A Systematic Review of Interaction Design Strategies for Group Recommendation Systems

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Systems involving artificial intelligence (AI) are protagonists in many everyday activities. Moreover, designers are increasingly implementing these systems for groups of users in various social and cooperative domains. Unfortunately, research on personalized recommendation systems often reports negative experiences due to a lack of diversity, control, or transparency. Providing a meta-analysis of the interaction design strategies for group recommendation systems (GRS) offers designers and practitioners a departure to address these issues and imagine new interaction possibilities for this context. Therefore, we systematically reviewed the ACM, IEEE, and Scopus digital libraries to identify GRS interface designs, resulting in a final corpus of 142 academic papers. After a systematic coding process, we used descriptive statistics and thematic analysis to uncover the current state of the art regarding interaction design strategies for GRS in six areas: (1) application domains; (2) devices chosen to implement the systems; (3) prototype fidelity; (4) strategies for profile transparency, justification, control, and diversity; (5) strategies for group formation and final group consensus; and, (6) evaluation methods applied in user studies during the design process. Based on our findings, we present an exhaustive typology of interaction design strategies for GRS and a set of research opportunities to foster human-centered interfaces for personalized recommendations in cooperative and social computing contexts.

CCS Concepts: • **Human-centered computing → Collaborative and social computing**; **User centered design**.

Additional Key Words and Phrases: group recommendations, recommender systems, interaction design, algorithms, systematic review

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1 INTRODUCTION

Systems including various kinds of artificial intelligence (AI) steer many of our daily activities and decisions [212]. Among many different technologies, recommendation systems play a crucial role in allowing users to navigate efficiently the vast amount of options and information that is currently available [100]. Nevertheless, these systems are mostly known for their services and impact on individual users, often neglecting the possibility of picturing their services for groups of people.

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To fulfill this gap, designers and practitioners are increasingly implementing these systems in various cooperative and social computing domains [37, 107]. In this context, group recommendation systems (GRS) provide useful functionalities for groups of users, such as selecting the most appropriate music for a group of people inside the same room [36], deciding which movie to watch jointly with friends [159], selecting together with your colleagues the next restaurant to visit during lunchtime [149], or deciding which scenery route to take during the coming family road trip [6]. To achieve these goals, GRS often consider the individual preferences of each group member, their social and behavioral aspects, among other cues to calculate good algorithmic recommendations, despite the different levels of heterogeneity inside the group [103].

In contrast with their "individual" counterparts, the nature of GRS entails particular interaction design challenges, including how to collect the preferences of each of the group members, how to define a particular group of users to calculate their recommendations among many possible group members, how to achieve a final group consensus regarding the algorithmic recommendations, and others [61]. Additionally, previous research has also reported how personalized recommendation systems produce negative experiences for their users, such as invisibility, anxiety, and panic [18], biases in the personalization processes [21], lack of control and meaningful feedback [55], low algorithmic awareness [57], and an extensive list of ethical issues including unjustified actions, opacity, discrimination, and challenges for user autonomy [132].

Extensive academic work has provided mixed results for various areas of GRS, including techniques for achieving better recommendations, evaluation of their accuracy, application in various domains, preference elicitation, and explanation interfaces, compiled in surveys and reviews [37, 61]. Nevertheless, to the best of our knowledge, no exhaustive meta-analysis departs from a human-centered stance to determine the interaction design strategies for GRS, centering on the specific issues associated with these systems such as transparency, justifications, control, diversity, group formation, or achieving a final group consensus. We consider it urgent to provide such a systematic review, offering designers and practitioners a needed departure to address these issues and imagine new ways to interact with GRS.

Therefore, we decided to do a systematic meta-analysis of the current academic corpus related to this domain, following six main research questions: (1) What are current application domains selected to design human interfaces for GRS?; (2) What are devices chosen to implement human interfaces for GRS?; (3) What is the level of fidelity of the human interface prototypes designed for GRS?; (4) What are the interaction design strategies selected to achieve user and group profile transparency, recommendation justification, algorithmic control, and diversity or serendipity over the resulting recommendations for GRS?; (5) What are the interactive approaches applied to address group formation and achieve a final group consensus in GRS?; and, (6) What are evaluation methods applied with users to address the design of human interfaces for GRS?

To accomplish these goals, we systematically reviewed three leading computer science academic publication venues: ACM, IEEE, and Scopus digital libraries, identifying English work that contained at least an interface design description for a GRS. Our revision of these digital libraries produced an initial set of 5346 records, which followed a systematic selection process resulting in a final corpus of 142 academic outputs for our analysis. Following a systematic coding process for the resulting corpus, we used descriptive statistics and thematic analysis to identify current trends and gaps in academic research concerning our research questions.

Based on our findings, we propose an exhaustive typology containing 28 different interactive design strategies for GRS in six different areas: user and group profile transparency, recommendation justifications, control, diversity and serendipity, group formation, and final group consensus. Additionally, we extend an invitation to the HCI, CSCW, and related communities to investigate multiple research opportunities that we identified during our analysis, to foster and create novel interaction design strategies for personalized recommendation systems in collaborative, cooperative, and social computing contexts.

2 METHODOLOGY

This section describes all details regarding the methods we followed for our meta-analysis. We organized the methodology of our systematic review inspired by The Prisma Statement [111] for reporting systematic reviews and meta-analysis, making minor adjustments to adapt their guidelines to what is customary in HCI publications and to our research scope.

2.1 Eligibility Criteria

The academic scope of group recommender systems (GRS) is vast and diverse. Therefore, we decided to delimit our meta-analysis for a population of academic outputs that contained at least a clear *interface example or description of a human interface* designed to interact with a GRS.

Additionally, we intentionally avoided GRS designed to calculate *recommendations related to people* such as personal recommendations for team formation or study groups, employees, groups of people recommendations such as photo enthusiasts or clubs, and similar kinds of recommendations related to the suggestion of real people or profiles of people. We consider that these systems deserve a particular study case because of their relevance and ethical or social implications. Consequently, our systematic review centers only on products or service recommendations such as music, movies, products, events, points of interest, hotels, restaurants, and similar kinds of nonhuman-related recommendations.

Besides the previous guiding principles, we considered additional initial requirements to define the scope of our systematic review: (1) Incorporate all academic outputs *disregarding their publication year*; (2) Include *all kinds of academic outputs*, including journal papers and conference/workshop proceedings of varied nature such as regular papers, posters, demonstrators, and book chapters; (3) Accept *all kinds of methodological contributions*, including empirical studies, reviews or meta-analysis, theory-oriented papers, books, essays, and others; (4) Embrace *all kinds of interface modalities, platforms, methods of interaction, and fidelity* of the interface presented in the academic output; (5) Consider *academic outputs with and without user studies*; (6) Involve *all kinds of academic venues*; (7) Include *only academic outputs written in English.*

2.2 Information Sources

We delimited the information sources for our systematic review to the top three full-text academic databases that commonly include all sorts of contributions in areas related to HCI, interaction design, interface design, and similar Computer Science and technology topics: ACM Guide to Computing Literature, IEEE Xplore, and Elsevier Scopus digital libraries. These three databases provided relevant academic outputs to create a comprehensive revision of the current academic state of the art in interaction design for GRS. Moreover, in contrast with similar academic search engines such as Google Scholar and Web of Science, our selected digital libraries brought additional features beneficial to systematically manage our resulting search records, such as advanced search queries, file creation, formatting, and downloading their results.

2.3 Search Strategy

Departing from the previous information sources, we decided to delimit our search strategy with two main criteria. After various iterations of trying different sets of keywords in the selected online libraries, we decided to define a set of seven keywords (exact phrases) that describe GRS. Later, we decided to use advanced search functions to locate these seven keywords in the title, abstract, and author keywords of the academic outputs.

Table 1 describes in detail our search strategy, relating each of our information sources, search query syntax used in every digital library, sets of keywords, and their correspondent results. We performed all search queries in these three digital libraries between August 6th and 7th, 2020.

This search strategy produced 768 records in the ACM Guide to Computing Literature, 380 records in the IEEE Xplore, 4198 records in the Elsevier Scopus, for a total of 5346 found records. These academic outputs constituted an initial corpus of academic outputs and a departure point for our systematic review.

Table 1. Information Sources, Search Strategy, Selected Keywords and their Number of Records

Digital Library	Full Search Query Syntax	Keyword and its Results
ACM Guide to Computing Literature	`{"query": { Title:("KEYWORD") OR Abstract:("KEYWORD") OR Keyword:("KEYWORD") } "filter": { NOT VirtualContent: true }`	*Group recommender:* 118 *Group recommendation:* 204 *Group recommendations:* 125 *Collaborative recommendation:* 166 *Collaborative recommendations:* 38 *Collaboration recommender:* 0 *Collaborative recommender:* 117
IEEE Xplore	`((("Document Title":"KEYWORD") OR "Abstract":"KEYWORD") OR "Author Keywords":"KEYWORD")`	*Group recommender:* 45 *Group recommendation:* 103 *Group recommendations:* 33 *Collaborative recommendation:* 112 *Collaborative recommendations:* 15 *Collaboration recommender:* 2 *Collaborative recommender:* 70
Elsevier Scopus	`(TITLE("KEYWORD") OR ABS("KEYWORD") OR KEY("KEYWORD"))`	*Group recommender:* 308 *Group recommendation:* 1268 *Group recommendations:* 1268 *Collaborative recommendation:* 536 *Collaborative recommendations:* 536 *Collaboration recommender:* 4 *Collaborative recommender:* 278

2.4 Literature Selection

We followed eight steps to filter out repeated and irrelevant academic outputs from this preliminary corpus of 5346 records. Figure 1 describes the entire process we applied for our literature selection process until we reached a final corpus of 142 academic outputs. Additionally, Appendix B includes the Prisma flowchart describing our literature selection process.

2.4.1 Downloading Query Results. We first downloaded a text file containing each query result corresponding to each of our keywords. We recorded each file individually for further steps.

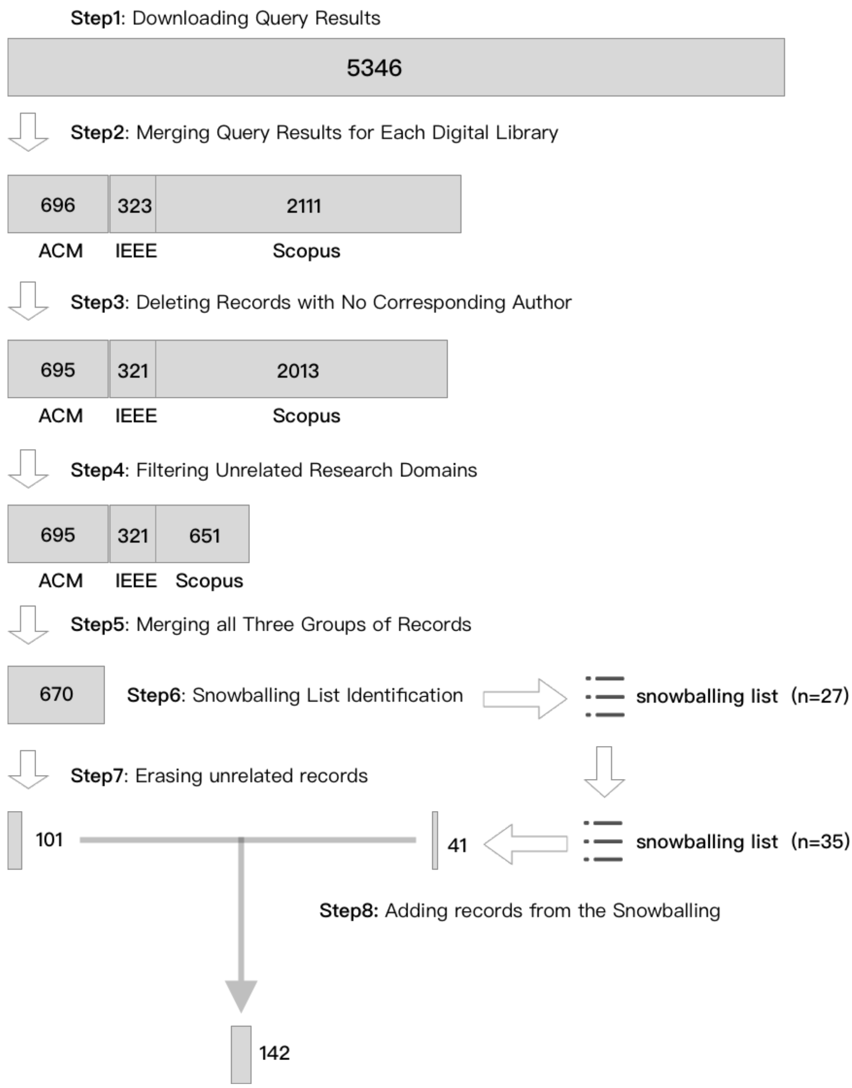


Fig. 1. We Collected 142 Academic Outputs Following our Literature Selection Process

2.4.2 Merging Query Results for Each Digital Library. We later merged each of the files corresponding to each of the selected digital libraries, deleting repeated records. This step produced 696 records for the ACM DL, 323 records for IEEE DL, and 2111 for Scopus.

2.4.3 Deleting Records with No Corresponding Author. Afterward, we noticed that some records had no corresponding author and proceeded to remove them from our corpus. These cases corresponded mainly to publishing venues such as the entire published proceedings booklet that contained our keywords but had no real author supporting them. This deletion produced 695 records for ACM DL, 321 for IEEE DL, and 2012 records for Scopus.

2.4.4 Filtering Unrelated Research Domains. We also noticed that many records from the Scopus digital library contained academic outputs that were not relevant for our purposes, such as psychological papers related to addiction and group intervention, papers dealing with group interactions in biology, chemistry, and similar topics outside the scope of Computer Science. Therefore, we checked the publishing venues and titles of the remaining records manually to remove those not related to Computer Science. This step produced 651 records for Scopus.

2.4.5 Merging all Three Groups of Records. We then merged all three files corresponding to each digital library. Since each digital library registers different metadata, we needed to check and remove repeated records again. We found these repetitions manually, looking for repeated titles, publication venues, and corresponding authors. When in doubt, we corroborated the possible repeated record using Google Scholar to determine if two records referred to the same academic output. This step produced a set of 697 records.

2.4.6 Snowballing. Following the PRISMA statement, we also included complementary records to our final corpus following the "identification of new studies via other methods" [148]. This method allows searching for additional publications by going through databases, registers, websites, organizations, reference lists, and others.

For our case, we looked for keywords in the remaining records of our final corpus to identify surveys, literature reviews, systematic reviews, talks, courses, conference tutorials, workshop descriptions, and similar academic outputs that did not offer any empirical input for our analysis because of their academic nature. We separated those records into a different list because they could contain pertinent references we can consider in our final corpus. Therefore, we removed these identified records from the remaining corpus and grouped them in a list we called "Snowballing List" (SL), producing a set of 670 records for our final corpus and 27 records for our SL.

2.4.7 Erasing unrelated records. Afterward, we manually checked our remaining corpus to identify and erase academic outputs that did not offer any description or example of a human interface. These records were primarily technical papers describing algorithms and accuracy improvements for GRS but did not contain any prototype or human interface description. Additionally, we erased other records related to the eligibility criteria we described in Section 2.1: (1) those academic outputs referring to "people" group recommendations, (2) those academic outputs not written in English, and (3) other academic outputs that we overlooked and we were supposed to discard in previous steps.

Since we found new academic outputs that did not offer any relevant input for our analysis but still contained relevant references, this step also added new entries to our SL created in the previous step, defining a final corpus of 101 records and an SL of 35 records. Appendix A presents the final SL used to add complementary references to our final corpus.

2.4.8 Adding records from the Snowballing. Finally, we checked for relevant references in the SL, identifying 41 new entries for our final corpus. This process resulted in a definitive corpus of 142 papers in total for our analysis.

2.5 Data Extraction Process, Risk of Bias Assessment, and Final Data Items

The previous literature selection process produced a final corpus of 142 papers in total. We decided to systematically extract data from this corpus, coding each academic output using a spreadsheet designed for this purpose.

In total, we applied four iterations to define a final version of our coding spreadsheet. In every iteration, the two first authors used the most recent version of the spreadsheet to code 20% ($\approx$28) of academic outputs randomly selected from the final corpus. After coding this portion of our final corpus, we used Cohen's kappa statistics for two coders to determine the resulting inter-coder reliability of that version of the spreadsheet [127, 128]. If the results did not reach an overall kappa value greater than 0.70, the spreadsheet was modified in its weakest variables (questions) to achieve a better result in the next iteration, restarting the entire process.

We used an online tool called ReCal2 Reliability for two coders to determine Cohen's kappa values for every variable in our spreadsheet during each iteration [68, 69]. Additionally, the two first authors organized this process and solved possible issues or disagreements during meetings.

After having a reliable coding spreadsheet, these two first authors continued coding the entire final corpus, dividing the final version of our spreadsheet into seven main categories containing the following variables:

2.5.1 Type of the Academic Output. This category included options to code whether the academic output was a journal paper or conference paper. It also considered an option to specify if the academic output did not fit in those two categories.

2.5.2 Application domain. We included this category to collect whether the paper described specific application domains such as accommodation services, points of interest, restaurants, watching content, music, or product recommendations. It also included if the authors of the academic output analyzed more than one application domain. Finally, this category presented an option to specify if the academic output did not fit any previous categories.

2.5.3 Type of Platform or Device. This category included variables in determining the kind of platform or device for which the designer implemented the prototype expressed in the academic output. It included options such as desktop, mobile, and TV. This category also presented a final option to specify if the academic output did not fit any previous categories.

2.5.4 Prototype Fidelity. We included this category to code the level of fidelity of the prototype presented in the academic output. This category included two options: high or low fidelity.

On the one hand, high-fidelity prototypes are often functional designs that have very similar interaction techniques and appearance as the intended final system [207]. They usually require programming or high technical knowledge for their implementation, often resulting in a more expensive, time consuming, and challenging design process.

On the other hand, low-fidelity prototypes are conceptual ideas or very preliminary design proposals, with no or minimal interactivity, designed often to show the generalities of a design or a system [207]. Consequently, they are often cheap, easy, and fast to produce and test in design contexts.

2.5.5 Interaction Strategies for Transparency, Control, and Diversity. This category considered the interaction features included in the prototype described in the academic output. Because of the relevance of this category, we followed similar variables to the ones evaluated in a previous survey about visualization strategies to reduce the black-box nature of individual recommender systems [79]. We also took inspiration from design frameworks to achieve a better algorithmic experience in social media [5] and movie recommendations [2].

Therefore, without claiming a definitive list of aspects to analyze the interaction with GRS, we analyzed in this category whether the prototype or human interface presented in the academic output considered design features to (1) represent the individual user profile, (2) describe the calculated group profile, (3) justify calculated recommendations, (4) control, adjust, or provide feedback about the calculated recommendations, and (5) consider diversity or serendipity of the recommendations.

In this group, we intended to divide the analysis of the transparency of GRS into three main aspects: representations for both the (1) individual or (2) group profiles, and (3) justifications to explain the calculated recommendations. We preferred here to use the term *justifications* rather than *explanations* since recommender systems can also offer "complementary information or explanations" about the recommended items not strictly related to the "justifications" for the personalized, algorithmic recommendations. For instance, a news recommender system can *explain* the financing scheme or news source of a particular recommended news item, without *justifying* why the system is considering that particular news item as a recommendation.

Additionally, it is worth noticing how we included feedback, adjustment, and control of the GRS inside the same variable. Even if research often distinguishes these terms, we considered including them in the same variable as they all offer a certain level of perceived control over the recommendation system.

Finally, we considered diversity as interactive features included in the interface to deliberately diversify the recommendations, reducing the chance to negatively narrow down the spectrum of possible recommendations, increasing user satisfaction [108]. Similarly, we used the concept of serendipity as interactive options meant to increase the chances of getting unforeseen or unexpected but still valuable recommendations [91]. Although they do have specific differences, we considered these two characteristics jointly in a single variable because of their interactive similarity in line with the goals of this review.

2.5.6 Group Interaction Approaches. We included this category that analyzed whether the prototype presented in the academic output offered features to address particular dynamics of groups and social contexts. Without claiming a definitive list of aspects to analyze these particularities of GRS, we considered two variables: (1) whether the system offered a feature to achieve group formation, and (2) if the system included a feature to achieve a final consensus about the recommendations among the group members. While we considered only these two aspects as particular interaction requirements for GRS, we do not claim these are the only ones.

2.5.7 Evaluation Methods. Our final category determined if: (1) the academic output presented at least a user study, (2) the paper included simulated or artificially created users in its methods, (3) if the paper presented more than one user study, and (4) if the user study included a method applied inside the lab or a method applied outside the lab. Additionally, for those papers that contained at least a user study, we included variables to uncover whether (5) the academic output reported methods such as survey or questionnaire, observation, any form of logging user activity, focus group, interview, and any form of performance study to determine accuracy or effectiveness of the algorithm. We also checked whether (6) the academic output reported more-than-one-session user studies, considered for us as a longitudinal methodology in which users were involved in the study over multiple days. Finally, we reviewed the (7) data analysis method of the academic outputs with user studies, including if the paper presented qualitative analysis, quantitative analysis with descriptive statistics, quantitative analysis with inferential statistics, or mixed methods including both qualitative and quantitative methods of analysis.

In this section, we intended to give a general overview of how researchers involve users in their design process. While a more comprehensive review of all evaluations methods is precious for the community, we believe this kind of exploration requires a dedicated systematic review, falling outside of the scope of our current meta-analysis. Nevertheless, we consider this an exciting research opportunity that researchers can address in subsequent studies, as described in Section 4.5.

2.6 Methods of Analysis

After achieving a final list of variables to analyze our final corpus, the same two authors performed the rest of the coding process in the final corpus. This coding process consisted of answering yes or no (a one or a zero) in every spreadsheet variable. We later analyzed these results using descriptive statistics and thematic analysis.

Descriptive statistics mainly consisted of counting occurrences for each variable in our spreadsheet. We calculated percentages for each of the variables in our spreadsheet about the final corpus of academic outputs or the analysis category.

Additionally, the categories "Interaction Strategies for Transparency, Control, and Diversity" and "Group Interaction Approaches" deserved a more qualitative approach to find current design tendencies in each domain. Therefore, the two first authors first coded each of the academic outputs manually as a yes (one) or no (zero) in these two categories to group those positives later and apply thematic analysis for each variable. All the authors applied thematic analysis for both categories following its six phases, recognizing its recursive nature, and going "...back and forth as needed throughout the phases" [22]. First, we separately read several times each academic output to get familiarized with its content. Second, each of us wrote initial open codes individually, relating them to specific expressions from each academic output. Third, we grouped these codes, gathering all relevant data searching for potential themes. Fourth, we met to review our unique themes and solved possible theme discrepancies to achieve a consensus. Fifth, we defined a final list of themes for each variable, named each theme, and refined their specifics and overall characteristics. Sixth, we reported in detail all analysis results in the following section.

3 SYSTEMATIC REVIEW RESULTS

3.1 The Academic Characteristics of Interaction Design for GRS

Our coding process categorized all the records of our final corpus based on three publication types: (1) conference academic outputs, including conference or workshop papers, demonstrators, and posters; (2) journal papers; and (3) book chapters. Among the 142 papers in our final corpus, we categorized 103 (73%) academic outputs as conference papers, 37 (26%) were journal papers, and only two (1%) as book chapters.

We also determined the most recurred publishing venues for conference and journal papers in our corpus. Table 2 presents in detail these findings, including details on conference papers separated into regular papers, workshops, posters, and demos.

We can notice how the top conferences for academic outputs containing at least a GRS interface are conferences such as RecSys, UMAP, IUI, and AVI. Most of these venues have a significant coincidence: they study the intersection between Human-computer Interaction (HCI) and Artificial Intelligence (AI) mainly with quantitative methodologies and behaviorist approaches.

Interestingly, while CSCW is the premier venue for research, designing, and using technologies affecting groups of people, including cooperative and social computing, we did not find any academic output in our final corpus corresponding to this venue. We consider there is an opportunity and a research gap here for CSCW researchers to address the design and exploration of GRS, considering complementary methods and approaches besides the quantitative or behaviorist methodologies. The following sections present more details on this particular gap.

3.2 The Application Domains Selected to Design Human Interfaces for GRS

Our coding process also produced a comprehensive list of application domains selected to design human interfaces for GRS. We present an overview of these results in Table 3.

Table 2. Most recurred Publication Venues for the Academic Outputs Contained in our Final Corpus

Publication Types	Venues	Total
Conference Papers (regular papers)	ACM IUI	6
	ACM UMAP	6
	ACM RecSys	5
	ACM AVI	4
Conference Papers (workshop papers)	RecSys workshops	8
	UMAP workshops	2
	Dagli Oggetti agli Agenti workshops (in English)	2
Conference Papers (poster and demos)	RecSys demos and posters	4
	UMAP demos and posters	3
	CHI Extended Abstracts	2
Journal Papers	User Modeling and User-Adapted Interaction	3
	Multimedia Tools and Applications	3
	Personal and Ubiquitous Computing	2
	Expert Systems With Applications	2
	Applied Artificial Intelligence	2

The Movie/TV/video recommendation domain seems to be the most popular application domain, making up 28% of our final corpus. Touristic routes or Point of Interest (POI) got the second place, making up 25%. The third most common domain is music group recommendations with 13%.

Overall, GRS for entertainment, leisure, restaurants, and events are the most widely researched. We consider the main reason for these results is that such activities are commonly conducted among groups of people, making them a preferred context to design human GRS interfaces.

Interestingly, we also discovered a small percentage of academic outputs (4%) designed to be domain-independent. For instance, the work of Stettinger et al. often focused on a group decision-making system called Choicla, which allows users to form groups and define specific tasks for diverse domains [64, 191–195]. Here lays a possible research gap: to further explore the design, uses, and implications of domain-independent GRS.

Even a smaller percentage of work (3.5%) supported more than one application domain but was not domain-independent. For instance, Christensen and Schiaffino [33] proposed a system for both movie and music recommendations. Similarly, Hussein et al. [90] showcased their system in both video and POI recommendation domains. Again, our systematic review shows another research gap: exploring the usefulness and impact of GRS for multiple application domains and how they behave in comparison with GRS implemented for single or dedicated application domains.

Additionally, we can notice there are still some application domains that could deserve further explorations, opening new research gaps for GRS. For example, application domains including house or car recommendations for all family members, book recommendations for reading clubs, and similar domains are examples that have not received much attention but can also provide exciting spaces for research or business opportunities.

Finally, although researchers have considered touristic route group recommendations quite frequently, we did not find any work on non-touristic group route recommendations. For instance,

Table 3. Application Domains Containing Human Interfaces for GRS

Application domain	Total	References
Movie/TV/video Recommendations	40	[15–17, 23, 24, 33, 34, 42, 47, 53, 66, 72, 74, 80, 87, 90, 102, 104, 105, 114, 147, 158–162, 164, 167, 172, 173, 185, 196, 204, 206, 208, 209, 213–215, 217]
Touristic Routes or Point of Interest (POI) Recommendations	36	[6–10, 13, 31, 32, 44, 45, 51, 52, 58, 82–86, 88, 101, 115, 122, 124, 126, 134, 141–145, 169, 174, 179, 181, 189, 202]
Music Recommendations	18	[14, 25, 27–30, 33, 36, 40, 121, 135, 136, 152, 154–157, 190]
Accommodation Recommendations (e.g. hotel, Airbnb, or places for staying)	11	[6, 35, 93–95, 116–118, 125, 150, 177]
Restaurants Recommendations	6	[56, 78, 90, 120, 149, 200]
Social Events (e.g. dining out, drinks, movie, etc.)	6	[49, 92, 163, 188, 210, 211]
Domain Independent Recommendations	6	[64, 191–195]
More than one application domain (not domain independent)	5	[33, 39, 59, 90, 109]
Engineering Requirements	4	[63, 65, 146, 178]
News Recommendations	4	[39, 41, 153, 166]
Websites, Social Media Content, Microblogs	4	[110, 112, 168, 184]
University/learning Context	3	[11, 109, 216]
Product Recommendations	2	[59, 71]
Artworks Sequence in Museums	2	[170, 171]
House Recommendations	1	[151]
Book Recommendations	1	[54]
Car Recommendations	1	[180]

given the increasing mobility and ride-sharing among commuters, this could be an exciting research direction to explore GRS in which commuters could collectively choose which is the best route to take every time they share a ride based on their interest, such as scenic views, gas or time saving, arriving order, and others.

3.3 The Devices Commonly Chosen to Implement Human Interfaces for GRS

As presented in Table 4, most academic outputs in our corpus (58%) designed their interfaces for desktop devices. In the second place, mobile devices represent up to 35% of the systems we found.

Table 4. Devices Commonly Used to Develop Human Interfaces for GRS

Devices	Total	References
Desktop	82	[6, 8–10, 13, 14, 17, 23–25, 27, 31–36, 42, 44, 45, 54, 58, 63–65, 71, 72, 80, 87, 90, 92–95, 102, 110, 112, 116–118, 121–124, 134, 135, 146, 147, 150, 152, 154–162, 166, 168, 169, 174, 178–181, 184, 188, 190–195, 202, 206, 208, 211, 215–217]
Mobile	49	[8, 10, 11, 15, 16, 28–30, 39, 41, 49, 51, 52, 56, 59, 66, 74, 78, 82–86, 88, 104, 105, 115, 120, 141–145, 149, 151, 153, 164, 167, 170–173, 189, 196, 209–211, 213, 214]
Multiple Devices	13	[8, 10, 39, 41, 84, 86, 90, 118, 120, 153, 211, 213, 214]
Touch Sensitive Public Display	8	[41, 83, 84, 86, 120, 123, 153, 213]
Tabletop	6	[123, 125, 126, 177, 213, 214]
Non-interactive Public Display	4	[39, 41, 109, 153]
TV	3	[114, 185, 204]
Home DLNA MediaProvider	2	[47, 53]
Remote Control Display	1	[185]

Interestingly, despite the movie recommendations domain being the most widely researched, most of the systems are not designed for a TV operating system: only 2% of the systems were explicitly designed for a TV operating system. Additionally, very few works had designed GRS for home gateways which act as a media server for in-home entertainment. We also found a unique paper that focused on recommending content for a display built into a remote-control [185]. Moreover, only one paper created a GRS using Augmented Reality (AR) [164]. Consequently, Smart TV apps, home gateways for in-home entertainment, displays on remote-controls, and AR offer novel opportunities to explore novel design guidelines for movie GRS.

A small percentage (9%) of the papers also proposed various versions of the system to support multiple devices. For instance, Herzog et al. designed their tourist trip recommender system for mobile phones and public displays, which consisted of a kiosk system equipped with a 55-inch multi-touch screen in portrait orientation [84]. This also opens an opportunity to study GRS: design strategies implemented in multiple and complementary devices.

Finally, we consider there is an opportunity for researchers to study further non-traditional devices. It is clear how desktop and mobile applications are the norm in GRS. For instance, it is interesting how academics have not yet considered tangible user interfaces (TUIs) to implement GRS.

TUIs provide tangible representations to digital information, allowing users to grasp and physically interact and manipulate data with their hands, body, or environmental cues [182]. For example, FlowBlocks is a tangible interface designed to enable children to manipulate abstract structures of dynamic processes, attending educative purposes [218]. With FlowBlocks, the authors allow users starting at preschool and until college to join several playful blocks to simulate concepts related to counting, probability, looping, and branching, learning about those concepts playfully and tangibly. Another example is reacTable, a tabletop physical interface intended as a musical instrument [99]. In this case, the authors offer an installation that offers different instruments, sound distortions, and similar controllers with different blocks on an interactive table, a useful approach for both casual users or expert musicians.

Moreover, previous scholars have pointed out advantages of TUIs over GUIs such as physical manipulation, spatial interaction, embodied facilitation, and expressive representation [89], among others [183]. In particular, embodied facilitation and expressive representation seem to have relevant implications for promoting more collaborative and social interactions [89]. Consequently, we believe TUIs offer a researcher opportunity that could enable a different experience with GRS.

3.4 The Level of Fidelity of Human Interfaces for GRS

As described in Table 5, most of our corpus presented high fidelity prototypes (93%), and only a few presented low fidelity or conceptual prototypes.

Table 5. Level of Fidelity of Human Interfaces for GRS

Fidelity	Total	References
High	132	[6, 8–11, 13–15, 17, 23–25, 27–30, 32–36, 39–42, 44, 45, 47, 49, 51–54, 56, 58, 59, 64–66, 71, 72, 74, 78, 80, 82–88, 90, 92–95, 102, 104, 105, 109, 110, 112, 114–118, 120–126, 134, 135, 141–147, 149–162, 164, 166, 168–174, 177–181, 184, 185, 188–196, 204, 206, 208–211, 213–216]
Low	10	[7, 16, 31, 63, 101, 163, 167, 200, 202, 217]

We can notice a strong tendency to develop high-fidelity GRS prototypes in our final academic corpus. These findings relate to the nature of the academic venues identified in Section 3.1 in which academics also tend to present their findings supported with high-fidelity prototypes.

Nevertheless, we also found some papers presenting low-fidelity prototypes. We consider this an opportunity that scholars could also explore to provide novel inputs to GRS research. While researchers usually implement high-fidelity prototypes to evaluate design solutions, we consider low-fidelity prototypes are still helpful to explore the design space of GRS. Researchers at CSCW and similar communities can consider this gap as an opportunity to move forward research on less technical approaches but more in-depth analysis of the social and broader implications of GRS.

3.5 The Interaction Design Strategies to Achieve Transparency, Justifications, Control, and Diversity in GRS

3.5.1 User and Group Profile Representations in GRS. Table 6 summarizes a list of strategies used to describe individual user and group profiles. These profile representations display what the GRS has calculated about its users to generate the recommendations.

In total, we found 29 academic outputs (20%) that describe a way of representing group profiles. Seventeen papers (12%) also represent individual user profiles corresponding to the group members.

We also defined a total of five different themes to describe individual and group profiles. Two of them were the most common in our final corpus: *feature-based rating* and *recommended item-based rating*.

First, a feature-based rating shows the ratings corresponding to features used to calculate the recommendations. In a GRS for movies, the representation would show ratings for features such

Table 6. User and Group Profile Representations in GRS

Strategy Used to Represent the Group Profile	Total	References
Ratings for features*	8	[93–95, 116–118, 121, 152]
Ratings for features	4	[63, 146, 163, 178]
Ratings for items*	4	[157, 193, 216, 217]
Ratings for items	4	[166, 191, 194, 195]
Critiques for features*	3	[65, 123, 202]
Critiques for features	1	[14]
Visualization of songs in a 2D space	2	[36, 190]
Multi-graph visualization of preference*	1	[87]
Sankey and pie visualizations of profile relations*	1	[208]
Keywords representing interest*	1	[112]

*Includes Individual Profile Representations

as movie genres, casts, actors, among others. For instance, in Figure 2 the system shows feature importance ratings of each group member [93].

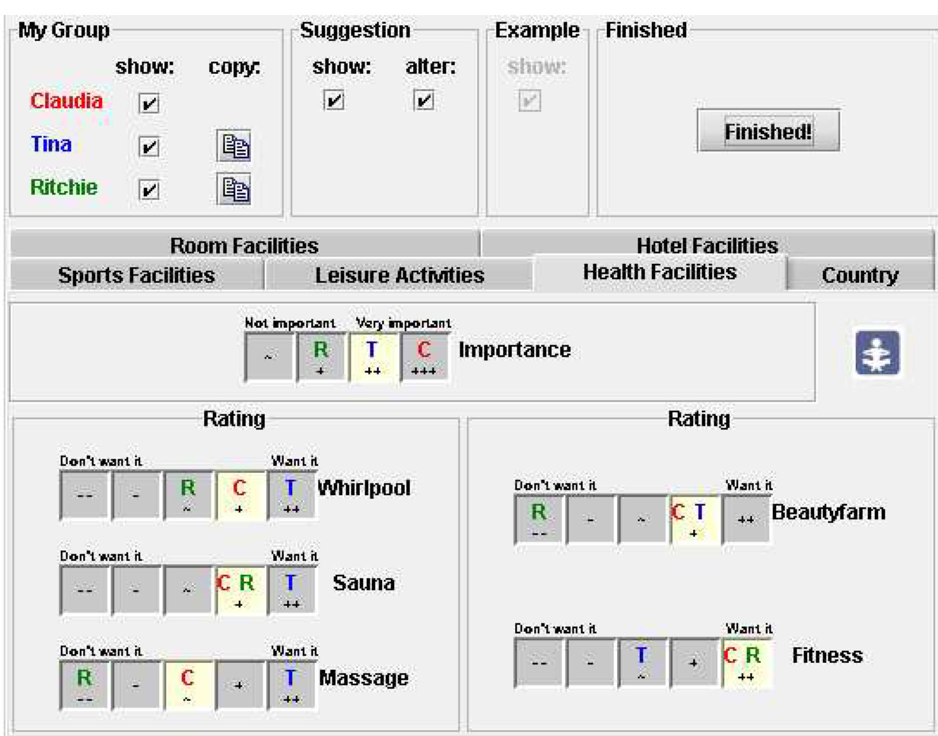


Fig. 2. Panel Below Showing How Relevant is Each Feature for Every Group Member [93].

Second, recommended item-based ratings also show ratings elicited by each group member but for each recommended item. For example, Figure 3 presents the Choicla system that shows star ratings for each recommended item [193].

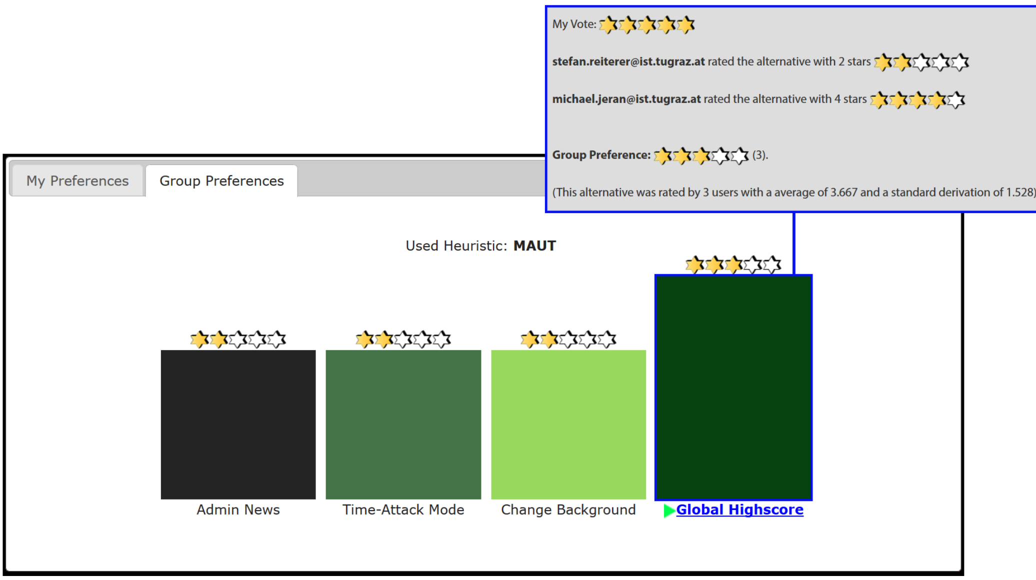


Fig. 3. Choicla Shows Star Ratings of Each Recommended Item [193].

A third theme displays user *iterative critiques* of features. Unlike the rating approach, critiquing-based GRS allow users to refine the recommendations by iteratively critiquing the features such as "I would like something cheaper" or "with faster processor speed" [26]. The CATS system dedicated to recommending POIs for skiing [123], for example, shows each the critiques of every user in its main interface as shown in Figure 4.

Few academic outputs used *visualizations* to represent user profiles. For example, a GRS for music called Flytrap pictured in Figure 5) scattered songs in a 2D space based on the group preference [36]. The votes of each group member affected the brightness of every song. Additionally, the interface locates those songs with higher weights near the center and, thus, more likely to be played.

Hong and Jung also presented another example using graphs in a GRS for movies pictured in Figure 6 [87]. They used different graph visualizations, including line and force-directed graphs, to visualize a range of user preferences and affinity among group members. Similarly, another paper presented a visualization of members in GRS [208] as shown in Figure 7, using a combination of Sankey diagrams and pie charts to display connections between group members and their contributions towards the recommendations.

Finally, another theme in this variable proposes a system showing *keywords* to represent the interests of each group member [112]. In this system, the system extracts keywords using a TFIDF (Term Frequency - Inverse Document Frequency) analysis to approximate the subject matter of each user profile as represented in Figure 8.

Even if some papers present visualizations and keywords to represent individual and group profiles for GRS, it seems there is still some space to continue exploring these alternatives. As

[1]Please refer to the citations listed in every caption to see the original images from their original authors.

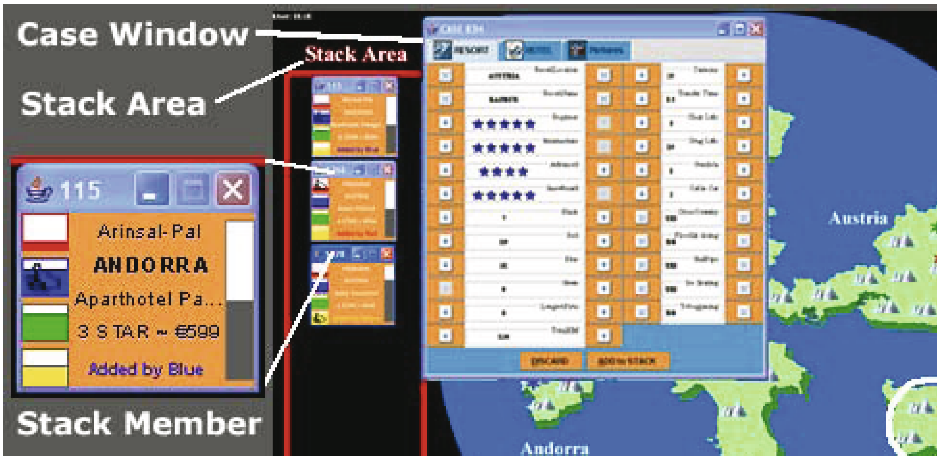


Fig. 4. CATS Shows the Critique of Every Group Member [123][1]

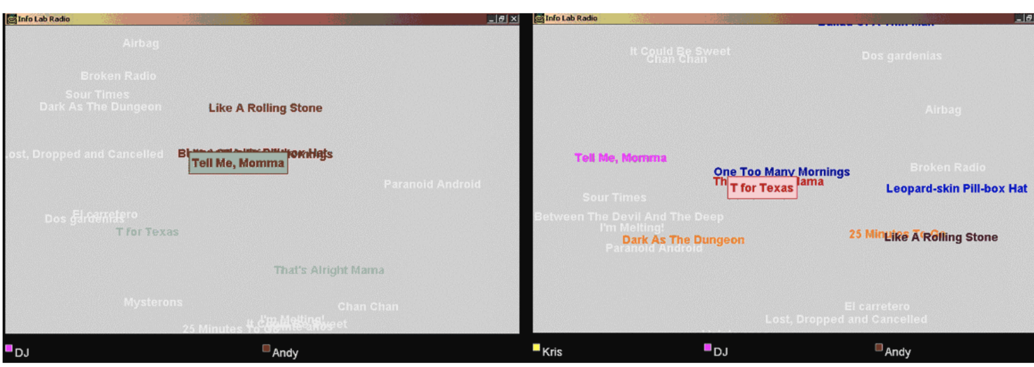


Fig. 5. Flytrap Visualizing Songs in a 2D space [36].

previous research has explored [98, 130], visualizations can increase perceived transparency and represent user profiles in individual recommendations. Therefore, we believe they will also be effective in representing individual and group profiles for GRS.

3.5.2 Justifications in GRS. We also analyzed which papers provided justifications and reasons for presenting a particular item as a recommendation. Our final corpus exposed 53 (37.32%) academic outputs that presented a form of justification for their recommendations.

In this variable, we identified three main themes of justifications: 1) text-based, 2) coordinator-based, and 3) visualization-based. For instance, 37 (26%) academic outputs showed *text-based justifications*.

Interestingly, while the system is in charge of generating the majority of justifications in our final corpus, six academic outputs proposed a *coordinator-based justification*. This strategy requires a third person to coordinate the communications and negotiations among the group members, who also offer justifications for the recommendations. Table 7 describes both of these themes.

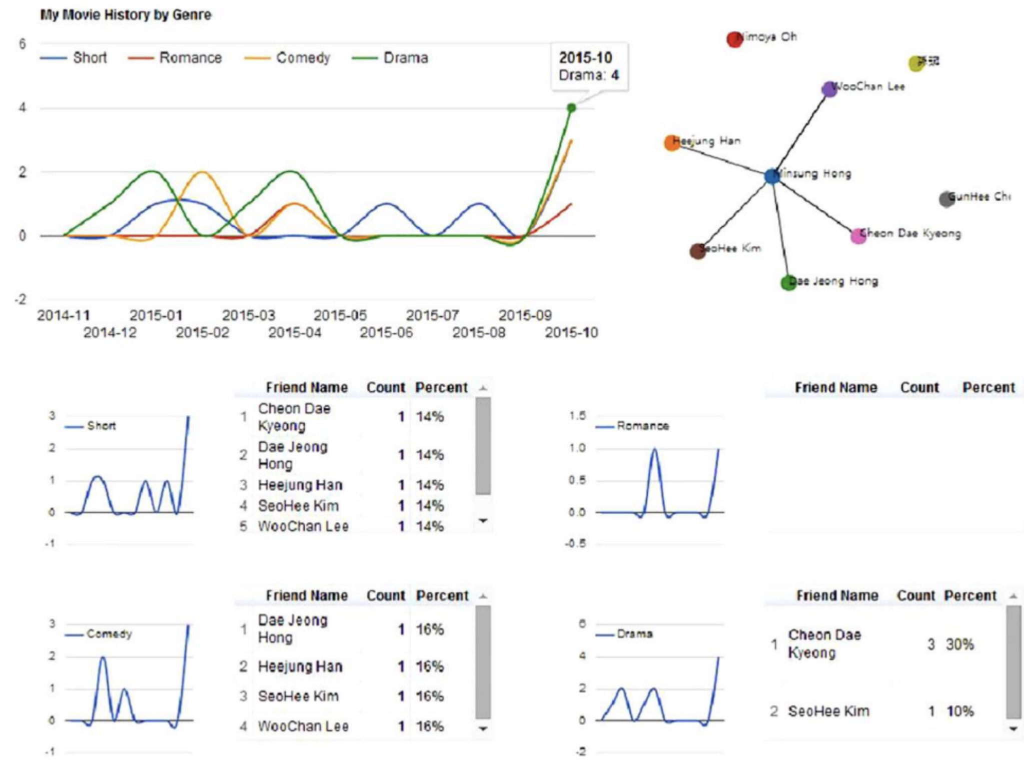


Fig. 6. User Preferences and Affinity Among Group Members Using Multiple Graphs [87].

Table 7. Text-based and coordinator-based justifications for GRS

Justification type	Total	References
Text-based	37	[8–10, 15, 17, 27, 33, 51, 52, 54, 56, 78, 80, 101, 105, 112, 134–136, 141–145, 156, 162, 166, 178, 184, 188, 191, 193–195, 200, 206, 216]
Coordinator-based	6	[8, 178, 191, 193–195]

We also identified 16 (11%) papers that presented *visualization-based justifications*. Table 8 presents this theme exposing nine different categories of visualizations designed to justify GRS recommendations.

For instance, Figure 9 shows an example of the list view visualization, which is the most common visualization for justifying group recommendations. Figure 10 portraits an example of carousel view in this theme: combining a gauge (circles or bars) and a group member identification (photos or names) to relate how much a recommended item fits that group member. Another visualization example is presented in Figure 11, showing a wheel-based visualization used to represent emotions in a music GRS.

These results show that only 37.32% of GRS in our final corpus support some form of justification for their recommendations. We believe this is a small number, considering how many previous studies demonstrate the benefits of justifications as a form of transparency that improves the user

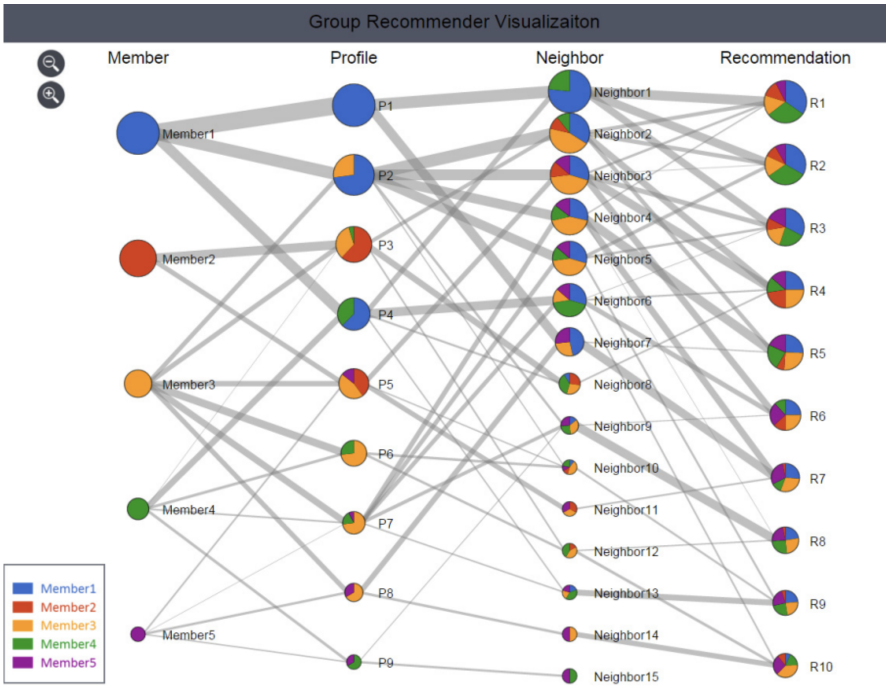


Fig. 7. Sankey Diagram and Pie Charts to Represent Connections and Contributions of Group Members [208].

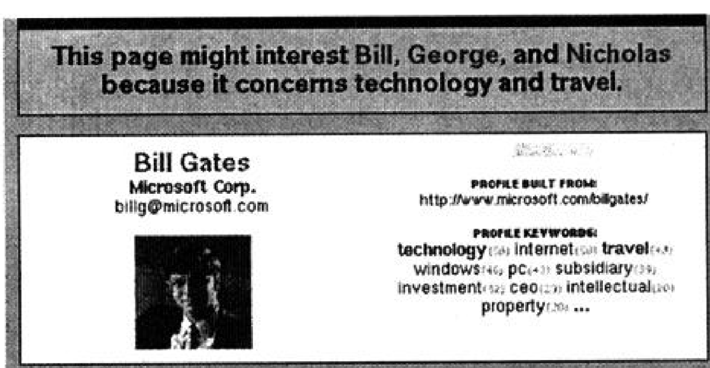


Fig. 8. Let's Browse Shows Profile Keywords to Approximate the Interests of Each User Profile [112].

confidence and behavioral intention when interacting with recommender systems [97, 187, 205]. Therefore, it seems that justification for GRS still deserves more consideration for further research.

Additionally, most of the systems presenting some form of justification provided only textual explanations. Since visualizing the recommendation process seems useful for justifying recommendations [129], we considered there is an excellent opportunity to continue exploring more and diverse visualizations to justify GRS recommendations.

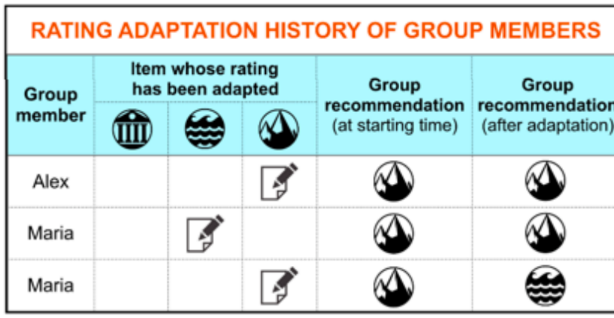


Fig. 9. List View Showing the Rating Adaptation History of Group Member [202].

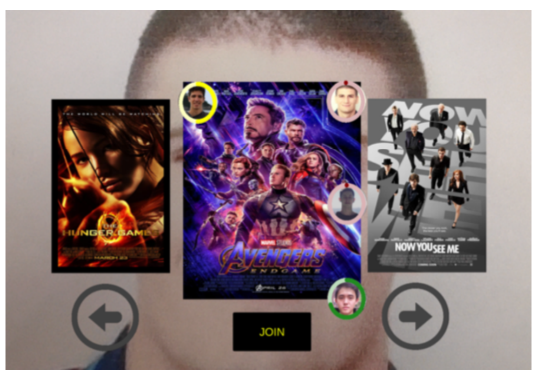


Fig. 10. Gauges the Corners of the Central Movie Represent the Prediction for Every Group Member [164].

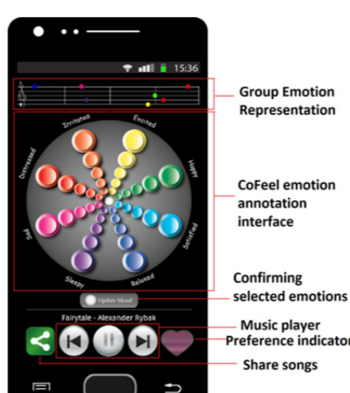


Fig. 11. A Wheel-Based Visualization for a Emotion Aware Music Recommender System [29, 30].

Table 8. Visualizations Designed to Justify Group Recommendations

Visualization type	Total	References
List view	5	[11, 42, 125, 126, 202]
Grid view	3	[49, 112, 116]
Wheel-based view	2	[29, 30]
Carousel view	1	[164]
Graphical social relation	1	[162]
Space-themed visualization	1	[190]
Sankey diagram	1	[208]
Map-based view	1	[7]
Line chart	1	[17]

We also found very scarce systems allowing coordinator-based justifications for GRS. We consider it interesting to further explore how this kind of justification alters trust, fairness, and similar perceptions towards GRS when a human, possibly dominant group member, is the one in charge of extending the justifications.

3.5.3 Control in GRS. We also analyzed which papers described interaction strategies to support user control. Sixty-six (49.30%) academic outputs mentioned that users could control, adjust or give feedback on the recommendations.

In this variable, we identified two main themes: the recommendation results and the user preferences. In contrast with a previous study that categorizes these two areas and a third one in which users can exert control of individual recommender systems [98], we could not find an academic output presenting a way to control the algorithm parameters.

Table 9 lists the academic outputs providing some form of controlling and providing feedback to the *recommendation results*, including three different interaction strategies: *numeric rating, binary rating, and ranking*.

Table 9. Interaction Strategies to Control Recommendation Results

Interaction Strategy	Total	References
Numeric rating	26	[11, 14, 27, 33, 63, 66, 85, 102, 110, 155–158, 160, 178, 189, 191, 193–195, 202, 206, 213, 214, 216, 217]
Binary rating	22	[25, 40, 47, 49, 53, 54, 63, 78, 83, 86, 94, 95, 117, 118, 141–143, 145, 163, 164, 190]
Ranking	4	[35, 44, 45, 150]

For instance, *numeric rating* refers to a score assigned to the recommended item as in Figure 12, in this example, users can rate current recommendation candidates according to their preferences. *Binary rating*, pictured in on the left side of Figure 13 refers to the explicit user acceptance of a particular recommendation limited with only two options, such as likes or dislikes, accept or reject the item, thumb up or down, or like or skip. Finally, in contrast with a numeric rating that provides a grade to the recommendations, *ranking* defines a way to express feedback to the recommendations

Fig. 12. Choicla Offers Star Rating to Provide Feedback to the Recommendations [191].

considering an order of preference, as shown in Figure 14. Interestingly, one academic output presented a combined strategy to rate recommendation results which included voting (binary rating) and sliders (numeric rating) [217].

We also found different interaction strategies in our second theme regarding the control of the *user preferences*. Table 10 includes those academic outputs that supported control on user preferences.

Table 10. Interaction Strategies to Control User Preferences in GRS

Interaction strategy	Total	References
Personal Constraints	28	[35, 44, 45, 51, 63, 82, 83, 85, 86, 90, 94, 104, 115–118, 122–126, 150, 177, 179, 193, 215, 216]
Filtering Constraints	9	[8, 10, 45, 49, 65, 78, 105, 116, 188]
Weight Group Members	4	[15, 47, 53, 118]

First, we identified *personal constraints* to control the user preferences when the user can change their liked items. Second, we also found another strategy in which users control their preferences by setting up their *filtering constraints* as shown on the right side of Figure 13 in which the user can exclude recommended events that are more than 25 km away. Third, we also identified another strategy that defines the *weight of group members* that will have an impact on the final recommendations.

Fig. 13. "Thumbs up/down" as Binary Rating in a Social GRS [49].

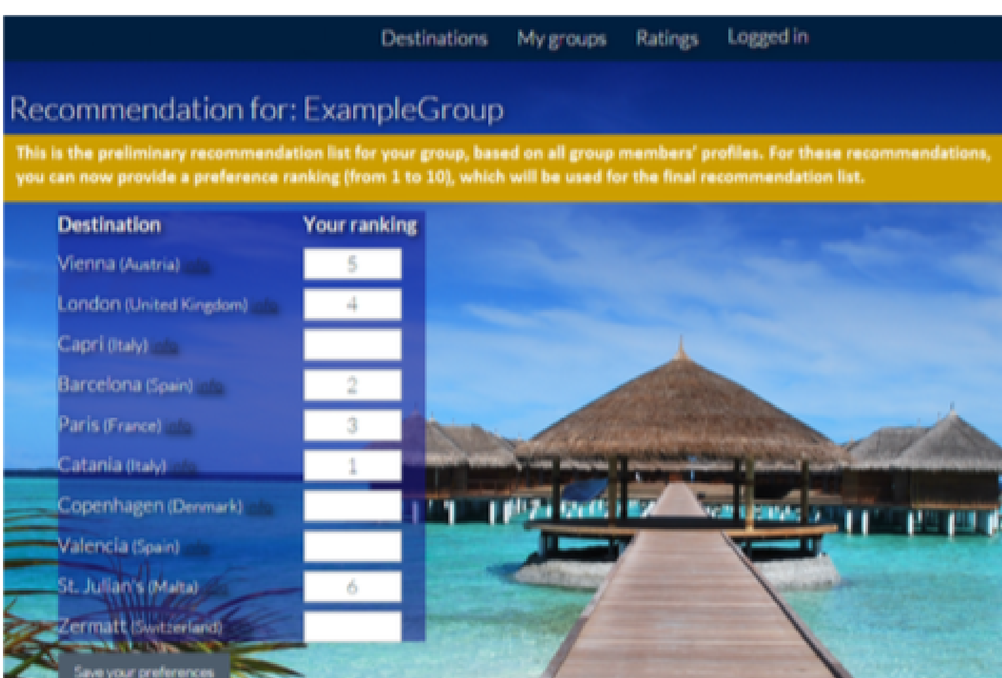


Fig. 14. Ranking to Provide Feedback in a Touristic GRS [45].

We also identified some academic outputs presenting a *combination of multiple strategies* to control GRS. Table 11 presents all the academic outputs enabling users to control at least two of the previous control strategies for group recommendations, using "PerCons" to identify personal constraints, "FilterCons" to identify filter constraints, and "WeightMembers" to identify the weight of group members.

Table 11. Academic Outputs Including Control for Multiple Aspects of GRS.

Aspects of GRS	Total	References
BinaryRating+PerCons	6	[63, 83, 86, 94, 95, 117]
Ranking+PerCons	4	[35, 44, 45, 150]
NumericRating+PerCons	3	[85, 193, 216]
Binary+FilterCons	2	[49, 78]
Binary+WeightMembers	2	[47, 53]
FilterCons+WeightMembers	2	[45, 116]
Binary+WeightMembers+PerCons	1	[118]
Ranking+FilterCons+PerCons	1	[45]

Figure 15 presents an example in which the system allows the users to control the recommendations and personal constraints.

We also found systems that enabled control on three different components as pictured in Figure 16 including rating recommendations, modifying personal constraints, and changing the weight of group members.

While we consider it is challenging to design a GRS that completely satisfies all group members without any form of control to provide adjustments or user feedback, less than half of our corpus supported any interaction strategy to achieve these goals. Therefore, we believe there is an opportunity to explore different control forms for GRS in both recommendation results and user preferences.

Additionally, we notice a clear research gap in exploring interaction design strategies to control the weight of the selected or generated data that GRS considers to estimate the recommendations. Previous research [98] and similar studies have explored these ideas for individual recommender systems, offering an exciting scope in GRS to evaluate these and additional design suggestions.

3.5.4 Diversity and/or Serendipity in GRS. We also analyzed which papers proposed a design solution to address diversity or serendipity in GRS. Unfortunately, in line with results in previous surveys [79], we found only 15 (11%) academic outputs in our final corpus, at least referring to diversity or serendipity in their texts.

As a first theme, we found that only one paper explicitly applies a design feature intended to diversify GRS. Christensen and Schiaffino allowed users to *filter the recommendations based on unknown items*, in this case, songs that have not been played previously by anyone in the group [33]. Figure 17 shows a snapshot of their system.

We also identified two other themes in this variable: academic outputs mentioning an intention to produce more diversity or serendipity in GRS through *better algorithmic calculations*, and academic outputs measuring *perceived diversity or serendipity* with users. Table 12 presents how we assigned each academic output in both themes.

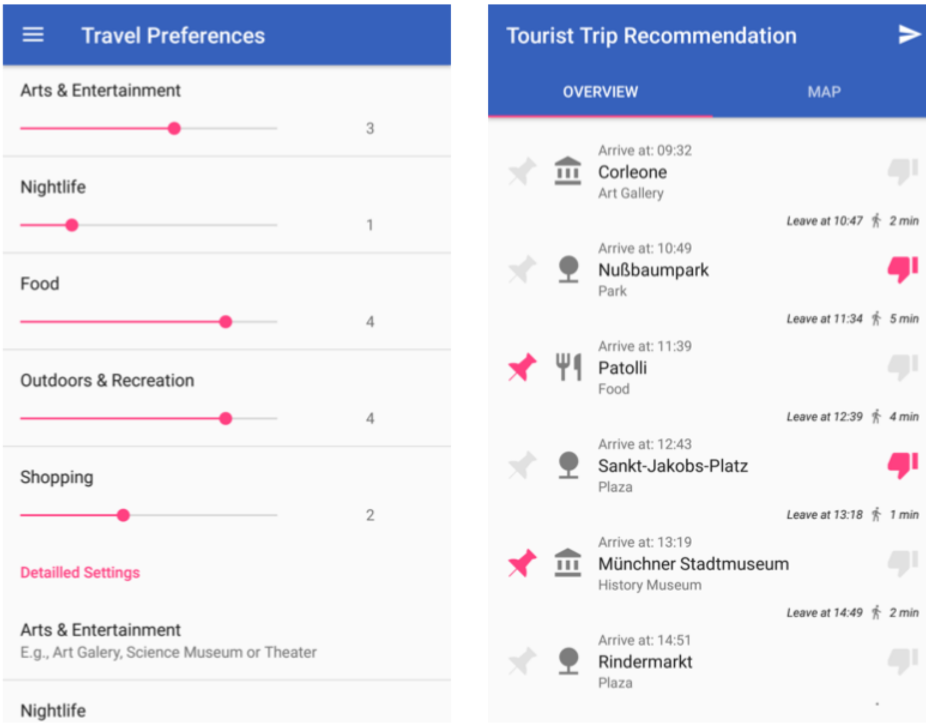


Fig. 15. Sliders (Left) and Personal Selection (Right) to Support User Control [86].

Table 12. Academic Outputs Looking for Better Calculated and Perceived Diversity

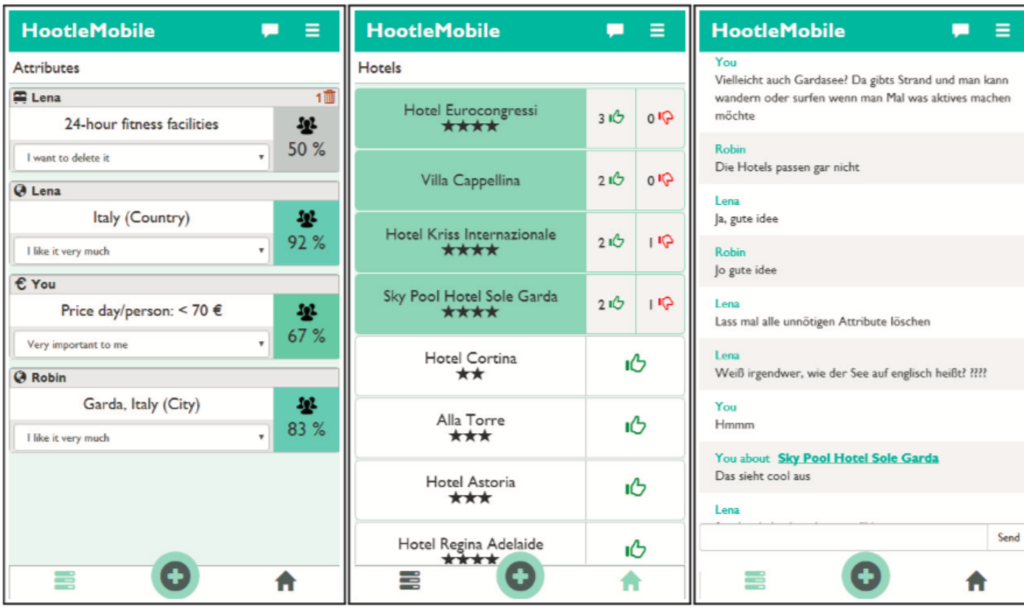
Themes	Total	References
Better Algorithmic Calculations	10	[11, 40, 45, 49, 115, 121, 156, 188, 204, 209]
Perceived Diversity or Serendipity	4	[43–45, 64]

Interaction design to achieve diversity or serendipity is still a gap in the research for individual recommender systems. Consequently, our results also show a gap regarding these opportunities in GRS. We believe that design features to address this gap present a research opportunity to diversify recommendations and provide serendipitous results for GRS.

3.6 The Interactive Approaches that Address Group Formation and Achieve a Final Group Consensus in GRS

3.6.1 Group Formation in GRS. Regarding group formation, we found 61 (43%) academic outputs expressing at least a design feature to allow group formation. The thematic analysis in this variable identified six main themes. Table 13 presents all the academic outputs coded in this variable.

A first theme contains academic outputs that opted to design their GRS inside social media platforms. We consider this theme includes a *social media strategy*. They used social media interaction to allow users to form groups, usually sending invitations to friends inside the same social network.



(1) Features (2) Recommendations (3) Chat

Fig. 16. User Control Combining Weight of the Group Members and Personal Constraints [118].

Table 13. Interaction Strategies for Group Formation

Strategies	Total	References
Admin-centered	28	[9, 15, 32, 33, 51, 64, 66, 92, 141, 143–145, 147, 149, 152, 172–174, 191–196, 206, 209, 211, 216]
Social Media	13	[13, 27, 28, 87, 154–161, 169]
Unconventional Strategies	9	[78, 83, 86, 90, 112, 114, 204, 214, 215]
Discoverable Team	6	[29, 44, 45, 104, 105, 171]
Horizontal	3	[47, 53, 164]
Automatic Decision	2	[72, 179]

Systems in this topic often considered the information collected by social media to identify patterns and preferences for each group member and generate pertinent recommendations. Interestingly, most of these academic outputs decided to implement their systems on Facebook.

A second theme followed an *admin-centered strategy* for group formation. In these systems, just one user, often the administrator and creator of the group, can invite members and form a group. This strategy was the most recurrent in this variable, with 28 academic outputs containing a description of this idea. In contrast with the previous theme, this admin-centered strategy occurred without features supported by a social media platform. For instance, Figure 18 presents the admin interface to add members in a group of POI recommendations, a design feature included in five different academic outputs from Nguyen and Ricci [51, 141, 143–145].

Fig. 17. The System Includes an Option to Filter the Recommendations Based on Unknown Items [33].

A third theme encompassed academic outputs that decided to establish a more *horizontal strategy* for the group formation. In this case, the system allowed all users to create new groups, but also, all members of a group could freely invite other users to enter the group.

There are only three papers on this theme. For example, Figure 19 shows how Dooms et al. and DePessemier et al. offered this functionality in their system called Omus [47, 53]. Additionally, Recio-Garcia and Jimenez-Diaz proposed to explain group recommendations using AR, allowing all users to invite members to their groups [164].

A fourth theme was related to a similar horizontal dynamic to form groups for recommendations, but with a crucial difference: users can find groups and incorporate them to participate in the group recommendations. We considered this theme a *discoverable team strategy*. For example, Figure 20 describes how two academic outputs applied this strategy in Folkommender to allow users to manage many groups simultaneously for movie recommendations [104, 105].

A fifth theme represented two academic outputs applying an *automatic decision strategy* for group formation. According to their description, two academic outputs decided to calculate the individual preferences of many users and organize them in a group automatically according to their affinities. In this case, Sanggetha and Subramaniyaswamy decided to apply this design solution in a travel recommender system for groups [179], while Goren-Bar and Glinansky applied it for TV programs group recommendations [72].

A sixth theme contained nine academic outputs with *unconventional strategies* for group formation. These cases applied adapted techniques according to their application domain and context of use or presented combined approaches. For instance, Lieberman et al. used Tag Readers (RFID readers and electronic badges) to identify users in a group and offer website recommendations [112].

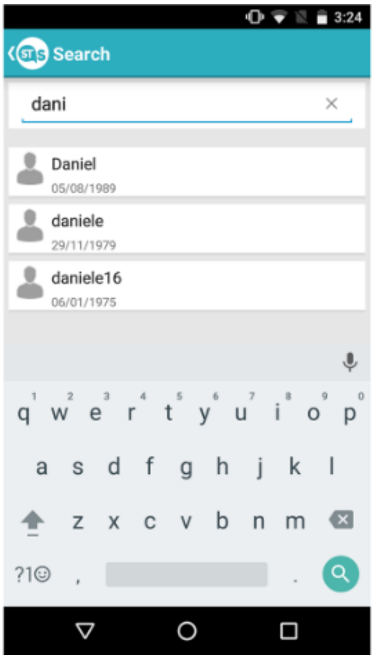


Fig. 18. Searching for Group Members in a Admin-Centered Strategy for Group Formation [33].

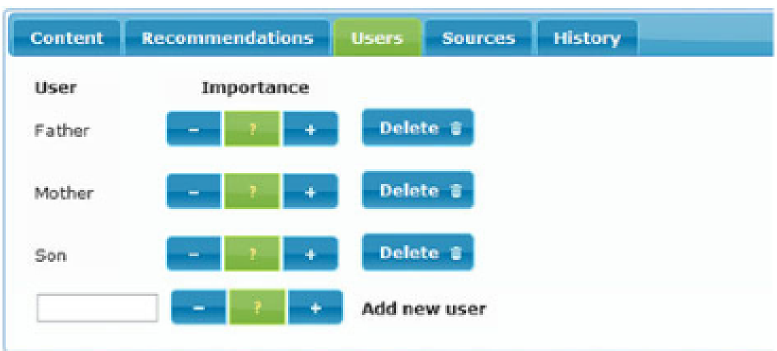


Fig. 19. Design Feature to Horizontally Invite Users to a Group [47, 53].

In the realm of TV program recommendations, Yu et al. presented a system in which users that want a group recommendation need to log in simultaneously to the system [215]. Lin et al. opted for face recognition to log in to the IPTV system [114]. Van Deventer et al. preferred QR-codes appearing on the TV screen that allowed users to join a watch party [204].

Other proposals used their context to form groups for the recommendations. Wörndl and Saelim decided to allow users to join a group using their mobile phones where preferences are stored and group members interact on a tabletop display [214]. Also, Herzog et al. presented a mobile app that captures the geographical position of the user to find other close users and form a group for

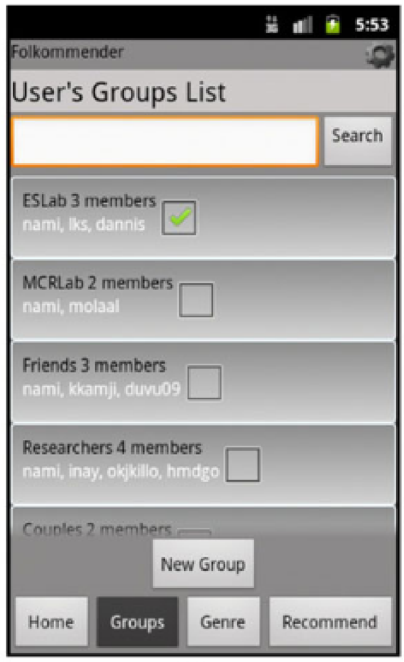


Fig. 20. Design Feature to Find and Enter into Groups in Folkommender [104, 105].

travel recommendations [83]. In a precedent work, Herzog and Wörndl combined gathering the user proximity with with a mobile app and a public display, which consisted in a kiosk system equipped with a 55-inch multi-touch screen in portrait orientation. [86].

Hussein et al. offered a combined case presenting three different strategies for three different prototypes in the same academic output: individual recommendations, Facebook invitations, and lunch-time invitations limited for groups of two people [90]. Finally, Guzzi et al. proposed single invitations to form groups limited to two people only [78].

In conclusion, we consider that interactive features in this variable are diverse, offering different possibilities for different use contexts. Nevertheless, to the best of our knowledge, the papers in this group are not yet studying in detail the social implications that each group formation strategy could produce in specific contexts. Studying these social implications in different group dynamics will determine how each design feature influences this aspect and bring novel ideas to design the interaction about group formation.

3.6.2 Achieving a Final Group Consensus in GRS. We also analyzed existing design solutions for achieving a final consensus regarding the recommendations inside the group. In this regard, we found that 48 (34%) of the academic outputs in our corpus presented at least a design feature for this area. Additionally, the thematic analysis identified five groups of design strategies in this variable. Table 14 presents all the academic outputs coded for this variable.

The first theme opted for a *democratic approach*. In this theme, academic outputs offered a way for group members to vote for their preferred option and decide which would be a final decision regarding the group recommendations. Some systems offered to vote negatively, positively, or a combination of both expressions to determine the final decision. For instance, Figure 21 shows how

Table 14. Design Approaches to Achieve a Group Consensus

Approaches	Total	References
Democratic	16	[11, 14, 34, 54, 56, 122, 124, 154, 155, 158–161, 163, 190, 214]
Mutual Agreement	13	[51, 116–118, 141–145, 178, 211, 216]
Veto-power	6	[9, 92, 191, 193–195]
Third-party	6	[40, 93–95, 174, 206]
Other approaches	5	[25, 78, 83, 181, 202]
Filtering and Sorting	2	[172, 173]

Fig. 21. Right Panel Reviews Other Group Members Voting for Music Recommendations [154, 155].

Popescu offered a view in which members of a group could check which is the rating performed by the other group members in a music group recommendation system [154, 155]. The majority of academic outputs fell into this theme, with a total of 16 papers.

A second theme relied upon a *veto-power approach*. In this case, there is one group member (an admin) with the power of making a final decision over the group recommendations. An example of this veto-power approach is the system proposed by Ioannidis et al. in which they considered first a democratic approach allowing group members to vote for the recommendation but still allowed the admin of the group to make the final decision [92], including the possibility to avoid the democratic expression. The third theme in this variable proposed implementing design features that allowed users to discuss their preferences and opinions about the group recommendations to achieve a *mutual agreement approach*. Figure 22 describes how chat boxes are a norm to achieve negotiation and expression, a design strategy on which Nguyen T.N. relies on for POI recommendations in various academic outputs [141–145]

The fourth theme in this variable represents a design decision to implement a *third-party approach*. This theme contained academic outputs designing representatives that will negotiate a final decision on the group recommendations considering all preferences inside a group. The majority of academic outputs in this group used virtual agents as third-party representatives [93–95], as shown in Figure 23. Villavicencio et al. [206] and Rossi et al. [174] also use virtual agents for these purposes.

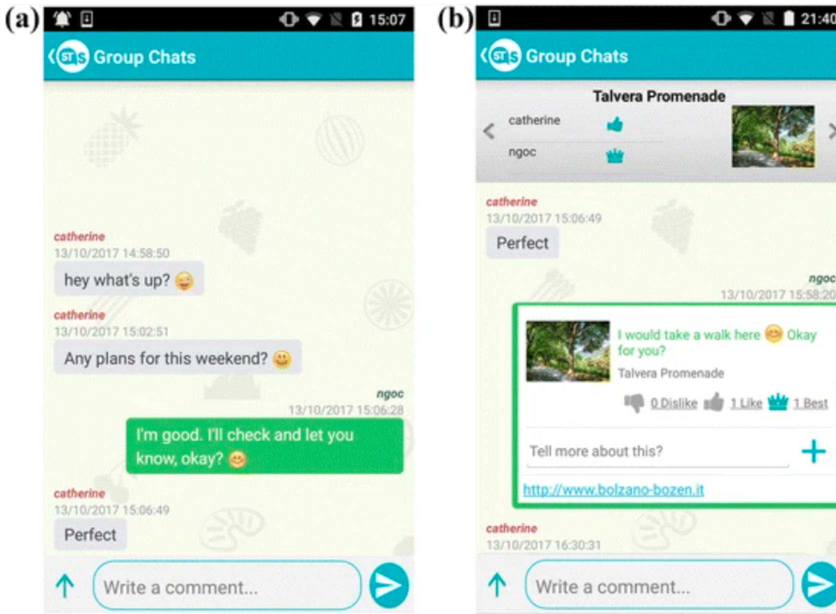


Fig. 22. A Chat Box to Address Final Consensus for POI Group Recommendations [144].

Fig. 23. Third-Party Virtual Agents to Address Final Consensus for Travel Group Recommendations [93–95].

We found only one academic output presenting a third-party human representative as a strategy to achieve a final consensus. Based on their use context, De Carolis et al. decided to allow the instructor of a spinning class to decide on music recommendations for the group of spinning class attendees [40]. In contrast with a veto-power approach in which a user who belongs to the target

Fig. 24. Filtering (Left) and Sorting (Right) to Address Final Consensus for Movie Group Recommendations [172].

group for the recommendations takes a final decision, De Carolis et al. present a third-party person not related to the target group for the recommendations responsible for making this final decision.

The fifth theme for this variable encompassed a *filtering and sorting approach*. Figure 24 shows how Rossi proposed in two academic outputs a system in which users have to first choose three movies from a list recommended for the group of viewers and then sort this selection according to their strongest preference [172, 173]. In the end, the system considers these decisions to propose a joint solution for the movie recommendation.

Our thematic analysis also showed a sixth theme containing five academic outputs with *different design approaches* not so related to the last five groups. For instance, Guzzi et al. presented an interactive multi-party critiquing approach by which each user receives new recommendations similar to the proposals made by the other group members and asks them to explain the rationale behind the counterproposals, combining a veto-power with a mutual agreement approach [78]. In the context of trip recommendations, Herzog et al. added a feature in their app to allow users to split into groups of tourists according to their preferred group recommendations [83]. Sebastia et al. opted for an absolute acceptance approach in which the system will provide recommendations that all group members should agree with [181]. Chao et al. included a negative elicitation approach in which users can neglect specific music recommendations to avoid them in the play list [25].

Finally, Tran et al. decided to allow the system to make an automatic final decision for the group recommendations [202].

Similarly, we consider that design approaches to address final consensus over group recommendations are currently diverse to address many use contexts. Still, researchers in this variable do not consider social group dynamics to determine whether specific design solutions produce different outcomes for the group. We consider this is a crucial aspect to explore in future research.

Additionally, researchers could also explore further third-party human representatives. We consider that having this third-party approach will provoke interesting dynamics for GRS worth to be explored.

3.7 The Evaluation Methods Applied With Users to Design Human Interfaces for GRS

We also uncovered the evaluation methods commonly applied to design human interfaces for GRS. While this section does not pretend to be a dedicated and exhaustive systematic review centered on methodologies and user-centered research methods for GRS, we present an overview that shows the current tendencies towards the level of user participation in GRS interface design. This general description also presents interesting research gaps that researchers could attend applying methods that seem not to be so popular for GRS.

3.7.1 Incidence of User Studies. We first identified those academic outputs that contained user studies. In our corpus, 102 (72%) of the academic outputs reported at least one user study, while 19 of those presented more than one user study. Forty (28%) of the academic outputs in our corpus presented no user study at all, implying that more than a quarter of the current academic work related to the design of GRS does not involve users in their design or evaluation processes.

3.7.2 Context of Reported User Studies. We also described the context of all the 102 academic outputs, including at least one user. Seventy (69%) reported methods taking place inside a lab environment considering real users, while 27 (26% of user studies) reported being inside the lab but using simulated or automatically generated users. Additionally, only 20 (20% of user studies) applied methods outside the lab, meaning that less than a quarter of the current state of the art about the design of GRS visited the user in their use context. Moreover, two academic outputs of this variable were not clear or explicit enough to properly determine their user studies context. Table 15 show results of this variable

Table 15. Study Context of Reported User Studies

Context	Total	References
Lab Study with Real Users	70	[6, 11, 16, 17, 28, 29, 34, 35, 44, 46, 52, 53, 58, 66, 74, 78, 80, 82, 84–86, 90, 93, 102, 104, 112, 116–118, 122–124, 143, 144, 146, 149, 150, 152–156, 158, 159, 161, 162, 166, 169–174, 178, 179, 184, 185, 188, 191, 193–196, 200, 202, 208, 210, 213–215]
Lab Study with Simulated Users	27	[6, 23, 24, 29, 31–33, 43, 47, 54, 72, 87, 92, 102, 104, 105, 114, 115, 145, 160, 161, 167, 170, 171, 174, 177, 215]
Outside the Lab with Real Users	20	[14, 25, 27, 39–41, 49, 54, 64, 65, 109, 110, 121, 134, 135, 147, 168, 190, 216, 217]

3.7.3 Data Analysis of Reported User Studies. We also identified data analysis methodologies applied in the 102 academic outputs reporting user studies. The biggest group of 78 (77% of user studies) contained at least a descriptive quantitative analysis of the collected data, while 40 included quantitative inferential analysis.

Only 11 (11% of user studies) reported some qualitative analysis of the data. From this group, it is worth noticing that some studies did not explicitly include their analysis method, and some included minimal reported data or analysis. Finally, 12 academic outputs presented a combination of both qualitative and quantitative methods of analysis. Table 16 presents an overview of the papers we identified containing both forms of data analysis.

Table 16. Qualitative, Mixed, and Longitudinal Studies for GRS

Evaluation Methodologies	Total	References
Both Qualitative and Quantitative Analysis	12	[25, 28, 49, 52–54, 86, 109, 121, 147, 154, 215]
Qualitative Analysis	11	[16, 17, 29, 74, 93, 112, 153, 166, 184, 190, 213]
Longitudinal Studies	8	[25, 49, 54, 109, 110, 121, 147, 158, 166]

Therefore, we find here an opportunity for qualitative scholars to address the interaction design research of GRS. We consider that qualitative approaches would provide interesting insights about the values and concerns that users could face in this use contexts. For instance, GRS research would greatly benefit from qualitative approaches to explore the particular implications of specific design decisions towards social dynamics and group cohesion.

3.7.4 Methods Incidence of Reported User Studies. We also identified the incidence of methods applied in the 102 academic outputs reporting a user study. These results are related to the previous variable, in which methods usually related to a quantitative analysis presented a more significant incidence, in contrast with methods usually applied for qualitative analysis.

A majority of 67 (66% of user studies) academic outputs reported surveys or questionnaires in their methods, 37 (36% of user studies) included a form of performance study analyzing accuracy and behavior of the recommender algorithm, and 33 (32% of user studies) showed a form of logging user activity to collect data. Smaller groups of academic outputs such as 14 (13.73% of user studies) papers reported some observation, 6 (6% of user studies) applied interviews, and 3 (3% of user studies) expressed focus groups. Moreover, four academic outputs were not clear enough to be categorized in any of the previous groups.

3.7.5 Incidence of Longitudinal User Studies. Finally, we checked whether the academic outputs applied any form of a longitudinal study. As shown in Table 16, our final corpus found only nine (8% of user studies) of academic outputs with these characteristics. In this context, Düzgü and Birtürk conducted a year long user study [54], O'Connor et al. conducted user studies for nine months [147], Chao et al. expressed that they applied their methods during "a few months" [25], Quijano-Sánchez et al. reported applying a one month user study [158], McCarthy and Anagnost a six weeks user study [121], Kurdyukova et al. a three weeks user study [109], and DePessemier et al. a one-week user study [49]. Finally, Lage et al. performed a user study during five days [110].

We consider longitudinal studies could provide valuable inputs for the design of algorithmic group recommendation systems. Longitudinal studies are lacking in most HCI venues [106]. Therefore, we also highlight this gap in current research as an opportunity to properly understand the interaction with group recommendations in the long run.

4 INTERACTION DESIGN STRATEGIES AND RESEARCH OPPORTUNITIES FOR GRS

We performed a meta-analysis of the current interaction design strategies for GRS considering six areas: (1) application domains of user interfaces; (2) devices chosen to implement user interfaces; (3) level of fidelity of those user interfaces; (4) interaction strategies to achieve user and group profile transparency, recommendation explanation, algorithmic control, and diversity or serendipity over the resulting recommendations; (5) interactive approaches to address group formation and achieve a final group consensus; and, (6) research methods applied with users to address the design of algorithmic group recommendation systems.

Our analysis brought a set of design strategies and research opportunities in the context of GRS. First, we propose a typology of interaction strategies for algorithmic group recommendations. Second, we describe an opportunity we found to promote more qualitative research for GRS. Third, we present an invitation to further research on group formation, achieving a final consensus, and similar specific interaction design areas for GRS. Fourth, we encourage more research on specific areas of transparency including group profile representations and justifications, control, and diversity or serendipity, as pending GRS researcher areas. Fifth, we list novel application domains and platforms to develop and study GRS. Sixth, we expose an opportunity to review evaluation methods and the inclusion of users in GRS interface design.

4.1 A Typology of Interaction Design Strategies for GRS

Our systematic review brought various design strategies for GRS. Considering the exhaustive nature of our meta-analysis, we believe it is possible to present a set of interaction design strategies for GRS based on our thematic analysis results. This section presents in detail our proposed typology, including all the categories we analyzed and the corresponding themes we unpacked in each of them.

We believe that this typology is a practical departure point for researchers and practitioners to inspire, imagine, and design GRS interaction in various social and cooperative contexts. It can also serve to add these or similar features in current popular recommender systems for "individual" users. Finally, we expect this exhaustive overview serves researchers focused on cooperative and social computing domains to devise new and exciting ways to interact with GRS. Figure 25 presents an overview of our proposed typology.

4.1.1 User/Group profile Transparency. Presented in Section 3.5.1, this variable brought five different interaction design strategies:

- (1) Feature-based rating: The system represents the user or group profile showing the current weight for each feature considered to create the recommendations.
- (2) Recommended Item-based rating: The system describes the user or group profile, exposing the current weight that each recommended item has to be included as a recommendation, according to the system.
- (3) Iterative critiquing-based: In this strategy, the system describes the user or group profile by exposing how the group members have iteratively criticized each of the recommended items.
- (4) Visualization-based: The interface shows different visualizations representing the current preferences of both the user or the entire group considered to create the recommendations. We identified four different kinds in our final corpus: 2D space, multi-graph, and Sankey and pie.

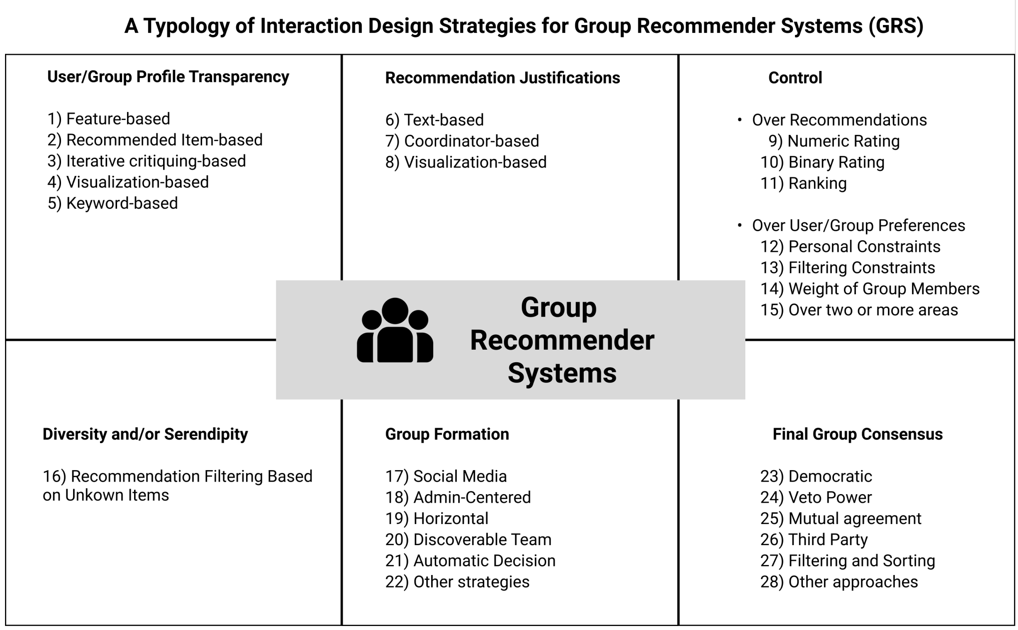


Fig. 25. A Typology of Interaction Design Strategies for GRS

- (5) Keyword-based: The system has a predefined set of keywords to represent the user or group profile.

4.1.2 Recommendation Justifications. Exposed in Section 3.5.2, this variable showed three interaction design strategies:

- (6) Text-based justifications: The system justifies each recommendation with textual explanations, including argumentation, ratings of the group members, preferences of the group members, the system predicted ratings, and item features.
- (7) Coordinator-based justifications: The system allows an admin-like user to justify each recommendation manually.
- (8) Visualization-based justifications: The system justifies each recommendation with graphs and multiple visualizations, including list view, wheel-based view, and grid view.

4.1.3 Control. Shown in Section 3.5.3, this variable brought seven interaction design strategies to offer the user control and offer explicit feedback, divided into three main groups:

- Control over the recommendations: The system allows the user to control and offer feedback on the recommended items. Here, we found three different strategies:
  - (9) Numeric Rating: The system offers to control the recommendations with numeric ratings such as 1-100%.
  - (10) Binary Rating: The system offers to control the recommendations with a binary yes/no system such as like/dislike or thumbs up/down.
  - (11) Ranking: The system offers the user to rank the recommendations in an ordered sequence of likelihood.

- Control over the user/group profile: The system allows the user to control the user or group profiles, changing their current preferences or weights to create the recommendations. Here, we found three different strategies:
  – (12) Personal Constraints: The system offers to control the profile following personal preferences for the characteristics of the recommendations.
  – (13) Filtering Constraints: The system offers to control the profile by adding filters to the possible recommendations.
  – (14) Weight of Group Members: The system offers to control how relevant is each group member profile to produce the recommendations.
- (15) Two or more areas: The system allows controlling or providing feedback on two or more of the previous control strategies.

4.1.4 Diversity and Serendipity. Explained in detail in Section 3.5.4, this variable only brought one interaction design strategy:

- (16) Recommendation Filtering based on Unknown Items: This interaction strategy includes allowing users to limit the recommendations list to items currently unknown by the group members.

4.1.5 Group Formation. Section 3.6.1 contains the six interaction design strategies identified in this variable, summarized as:

- (17) Social Media Strategy: The system uses the features of the social media platform to invite other group members
- (18) Admin-centered Strategy: One admin user handles all group formation features and decisions
- (19) Horizontal Strategy: All users handle group formation features and decisions
- (20) Discoverable Team Strategy: Users can find groups and join them
- (21) Automatic Decision Strategy: The system creates automatically the group of users based on their preferences
- (22) Other Strategies: A diverse set of options to forms groups, including tag reading, logging in simultaneously, face recognition, QR codes login, physical distance, combined strategies, and grouping two people by invitation.

4.1.6 Achieving a Final Group Consensus. Section 3.6.2 contains the six interaction design approaches we uncovered in this variable, summarized as:

- (23) Democratic Approach: All users vote for their preferred recommendation, and the most voted option wins
- (24) Veto-power Approach: One user possess the final word to choose among the recommended items
- (25) Mutual Agreement Approach: The system offers features for users to discuss and decide which is their preferred items until the members in the group reach a mutual agreement
- (26) Third-party Approach: Each group members delegate to a third party the final decision over the recommended items. This third party knows in advance the preferences of each user and negotiates with other third parties to make a final decision. There are two kinds of third parties: virtual agents or human agents.
- (27) Filtering and Sorting Approach: The system offers users different levels of filtering and sorting to reduce the number of group recommendations until the group reaches a final decision

- (28) Other Approaches: A diverse set of options to achieve a final consensus over the recommendations such as discussion and critiquing, allow group splitting, absolute acceptance, negative elicitation, and automatic final decision.

4.2 An Opportunity for GRS Research using Qualitative Approaches

Section 3.1 showed that our final corpus of academic outputs published their results in venues where quantitative results are traditionally the most common method to approach interaction design. Correspondingly, the results projected in Section 3.7.3 and Section 3.7.4 showed a tendency towards quantitative methodologies and behaviorist approaches centered chiefly on surveys and questionnaires. It seems then that quantitative approaches are the current protagonists that have informed most of the current state of interaction design for GRS.

Therefore, we consider an opportunity to include more qualitative approaches that could expand current notions about GRS interaction and discover novel design areas. Such qualitative approaches could depart from various frameworks that serve as theoretical standpoints to explore the values, experiences, and understandings of users while using these systems. For instance, a way to analyze these interfaces is to follow design frameworks and concepts about the user experience with recommender systems for individual users [2, 5] or similar surveys in this domain [79]. We also consider that even low fidelity prototypes could provide interesting insights, as some examples shown in Section 3.4.

Moreover, we consider that a human-centered approach involving users from the beginning of the design process should be a norm for this domain to achieve appropriate interfaces. For example, previous work has exposed interesting methodological recommendations to address the design of algorithmic interfaces following co-design strategies, involving participants actively very early and during the entire design process [3].

We also found in Section 3.7.5 and Section 3.7.2 that longitudinal studies and outside-the-lab are far lacking studies. Again, these two contexts could include qualitative methodologies such as diary studies in the former or ethnographic explorations for the latter.

We believe that these gaps in our final corpus offer a great opportunity. The HCI and CSCW communities can provide a more qualitative stance for the interaction design of GRS, departing from already existing frameworks, studying the impact of interaction design on group dynamics, exploring how co-design can inform this context, or trying both longitudinal and outside-the-lab methodologies.

4.3 Specific Interaction Design Opportunities for GRS

In Section 3.6, we analyzed two interaction areas that exist mainly in GRS, in contrast with individual personalized recommender systems: group formation and achieving a final group consensus. Without claiming that both areas are exclusive for GRS, they showed a diverse set of interactive options that could inspire future interfaces for GRS.

Nevertheless, novel forms to achieve an understanding of their effects are still pending. For instance, in Section 3.6.2 we found that only one academic output respectively explored the implications of having a human third-party to achieve a final consensus over the recommendations for all the group members, opening an exciting space to explore the implications of this design decision over the rest of the group members. Similarly, Section 3.6.1 offered various design options that researchers seem not to explore yet to determine how each of these possibilities affect group formation or the dynamics inside the group.

Additionally, studying the different social dynamics occurring while using GRS can uncover the effects of different interaction strategies among group members. This area seemed to remain unexplored. An opportunity to start these explorations is the concept of *Group cohesion* [73] or similar frameworks that could trigger conceptual understandings of the effect of different interfaces in social and cooperative contexts such as GRS. Moreover, the typology we presented earlier can be used as guidance to address the implications of each interaction strategy towards the social group dynamics in GRS.

Here lies another opportunity for the HCI and CSCW communities to study further these domains that could advance the GRS experience. Achieving a final consensus over the recommendations, group formation, and the group dynamics of GRS offers a fruitful ground to explore new ways to interact with GRS. Notably, we find engaging how academics can explore all of these research gaps following qualitative approaches as stated in the previous section above.

4.4 Pending Areas for User/Group Profile Representations, Justifications, Control, and Diversity or Serendipity for GRS

Our systematic review also identified research gaps to explore in GRS. Based on the negative experiences that users constantly report in these systems [18, 55, 57] and the ethical implications involved [132], we believe researchers should consider this group of research gaps as pending areas that deserve a particular connotation.

For instance, Section 3.5.1 showed how researchers could explore information visualizations to represent individual or group profiles in GRS. We consider this an exciting opportunity to improve perceived transparency in these systems.

Similarly, in Section 3.5.2 we found that researchers have not explored the coordinator-based (human) generation of recommendation justifications widely in GRS. We believe this form of justification deserves a more profound analysis to notice how it affects perceived transparency, control, or trust over the system. Moreover, we believe this research gap also offers an opportunity to explore the implications of this design decision on all the members of the group.

Additionally, in the same section, we noticed some opportunities to explore how visualizations can justify recommendations. As previous research has shown in individual recommendations [129], visualizations can also provide a valuable way to increase GRS transparency and provide better justifications to groups of users.

Moreover, departing from previous studies on the control of individual recommender systems [98], we found in Section 3.5.3 little to no interactive approach to control the weight of the selected or generated data used to calculate the recommendations in GRS. For instance, we believe that allowing the users to choose among different algorithms to produce GRS recommendations can be an exciting alternative to explore.

Finally, in Section 3.5.4 we also found that interaction strategies to achieve diversity or serendipity are a significant gap in GRS. We believe that diversity and serendipity can become crucial aspects to increase GRS satisfaction and create new solutions applicable to individual recommendations. We invite here for more research aimed to uncover new interaction design strategies to achieve more diversity over GRS.

4.5 Novel Application Domains and Platforms to Develop GRS

Finally, our review also identified various opportunities to explore GRS and their implementation in novel contexts. We divided these opportunities into application domains and devices.

For instance, Section 3.2 uncovered how domain-independent or multiple-domain GRS have little to no exploration. Similarly, we found that many papers dealing with touristic routes or POI group recommendations are only dealing with leisure activities, but there are no studies dedicated to exploring route recommendations for more serious purposes. For instance, we believe there is an opportunity to explore GRS for collective commuting routes, such as in carpooling activities.

Another application domain barely explored in our final corpus is GRS for book clubs or groups of book enthusiasts. We believe that book clubs are a widespread activity shared worldwide, and we were surprised to notice how little researchers have explored this context to design GRS. We also identified similar opportunities in the context of a house or car recommendations for groups of people or families.

We also found that Smart TV apps, home gateways, and displays in remote controls offer devices that have minor studies for GRS, particularly for movie recommendations. Interaction design strategies considering multiple complementary devices or platforms seem to offer similar research opportunities.

Additionally, in Section 4 we noticed no exploration addressing tangible user interfaces (TUIs) to interact with GRS. The idea to use TUIs to interact with AI systems such as personalized recommendations seems to be too novel in research, including individual AI systems [70]. Nevertheless, incipient explorations state and prove how TUIs offer an opportunity to interact with individual personalized movie recommendations [4]. Considering how TUIs promote collaborative and social interactions, besides other benefits, in contrast with traditional graphical user interfaces [89, 183], we believe TUIs offer a novel opportunity to foster a better interaction with GRS.

Finally, the same section presented only one paper dealing with a GRS using AR [164] and no study for VR. For instance, we consider it interesting to explore GRS applications during VR meetings, such as collaborative meeting scheduling or VR gaming recommendations for groups of users. Additionally, practitioners and researchers can support several GRS application domains we found in our final corpus with AR applications for groups of users, such as POI, restaurants, and similar recommendations.

4.6 An Opportunity to Review Evaluation Methods and the Inclusion of Users in GRS Interface Design

This systematic review also uncovered the analysis and evaluation methods commonly applied to design human interfaces for GRS. While we did not pretend to provide a dedicated or exhaustive systematic review centered on analysis or user-centered research methods for GRS, we presented an overview that shows the current tendencies towards the level of user participation in GRS interface design. This general description also exposed several research gaps that researchers could attend with analysis and research methods that seem not to be so popular for GRS.

Nevertheless, we believe there is still a research gap that fosters an invitation to explore systematically the current analysis and research methods that include users in the design process for GRS interfaces. Considering that only 102 (72%) of the academic outputs in our final corpus reported at least one user study (subsubsection 3.7.1), with a strong tendency towards quantitative and behaviorist approaches (Section 3.7.3 and Section 3.7.4), it seems urgent to foster the active inclusion of users to design GRS interaction with diverse analysis and research methods.

We believe a dedicated systematic review with this scope can provide a departure to achieve this goal. For instance, it would be interesting to discover if the user studies conducted in the lab were within, between, or hybrid subject design experiments, the type of instruments or questionnaires used to measure the experience or satisfaction of the users, whether researchers gave the participants specific tasks to complete and the specific characteristics of these tasks, the number of users often considered in every kind of study, among others. These types of details can help future researchers to address novel ways to evaluate GRS and explore how users experience, imagine and perceive the interaction with GRS.

5 LIMITATIONS

It is worth considering some limitations of our systematic review. For instance, our meta-analysis considered only three digital libraries: ACM Guide to Computing Literature, IEEE Xplore, and Elsevier Scopus. This selection implies that our results include only the academic outputs contained in these venues.

Second, we performed some parts of our literature selection and data extraction (coding) manually, which implies possible unintended human mistakes in the process. While we aimed for Kappa values greater than 0.7 to reduce coding biases and increase reliability, the process could still include some chances for undesired errors.

Third, while some papers presented what we consider as low academic quality, we still considered that these papers could provide valuable design features to address the interaction of algorithmic group recommendations. Therefore, we still considered all academic outputs selected in our process regardless of their academic quality, level, or venue.

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A ACADEMIC OUTPUTS IDENTIFIED FOR THE SNOWBALLING REVIEW

(1) A systematic review of group recommender systems techniques (Katarya R. 2017) [103]
(2) Recommendation system using machine learning: A review paper (Tentuaa and Supraptob 2020) [197]
(3) Enhancing the facilitation of online groups in higher education: a review of the literature on face-to-face and online group-facilitation (Thomas and Thorpe 2019) [198]
(4) A survey on group recommender systems (Dara et al. 2020) [38]
(5) Group recommendations: Survey and perspectives (Kompan and Bielikova 2014) [107]
(6) Tour recommendation and trip planning using location-based social media: a survey (Lim et al. 2019) [113]
(7) Efficient Mining and Recommendation of Extensive Data Through Collaborative Filtering in E-Commerce: A Survey (Naveen and Kumar 2018) [137]
(8) A survey of recommendation techniques based on offline data processing (Ren et al. 2015) [165]
(9) Group recommender systems: State of the art, emerging aspects and techniques, and research challenges (Boratto L. 2016) [19]
(10) State-of-the-art in group recommendation and new approaches for automatic identification of groups (Boratto and Carta 2010) [20]
(11) An overview of recommender systems in the healthy food domain (Tran et al. 2018) [201]
(12) A study of recent recommender system techniques (Bansal and Baliyan 2019) [12]
(13) Group recommender systems (Boratto L. 2016) [19]
(14) Group recommender systems* (Delic and Masthoff 2018) [50]
(15) Group recommender systems: An introduction (chapter 4, 5 and 6) (Felfernig et al. 2018) [60]

(16) RecTour 2016: Workshop on recommenders in tourism (Fesenmaier et al. 2016) [67]
(17) Workshop on Group Recommender Systems: Concepts, Technology, Evaluation (GroupRS) (Gross et al. 2013) [76]
(18) Towards Human (s)-in-the-Loop (Gross T. 2019) [75]
(19) Task allocation in spatial crowdsourcing: Current state and future directions (Guo et al. 2018) [77]
(20) Informing the design of group recommender systems (Herr et al. 2012) [81]
(21) Recommendation to groups (Jameson and Smyth 2007) [96]
(22) TouRS'15: Workshop on Tourism Recommender Systems (Moreno et al. 2015) [133]
(23) Proceedings of the 2nd Workshop on Recommenders in Tourism co-located with 11th ACM Conference on Recommender Systems (RecSys 2017), Como, Italy, August 27, 2017 (Neidhardt et al. 2017) [138]
(24) RecTour 2019: workshop on recommenders in tourism (Neidhardt et al. 2019) [140]
(25) ACM recsys workshop on recommenders in tourism (rectour 2018) (Neidhardt et al. 2018) [139]
(26) Personality and recommender systems (Tkalcic and Chen 2015) [199]
(27) Design guidelines for mobile group recommender systems to handle inaccurate or missing location data (Tschersich M. 2011) [203]
(28) Tailoring Recommendations to Groups of Viewers on Smart TV: A Real-Time Profile Generation Approach (Alam and Khusro 2020) [1]
(29) Basic approaches in recommendation systems (Felfernig et al. 2014) [62]
(30) Group recommender systems: aggregation, satisfaction and group attributes (Masthoff J. 2015) [119]
(31) Comparison of group recommendation techniques in social networks (Minaei-Bidgoli et al. 2011) [131]
(32) Comparison of group recommendation algorithms (De et al. 2014) [48]
(33) Learning the Role and Behavior of Users in Group Decision Making. (Sacharidis et al. 2015) [175]
(34) Challenge on context-aware movie recommendation: CAMRa2011 (Said et al. 2011) [176]
(35) Latest Trends in Recommender Systems 2017 (Singh et al. 2019) [186]

B PRISMA FLOW DIAGRAM FOR ILLUSTRATING OUR LITERATURE SELECTION PROCESS

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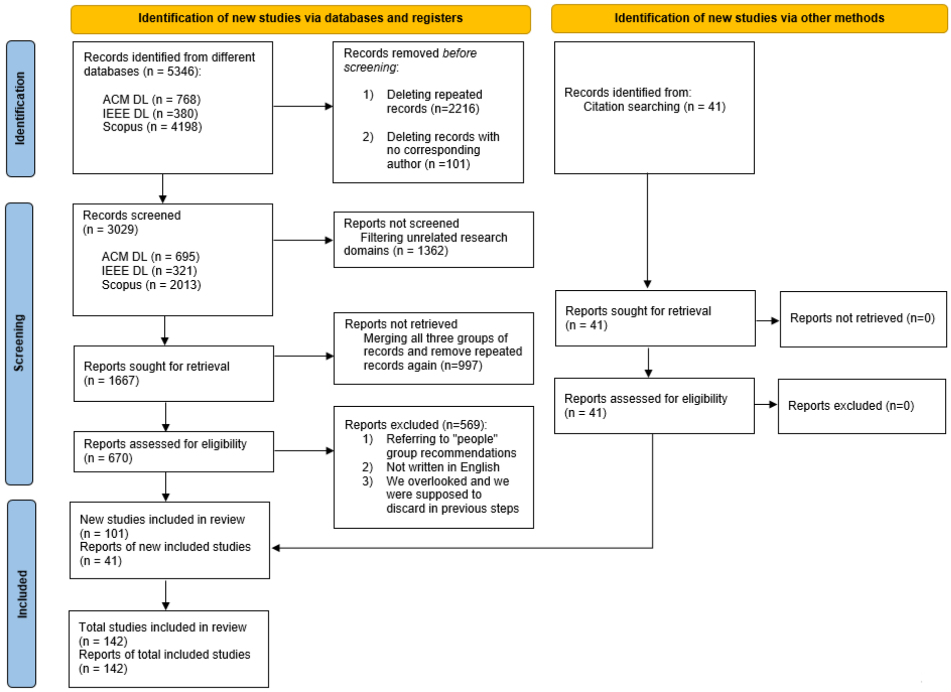

Fig. 26. Prisma Flow Diagram of our Literature Selection Process