in-Car Entertainment via Group-wise Temporary Mobile Social Networking

Mario G. C. A. Cimino[1][a], Antonio Di Tecco[1,2][b], Pierfrancesco Foglia[1][c], Raffaele Giannessi[1], Jacopo Malvatani[1], Cosimo A. Prete[1][d] and Giulio Rossolini[1]
[1]*Department of Information Engineering, University of Pisa, Pisa, Italy*
[2]*University of Florence, Florence, Italy*

Keywords: Autonomous Car, in-Car Entertainment, Temporary Mobile Social Networking, Music Streaming Service.

Abstract: Next generation cars will increase the passengers' time for fun and relax, as well as the number of unknown passengers traveling together. A key functionality to improve the users' experience is that of Temporary Mobile Social Networking (TMSN): where passengers form, for a limited-time, a mobile social group with common interests and activities, using their already available social network accounts. The goal of TMSN is to automatically redesign the users' profiles and interfaces into a group-wise passengers' profile and a common interface, by reducing isolation and enabling socialization. In this paper, a TMSN-inspired music selection is proposed and developed via the Spotify music streaming service. Early results are promising and encourage further developments towards the concept of in-car entertainment.

1 INTRODUCTION

Nowadays mobile technology guarantees seamless network connectivity and application functionality to travelers. As a consequence, car passengers can easily enrich their traveling experience via mobile social networks, providing various entertainment such as music and video streaming, feed, stories, and so on (Coppola, 2016; Bilius, 2020).

In the current social network market, some major products of interest for in-car entertainment are represented in Figure 1. Facebook is characterized by focus on user's feed and status; it allows to share thoughts and emotional feedback. YouTube is the most popular social video platform, on which users can find and share video about their interests. Spotify is leading the market of social music, where favorite artists, genres, and playlists are managed. Finally, Instagram is the repository of stories, with photographs and short videos of friends and influencers.

Given the role that Mobile Social Networking (MSN) can play in the smart city paradigm and in the next generation cars, a great development of MSN industry is expected towards in-car infotainment, enabled by the ongoing, high usable car's interior redesign (Coppola, 2016; Foglia, 2014) and the increasing AI-based interaction (vocal interaction, emotion recognition, and so on) (Rong, 2021). Indeed, MSNs have already been introduced in cars via Android Auto or Apple CarPlay, the major platforms for smart phone interoperability with car's dashboard information and entertainment unit. Specifically, Figure 2 illustrates the autonomous driving levels classified by the Society of Automotive Engineers (SAE) (Coppola, 2016):

- *level 0 – manual driving*, i.e., a completely manual vehicle, without electronic stability program, paring assistance, or any kind of assistance system;
- *level 1 – driver assisted* but steering the vehicle independently, i.e., cruise control, lane departure warning, emergency brake assistance;

[a] https://orcid.org/0000-0002-1031-1959
[b] https://orcid.org/0000-0003-0126-8079
[c] https://orcid.org/0000-0001-6432-4504
[d] https://orcid.org/0000-0002-8467-8198

Cimino, M., Di Tecco, A., Foglia, P., Giannessi, R., Malvatani, J., Prete, C. and Rossolini, G.
in-Car Entertainment via Group-wise Temporary Mobile Social Networking.
DOI: 10.5220/0011096000003191
In *Proceedings of the 8th International Conference on Vehicle Technology and Intelligent Transport Systems (VEHITS 2022)*, pages 432-437
ISBN: 978-989-758-573-9; ISSN: 2184-495X

- *level 2 – partial automation*, i.e., the vehicle *can* independently perform individual driving, such as parking, navigating stop-and-go traffic, lane departure warning, distance warning;
- *level 3 – conditional automation*, i.e., *autonomous* driving under certain conditions;
- *level 4 – high automation*, i.e., vehicle controls complete journeys on the highway, or in city traffic predominantly *independently*;
- *level 5 – full automation*, i.e., neither driving *ability* nor a driving license are required to use the vehicle.

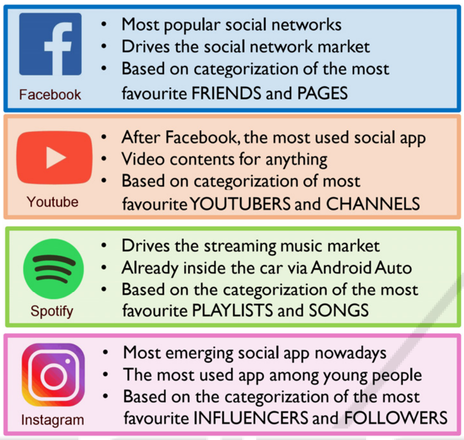

Figure 1: Some major social network platforms of interest for in-car entertainment.

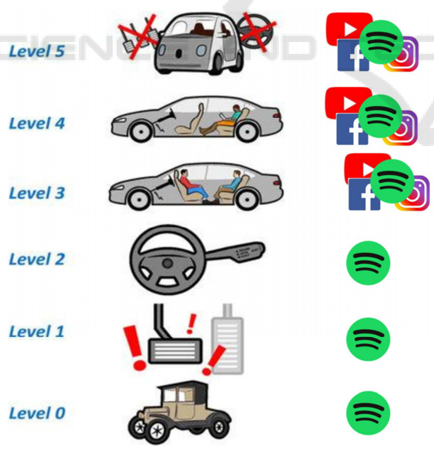

Figure 2: Autonomous driving levels and MSN access.

At level 3, in which the car controls a significant number of driving operations, the number of MSN products can sensibly increase. In this trend, car sharing is also expected to become popular. As a consequence, next generation cars will increase the passengers' time for fun and relax, as well as the number of unknown passengers traveling together.

A deeply discussed issues of MSN is the negative effect of the prolonged use of mobile apps: many studies show the orthopedic injuries and the psychological diseases that can affect a social user, resulting in isolation, anxiety, depression, and so on. In this regard, ambient intelligence and next generation car (Bilius, 2020) are expected to solve the inherent limits of smart phones and of current MSN.

To further enrich the interaction of an MSN user with the physical world, by reducing his isolation, an important paradigm made possible by next generation car is the *group-to-many* interaction, illustrated in Figure 3. In the traditional *one-to-many* interaction, the user is alone in his physical world and is connected to the others via MSN. With the *group-to-many* interaction, a group of users is temporarily living in a common physical space, interact in person and share their experience with the MSN as a whole group.

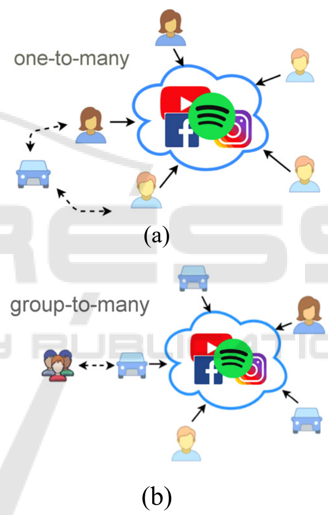

Figure 3: One-to-many interaction paradigm vs. group-to-many in the context of in-car MSN.

In the literature, the concept of Temporary MSN (TMSN) has attracted attention as a conceptual framework to be used at hotels, concerts, theme parks, sports arenas, where people form a mobile social group for a limited time, by having a common physical interaction (Yin, 2019). People confined in a specific place are allowed to join the TMSN using their personal account, and acting via a group-wise interaction with the others, improving the mobile users' experiences with such temporal friends. A surrogate of this concept is Spotify Group Session, a beta testing feature that allows up to six people to share control over the music playing in the background of a physical or virtual get-together (Spotify GS, 2022). There is an expansion of Spotify

Group Sessions available in Android Automotive OS, an Android-based infotainment system that is built into vehicles, such as the Polestar 2 (2022).

In the context of hotels, *LobbyFriend* was the first TMSN, enabling hotels to stay connected to guests throughout their stay, within the one hotel or across multiple hotels within the vicinity. It was inspired by loneliness while traveling often for business. When a guest checks out of the hotel, all interactions in the TMSN are erased (Yin, 2019).

TMSN is beyond sharing a common space and a collaborative playlist (Spotify CL, 2022; Spotify FM, 2022), it concerns algorithms for the exploitation of the user's profile and the current environmental context, enabling an augmented interaction via proactive services such as recommendation (Cimino, 2011). Social network platforms are today strongly managed by powerful analytics and algorithms (Lu, 2015; Zhang, 2019), also based on key techniques of modern sociology. As a such, in this study TMSN is an additional intelligent layer on an ecosystem of services available on next generation cars.

In this paper a group-wise TMSN is proposed as a design paradigm for in-car entertainment. Specifically, in the context of social music, a functional design is illustrated. A prototype has been implemented, based on Spotify API (Spotify API, 2022), and experimented.

The paper is structured as follows. Section 2 illustrates the core concepts and functional design of the proposed approach. Experimental studies are covered by Section 3. Conclusions are drawn in Section 4.

2 CORE CONCEPTS AND FUNCTIONAL DESIGN

In the context of audio streaming, a TMSN based playlist recommender exploits both ambient (car) and MSN data. For interoperability reasons, the design should be based on a standard music ontology (MO, 2022), which provides a vocabulary for managing music-related data across multiple applications (Ciaramella, 2010).

Figure 4 illustrates the fundamental concepts and static relationships in the context of audio streaming recommendation, as an ontology diagram. In figure, each concept is enclosed in a rectangular shape. Concepts are connected by relationships, represented with labelled directed edges. Some concepts are also characterized by properties, listed in lowercase letters. The fundamental outcome of this ontology is a recommendation of a track, based on the social profiles of the passengers (containing listened tracks, artists, and genres). Specifically, from the top-middle, a *Passenger is in* a *Car*, *is in* a *Mobile Social Net*, *listens* a *Track*. A *Track is made by* an *Artist*, and *belongs to* a *Genre.* A *Car plays* a *Track*, and *manages* a *Temporary Mobile Social Net*, which *generates* a *Passengers Profile*. On the other side, a *Mobile Social Net builds* a *Social Profile*, which is made by *listened tracks, artists* and *genres*. A *Social Profile is merged in* a *Passengers Profile*. Finally, the *Passenger Profile recommends* a *Track.*

Figure 5 shows a protocol of an audio streaming recommender based on TMSN and Spotify analytics, in a standard graphical representation called Business Process Model and Notation (BPMN). The protocol is built on the ontology in Figure 4 and covers only the essential aspects of the proposed approach, for the sake of readability.

The BPMN is based on a solid mathematical foundation, to enable the execution, simulation, and automation of consistency checking (Cimino, 2017). It is also suitable to standardize and facilitate communication between all stakeholders. In BPMN, a rectangular area represents a participant who takes part in a protocol, via message exchange. In each rectangular area, the protocol is managed via events, activities, and decision/merge nodes, represented by circles, rounded boxes, and diamonds, respectively. Sequence flows and data flows are represented by solid and dotted arrows, respectively. Finally, data storages are represented by cylindrical shapes.

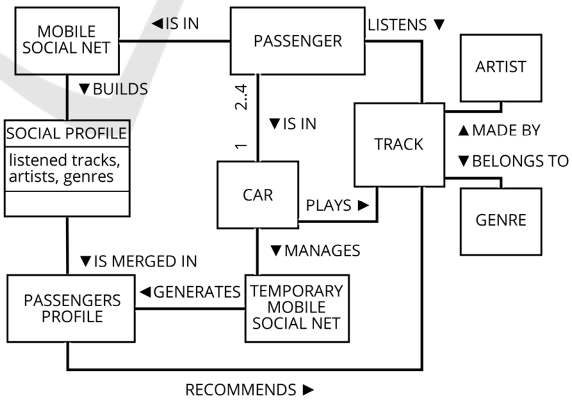

Figure 4: TMSN Ontology in the context of audio streaming recommendation.

The protocol starts on the top left (white envelope in a thin circle), when new passengers are detected by the TMSN, and ends when a playlist is determined (one of the black envelopes in thick circles). As a first task, the TMSN asks the social profiles of all

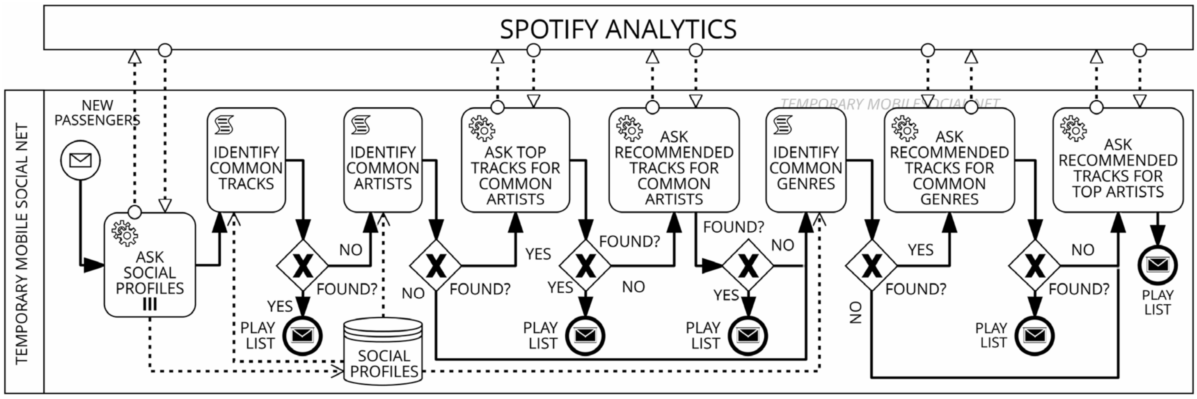

Figure 5: BPMN protocol of an audio streaming recommender based on TMSN and Spotify analytics.

passengers to Spotify Analytics. The gear icon for the task means that is a service task, i.e., supported by web services offered by Spotify. As defined by the ontology, the collected social profiles contain listened tracks, artists and genres of each passenger. Social profiles are archived for the next steps of the protocol. Then, a script task (i.e., a task internally developed, characterized by a sheet icon) identifies the set of common tracks between all passengers. If some tracks are found, then the recommended play list is generated. Otherwise, a script task identifies the common artists. If some common artists are found, a service task asks the top tracks for them to Spotify Analytics and, if some are found, the recommended play list is generated. Otherwise, a service task asks to Spotify Analytics the recommended tracks for common artists and, if some are found, the recommended play list is generated. Otherwise, a script task identifies the common genres in social profiles and, if some are found, a service task asks the recommended tracks for common genres to Spotify Analytics, to generate the recommended playlist. Finally, if the recommended tasks are not found, a service task asks the recommended tracks for top artist to generate the playlist.

3 IMPLEMENTATION AND EXPERIMENTAL STUDIES

The protocol is purposely designed to heavily exploit Spotify Analytics services. Indeed, it has been implemented and experimented on both a desktop computer and a *Raspberry PI3b+*, a small Chip Multiprocessor (CMP) (Foglia, 2014) single-board computer, equipped with WIFI for interfacing with smartphone, and 4G capabilities for interfacing with Spotify web services. The web application controller has been developed on *Apache2 web server*: it manages the authentication required by Spotify API, via Javascript. The host access point daemon has been implemented on *Hostapd*. The protocol logic has been developed on Python3, using *Spotipy*, a third-party library to access the Spotify APIs, and *DBConnection* to manage Social Profiles on a local *MariaDB* data base management system. The client-server communication is managed via the *OAuth2*, an industry-standard protocol for providing token-based authorization flows for web applications, mobile phones, and living room devices. A keep-alive mechanism has been also implemented to detect dynamic join/disjoin of passengers. Finally, a persistent buffering of social profiles and playlists has been implemented to speed up the recommendation requests time.

Six people have been involved to carry out the following sessions: 8 sessions made by 2 passengers, 5 sessions made by 3 passengers, and 5 sessions made by 4 passengers.

At the end of a recommended track, each passenger has provided a binary like/dislike rating. At the end of the recommended play list, for each passenger, the approval rate has been calculated as follows:

$$approval\ rate = \frac{|liked\ tracks|}{|total\ tracks|} \times 100 \quad (1)$$

As a result, Figure 6, Figure 7 and Figure 8 show the approval rate histograms for sessions of 2, 3 and 4 passengers, respectively. It is clear that, for increasing number of passengers, the approval rate decreases. This can be ascribed to the smaller common tracks, artists and genres between passengers. Figure 9 clearly shows this trend, via the mean approval rate against passengers' number.

Finally, Figure 10 shows the generalization ability of the recommender, i.e., to go beyond the passenger's playlist (known tracks). It is calculated as follows:

$$generalization\ rate\ =\ \frac{|known\ tracks|}{|liked\ tracks|} \times 100 \quad (2)$$

Assuming that the tracks in its own playlist are all liked, the maximum value is 1 (i.e., no additional liked tracks). For increasing unknown tracks that are liked, the value decreases (i.e., better generalization).

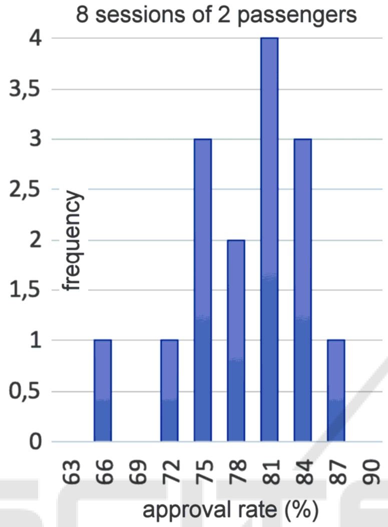

Figure 6: Approval rate histogram for 2 passengers.

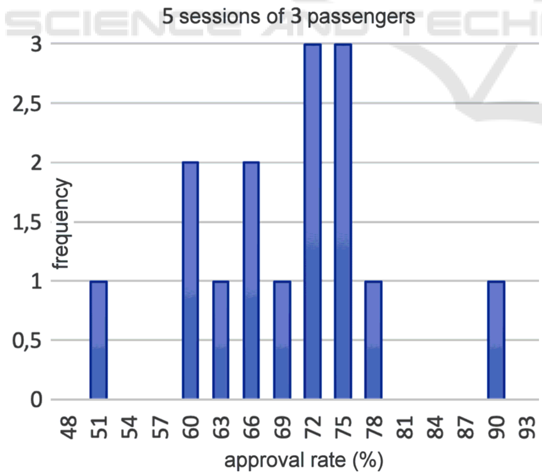

Figure 7: Approval rate histogram for 3 passengers.

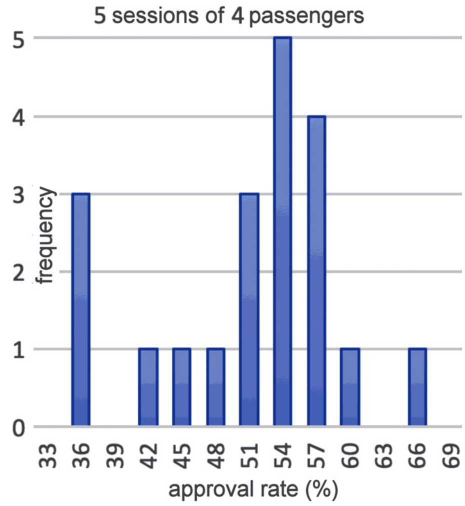

Figure 8: Approval rate histograms for 4 passengers.

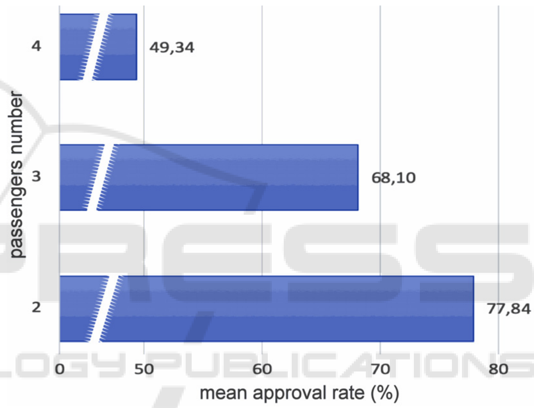

Figure 9: Mean approval rate against passengers' number.

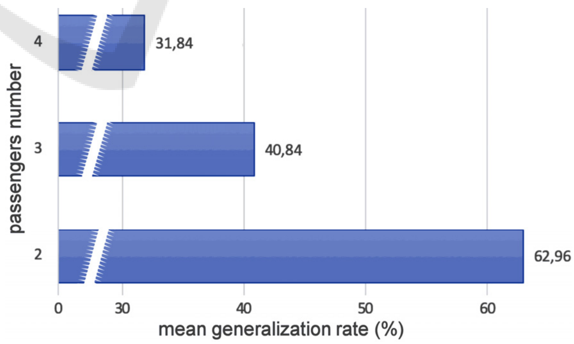

Figure 10: Mean generalization rate against passengers' number.

Overall, for increasing passengers the generalization ability increases, for the higher variety of tracks, authors and genres available.

4 CONCLUSIONS

In this paper, group-wise Temporary Mobile Social Networking recommender is proposed as a design paradigm for in-car entertainment. Specifically, in the context of social music, a functional design is illustrated. A prototype has been implemented, based on Spotify Analytics and Raspberry PI3, and experimented involving six people on various sessions.

The achieved approval and generalization rates show that, for increasing number of passengers, the approval rate decreases, for the smaller common tracks, artists and genres between passengers. However, for increasing number of passengers, the generalization ability increases, providing liked tracks that are not already known.

Although a more in-depth exploration of the techniques is needed, together with an enrichment of the experiments, the early results are promising, and show the potential of the proposed approach.

An extensive study in this direction can be a future work to bring a stronger contribution in the field.

ACKNOWLEDGEMENTS

Work partially supported by the Italian Ministry of Education and Research (MIUR) in the framework of the CrossLab project (Departments of Excellence, Lab Cloud Computing, Big Data & Cybersecurity, Lab Augmented Reality, Lab Advanced Manufacturing).

REFERENCES

Bilius, L. B., & Vatavu, R. D. (2020). A multistudy investigation of drivers and passengers' gesture and voice input preferences for in-vehicle interactions. Journal of Intelligent Transportation Systems, 25(2), 197-220.

Castellano G., Cimino M.G.C.A., Fanelli A.M., Lazzerini B., Marcelloni F., Torsello M.A. (2013). A Collaborative Situation-Aware Scheme based on an Emergent Paradigm for Mobile Resource Recommenders, Journal of Ambient Intelligence and Humanized Computing, 4:421-437, doi: 10.1007/s12652-012-0126-y

Ciaramella, A., Cimino, M.G.C.A., Marcelloni F., Straccia, U. (2010). Combining Fuzzy Logic and Semantic Web to Enable Situation-Awareness in Service Recommendation", Lecture Notes in Computer Science, 6261:31-45.

Cimino M.G.C.A., Lazzerini B., Marcelloni F., Castellano G., Fanelli A.M., Torsello M.A. (2011). A Collaborative Situation-Aware Scheme for Mobile Service Recommendation, Proceedings of the 11th International Conference on Intelligent Systems Design and Applications, 130-135 (2011), doi: 10.1109/ISDA.2011.6121643

Cimino, M.G.C.A., Palumbo, F., Vaglini, G. *et al.* (2017) Evaluating the impact of smart technologies on harbor's logistics via BPMN modeling and simulation. Information Technology Management, 18, 223–239.

Coppola, R., & Morisio, M. (2016). Connected car: technologies, issues, future trends. ACM Computing Surveys (CSUR), 49(3), 1-36.

Foglia, P., & Solinas, M. (2014). Exploiting replication to improve performances of NUCA-based CMP systems. ACM transactions on embedded computing systems (TECS), 13(3s), 1-23.

Foglia, P., Zanda, M., & Prete, C.A.:, I. (2014). Towards relating physiological signals to usability metrics: a case study with a web avatar. WSEAS Transactions on Computers, 13, 624.

Lu, J., Wu, D., Mao, M., Wang, W., & Zhang, G. (2015). Recommender system application developments: a survey. Decision Support Systems, 74, 12-32.

MO, Music Ontology, musicontology.com, accessed 2022.

Polestar 2 electric car, www.polestar.com/us/polestar-2/, accessed Jan 2022.

Rong, Y., Han, C., Hellert, C., Loyal, A., & Kasneci, E. (2021). Artificial Intelligence Methods in In-Cabin Use Cases: A Survey. IEEE Intelligent Transportation Systems Magazine.

Spotify API, support.spotify.com/us/article/spotify-in-the-car/, accessed Jan 2022.

Spotify CL, Collaborative Playlist, support.spotify.com/us/article/collaborative-playlists/, accessed Jan 2022.

Spotify FM, Family Mix, support.spotify.com/us/article/family-mix/, accessed Jan 2022.

Spotify GS, Group Session, support.spotify.com/us/article/group-session/, accessed Jan 2022,

Yin, Y., Xia, J., Li, Y., Xu, W., & Yu, L. (2019). Group-wise itinerary planning in temporary mobile social network. IEEE Access, 7, 83682-83693.

Zhang, S., Yao, L., Sun, A., & Tay, Y. (2019). Deep learning based recommender system: A survey and new perspectives. ACM Computing Surveys (CSUR), 52(1), 1-38.