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Review

Content and Other Resources Recommendations for Individuals with Intellectual Disability: A Review

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Abstract: In this review paper, we look into how a recommendation system can be adapted to and support people with intellectual disability (ID). We start by reviewing and comparing the main classes of techniques for general-purpose content recommendation. Then, centering on individuals with ID, we collect information on their special needs that may be relevant to or affected by content recommendation tasks. We review the few existing recommendation systems specifically designed or adapted to the needs of this population and finally, based on the reviewed literature sources, we catalog the traits that a future content recommendation system should have in order to respond well to the identified special needs. We hope this listing of desirable traits and future directions in our concluding sections will stimulate research towards opening the doors to the digital world for individuals with ID.

Keywords: digital content recommendation; intellectual disability; special needs; recommendation systems; collaborative filtering; content-based filtering; hybrid recommendation systems

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1. Introduction

The "paradox of choice" [1] states that despite the belief that being presented with multiple options makes it easier to choose one that makes us happy, having an abundance of options actually calls for more effort to make a decision, leaving us feeling unsatisfied with our choice. With the internet and modern web services flourishing during the last couple of decades, offering a surplus of information and digital content, the Web has evolved into a prime example of the paradox of choice. Indeed, browsing through all possibilities can be overwhelming, eventually leaving users with a feeling of not being satisfied with their choices. Recommendation systems aim to tackle this by delivering personalized recommendations of items to users according to their preferences.

There is a broad range of recommendation systems that suggest different resources. There are systems that help us find our favorite items to purchase (e.g., in e-commerce stores, suggesting products to customers), discover new friends on social networks (e.g., Facebook recommends pages to like and people to follow), or help shape our future life choices (e.g., Linkedin proposes suiting job openings). Focusing on digital content, a content recommendation system suggests media items to consume. Content recommendation is an inseparable part of our everyday lives, from video (e.g., on YouTube) and music recommendation (e.g., Spotify, iTunes, and Deezer) to suggestions for movies to watch (e.g., Netflix, Amazon Prime, HBO, Hulu, and Hotstar) and news to consume, which has become a feature of major web-search portals (e.g., Google News and Bing). The business models of these companies and their success revolves around the potency of their recommendations; an indicative example of this importance is that Netflix offered, back in 2009, a million dollars to anyone who could improve its system by 10% [2]. It should be noted that recommendation systems typically use some personal data for providing their recommendations, and for this reason, they must also obey certain legal and ethical rules, depending on the social population targeted.

Regardless of the type of the resources being recommended, navigating through all the information and finding the desired item without some kind of personalization is particularly difficult for people with intellectual disability (ID), who encounter several difficulties regarding their interaction with the environment in terms of daily needs, activities, and communications [3]. Using the Web and digital devices is a challenge for this population, and a digital divide has gradually formed between them and connected individuals with normal intellectual ability [4]. This necessitates taking special care towards people with ID: a content recommendation system must be adjusted to their special needs before it can be successfully used. It is important to bear in mind that in a recent systematic review [5], beneficial effects were evidenced by digital interventions (mainly personal computers or mobile devices but also touch screens or input devices) on trained skills in children and adolescents with ID.

In this paper, we look into the question of how a recommender system can be adapted regarding the aspects of user–system interaction, as well as the underlying mechanisms for generating recommendations, in order to alleviate specific difficulties and limitations that affect the everyday life of individuals with ID (e.g., learning difficulties, slow cognitive processing time, difficulty in understanding new information and abstract notions, and limitations in social inclusion and community participation) and ultimately make the use of a recommender system by this population easier and more meaningful. First, we review and compare the main classes of techniques for content recommendation, in Section 2. Then, we collect information from the literature on the special needs of individuals with ID in Section 3. In Section 4, considering content recommendation, as well as other resource recommendation systems specifically targeted to individuals with ID, we review their characteristics. This analysis enables us to conclude in Section 5 with a list of future directions in relation to the traits that a content recommendation system should have, in order to effectively address the special needs of this population.

A short description of the adopted methodology for detecting all the relevant studies reviewed in Section 4 is in order. First, we initiated a bibliographic search based on Google Scholar using various combinations of the keywords "intellectual disability" and "recommendation" or "recommender systems" as queries. This resulted in approximately 150 publications. Then, we discarded the studies that were: (1) duplicates, (2) not published in a peer-reviewed venue, (3) older than the year 2000, or (4) written in a non-English language. This procedure eliminated some works and left approximately 90 for a second assessment round. During this second round, we identified relevant studies judging by their title, abstract, and, where necessary, the entire document. We included all works that describe a recommender system (regardless of what resources are recommended) and at the same time aim to serve the resulting recommendations to people with ID, thus explicitly addressing the characteristics of this population that is the focus of the present review. We excluded works that only partially comply with the above inclusion criterion, i.e., (1) deal with recommendations for the general population, thus are not explicitly targeting people with ID, and (2) propose a digital system that is targeted to individuals with ID but are irrelevant to the task of recommendation. Additionally, we excluded works that target other populations with special needs, such as people with Attention-Deficit/Hyperactivity Disorder (ADHD), Post-Traumatic Stress Disorder (PTSD), or elderly people. The reason for this last exclusion criterion is that such conditions do not fall under the definition of ID, and the variety and complexity of the special needs of people with ID differ to some extent from those of elderly populations or people with PTSD or ADHD. Studies not focusing specifically on our target population are out of the scope of this review.

This led to a total of 13 articles that are included in our review (4 content recommendation systems for individuals with ID and 9 works regarding other resource recommendations for individuals with ID). We note that, although we put significant effort into identifying works that propose a recommendation scheme for individuals with ID, the possibility that some studies may have gone unnoticed remains open. The aforementioned process is illustrated in Figure 1. Finally, we followed a similar procedure for collecting the background information discussed in Sections 2 and 3, i.e., general information on recommendation techniques, intellectual disability and indicative initiatives, and research projects targeting individuals with ID.

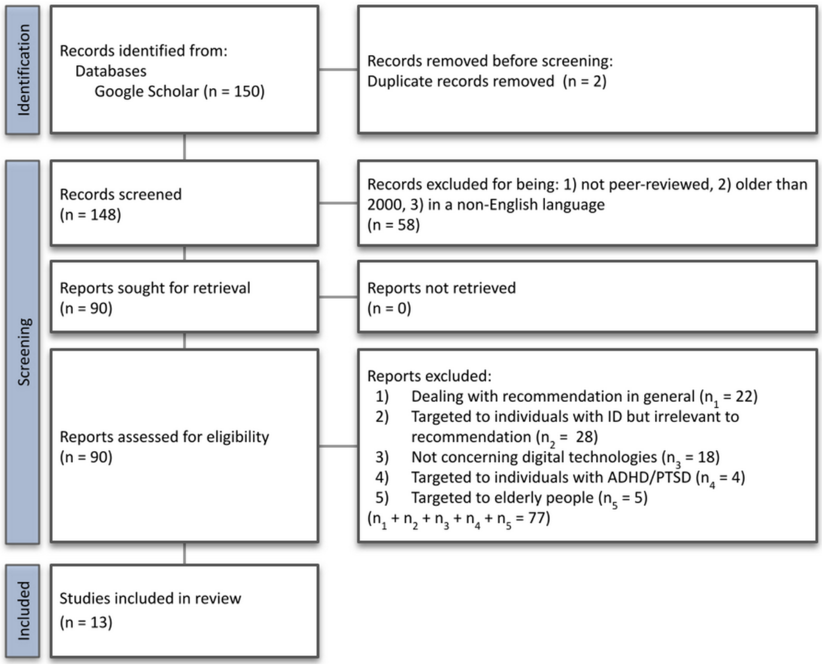

Figure 1. Our methodology for searching the literature for works that deal with recommendations to individuals with ID.

2. An Overview of Content Recommendation for the General Population

2.1. Content Recommendation System Categorization

Content recommendation techniques can be distinguished based on their knowledge source [6], with a common categorization [7,8] being based on the two main approaches of building a recommender system [9]: (1) collaborative filtering and (2) content-based filtering (see Figure 2).

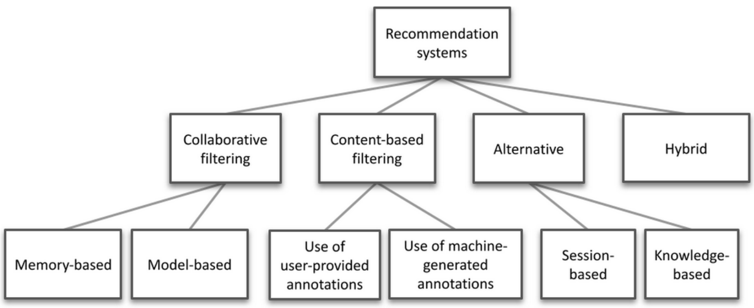

Figure 2. A taxonomy of recommendation systems.

2.1.1. Collaborative Filtering

Collaborative filtering computes the similarity of the users, or the similarity of content items, in both cases on the basis of user preferences. It is based on the assumption that people who agreed in the past will agree in the future [10]; therefore, they will like similar kinds of items as they liked in the past.

Collaborative filtering techniques are classified into two categories [11]: (1) memory-based and (2) model-based. Memory-based collaborative filtering recommendation estimates the rating of a target user for different items based on the ratings of a set of users who share a similar transactions history. Memory-based methods, e.g., [12], are simple since they use no user model at all; instead, they employ heuristic algorithms to calculate the similarity of users or items (typically using a simple distance measure). Model-based collaborative filtering approaches, on the other hand, build a model to predict a user's rating on items using machine learning or data mining methods [13]. The most popular approach for model-based collaborative filtering is Matrix Factorization, e.g., [14,15], which models each user and each item by vectors of learned features and computes a similarity score for inferring the preferences of users for items.

2.1.2. Content-Based Filtering

Content-based filtering analyzes the content of items and treats recommendation as a user-specific classification problem, aiming to learn a model of the user's preferences by means of a feature-based representation of the recommendable items [16]. In other words, these algorithms compute the similarity of the items—they do not require computing the preference similarity between users [17]—aiming to recommend items that are similar to those that a user liked in the past (or consumes at present), with various candidate items being compared with items already rated/consumed by the user and the best-matching items being finally recommended. For performing personalized recommendations, they need detailed user preferences stored in user profiles.

Since such a system compares items, the item's features that are employed are of great importance, and selecting such features that can successfully represent an item's content is challenging [18]. These features can be identified either (1) via readily-available metadata (e.g., tags) of the items (e.g., [19], or (2) via a—possibly semantic—analysis of the item's content (e.g., [20]). Equally important is how the user's preferences (i.e., the favorite items' features) are determined, with the approaches used being categorized in the following [17]: (1) users are given a list of features out of which they choose whatever they identify with the most (i.e., explicit information collection), and/or (2) the system keeps track of the items the user has chosen before and adds their features to the users' profile (i.e., implicit information collection).

2.1.3. Alternative Recommendation Systems

Session-based recommendation systems [21,22] use the interactions of a user within a session to generate recommendations. Most often they aim to predict user actions based on anonymous sessions, for example, when a user visits a video-sharing platform without having created a profile. Therefore, such systems are particularly useful when the history of the decisions made by a user is not available or not relevant in the current user session. A major advantage of session-based recommendation systems is their ability to rely on the sequence of recent interactions within a session without requiring any additional user details (historical, demographic).

Knowledge-based recommendation systems [23,24] are based on explicit knowledge related to the items, user preferences, and recommendation criteria [25], i.e., which item should be recommended in which context. These systems are applied in scenarios where pure collaborative filtering or content-based filtering approaches cannot be used, for example, in a recommendation system for purchasing real estate, since such transactions involve high-value items that each single user purchases very infrequently. A major advantage of knowledge-based recommendation systems is that the cold start problem (discussed in Section 2.2) is practically non-existent, since knowledge about a new item or a new user is readily available when the new user or item is inserted into the system. A notable weakness is that laborious knowledge acquisition is needed to define recommendation criteria in an explicit fashion.

2.1.4. Hybrid Systems

A hybrid recommendation system is one that combines different recommendation techniques in order to overcome some limitations and problems of pure collaborative filtering or content-based recommendation systems [26]. For example, an approach to combining collaborative and content-based filtering is using collaborative filtering as the primary method and resorting to content-based predictions when the neighborhood size of the active user is limited [27].

Additionally, recent breakthroughs in artificial intelligence (AI) and machine learning made possible the semantic analysis of various media modalities, improving the accuracy of content-based recommendations and alleviating the data sparsity and cold start problems [7] (see Section 2.2 for a discussion of these problems). Several deep learning techniques such as Convolutional Neural Networks (CNN) [28,29], recurrent neural networks [30,31], generative adversarial networks [32,33], variational auto-encoders [34], and denoising auto-encoders [35] have been used to build recommendation systems that perform well both on benchmark datasets and in real-world settings [14,36]. The results of a recent review [37] indicate that auto-encoders are the most widely exploited deep learning architecture for recommendation systems, followed by CNNs, while a more recent review [38] claims that recommender systems based on deep learning will become part of our daily lives and discusses the factors that will help in this direction. For further details on hybrid recommendation systems that are based on deep learning techniques, the interested reader is referred to the recent survey by [39].

2.2. Challenges

There are a number of challenges brought up in the literature [14,40–47] that content recommendation systems face. In this section, we collect the identified challenges and discuss each one; a summary of the advantages/disadvantages of collaborative filtering and content-based filtering approaches in relation to these challenges is also given in Table 1. We use this analysis of challenges as the basis for discussing recommender systems specifically for individuals with ID in the subsequent sections.

Table 1. A summary of the advantages and disadvantages of collaborative filtering and content-based filtering approaches.

	Advantages	**Disadvantages**
Collaborative filtering	- No need for item representation - Cross-media support - Good exploration capabilities - Easy implementation - Scalability with respect to number of items	- New user cold start problem - New item cold start problem - Data sparsity - Needs “long shelf life” items - Need for popular items - Gray sheep problem
Content-based filtering	- No new item cold start problem - Independence from users - Adaptability - Increased privacy - No data sparsity concerns - Scalability with respect to number of users - Explainability	- Need for item representation - Poor cross-media performance - Poor exploration - Overspecialization - New user cold start problem

Cold Start. The cold start problem in recommendation systems refers to the situation where there is insufficient information about users or items for producing any effective recommendations [17]. There are three specific cases where this problem appears:

- New community: Refers to the start-up of the recommendation system, when a collection of items exists yet no (or not enough) information about users and their interaction makes it very hard to provide reliable recommendations [48].
- New item: A new item is added to the system; this may be accompanied by metadata, but the lack of previous interactions between users and this item leads to the system not being able to provide recommendations for it [49].
- New user: A new user is introduced to the recommendation system; since this user has not completed any interactions yet, it is not possible for the system to provide a personalized recommendation to this user [14].

Typical recommendation strategies (i.e., pure content-based filtering and collaborative filtering) are susceptible to the cold start problem due to lack of information [42]; therefore, most methods that deal with the cold start problems aim at discovering sources of existing information, e.g., a prevalent strategy to address the user cold start problem is to rely on metadata related to the new users. For the interested reader, a thorough discussion on the matter can be found in the survey by [42].

Information Collection. A profile of the user's interests is needed by most recommendation systems, whether this is used to compare users (in collaborative systems) or compare user and item data (in content-based filtering systems). The information elicitation techniques for assembling such profiles are divided into two main categories [7,42]: (1) explicit and (2) implicit. A straightforward approach relies on the saying "One of the best ways to know something about someone is to ask them" [42,50]. In order to build a user model, we can ask the user to rate a selection of items [51] or to fill up a questionnaire. A significant challenge in this approach is that users are often reluctant to participate in a query process [52]; thus, the explicit collection of information is essentially a trade-off between time and effort from users and the richness of the recommendations that they will be provided [53].

Implicit information collection solutions seek to understand new users' preferences via minimum interaction, exploiting alternative sources such as user history (e.g., visited pages and users' search queries) or social media (e.g., usage patterns on social platforms such as Facebook or Twitter, which are promising sources of information for a person [42]). Implicit information collection techniques require the least interaction of the user with the system, however, they raise privacy concerns.

Privacy. The more information a system possesses about a user, the more accurate recommendations it can provide to that user [54]; however, collecting rich personal information also raises the risk of unwanted exposure of that information [55], and this is why often the personalization ability of recommendation systems and their privacy are treated as somewhat conflicting requirements [43]. With an increased volume of information stored by a system often comes an increased concern on the part of the user regarding what information is collected and how it is used [56,57]. In a centralized collaborative filtering architecture, a single repository stores all user ratings; therefore, if the central server becomes compromised, then the users' anonymity is at risk. Many methods have been developed to alleviate privacy concerns, e.g., [46] proposes a system that, although it collects the data of a user, the storage and building of the user profile is performed exclusively on the client side, with a similar technique being employed on personalized advertisement systems in [58]. Other methods propose using encryption techniques, such as locality-sensitive hashing [59] or using de-centralized repositories with the help of blockchain techniques [60].

Trust. Recommendation systems may break trust when malicious users give ratings that do not correspond to their true preferences [61]. One or more users can "attack" an item: in [62], it was shown that users could artificially raise and lower ratings. Similarly, a company can bombard a recommendation system with inflated ratings of its own products ("shilling" attacks [47]), e.g., fake reviews [63]). Moreover, malicious users can bias the recommendations that are provided to other users [64]. The issue of fragile trust remains a significant vulnerability to collaborative filtering systems [65], with a common counteracting method being to weigh a user's rating based on certain trust metrics [17].

Data Sparsity. When most of the users choose not to give ratings or reviews to the items they consume, the rating model becomes inadequate due to data sparsity. Specifically, in the absence of sufficient data, the possibility of discovering users with similar interests becomes very low [66,67]. Data sparsity particularly affects collaborative filtering systems [68]: when the system cannot identify groups of similar users, it can only recommend to a user items scoring highly against this same user's profile; thus, the items being recommended are similar to those already consumed by this user [17].

Exploration–Exploitation Dilemma. The exploration–exploitation dilemma indicates how the system has to choose between recommending an item that allows it to learn more (explore) about the user or an item that keeps the user interested (exploit). Finding the delicate balance between exploration (i.e., recommending new/"fresh" or "unexpected" [69] items) and exploitation (i.e., proposing well-established items) is a great challenge [70] and a common trade-off in recommendation systems [41]. In a system that has a very dynamic corpus of items, i.e., a very large or rapidly changing set of items, the recommendation approach should be responsive enough to model newly uploaded content and occasionally make more "exotic" recommendations [28].

Cross-Media Recommendation. In today's Web, where items are available for consumption in many modalities, it is imperative to be able to analyze a certain type of item and draw general conclusions that are also applicable to recommending a variety of different media types [71]. When a system is restricted to recommending content of the same type as the user is already using, the usefulness of its recommendations is decreased [17]. For example, recommending news articles while browsing a news website is useful, but it would be much more useful if music, videos, products, or discussions from different services could also be recommended based on the specific news a user is browsing. Similarly, active users in a movie domain are likely to also be interested in recommendations of books and music related to the movies they like [7].

3. Intellectual Disability and Its Impact

3.1. Intellectual Disability Definition

Three major institutes have dealt with defining the characteristics, severity levels, and criteria for ID: the American Psychiatric Association (APA), the American Association on Intellectual and Developmental Disabilities (AAIDD), and the World Health Organization (WHO). Specifically, the APA published, in 2013, the Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition [72] (DSM-5), a taxonomic and diagnostic tool. The WHO published, in 2018, the eleventh revision of the International Classification of Diseases, ICD-11 [73], while the AAID proposed major changes for specific revision [74].

The definition of ID has changed throughout the years. Historical definitions of ID were based on observing an Intelligence Quotient (IQ) score below 70, with the average IQ of the population being 100, and the majority of people scoring between 85 and 115. However, this simple rule is no longer sufficient for a diagnosis. According to the DSM-5, the definition of intellectual disability is "neuro-developmental disorders that begin in childhood and are characterized by intellectual difficulties as well as difficulties in conceptual, social, and practical areas of living", which is in line with the definition of ICD-11—they differ in the specificity of defining the condition (https://www.flatworldsolutions.com/healthcare/articles/icd-vs-dsm-key-differences-and-similarities.php (accessed on 15 September 2022)). Individuals with ID present significant difficulties in adaptive behaviors and daily living skills such as self-care, communication, and community participation [75]. Limitations in adaptive skills are likely to include effects on social and communicative functions [76]. In summary, the criteria for an individual to be diagnosed with ID, especially noticeable in children, include (https://www.adcet.edu.au/inclusive-teaching/specific-disabilities/intellectual-disability (accessed on 15 September 2022)):

- Difficulty understanding new information.
- Difficulties with communication and social skills.
- Slow cognitive processing time.
- Mild or severe learning difficulties.
- Difficulty in the sequential processing of information.
- Difficulties comprehending abstract concepts such as money, time, and the subtleties of interpersonal interactions.

ID severity is categorized as mild, moderate, severe or profound based on the level of support needed [77–79]. However, as it is often difficult to assess the severity of ID solely by employing standardized testing, a proper diagnosis should be made by also considering clinical findings and judgment [80]. According to the DSM-5 classification system [72], the different levels of ID severity are determined based on adaptive function rather than IQ, since adaptive function is the one that specifies the required support grade.

The more severe the disability, the more probable the co-occurrence of associated sensory impairments, which further undermine individuals' ability to engage and learn [81]. While most individuals have mild ID, 6 per 1000 individuals have severe ID [80]. Persons with ID, particularly those who have moderate or severe intellectual impairment, need professional care and support in their everyday lives [75], and the kind of support they require further depends on: (1) their cognitive ability, (2) expectations of them within particular environments, and (3) whether they have other associated developmental disabilities such as cerebral palsy, autism or sensory impairments [82]. The different categories of ID severity, along with the level of support needed that typically characterizes each one [3,77,78], are:

- Mild (periodic support)—can live independently with minimum levels of support and have a good level of self-sufficiency (with some limitations in their psychosocial function), provided that the individual has the help and support of family and appropriate infrastructure and services.
- Moderate (limited support)—independent living may be achieved with moderate levels of support, for example, the support offered in group homes. The individuals are able to perform some tasks and actions related to taking care of themselves, with appropriate supervision and encouragement. They usually acquire some social skills, through a specific childhood education scheme, and are able to operate successfully in a supervised community.
- Severe (extended support)—this disorder is usually due to some neurological damage and requires daily assistance with self-care activities and safety supervision. The individuals need systematic training and structured protection in order to be able to develop some basic self-care and communication skills and operate in a basic and risk-free manner.
- Profound (ongoing support)—requires 24 h care, as these individuals cannot support themselves, while the limitations in their daily functionality and their cognitive function become immediately perceptible and the possibility of education is low.

As far as healthcare services for people with ID are concerned, they have undergone significant changes in recent decades, moving from institutional to community care models. These changes become apparent with the transition from a medical disability model to a social disability model, which emphasizes changing negative or discriminatory behaviors, as well as removing barriers from equal access to services, care, and support [83]. In the same direction, studies have demonstrated that the individuals attending day centers are characterized by greater autonomy of choice and self-determination in their daily activities compared with people living in institutions [84]. Additionally, according to community care models, disabled individuals can be supported by means of a variety of digital assistive platforms and technologies, which are accessible from anywhere, including their homes. Such systems can include personalized recommendation services, corresponding to their special needs and preferences.

3.2. Impact of Intellectual Disability in Everyday Life

Difficulty Expressing their Feelings. Individuals with ID have a profound difficulty with communication, especially verbal communication [85]. Children with ID, in particular, show specific difficulties in processing emotional expressions—a trait not shared by typically developing children [85]. Other research suggests that adults with ID also exhibit deficits in their ability to identify emotional states in themselves and others [86]. However, there are indications they may improve their ability to understand emotion when presented with additional contextual cues [85].

Special Needs in Education. In addition to their innate inability to follow a school program designed for the general population, children with special needs may face difficulties in such schools since they feel rejected by their peers [87]. A study in [88] confirms the link between "feeling of difficulty" and cognitive performance, highlighting the important role of meta-cognitive experiences in cognition. Furthermore, adolescents with ID have difficulty in anticipating the complexity of a task just after it has been explained to them, supporting again the view of meta-cognitive inefficiency [88]. Therefore, it is imperative to address their special needs in education [89]. Inclusive education is a strategy based on human rights and democratic principles that confronts all forms of discrimination [90]. The mainstay of treatment and management of ID developmental delay is the utilization of special education and early intervention programs [91].

Mental Health. People with ID are 3–5 times at higher risk of any psychiatric disorder compared with the general population at all ages [79]. Individuals with intellectual and developmental disabilities are at high risk of co-occurring mental health conditions, including major depressive disorder, bipolar disorder, anxiety disorders, psychotic illnesses, and impulse control disorders [92,93]. Additionally, mood disorders are frequently identified in them, although suicide is still quite rare [94]. Since mental health issues are common in people with ID, more attention needs to be paid to improving the recognition and the treatment of mental health problems that they suffer from [95]. Especially those with moderate to profound ID should also be evaluated for co-morbid medical and mental health conditions, since these are more prevalent in this population than in the healthy population [91].

ID also affects the inner circle of these individuals: results of a study conclusively found out that the mothers of children with ID were experiencing higher anxiety and depression than mothers with healthy children, with depression having a negative correlation with their quality of life [96]. The under-employment of mothers with children with ID may be another factor that contributes to their depression [97].

Victims of Crime. An individual with ID is likely to be unaware of many of the subtle cues that guide our everyday behavior and alert us to the possibility of criminal victimization [98]. They are reported frequently to fall for online forms of fraud, bullying, and harassment [99–101] as well as succumbing to sexual harassment [102].

3.3. How Digital Technologies Can Help Individuals with ID

Technological development itself emerges as one of the most important issues for people with ID, since they are not capable enough to use and take advantage of the products designed for individuals with developed intellectual ability. Several studies have investigated the access and use of digital technology by individuals with ID, as well as the influence of assistive and cognitive technologies on improving their active behavior, entertainment opportunities, and communication abilities [103]. Assistive technologies, including custom software solutions, devices, and equipment, used to maintain and/or enhance the functional capabilities of people with ID are increasingly being developed. Such solutions aim to help disabled users utilize adaptive and rehabilitative devices and improve their accessibility options to various technological products (Assistive Technology Software Solutions for all Adaptive Devices—https://www.chetu.com/healthcare/assistive-technology.php (accessed on 15 September 2022)) (7 Cool Assistive Technologies Driving Accessibility for Intellectual Disabilities—https://communitymainstreaming.org/assistive-technologies/ (accessed on 15 September 2022)). While research is active in the area of using technological devices by individuals with ID [4], and effort is being put into raising awareness in technological accessibility by promoting the use of standards, e.g., (https://digital-strategy.ec.europa.eu/en/library/commission-publishes-study-inclusive-web-accessibility-persons-cognitive-disabilities (accessed on 15 September 2022)), there is still a lot to be done to bridge the gap of the digital divide for people with ID [104].

The necessity of implementing flexible, adaptable, and personalized systems, which allow and assist such individuals in performing various activities using Information and Communication Technologies (ICT), has become apparent. Along this direction, the work of [105] emphasized describing and grouping key uses of Semantic Web tools towards more personalized and adaptive computerized systems, enabling people with disabilities to easily interact and communicate. The key concept beyond this study lies in the fact that information can be modeled in different domains related to people with various kinds of disability using ontologies and models, which can be adapted and/or reformulated depending on the case. The fundamental outcome is that it is possible to construct a meta-ontology, adopting different ontological models, that covers some or all disability areas and provides a functional framework for the management, integration, sharing, and reuse of such data on the Web.

There is a number of initiatives and research projects revolving around the use of digital technologies, but not involving recommendation techniques, that aim to help individuals with ID. We included these in our review since we can draw some inspiration from how they support the target population. Furthermore, we would like to highlight certain cases where the cited initiatives could benefit from recommendation techniques. Examples include:

- Inclusion international (https://inclusion-international.org/ (accessed on 15 September 2022)) is an international network of people with ID and their families. Inclusion is part of the Inclusive Futures initiative, a wider drive funded by United Kingdom Aid to create an equal world for people with disabilities in low- and middle-income countries, which is testing innovative ways to improve economic empowerment and inclusion for people with disabilities, enabling them to find employment and earn a living.
- DisabledBook (https://www.facebook.com/disabledbook/ (accessed on 15 September 2022)) is a Greek social networking platform targeted towards individuals with physical, as well as intellectual, disabilities, suggesting that the online world can change for the better the lives of such persons. Users of this platform can watch movies for free or listen to music from radio producers that are disabled. Additionally, DisabledBook offers the possibility to "like" specific content or other users. As a means of motivation to use the platform, if a user is actively social, i.e., collects many "likes" from other users, logs in to the platform every day, and has a lot of friends, then the platform recommends "secret" social events to him/her. Such a social networking platform could benefit from content recommendations, yet no effort has been taken in this direction.
- ELPIDA project (https://www.elpida-project.eu/index.php/en/ (accessed on 15 September 2022)) is an e-Learning Platform for Intellectual Disability Awareness. It is the outcome of efforts from six organizations from five European countries. The e-platform contains six interactive educational modules aiming at providing training, awareness raising, and/or attitude change in the areas of Human Rights, Communication, Stress Management, Transition to Adulthood, Sexual Health, and Aging. It claims to improve the quality of life of persons with ID by empowering family members, especially their parents, providing them with the necessary knowledge and skills on how to better support the needs of children of all ages with ID.
- ENABLE project (https://arfie.info/2017/12/08/enable-project/ (accessed on 15 September 2022)) proposes an inclusive training/learning platform regarding co-designing, co-delivering, and co-evaluating services for people with ID, along with their families, professionals in ID, and local community representatives.
- The MAS platform [106] is a software system that aims to assist and reinforce the learning capabilities of people with ID, as well as other health issues such as visual and hearing impairments and coordination and movement difficulties. The system offers various features including adaptive games and data processing and monitoring tools. These were installed in an education institution for people with special needs in Madrid, providing caregivers tools that are shown to improve students' education processes. The MAS platform, along with the educational platforms of the two aforementioned projects (i.e., ELPIDA and ENABLE), lack the implementation of content recommendation techniques, which could significantly improve the learning procedure.
- Stomp [107] is a three-year program supported by the National Health Service (NHS) of England that resulted in an interactive platform for people with ID, offering tangible user interfaces, such as the Stomp drum kit and piano keyboard and many games,

which makes use of a floor mat that acts as both input and output. Stomp is designed to provide and encourage new participatory experiences in order to support social and physical interaction.
- Healthy Mind [108] is a website that was developed in order to serve adults with ID and explore the accessibility and interaction of disabled users and their caregivers.

In the **educational** domain, school-age children with ID need special education, including being involved in group activities, which can also be achieved using modern technology tools. The study in [109] claims that developing life skills in children with ID is important, and proposes KIDEA: an innovative application using a Kinect sensor, whose main objective is providing multimedia content for learning fundamental life skills, as well as increasing autonomy and independence. Other multimedia systems (games, educational applications for mobile devices or in a Web-based format) also exist for supporting children with disabilities to overcome their difficulties and develop essential life skills. Including multiple stimuli, such as touch, audio, and body movements, increases the child's attention to the educational applications; therefore, the use of mobiles and tablets with such multimedia systems for educational purposes, particularly in children, is encouraged in [110]. Parents and teachers are optimistic regarding the use of mobile devices in the classroom and at home for educational purposes, but both declare a lack of knowledge on their part to help these children in finding the right content [111]. Various mobile devices (e.g., tablets, smartphones, computers, and music players) can be used successfully, for example, as self-operated prompting systems or for simulated instruction when the provision of specific instructions from the community or a caregiver is not possible [112]. The fundamental issue of profiling users with disabilities on e-learning platforms was discussed in [113], where a model for the generation of the profiles of users with disabilities is proposed, assisting e-learning platforms to capture and standardize information on users' accessibility needs and automatically adapt content and interfaces for each individual.

The **digital entertainment** domain (e.g., socializing platforms and video sharing platforms on the Web) can contribute to the goal of individuals with ID gaining a sense of belonging and improving their mood. In particular, the "flattening effect" of social media applications, i.e., "the blending and melding together of different social circles in the online environment" as explained in [114], may help individuals with ID to socially interact and promote their sense of well-being [101]. A recent study in [115] showed that the majority of formal caregivers attributed great benefits to smartphone usage for people with ID regarding easy internet access and operation as well as the available opportunities (e.g., communication via WhatsApp). On the other hand, they associate negative feelings towards Facebook and specific websites which are not accessible to people with ID, due to these websites using too much text, difficult language, complex website navigation, captchas [116], and advertisements. Ultimately, there is no consensus between caregivers of individuals with ID on the use of social media [117]. In general, it was found that the majority of individuals with ID use Facebook in the same ways as the general population does, that is at least once a day. However, as opposed to the general population, and especially the youth, it seems that the participants in the survey of [117] gave more than they received in their interactions with their Facebook friends: they mainly observed and liked pictures or video clips of their friends [118]. However, when individuals with ID's Facebook friends reacted using "active" functions (such as liking or replying to their posts), they gained a sense of social presence, which compensated for the lack of shared physical space. Another positive conclusion comes from [117], where it is observed that individuals with ID gained a sense of belonging also by joining Facebook Groups.

Apart from web platforms, [111] discusses the kind of activities people with ID do with their **mobile devices** by conducting an empirical study. The study focuses on the negative effects of the use of mobile devices, i.e., distraction, dependency, and isolation. Results demonstrate that mobile devices were mainly used by teenagers with ID for entertainment purposes, YouTube being the most popular application. The performance of users on the utilization of such devices varied widely, depending on their particular experience.

However, all of them had trouble with text and tiny touchable objects. Similarly, [119] studied how individuals with ID interact with the layout of the YouTube video sharing platform and demonstrated that they had a generally good experience with the interface. However, they could not make proper use of the search functionality, at least without any external help [119]. On the other hand, [120] studied the efficiency of individuals with ID using e-mail when they are trained beforehand on how to access, receive, and send e-mails across different platforms and devices. The results indicate that individuals with ID are able to communicate effectively using a variety of technological devices, a conclusion also highlighted in [121]. Furthermore, as discussed in Section 3.2, mental health conditions such as depression have a high prevalence among people with ID [122]. In this context, it is interesting to mention MUBS, a smartphone-based recommender system for Behavioral Activation (BA) in mental health [123]. MUBS introduced a personalized content-based activity recommendation model using a unique list of 384 enjoyable (pleasant) activities. Each of these validated activities is designated with a default difficulty level and classified into one of the following six categories: work and education, daily living, practical, spare time, movement, and social. The content-based recommender model in MUBS is implemented by utilizing a multinomial Naive Bayes algorithm.

Having discussed, on the one hand, how digital technologies can help individuals with ID and, on the other hand, the necessity of implementing adaptable solutions of such systems, in the next section, we see how recommendation systems have been adapted to the needs of individuals with ID.

4. Recommendation for Individuals with ID

4.1. Education

In Section 3.2, we highlighted the special needs of individuals with ID in education. An effective approach for teaching students with ID is direct and systematic instruction [89], and digital technologies can greatly support this direction. In [124], it is argued that the learning processes can be improved through the use of information and communication technologies that include the use of multimedia. Videos, in specific, allow combining audio, text, and visual data for the explanation of a topic. A hybrid recommendation system (content-based in its basis, with knowledge-based characteristics) is proposed as a tool for the selection of the most interesting and useful multimedia, corresponding to the preferences and needs of children with ID and their caregivers (a.k.a therapists). More specifically, aiming at supporting the processes of teaching and the learning of language and communication, the proposed system automates multimedia content management, building on the potential of YouTube videos. The analysis of videos is carried out automatically by employing AI techniques, in order to improve the selection of videos related to language development therapeutic interventions. Particularly, the video's subtitles are analyzed for discovering videos with educational content, while when subtitles are not available, a library for audio-to-text conversion is utilized to avoid the risk of discarding content with educational value. A textual summary of the video is then constructed, and video classification is performed according to a text similarity index between user-submitted textual description and the text summary, also taking into consideration expert knowledge, specifically a categorization of the videos defined by an expert in the area of language. Consequently, this system allows people with disabilities to access educational video content easily, without needing to engage in a manual filtering process. It is worth highlighting that the method is deployed in a way that takes into consideration the wishes of both end user and therapists/caregivers, collecting information about their preferences in an explicit way. Furthermore, while it analyzes different types of multimedia (e.g., processes audio, converts speech to text, and introduces a scheme that can measure the similarity between videos and text), the system can only recommend videos.

In the direction of integrating students with mild disabilities into regular education classes, in [125], an adaptive case-based learning approach for regular and special education teachers was developed, specifically a specialized model of problem-based e-learning for identifying the most appropriate learning cases for mathematics teaching. The proposed approach is addressed to students with mild disabilities, taking into consideration the weaknesses, strengths, types of disabilities of the students, and teachers' characteristics, as well as the teaching content and context. Clustering and information retrieval techniques are used to construct a mapping between said features. A strong point of the employed clustering approach is that it can take into consideration different data types. Moreover, based on the method's design, it is likely that it can achieve a good balance in the exploration–exploitation dilemma by recommending intra-cluster items for exploitation purposes and items from similar clusters for promoting exploration. However, this aspect is not assessed in [125].

4.2. Entertainment

Digital entertainment can help people with ID (e.g., to promote a sense of belonging, as discussed in Section 3.3), however, this population is largely excluded from digital participation, since, more often than not, digital entertainment platforms are designed without taking into account the needs of such individuals. The work of [126] proposes the delivery of personalized multimedia content in interactive Internet Protocol (IP) television environments (IPTV—the delivery of television content over Internet Protocol networks), employing a hybrid recommendation scheme on programmable IP services, also supporting features for users with disabilities. Moreover, it proposes a system that takes advantage of information gathered through the users' interaction with the system, generates profiles that reflect groups of similar users, and consequently adapts the group profile to each user's preferences (using a technique they call "profile separation"). In this way, the time needed for matching user patterns and profiles when forming a recommendation is significantly reduced. Additionally, this technique helps combat data sparsity and cold start problems.

An interactive support system for individuals with ID is proposed in [3]. This under-development system covers multiple needs: from detecting/measuring specific medical bio-signals or location parameters using a network of wearable sensors and mobile devices to interacting with the internet for educational and entertainment purposes by offering, among others, content recommendation functionalities through a content-based filtering scheme, while being able to recommend a variety of multimedia types. Ultimately, the whole integrated system makes it easier for users to cope with a multitude of everyday issues.

In [127], the design of an interactive system for users with severe ID is proposed. This paper identifies the challenges and characteristics of providing effective methods for visual browsing through a session-based video recommendation system while focusing on the utilization of non-verbal communication of autistic/ID individuals with the system. The reported case study is accompanied by a discussion on personalization, ethical, and flexibility considerations of the design, presenting an iterative application design concept that can continuously log and understand the browsing patterns of a participant (i.e., implicit collection information, as discussed in Section 2.2) on a video platform. It concludes that pre-defined queries, verbal instructions, and standardized environments that seem unappealing to a user with developed intellectual ability are better-suited for participants with ID.

4.3. Employment

A multitude of complicated issues concern individuals with ID and their employment, e.g., job coaching and support [128], employer attitudes and the culture of the workplace [129], and self-determination [130]. It is documented that individuals with ID have difficulty in following complex directions [131]. However, research has shown that assistance in increasing their job skills [128] can eventually render them capable of holding paid jobs [132]. Therefore, systems that prompt, offer guidelines, and recommend subsequent tasks, in the context of paid work, can help the integration of individuals with ID into the workforce, yielding a sense of participation and contribution to society. In this direction, [131] proposes N-CAPS, a cognitive assistive system that provides verbal and visual prompts to a worker with ID during the monitoring of a specific assembly task. The results reported in [131] show that the individuals with ID that participated in the study completed most of the proposed steps without assistance from the job coach, indicating that such a system can assist individuals with ID in their jobs. An ontology-based recommendation system, namely JRD, is proposed in [133]. This system consists of knowledge-based and recommendation modules and aims at presenting appropriate jobs to disabled individuals. For this purpose, it investigates the existence of assistive technologies for specific application domains associated with certain disabilities, resulting in the recommendation of available suitable jobs. It also discusses how they built a questionnaire form in a Java application for the employed explicit information collection scheme. Furthermore, a recommendation system is proposed in [134] focusing on Disability Employment Services (DES); it aims to recommend the right skill to be upgraded and its optimal level needed for disabled job seekers, in order to enhance their employment potential. A two-stage causality-based method is presented, according to which factors for employment are initially recognized from user information, and then personalized recommendations are automatically provided via an interpretable model, built adopting a counterfactual reasoning (https://en.wikipedia.org/wiki/Counterfactual_thinking (accessed on 15 September 2022)) framework. It is worth underlining that [134] not only recommends suiting jobs to users, but goes one step further (compared with [133]), proposing the necessary skills to develop for a specific job.

4.4. Outdoor/Indoor Mobility

Systems that deal with transportation and traveling for tourism have been designed with the general population in mind. Individuals with ID may face difficulties using such systems. In [135], the utility of a system called Smart Travel Concierge System (STCS) is examined based on the assumption that people with ID often rely on friends and family to get where they want and need to go. This system can contribute to pre-trip assessment and planning activities to support people with ID to transit more independently, even using fixed-route public transportation. It is a hybrid recommender, borrowing features from knowledge-based systems (i.e., having stored information about the products) and collaborative filtering (i.e., constructing and comparing user profiles). An interesting feature of the system is a "cognitively accessible" approach in designing the user interface, which results in using multimedia for the questions asked during the explicit information gathering stage. In [136], Vulcanus 2.0 is proposed, which is a recommendation system for accessibility, where "resources" are the items that the system recommends to the user and a "trail" represents the path that each user follows throughout the day, maintaining a chronological history of the usage of such resources. The resources may be generic, providing conveniences to all disabilities (e.g., a parking space), or specific, supporting only some types of disability (e.g., an access ramp). It collects the needed information about users employing mostly implicit information collection. Specifically, it takes advantage of information extracted from the user's history, thus achieving its goal of transparent operation. However, such a design approach can raise privacy issues in a real-life setting. It follows a hybrid approach, using information from the other users to make better recommendations (a collaborative filtering notion), while also utilizing information about the items (a content-based filtering feature). SOLVE-D [137] is a context-sensitive service recommendation framework for disabled people in smart home environments. For example, when a certain disabled user physically approaches a specific home appliance, such as a laundry machine, the system recommends a standard process to operate it. The aforementioned paper does not delve into details regarding their "User Identification Module", but a figure depicts this module built in a home server with no access to the Web, a feature which makes privacy and security inherent in the system design. The end result is a complete system to support users with ID in making good use of a smart home setting.

4.5. Online Shopping

In the online shopping domain, there are recommender systems adapted to people with ID, as well as specialized products targeted to those individuals. SMART-ASD [138] is a recommendation system that aims to assist people with autism and ID, as well as their relatives and caregivers in the selection of technology products, such as devices, related accessories, and applications, which are tailored to their special needs or can be effectively used by disabled individuals. SMART-ASD is based on an ontology where the users and the information regarding the products are stored. It introduces the notion of a "supporting user" as a supervisor of the recommender system. In the case of individuals with ID, this "supporting user" can be their teacher, parent or caregiver. It compares the information it collects from the user and the supporting user to filter out the recommendations, which is an interesting concept, balancing on a fine line between privacy and support/trust of the recommendations. Similarly, [139] describes the initial results of a recommendation system, which attempts to match technology products to individuals with intellectual or developmental disabilities. During the implementation of the prototype, a group of experts (teachers, doctors, speech and language pathologists, and other professionals) was enlisted to gather information to use in their knowledge-based system. This system is based on the use of machine learning methods and exploits a large volume of data concerning (1) the people with disabilities, (2) the corresponding technology products, and (3) the outcomes these individuals aim to achieve with technology. It employs a deep neural network specifically for matching products to users.

4.6. Summary of Recommendation Methods for Individuals with ID

In Table 2, we present a summary of the literature works discussed in Section 4. The works are listed in the order they appear in the text, with each row containing information about a single work. We make the following observations:

- Recommendation systems have been shown to be able to assist individuals with ID in a variety of ways, and in different domains, from entertainment to finding a job.
- The number of literature works on content recommendation specifically for individuals with ID indicates that very limited research has been performed on this subject.
- Taking a closer look at the fourth column, we observe that very few methods follow a pure collaborative filtering or content-based filtering approach; instead, most works follow alternative schemes such as session-based or knowledge-based recommendation or combine different types of approaches, as discussed in Section 2.
- Explicit information collection is adopted by the works in the jobs and education recommendation domain (for example the bottom four rows), since this is the only way to acquire such precise and sensitive personal data.
- Only one of the reviewed methods reported on specific provisions in the system's design for protecting the privacy of users.
- Cold start may remain a significant challenge, yet most of the reviewed methods exploit prior knowledge (e.g., knowledge-based systems, as discussed in Section 2.1.3, or an explicitly filled initial user profile) in order to avoid taking additional measures to deal with this challenge. Consequently, this is, most probably, the reason why most methods employ a knowledge-based recommendation scheme.
- Most of the existing content recommendation works for this specific population (the first three rows) lack the ability of multimodal recommendations.
- Most works deal with individuals with mild ID, while only one method (in the third row) addresses individuals with severe ID. This makes sense, since, as discussed in Section 3, severe and profound ID require extended and ongoing support, respectively, even for everyday self-care tasks.

Table 2. A summary of works in the literature that discuss recommendation for individuals with ID.

Literature Work	Application Domain	Recommendable Items Type	Recommender System Type	Information Collection	Specific Provisions for Privacy and Trust	Specific Provisions for Combating the Cold Start Problem	Users Target Group
[124]	Education	Videos	Hybrid	Explicit	None	Exploitation of prior knowledge	Children with ID
[125]	Education	Educational material	Knowledge-based	Explicit	None	Not needed	Students with mild ID
[126]	Entertainment	Videos	Collaborative filtering	Implicit and Explicit	None	Introduction of a "profile separation" technique	Disabled individuals or individuals with mild ID
[127]	Entertainment	Videos	Session-based	Implicit	Case study considering privacy aspects in personalization	None	Individuals with severe ID
[3]	Entertainment	Videos, images and text	Content-based	Implicit and Explicit	None	A first profile is constructed through an interview	Individuals with mild to severe ID
[131]	Employment	Job instructions	Knowledge-based	Explicit	None	Not needed	Workers with cognitive disabilities
[133]	Employment	Jobs	Knowledge-based	Explicit	None	Not needed	Disabled individuals and individuals with mild ID
[134]	Employment	Jobs and job skills	Knowledge-based	Explicit	None	Not needed	Disabled individuals and individuals with mild ID
[135]	Outdoor mobility	Trip arrangements	Session-based	Explicit	None	Not needed	Individuals with mild ID
[136]	Outdoor mobility	Accessibility resources	Hybrid	Implicit and Explicit	None	Explicit initial user profile	Disabled individuals, elderly and individuals with mild ID
[137]	Indoor mobility	Smart home functionalities	Knowledge-based	Explicit	Private home server with no access to the Web	Not needed	Disabled individuals and individuals with mild ID
[138]	Online shopping	Technology products	Knowledge-based	Explicit	None	Not needed	Autism Spectrum Disorder
[139]	Online shopping	Technology products	Knowledge-based	Explicit	None	None	Individuals with intellectual and developmental disabilities

5. Discussion

Having summarized in Section 3 the characteristics of ID and its impact on the everyday lives of individuals, in this section, we aim at connecting the challenges that people with ID face with the desirable traits of a future content recommendation system specifically designed for this population. To this end, we also rely on the review of the relevant literature presented in Sections 2 and 4. The specific desirable characteristics of such a content recommendation system are summarized in Figure 3; below, we elaborate on each of them.

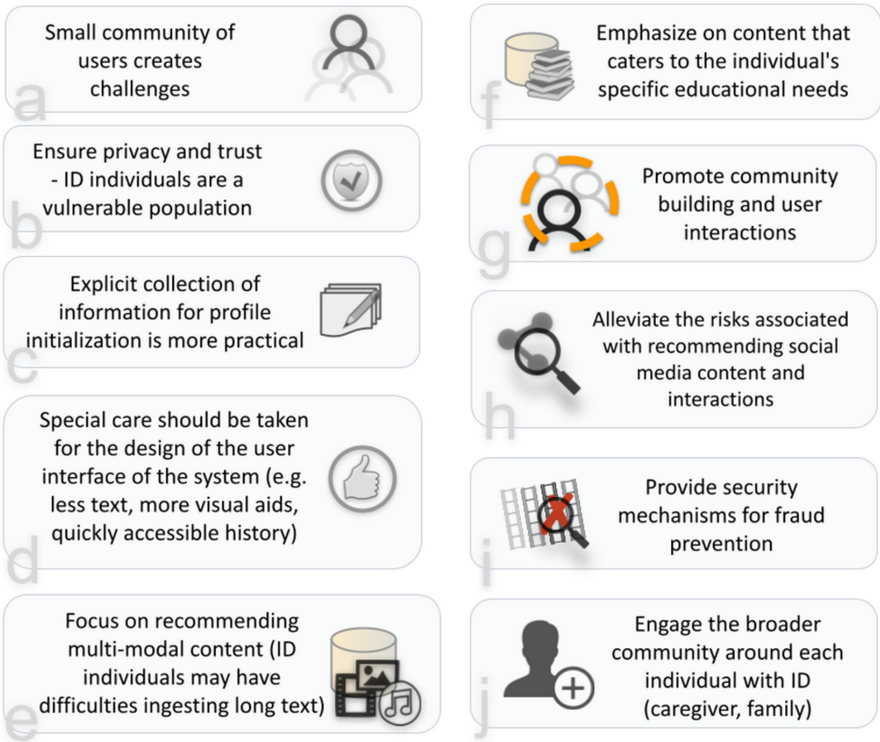

Figure 3. Infographic of the specific features that a content recommendation system targeted to individuals with ID must pay attention to.

- A recommendation system targeted to individuals with ID will most likely concern a relatively small community of people (Figure 3a. This favors the adoption of a content-based recommendation approach as its basis, instead of a collaborative filtering one, as can be ascertained from Table 1 (i.e., due to the relevant advantages of content-based recommendation, such as the independence from users and the absence of data sparsity concerns). This could be combined with introducing in the system prior knowledge about the specific characteristics of users with ID, drawing inspiration from knowledge-based recommendation systems.
- Privacy and trust, as discussed in Section 2.2, are of great importance; this applies to any recommendation system but even more so to systems used by a vulnerable population. Special attention should be paid to the exchange of information in a secure way, protecting personal data (Figure 3b). Minimizing the risk of exposing sensitive user profile data must be a priority, and this further advocates for the adoption of a content-based recommendation approach at the core of the recommendation system, due to the inherently increased privacy of such an approach, as can be ascertained by Table 1.
- The new user cold start problem, typical of content-based recommendation approaches, can be alleviated by employing interview-based techniques for the explicit collection of initial user information (Figure 3c), e.g., a questionnaire where the user (or the user's caregiver) rates a selection of items so that his/her preferences can be inferred. However, for updating these preferences over time, implicit information collection techniques (see Section 2.2) should be employed to collect data from the user's actions and interactions with the recommendation system. The reason for the latter design choice is twofold: explicit information acquisition from the user requires effort for a person with ID, particularly when their caregiver is not around, and such users

are really happy while freely using their mobile devices, as discussed in Section 3.3. Thus, implicit information collection can effortlessly provide a wealth of information for updating the users' profiles.

- Individuals with ID have difficulty in understanding abstract notions and cannot use complex systems, since the "feeling of difficulty" is a common characteristic in such populations [88]. Additionally, as discussed in Section 3, the verbal skills of individuals with ID are often poor. Therefore, a recommendation system targeted to them should include less text and more examples, e.g., visual aids complying with European standards for accessibility (https://en.wikipedia.org/wiki/EN_301_549 (accessed on 15 September 2022)) to guide them through every step that must be completed when using the system with a simple interface (Figure 3d), including cross-media recommendations (Figure 3e). As documented in [127], and also discussed in Section 4, pre-defined queries, verbal instructions, and a standardized environment fail to attract users with a developed intellectual ability but will suit users with ID; thus, the design principles of a system targeted to persons with ID are significantly different to what has evolved throughout the years and is now common for the general population.
- As discussed in [75,91], the mainstay of treatment and management of ID developmental delay is the utilization of special education. Thus, the recommendation of content items to users with ID should take into account, to the extent possible, the content's educational potential in relation to the specific educational needs of each individual user (Figure 3f).
- Particularly, when it comes to content consumption patterns, people with ID have difficulty adapting to changes and often prefer watching a very specific set of similar videos. For example, in [127], the subject with ID watched a particular video in different languages over and over again, sometimes for hours. Therefore, the history of consumed items should not only be taken into consideration by the recommendation algorithm but also be easily accessible in the user interface of the system to facilitate re-consumption (Figure 3d).
- User interaction in the digital world is an opportunity for individuals with ID. As discussed in Section 3.3, when Facebook friends of people with ID actively reacted, for example, by liking or replying to posts, the latter individuals gained a sense of social presence. Additionally, people with ID gained a sense of belonging by joining Facebook Groups. Therefore, a content recommendation system for individuals with ID should highlight the similarities of a user to various user groups and open communication channels with other members of these groups in order to trigger the sense of belonging and social presence and promote interaction among its users (Figure 3g).
- In addition to being an opportunity, user interaction can also be a threat. When it comes to social media and similar means of interaction, the caregivers of individuals with ID regularly express concerns over the possibility of bullying incidents. Therefore, a content recommendation system that uses social media as sources for recommendable items, or enables the interaction between its users and/or users of other social media platforms, should ensure that its recommendations will not lead to taking part in an online conversation with other community members that engage in bullying, use profanity, racial slurs or foul language (Figure 3h).
- Individuals with ID can easily fall victim to online forms of fraud, as discussed in Section 3.2. Therefore, a recommendation system targeted to such individuals must provide security mechanisms for the prevention of fraud and the protection of its users, for example, by pre-filtering recommendations to exclude potentially harmful content items (Figure 3i). Moreover, it should empower the user's caregiver (e.g., a parent) to supervise potentially inappropriate recommendations or interactions via suitable user interfaces and notifications about potentially threatening content or situations.
- Going beyond the core problem of content recommendation, the major challenge that content recommendation aims to help address is the need of individuals with ID for improved quality of life. This calls for a more holistic approach: seeing content

recommendation as part of a complete framework that will consist of interactive systems, devices, and services for this community of users. In this direction, an integrated platform with multiple functionalities that include but are not limited to content recommendation, capable of adapting to the individual characteristics of the different ID severity levels of its users, seems to be ideal. Such a platform should support the provision of health, avocation, communication, training, information, and amusement services [3] (Figure 3e,f). All this should be implemented through an interface accessible from multiple devices, providing personalized suggestions according to the specialized users' interests and skills.

- Finally, also considering the broader community around individuals with ID is important. Depression in the family circle of individuals with ID is a common phenomenon [96]; for this, initiatives such as the Inclusion International (see Section 3.3) urge, for example, the family circle to be involved in the activities of children with ID. A recommendation system should aim to support family members too, by giving them not only a feeling of control over the consumed material or the ability to update the profile of the user but also the ability to propose new recommendations, which can be later consumed together and promote their interaction with the family's disabled member (Figure 3j).

6. Conclusions

Our key takeaway from reviewing the relevant literature is that approaches targeted to the general population do not match the needs of individuals with ID (from information acquisition to combating cold start problems, even on the design principles of the graphical user interface). The most prominent future directions for recommender systems for the general population concern scalability issues, i.e., using distributed and elastic platforms [140] (a direction that seems irrelevant when it comes to recommendation for individuals with ID, since such systems deal with a relatively small community, as identified in Section 2.2) and modeling the user using machine learning techniques [141]. Additionally, large corporations consider recommendation as a marketing opportunity, i.e., to gather more personal data in order to increase customer satisfaction and ultimately spending, whereas, when dealing with individuals with ID, the primary focus should include privacy-ensuring techniques (e.g., taking care of security vulnerabilities in decentralized environments) and how the social and ethical concerns associated with dealing with a vulnerable population can be safeguarded. When it comes to individuals with ID as a target group, a possible solution would be the introduction of the recommender system to a complete platform, such as the idea drafted in [3]. This platform would offer features that could alleviate the identified challenges, as discussed in Section 2.2. For example, (a) a network of multiple sensors (cameras and wearables) could combat the difficulty of individuals with ID to express their emotions, and (b) the introduction of the role of supervisor will aid the explicit initial profile construction, at the same time dealing with security, privacy, and ethical issues. However, at this point, there is a very limited number of research projects and literature works that aim to support individuals with ID, as reported in our review. We hope that, by cataloging the traits that a future content recommendation system should have in order to respond well to the special needs of individuals with ID, our review contributes to promoting recommendation schemes targeted specifically to this population. This work and future studies in this domain should ultimately result in validated recommendations for policymakers at the local and European level.

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