos generated by this platform usually have a news structure style (i.e. the initial part of the video carries a content overview, *aka* lead[1]). The user interest in each content would be proportional to the amount of watched time (i.e. weights grow over time), having the initial part a greater weight in the score attributed

[1] https://en.wikipedia.org/wiki/News_style.

to the viewing experience (see Fig. 4). Thus, as the user watches a given video the initially negative weight gradually turns into a positive value after the lead is presented[2].

Findings from interviews and tests contributed to choose the second interaction scheme (see Fig. 4), being the lead time of the informative video the turning point in the positive-negative scale of viewing experience. The turning point value should range between 10 and 20% of the video. Adopting a continuous heuristic seems to be a less disruptive and more precise alternative than the first interaction scheme (see Fig. 3), which uses integer values only and an arbitrary value of 50% of minimum watching time to assign a positive value to the viewing experience. In addition, using non-integers weight values should be more effective and appropriate, though it clearly has a more complex implementation.

If making correlations between implicit feedbacks and user interests may be a rather labour-intensive and error-prone task, using explicit feedbacks, on the other hand, is a straight-forward strategy and often tells more about the user experience [15]. However, considering the +TV4E platform and its end-users, graphical interfaces should be as simple and less demanding for user inputs as possible, and thus explicit feedback requests would be preferably implemented should as a simple up-down voting, which could be optional for users to answer, and it should be presented with a countdown after the video presentation. In this way, it is expected to diminish the potential impact in the overall TV and informative video viewing experience. Explicit requests could be implemented as an advanced feature also, accessible at any time of the video presentation and available until few seconds after the presentation is finished, with a countdown. In addition, since only a visual notification of new video suggestion could go unnoticed by users (due to occasional hearing limitations of seniors), it would be advisable to use sound notifications in addition to the regular visual notification. Finally, though some seniors requested to use special buttons to tell their impressions on informative videos, assigning these buttons would possibly demand major changes in the platform as all remote-control keys are often reserved for specific system functionalities and designing a new remote would require extra costs.

## 5 Conclusions and Future Works

Challenges and opportunities of an ageing population, both at a personal and community level, are still drawing attention of public and private institutions [1, 33] due to the recurring info-exclusion [8], low literacy levels [9] and digital divide [10] among senior population. In this sense, technologies play an important role to promote higher levels of quality of life and independency by providing them with information about public and social services. In addition, to effectively provide more adequate and high-valued information, such technologies should be implemented considering personalization techniques.

This study is part of the conceptual phase of the +TV4E recommender system development [28], and in order to provide more accurate and personalized content suggestions, we set out a process to identify and weight feedbacks gathered from seniors

[2] An example of video generated by the platform is available at https://youtu.be/smZIA9oUad0.

interactions to elicit their interests on informative videos presented by the +TV4E platform. These implicit and explicit feedbacks composed an interaction scheme that will support the recommender system in optimizing video suggestions. For a more unobtrusive viewing experience, it was chosen to use the amount of watching time as implicit collected data and an up-down voting request as explicit feedback from seniors.

The main goal of any recommender systems is to provide users with contents in which they would be possibly interested. If defining *what* content should be suggested is essential, selecting *when* it would be presented may be indispensable, imperative for providing seniors with a compelling viewing experience, as good or bad timing may determine the openness of the users to receive the information provided. Therefore, further studies on defining the most relevant moment for content delivery are under discussion. Also, contextual aspects influencing content suggestion will also be addressed soon.

Finally, as the conceptual phase is concluded, future works involve the recommender system implementation and integration with the currently implemented +TV4E platform [15]. As expected, this work includes the proper implementation of the rating screens and implicit feedbacks also. Afterwards, the integrated system will be validated in a series of field tests to evaluate the real accuracy of the recommender system.

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