Psychology-informed Recommender Systems

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ABSTRACT

Personalized recommender systems have become indispensable in today's online world. Most of today's recommendation algorithms are data-driven and based on behavioral data. While such systems can produce useful recommendations, they are often uninterpretable, black-box models, which do not incorporate the underlying cognitive reasons for user behavior in the algorithms' design. The aim of this survey is to present a thorough review of the state of the art of recommender systems that leverage psychological constructs and theories to model and predict user behavior and improve the recommendation process. We call such systems *psychology-informed recommender systems*. The survey identifies three categories of psychology-informed recommender systems: *cognition-inspired*, *personality-aware*, and *affect-aware* recommender systems. Moreover, for each category,

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we highlight domains, in which psychological theory plays a key role and is therefore considered in the recommendation process. As recommender systems are fundamental tools to support human decision making, we also discuss selected phenomena related to human decision making that impact the interaction between a user and a recommender. Besides, we discuss related work that investigates the evaluation of recommender systems from the user perspective and highlight user-centric evaluation frameworks. We discuss potential research tasks for future work at the end of this survey.

1

Introduction

1.1 Motivation

In the past twenty years, research on recommender systems has emerged as a growing field within computer science (Ricci *et al.*, 2011). The emergence of online marketplaces, online social networks, online collaboration platforms, and online social information systems (Caverlee *et al.*, 2010) has created a need to support users with recommendations to help them cope with the increase of information and items online (Liu *et al.*, 2014).

A large amount of work exists that has tackled recommender systems research from a broad range of perspectives. Resources like the *Recommender Systems Handbook* (Ricci *et al.*, 2015) or *Recommender systems: An Introduction* (Jannach *et al.*, 2010) give a comprehensive overview of the field. So do review articles such as the one by (Jannach *et al.*, 2012). Recent surveys provide a concise overview of explainable recommendations (Zhang, Chen, *et al.*, 2020), deep learning in recommender systems (Xu *et al.*, 2020), adversarial recommender systems (Deldjoo *et al.*, 2021b) or conversational recommender systems Jannach *et al.* (2012).

Early work on recommender systems was motivated by the observation that humans tend to base their decisions on the recommendations provided by their social surrounding (Ricci *et al.*, 2011). Correspondingly, the first algorithms developed as recommender systems aimed to mimic this behavior (Resnick and Varian, 1997; Ricci *et al.*, 2011). In the early 2000s, the use of psychological models in recommender systems research has gained traction. Pioneering work was carried out by Gustavo Gonzalez, Timo Saari, and Judith Masthoff, which exploited the psychological characteristics of users to improve the recommendation process. To that end, Gonzales et al. (González *et al.*, 2002; González *et al.*, 2004) considered emotional aspects of the user to generate personalized recommendations. Saari et al. (Saari *et al.*, 2004b; Turpeinen and Saari, 2004; Saari *et al.*, 2004a; Saari *et al.*, 2004a; Saari *et al.*, 2005) designed recommender systems that incorporate a user's emotion and attention, as well as other related constructs, to deliver recommendations (Nunes, 2008). Masthoff et al. (Masthoff, 2004b; Masthoff, 2004a; Masthoff, 2005; Masthoff and Gatt, 2006), assessed the user satisfaction of individual users and predicted group satisfaction when recommending sequences of items to user groups. Their intuition was that the first few recommendations in a list of recommendations influence the mood of the user. That mood, in turn, can impact the views the user has about the next items in the recommendation list (Nunes, 2008). Felfernig *et al.* (2007) used insights from decision psychology to gain a deeper understanding of online buyer behavior and to improve knowledge-based recommender systems.

In the present survey article, we provide a review of research strands in the recommender systems community that enrich data-driven recommendation techniques with psychological constructs to design or improve recommender systems. We call such systems *psychology-informed recommender systems.*

This survey is organized as follows. We first give an introduction into common recommender systems methods in Section 1.2, and then, in Section 1.4, briefly describe our survey method and research scope. Next, in Section 2, we review related work on psychology-informed recommender systems, which we categorize into *cognition-inspired*, *personality-aware*, and *affect-aware* recommender systems. Also, in Section 3, we review works that investigate various decision-psychological phenomena that come into play when users interact with a recommender system. Besides, in Section 4, we discuss works that investigate recommender systems' evaluation from the user perspective. We conclude in Section 5 with key findings and possible directions for future work.

1.2 Main Approaches to Recommender Systems

The most prominent recommendation approaches are collaborative filtering (CF), content-based filtering (CBF), hybrid combinations of both (Ricci *et al.*, 2015), as well as knowledge-based recommmender systems (Burke, 2000b). CF (Schafer *et al.*, 2007) exploits interactions between users and items such as ratings and creates a user–item matrix that is then used to predict missing ratings for pairs of users and items. CF then recommends the items with the highest predicted ratings, with which the target user has not yet interacted. One can distinguish between *model-based CF* and *memory-based CF* (Koren and Bell, 2015). In the case of *model-based CF* (Aggarwal, 2016), the algorithm first projects users and items into a low-dimensional space and then, finds similar users/items in this space. In the case of *memory-based CF* (Sarwar *et al.*, 2001), CF computes similarities between users/items directly from the user–item matrix. *Memory-based CF* can be further divided into *user-based CF* and *item-based CF*, depending on whether recommendations are produced based on user or item similarity.

CBF exploits characteristic properties of items (e.g., movie genres) to recommend items with similar attributes as items the target user has liked in the past (Ricci *et al.*, 2015). For a recent overview of new trends in CBF, please refer to Lops *et al.*, 2019. Correspondingly, hybrid recommender systems (Burke, 2002) are, most commonly, a combination of collaborative and content-based methods. For example, when using CF in a cold-start scenario, a hybrid approach can incorporate CBF to predict items based on their features (Cremonesi *et al.*, 2011b; Ricci *et al.*, 2011).

In contrast to CF and CBF, knowledge-based recommender systems (Burke, 2000b) do not require a user history. Instead, they make use of pre-existing knowledge about the user and the application domain to reason about potentially relevant items. One can distinguish between two main types of knowledge-based recommender systems, namely, constraint-based recommender systems (Felfernig and Burke, 2008; Atas *et al.*, 2019) and case-based recommender systems (Lorenzi and Ricci, 2003; Burke, 2000a). In constraint-based recommender systems, explicitly defined constraints govern which items should be recommended to a user in a given context, whereas the constraints refer to the user and/or the item domain. Case-based recommender systems are early examples of psychology-informed recommender systems, which model reasoning as primarily memory-based (Leake, 2015). In this paper, they are, therefore, reviewed in more detail (see Section 2.1.4).

1.3 Selected Recommender Systems Software and Datasets

To facilitate getting started with recommender systems experiments, we provide an overview of relevant resources. Tables 1.1 and 1.2 give a non-exhaustive list of software[1] (libraries and open-source code repositories) and datasets, respectively.[2] We focus on the most popular resources as well as on those that provide code and data relevant to psychology-informed recommendation.

1.4 Survey Method and Research Scope

For this survey, we investigated research articles that appeared in relevant publication outlets in the fields of computer science, psychology, and human-computer-interaction. Regarding the scope of our review, we focus on papers that describe algorithms, techniques, and systems that exploit psychological features of the user for improving the recommendation process (see Table 1.5, Table 1.6, Table 1.7, Table 1.8, and Table 1.9). Also, we visualize the reviewed papers as a timeline in Table 1.3, and Table 1.4 to show the evolution of techniques over time. Please note that we split the timeline visualization into periods from 1885 to 2010 and 2011 to 2021 due to space constraints.

[1]See also https://github.com/grahamjenson/list_of_recommender_systems & https://recommender-systems.com/resources/

[2]GroupLens' list of datasets: https://grouplens.org/datasets/, Julian McAuley's list: https://cseweb.ucsd.edu/~jmcauley/datasets.html

Table 1.1: Overview of selected software for recommender systems.

Name	URL	Comments
LKPy	https://github.com/lenskit/lkpy	Python; classical models
Surprise	https://github.com/NicolasHug/Surprise	Python; classical models
pyRecLab	https://github.com/gasevi/pyreclab	Python; classical models
LibRec	https://github.com/guoguibing/librec	Java; classical models
Elliot	https://github.com/sisinflab/elliot	Python; classical and deep models
NeuRec	https://github.com/wubinzzu/NeuRec	Python; deep models
Spotlight	https://github.com/maciejkula/spotlight	Python; classical and deep models
Implicit	https://github.com/benfred/implicit	Python; for implicit-feedback datasets
TagRec	https://github.com/learning-layers/TagRec	Java; cognition-inspired and classical models

Table 1.2: Overview of selected datasets for recommender systems.

Name	URL	Domain	Comments
MovieLens	https://grouplens.org/datasets/movielens	movie	ratings, tags
FilmTrust	https://guoguibing.github.io/librec/datasets.html	movie	ratings, trust scores
Epinions, Ciao	https://www.cse.msu.edu/~tangjili/datasetcode/truststudy.htm	movie	movie ratings, reviews, review ratings, trust scores
Personality 2018	https://grouplens.org/datasets/personality-2018	movie	movie preferences, personality information, ratings (with timestamps)
Serendipity 2018	https://grouplens.org/datasets/serendipity-2018	movie	movie ratings (with timestamps), survey responses related to serendipity preferences
Million Song Dataset	http://millionsongdataset.com	music	listening events, tags, genres, lyrics
LFM-1b	http://www.cp.jku.at/datasets/LFM-1b	music	music listening events (with time stamps), tags, user demographics
Million Playlist Dataset	https://www.aicrowd.com/challenges/spotify-million-playlist-dataset-challenge	music	public user-generated playlists from Spotify
HetRec 2011	https://grouplens.org/datasets/hetrec-2011	social networking, social tagging systems	tag assignments, bookmarks, movie genres, movie genre assignments

The identification of papers for our survey was done according to the following strategy. We first considered the proceedings and volumes of a set of relevant conference series (e.g., *User Modelling, Adaptation and Personalization*, *ACM Recommender Systems Conference*, *The Web Conference*, *ACM SIGIR Conference on Research and Development in Information Retrieval*, *ACM CHI Conference on Human Factors in Computing Systems*, *ACM Hypertext*, *IEEE/WIC/ACM International Conference on Web Intelligence*) and journals (e.g., *User Modeling and User-Adapted Interaction*, *Transaction on Intelligent Information Systems*, *Cognitive Science*, *Journal of Consumer Research*, *IEEE Transactions on Affective Computing*, *Computers in Human Behavior*, *Journal of Personality and Social Psychology*, *ACM Transactions on Intelligent Information Systems*) for articles that fall into the above-described scope. Additionally, we used the keywords "psychology recommender systems", "psychology informed recommender", "cognition recommender", "stereotypes recommender", "case-based recommender", "affective recommender", "emotion recommender", "personality recommender", "decision making recommender", "user-centric recommender", "user evaluation recommender", "user experience recommender", "nudging recommender systems", "persuasion recommender", "cognitive dissonance recommender", "interaction recommender", and "interfaces recommender" to search for papers in Google Scholar. Using the resulting set of articles as a starting point, we followed the references of the retrieved articles to find additional papers.

A few survey works on the topic of psychological models in the context of recommendations already exist. When looking at these existing works, we find that some works on psychology-informed recommender systems are also summarized by Tkalcic and Chen (2015a) with respect to personality-based recommender systems, personality and learning styles (Graus and Ferwerda, 2019), and in (Tkalcic *et al.*, 2011) in terms of affective-based systems. Additionally, Buder and Schwind (2012) discuss personalized recommender systems as well as psychological theories and models that describe learning processes and mechanisms in educational contexts. They, however, focus only on learning as a domain. Yoo *et al.* (2012), and in earlier work, Gretzel and Fesenmaier (2006), discuss recommender systems and their persuasive role in decision-making processes; Felfernig *et al.* (2008b) outline persuasion in knowledge-based recommendation. These works also shed light on psychological constructs that play a role in persuasion, which corresponds to a mechanism that can be used in recommender systems to influence choices. For a detailed overview of persuasive recommender systems, please refer to Yoo *et al.* (2012). Jesse and Jannach (2021) review related work on nudging with recommender systems. They also discuss 58 psychological mechanisms that are described in the reviewed works. Pu *et al.* (2012) present a survey on evaluating recommender systems from the user perspective, including preference elicitation and refinement, presentation of recommendations, and user-centric evaluation frameworks. Also, the authors summarize the most important results in the form of design guidelines for effective recommender systems.

Explanations of algorithmic decisions made by artificial intelligence help making algorithms more transparent. The recent survey on explainable recommendations by Zhang, Chen, *et al.* (2020) discusses related work on explainable recommendation models. For an overview of the body of research on explanations in artificial intelligence in light of the social sciences, please refer to Miller (2019).

In Zhang, Chen, *et al.* (2020) explanations in recommender systems are related to cognitive science and human decision making. As the authors describe, humans sometimes decide using rational and careful reasoning, while in other cases, they first decide and find explanations for their decisions later. This is in line with the typical approaches to designing explainable recommendation models: either, such models are already designed with transparency and explainability in mind, or post-hoc explanations are used to explain decisions made by black box models (Lipton, 2018; Miller, 2019). Tran *et al.* (2019a) and Tran *et al.* (2020) take into account findings from social choice theory, i.e., the study of collective choices that impact groups (Sen, 1986), to introduce explanations to increase fairness, consensus, and satisfaction of users with group recommendations.

Given the rich body of work on explainability in recommender systems, which is already presented in the survey by Zhang, Chen, *et al.* (2020), we do not focus on this topic in the paper at hand, instead refer the reader to Zhang, Chen, *et al.* (2020) as well as to the respective chapter in the recommender systems handbook by Tintarev and Masthoff (2015).

The field of group recommender systems also uses social psychology constructs to produce recommendations that are helpful for groups. In this paper, we touch upon them when we discuss relevant work on personality in group recommender systems. For an overview of group recommender systems and mechanisms to model group behavior, please also refer to Felfernig *et al.* (2018c) and Masthoff (2015).

Summing up, with this article, we aim to close the gap between a computer science perspective (in particular, a technical recommendation systems point of view) and a psychological perspective. We hope to appeal to researchers in the information retrieval and recommendation systems communities who want to delve deeper into the psychological foundations of recommendation systems research. In addition, we also address an audience with psychological background who strives to deepen their knowledge on how psychological constructs and models can be incorporated into recommendation systems. Please note that basic knowledge of recommendation systems and psychology is sufficient to understand the article.

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Table 1.3: Part I of a timeline visualization of the reviewed publications to depict the evolution of techniques (from 1885 to 2010); note that the earliest works are psychological papers that describe relevant effects).

	Cognition-inspired	Personality-aware	Affect-aware	Decision Making	User-centric Eval.
1885	Ebbinghaus (1885)				
1954					Festinger (1954)
1957				Deese and Kaufman (1957)	
1966				Glanzer and Cunitz (1966)	
1967	Neisser (1967)				
1974	Anderson (1974)			Tversky and Kahneman (1974)	
1978	Matlin and Stang (1978)				
1979	Elaine Rich (1979)				
1980			Russell (1980) and Mehrabian (1980)		
1981				Tversky and Kahneman (1981)	
1982				Huber *et al.* (1982)	
1984	Ingwersen (1984)				McCroskey *et al.* (1984)
1990	Ormerod (1990)				
1992	Bellandi *et al.* (2012)			Tversky and Kahneman (1992)	
1993	Fehling (1993)			Payne *et al.* (1993)	
1994	Lamming and Flynn (1994)				Resnick *et al.* (1994)
1995		Costa and McCrae (1995)			
1997	Anderson *et al.* (1997)				
1999	Burke (1999)		Shiv and Fedorikhin (1999)		Berdichevsky and Neuenschwander (1999)
2000					Herlocker *et al.* (2000)
2001	Ricci and Werthner (2001)			Mandl *et al.* (2011)	Allen and Yen (2001)
2002	Ricci *et al.* (2002), Aguzzoli *et al.* (2002), and Gemmell *et al.* (2002)	Charness and Rabin (2002)		Chapman and Johnson (2002)	Fogg (2002) and Swearingen and Sinha (2002)
2003					McNee *et al.* (2003) and Cosley *et al.* (2003)
2004					Herlocker *et al.* (2004)
2005	Anderson (2005)			Dyer (2005)	Ziegler *et al.* (2005) and Ling *et al.* (2005)
2006	Ricci *et al.* (2006)			Pu and Chen (2006)	McNee *et al.* (2006a), McNee *et al.* (2006b), and Gretzel and Fesenmaier (2006)
2007	Fum *et al.* (2007), Rutledge-Taylor and West (2007), and Elsweiler *et al.* (2007)		Fontaine *et al.* (2007)	Felfernig *et al.* (2007)	Kuan *et al.* (2007) and Nguyen *et al.* (2007)
2008	Glushko *et al.* (2008), Fu (2008), Rutledge-Taylor *et al.* (2008), and Prins *et al.* (2008)				O'Brien and Toms (2008) and Felfernig *et al.* (2008a)
2009	Maanen and Marewski (2009), Gong (2009), and Yang and Wang (2009)			Craswell *et al.* (2008) and Thaler and Sunstein (2009)	
2010	Fu *et al.* (2010), Fu and Kannampallil (2010), and Yu and Li (2010)	Quijano-Sanchez *et al.* (2010)		Mojzisch and Schulz-Hardt (2010)	Bollen *et al.* (2010), Chen and Pu (2010b), Chen and Pu (2010a), O'Brien and Toms (2010), and Nanou *et al.* (2010)

Table 1.4: Part II of a timeline visualization of the reviewed publications to depict the evolution of techniques (from 2011 to 2021)

	Cognition-inspired	Personality-aware	Affect-aware	Decision Making	User-centric Eval.
2011	Blanco-Fernández *et al.* (2011)	Rentfrow *et al.* (2011) and Masthoff (2011)	Tkalcic *et al.* (2011)	Adomavicius *et al.* (2011), Zhang (2011), Mandl *et al.* (2011), and Moraveji *et al.* (2011)	Shani and Gunawardana (2011), Hu and Pu (2011), Pu *et al.* (2011), Ekstrand *et al.* (2011), Schwind *et al.* (2011), Yoo and Gretzel (2011), Knijnenburg *et al.* (2011), Cremonesi *et al.* (2011a), and Yannakakis and Hallam (2011)
2012	Fu and Dong (2012), Psychology (2012), Bollen *et al.* (2012), Wang and Yang (2012), Bellandi *et al.* (2012), and Doherty *et al.* (2012)	Tintarev and Masthoff (2012)	Konstan and Riedl (2012)	Yoo *et al.* (2012), Bettman *et al.* (1998), Teppan and Felfernig (2012), Murphy *et al.* (2012), Ranjith (2012), Bateman *et al.* (2012), and Smids (2012)	Pu *et al.* (2012), Knijnenburg *et al.* (2012a), Konstan and Riedl (2012), Knijnenburg *et al.* (2012b), Yoo *et al.* (2012), and Cremonesi *et al.* (2012)
2013	Sabater-mir *et al.* (2013), Kowald *et al.* (2013), Seitlinger *et al.* (2013), and Fehling (1993)	Golbeck and Norris (2013), Chen *et al.* (2013b), Wu *et al.* (2013), Tintarev *et al.* (2013), and Cantador *et al.* (2013)	Zheng (2013)	Chen *et al.* (2013a), Adomavicius *et al.* (2013), and Thaler *et al.* (2013)	
2014	Beel *et al.* (2014), Kowald *et al.* (2014), Zhao *et al.* (2014), Missier (2014), and Chavarriaga *et al.* (2014)			Adomavicius *et al.* (2014) and Hofmann *et al.* (2014)	Ekstrand *et al.* (2014), Surendren and Bhuvaneswari (2014), and Schwind and Buder (2014)
2015	Ren (2015), Kowald and Lex (2015), Musto *et al.* (2015), Bousbahi and Chorfi (2015), Muhammad *et al.* (2015), Beel and Langer (2015), and Beel *et al.* (2015)	Tkalcic and Chen (2015a)	Orellana-Rodriguez *et al.* (2015) and Deng *et al.* (2015)	Jameson *et al.* (2015), Karimi *et al.* (2015), Teppan and Zanker (2015), Stettinger *et al.* (2015a), Stettinger *et al.* (2015b), Turland *et al.* (2015), and Sunstein (2015)	Knijnenburg and Willemsen (2015)
2016	Seitlinger and Ley (2016), Jones (2016), Trattner *et al.* (2016), Kowald and Lex (2016), Stanley and Byrne (2016), Kopeinik *et al.* (2016), Schnabel *et al.* (2016), Harvey *et al.* (2016), and Mozer and Lindsey (2016)	Karumur *et al.* (2016), Fernandez-Tobias *et al.* (2016), and Rossi and Cervone (2016)		Grüne-Yanoff and Hertwig (2016)	Kaminskas and Bridge (2016), Ekstrand and Willemsen (2016), and Willemsen *et al.* (2016)
2017	Beel (2015), Kowald *et al.* (2017b), Kopeinik *et al.* (2017b), and Kopeinik *et al.* (2017a)	Ferwerda *et al.* (2017b), Ferwerda *et al.* (2017a), Nalmpantis and Tjortjis (2017), and Delic *et al.* (2017)	Piazza *et al.* (2017), Schedl *et al.* (2018), and Ravi and Vairavasundaram (2017)	Joachims *et al.* (2017), Elsweiler *et al.* (2017), Esposito *et al.* (2017), and Hertwig and Grüne-Yanoff (2017)	Herlocker *et al.* (2017), Jugovac and Jannach (2017), and Meske and Potthoff (2017)
2018	ALRossais and Kudenko (2018), ALRossais (2018), Thaker *et al.* (2018), Yago *et al.* (2018), Farrell and Lewandowsky (2018), and Chmiel and Schubert (2018)	Nguyen *et al.* (2018), Karumur *et al.* (2018), Wu *et al.* (2018), Lu and Tintarev (2018), Asabere *et al.* (2018), Adaji *et al.* (2018), and Felfernig *et al.* (2018a)	Ayata *et al.* (2018)	Jugovac *et al.* (2018), Felfernig *et al.* (2018b), Tran *et al.* (2018), Schneider *et al.* (2018), and Grüne-Yanoff *et al.* (2018)	Jugovac *et al.* (2018)
2019	Kowald *et al.* (2019), Jorro-Aragoneses *et al.* (2019), Zheng *et al.* (2019), Yang *et al.* (2019), and Zhang *et al.* (2019b)	Yang and Huang (2019), Sertkan *et al.* (2019), Recio-Garcia *et al.* (2009), and Nguyen *et al.* (2019)	Mizgajski and Morzy (2019)	Köcher *et al.* (2019), Karlsen and Andersen (2019), and Caraban *et al.* (2019)	Jin *et al.* (2019) and Goretzko *et al.* (2019)
2020	Kahana (2020), Lex *et al.* (2020), Kowald *et al.* (2020a), Contreras and Salamó (2020), and Güell *et al.* (2020)	Beheshti *et al.* (2020)	Perloff (2020)	Zimmerman *et al.* (2020)	
2021				Jesse and Jannach (2021)	Ortloff *et al.* (2021)

Table 1.5: Overview of surveyed papers that implement cognitive models to design and improve recommendation techniques.

Cognition	Sec.	References
Stereotypes	2.1	Elaine Rich, 1979; Rich, 1989; Blanco-Fernández *et al.*, 2011; Beel *et al.*, 2014; Beel and Langer, 2015; Beel *et al.*, 2015; Beel, 2015; ALRossais and Kudenko, 2018; ALRossais, 2018
Cogn. Models	2.1.1	Anderson, 2005; Fum *et al.*, 2007; Farrell and Lewandowsky, 2018; Neisser, 1967; Ormerod, 1990; Psychology, 2012; Jones, 2016; Glushko *et al.*, 2008; Fu, 2008; Fu *et al.*, 2010; Fu and Kannampallil, 2010; Fu and Dong, 2012; Anderson *et al.*, 1997
Memory	2.1.2	Seitlinger and Ley, 2016; Kahana, 2020; Ingwersen, 1984; Rutledge-Taylor and West, 2007; Rutledge-Taylor *et al.*, 2008; Anderson, 1974; Bollen *et al.*, 2012; Matlin and Stang, 1978; Ebbinghaus, 1885; Ebbinghaus, 2013; Yu and Li, 2010; Ren, 2015; Chmiel and Schubert, 2018; Yang *et al.*, 2019; Sabater-mir *et al.*, 2013; Maanen and Marewski, 2009; Kowald *et al.*, 2014; Trattner *et al.*, 2016; Kowald *et al.*, 2013; Kowald *et al.*, 2017b; Kowald and Lex, 2016; Kowald and Lex, 2015; Stanley and Byrne, 2016; Kowald *et al.*, 2020a; Kopeinik *et al.*, 2016; Kopeinik *et al.*, 2017b; Kowald *et al.*, 2019; Lex *et al.*, 2020; Zhao *et al.*, 2014; Missier, 2014; Schnabel *et al.*, 2016; Elsweiler *et al.*, 2007; Harvey *et al.*, 2016; Doherty *et al.*, 2012; Gemmell *et al.*, 2002; Lamming and Flynn, 1994
Attention	2.1.3	Seitlinger *et al.*, 2013; Kowald *et al.*, 2013; Kopeinik *et al.*, 2017a
CBR	2.1.4	Hammond, 2012; Kolodner, 2014; Riesbeck and Schank, 2013; Kolodner, 1992; Tversky, 1977; Burke *et al.*, 1996; Burke, 1999; Ricci and Werthner, 2001; Ricci *et al.*, 2002; Ricci *et al.*, 2006; Aguzzoli *et al.*, 2002; Gong, 2009; Yang and Wang, 2009; Wang and Yang, 2012; Musto *et al.*, 2015; Bousbahi and Chorfi, 2015; McSherry, 2005; Sharma and Ray, 2016; Muhammad *et al.*, 2015; Jorro-Aragoneses *et al.*, 2019; Pu *et al.*, 2012; McGinty and Reilly, 2011; Contreras and Salamó, 2020; Contreras and Salamó, 2020; Güell *et al.*, 2020
Competence	2.1.5	Fehling, 1993; Bellandi *et al.*, 2012; Chavarriaga *et al.*, 2014; Prins *et al.*, 2008; Yago *et al.*, 2018; Mozer and Lindsey, 2016; Thaker *et al.*, 2018

Table 1.6: Overview of our surveyed papers describing personality-aware recommendation algorithms and systems.

Personality-aware Rec. Sys.	Sec.	References
Personality	2.2	Tkalcic and Chen, 2015a; Ferwerda *et al.*, 2017b; Golbeck and Norris, 2013; Rentfrow *et al.*, 2011; Chen *et al.*, 2013b; Wu *et al.*, 2013; Nguyen *et al.*, 2018; Karumur *et al.*, 2018; Karumur *et al.*, 2016
Personality Elicitation	2.2.1	McCrae and John, 1992; Thomas, 1992; Felfernig *et al.*, 2018d; Holland, 1997; Bologna *et al.*, 2013; Stewart, 2011; Konert *et al.*, 2013; Paiva *et al.*, 2015; Goldberg *et al.*, 2006; Gosling *et al.*, 2003; John and Srivastava, 1999; Berkovsky *et al.*, 2019; Wu *et al.*, 2019; Ferwerda and Tkalcic, 2018; Golbeck *et al.*, 2011a; Golbeck *et al.*, 2011b; Golbeck, 2016
Personality Traits in RecSys	2.2.2	Asabere *et al.*, 2018; Yang and Huang, 2019; Adaji *et al.*, 2018; Nalmpantis and Tjortjis, 2017; Cantador *et al.*, 2013; Gelli *et al.*, 2017; Tintarev *et al.*, 2013; Wu *et al.*, 2018; Ferwerda *et al.*, 2017a; Lu and Tintarev, 2018; Fernandez-Tobias *et al.*, 2016; Beheshti *et al.*, 2020; Sertkan *et al.*, 2019
Personality in Group RecSys	2.2.3	Recio-Garcia *et al.*, 2009; Felfernig *et al.*, 2018a; Masthoff, 2011; Quijano-Sanchez *et al.*, 2010; Rossi and Cervone, 2016; Costa and McCrae, 1995; Charness and Rabin, 2002; Delic *et al.*, 2017; Nguyen *et al.*, 2019

Table 1.7: Overview of the surveyed papers describing affect-aware recommendation algorithms and systems.

Affect-aware RecSys	Sec.	References
Affect	2.3	Shiv and Fedorikhin, 1999; Orellana-Rodriguez *et al.*, 2015; Piazza *et al.*, 2017; Ferwerda *et al.*, 2017b; Golbeck and Norris, 2013; Rentfrow *et al.*, 2011; Chen *et al.*, 2013b; Wu *et al.*, 2013; Mizgajski and Morzy, 2019; Schäfer, 2016; Schedl *et al.*, 2018; Zheng, 2013
Modeling Affect	2.3.1	Russell, 1980; Mehrabian, 1980; Fontaine *et al.*, 2007
Affect in RecSys	2.3.2	Tkalcic *et al.*, 2011; Ravi and Vairavasundaram, 2017; Deng *et al.*, 2015; Ayata *et al.*, 2018

Table 1.8: Overview of the surveyed papers describing mechanisms of human decision making in light of recommender systems research.

Human Decision Making	Sec.	References
Decision Making	3	Yoo *et al.*, 2012; Chen *et al.*, 2013a; Bettman *et al.*, 1998; Jameson *et al.*, 2015; Adomavicius *et al.*, 2013; Tversky and Kahneman, 1974; Chapman and Johnson, 2002; Karimi *et al.*, 2015; Jugovac *et al.*, 2018
Decoy Items	3.1	Payne *et al.*, 1993; Huber *et al.*, 1982; Teppan and Felfernig, 2012; Teppan and Zanker, 2015
Serial Position Effects	3.2	Deese and Kaufman, 1957; Glanzer and Cunitz, 1966; Ranjith, 2012; Murphy *et al.*, 2012; Felfernig *et al.*, 2007; Schnabel *et al.*, 2016; Stettinger *et al.*, 2015a; Tran *et al.*, 2018; Hofmann *et al.*, 2014; Joachims *et al.*, 2017; Craswell *et al.*, 2008; Stettinger *et al.*, 2015b; Dyer, 2005
Framing	3.3	Tversky and Kahneman, 1981; Tversky and Kahneman, 1992; Mandl *et al.*, 2011
Anchor Effects	3.4	Mojzisch and Schulz-Hardt, 2010; Adomavicius *et al.*, 2011; Zhang, 2011; Köcher *et al.*, 2019; Adomavicius *et al.*, 2014; Felfernig *et al.*, 2018b
Nudging	3.5 & 3.6	Thaler and Sunstein, 2009; Thaler *et al.*, 2013; Tversky and Kahneman, 1974; Jesse and Jannach, 2021; Karlsen and Andersen, 2019; Caraban *et al.*, 2019; Elsweiler *et al.*, 2017; Esposito *et al.*, 2017; Turland *et al.*, 2015; Schneider *et al.*, 2018; Sunstein, 2015
Boosting	3.6	Grüne-Yanoff and Hertwig, 2016; Hertwig and Grüne-Yanoff, 2017; Grüne-Yanoff *et al.*, 2018; Zimmerman *et al.*, 2020; Ortloff *et al.*, 2021; Bateman *et al.*, 2012; Moraveji *et al.*, 2011

Table 1.9: Overview of the surveyed papers describing research on user experience and designing user studies.

User-centric Evaluation	Sec.	References
User-centric Evaluation	4.1	Ekstrand and Willemsen, 2016; Knijnenburg *et al.*, 2012a; McNee *et al.*, 2006b; Nalmpantis and Tjortjis, 2017; Chen and Pu, 2005; Konstan and Riedl, 2012; Xiao and Benbasat, 2007; Shin, 2020; McNee *et al.*, 2003; Ziegler *et al.*, 2005; O'Brien and Toms, 2008; Pu and Chen, 2006; Cosley *et al.*, 2003; O'Brien and Toms, 2010
Cognitive Dissonance	4.1.1	Festinger, 1954; Surendren and Bhuvaneswari, 2014; Schwind *et al.*, 2011; Kuan *et al.*, 2007; Schwind and Buder, 2014; Nguyen *et al.*, 2007
Persuasion	4.1.2	Fogg, 2002; Perloff, 2020; Meske and Potthoff, 2017; Yoo *et al.*, 2012; Gretzel and Fesenmaier, 2006; Jugovac *et al.*, 2018; Yoo and Gretzel, 2011; Nanou *et al.*, 2010; Cremonesi *et al.*, 2012; Felfernig *et al.*, 2008a; Herlocker *et al.*, 2000; Tintarev and Masthoff, 2012; Berdichevsky and Neuenschwander, 1999; Smids, 2012
Interactions & Interfaces	4.1.3	Knijnenburg *et al.*, 2011; Knijnenburg and Willemsen, 2015; Bollen *et al.*, 2010; Chen and Pu, 2010b; Chen and Pu, 2010a; Hu and Pu, 2011; Ekstrand *et al.*, 2014; Jugovac and Jannach, 2017
Attitudes & Beliefs	4.1.4	Cremonesi *et al.*, 2011a; Pu *et al.*, 2011; Swearingen and Sinha, 2002; Bollen *et al.*, 2010; Willemsen *et al.*, 2016; Jin *et al.*, 2019
User Study Design	4.2	Allen and Yen, 2001; McCroskey *et al.*, 1984; Yannakakis and Hallam, 2011; O'Brien and Toms, 2008; O'Brien and Toms, 2010; Goretzko *et al.*, 2019; Knijnenburg and Willemsen, 2015; Pu *et al.*, 2011; Knijnenburg *et al.*, 2012b; Ullman and Bentler, 2003

2

Psychology-informed Recommendation Approaches

In this chapter, we review three categories of psychology-informed recommender systems: (i) cognition-inspired, (ii) personality-aware, and (iii) affect-aware recommender systems.

2.1 Cognition-inspired Recommender Systems

Cognition-inspired recommender systems employ models from cognitive psychology to design and improve recommender systems. Cognitive psychology is a field of research within psychology that investigates human mental processes such as decision-making, memory, or attention. Early recommender systems research has extensively drawn on findings from cognitive psychology, among other disciplines (Adomavicius and Tuzhilin, 2005). In this respect, one of the earliest recommender systems was the Grundy system (Elaine Rich, 1979; Rich, 1989) that grouped users into *stereotypes* to create book recommendations. Stereotype-based recommender systems produce recommendations based on generalizing assumptions about users, such as that computer scientists like science fiction books and historians like biographies (Beel *et al.*, 2017). The underlying psychological principle of stereotypes is the *representativeness heuristic* by Kahneman and Tversky (1972), which people apply when making decisions under uncertainty. It is a mental shortcut that people use when assessing if an object belongs to a specific category. They make this decision based on how representative they think the object is for a category.

In the Grundy system, users described their interests based on adjectives, which were then grouped into stereotypes. The psychological literature describes stereotypes as a form of categorization that humans apply to reduce complexity. Using stereotyping, humans group others based on common characteristics. For an overview of the cognitive mechanisms behind stereotyping, please refer to (Hamilton, 1979; Hamilton, 2015). Please note stereotyping is a trivial application of psychological principles to model users.

Later work employed stereotypes in a library reference manager system to produce book recommendations (Beel *et al.*, 2014; Beel and Langer, 2015) and (Beel *et al.*, 2015; Beel, 2015) to recommend research papers to researchers at different stages of their academic career. In the latter case, stereotypes serve as a fallback mechanism when classic approaches such as collaborative filtering cannot deliver recommendations, e.g., in cold-start scenarios. Blanco-Fernández *et al.* (2011) use consumption stereotypes in a knowledge-based recommender system. Recent work by Al-Rossais and Kudenko (ALRossais and Kudenko, 2018; ALRossais, 2018) performs a comparative analysis of the performance of stereotype-based item modeling and non-stereotype-based item modeling. Specifically, they evaluate the efficacy of two stereotype-based recommendation approaches: First, they create user-based stereotypes using demographic data such as age and gender, and second, item-based stereotypes based on user preferences. They find that incorporating stereotypes can improve recommendation accuracy and that stereotypes can help with the new item problem, i.e., an item comes to the system for which no interactions are available. However, the authors also note that the creation of stereotypes is labor-intensive, especially in the case of manually created stereotypes. While stereotypes are a simple technique to model users, in the remainder of this paper, we review works that exploit more complex psychological constructs in recommender systems research.

In the following, we first briefly outline theories of cognitive processes. Subsequently, we review works which use computational cognitive models to generate and improve personalized recommendations.

2.1.1 Computational Modeling of Cognitive Processes

Cognitive processes and cognition are typically studied in cognitive science, a discipline in which researchers from neuroscience, artificial intelligence, and cognitive psychology aim to understand the functioning of the mind (Anderson, 2005). Cognitive scientists have developed a broad range of empirical methods to study cognition (Fum *et al.*, 2007). The predominant empirical approach is to conduct experiments and analyze behavioral data using statistical models from mathematical psychology, whose parameters represent cognitive constructs. A prominent example is the power law of forgetting (Anderson *et al.*, 1997), which models the rate at which the activation of memory units decays in time.

An increasingly popular technique is cognitive-computational modeling (Farrell and Lewandowsky, 2018) – an attempt to specify cognitive assumptions and to simulate parts of the human mind through computable models (Neisser, 1967; Ormerod, 1990; Psychology, 2012).

In recent times, cognitive-computational modeling also allowed to complement experimental studies with more data-driven approaches, which, e.g., make use of large-scale datasets of social information systems (e.g., (Jones, 2016)). Corresponding artifacts within these systems, such as tagged bookmarks can be interpreted as manifestations of cognitive processes (e.g., categorization of Web resources and evolving information needs) and used to test theories of human cognition (e.g., (Glushko *et al.*, 2008)). Illustrative examples can be found in the studies of Fu and colleagues (e.g., (Fu, 2008; Fu *et al.*, 2010; Fu and Kannampallil, 2010; Fu and Dong, 2012)), who draw on the cognitive architecture ACT-R (Anderson *et al.*, 1997) (see below) to perform theory-guided analyses and simulations of users' tagging behavior in social media, resulting in a socio-cognitive user model of social tagging (Fu, 2008; Fu and Dong, 2012).

2.1.2 Cognitive Models of Memory

Memory is a fundamental process of human cognition that supports goal-directed interactions with our physical and social environment (Seitlinger and Ley, 2016). The cognitive process memory enables the encoding and storing of information in memory structures, i.e., short-term, working memory, and long-term memory, so that it can be later retrieved. When information is recorded into memory (i.e., encoded) it is bound to temporal and spatial context information in order to later enable a context-guided search of memory content (i.e., the process of controlled retrieval) (Kahana, 2020). This makes memory processes closely related to research problems in Information Retrieval (Ingwersen, 1984) and Recommender Systems. In the following, we provide a number of examples where recommender systems have been inspired or motivated by memory models.

Memory models have been used in recommender systems in various forms. Rutledge et al. (Rutledge-Taylor and West, 2007; Rutledge-Taylor *et al.*, 2008) propose a recommender system that is based on a cognitive model of human long-term memory, i.e., dynamically structured holographic memory (DSHM) (Rutledge-Taylor and West, 2007), to resemble how a human expert makes recommendations. This system can model various human memory effects such as the fan effect (Anderson, 1974), i.e., recognition times for a concept increases as more information is available about the concept. Bollen *et al.* (2012) exploit positivity effects from human memory theory to investigate temporal dynamics of ratings in recommender systems. According to the psychological literature, memories become more positive over time (Matlin and Stang, 1978). In an offline study, the authors find evidence for the existence of the positivity effect in ratings, i.e., movies receive higher ratings as the time between release date and rating date increases. However, a corresponding user study shows a decline in the rating score when movies were rated in a larger interval between watching and rating.

Another memory model from psychology, the Ebbinghaus forgetting curve (Ebbinghaus, 2013) is used to model changes in the interests of users. The Ebbinghaus forgetting curve is a psychological theory from 1880 that describes the decrease in ability of the human brain to retain memory over time. In recommender systems research, the curve has been used in several works (e.g., (Yu and Li, 2010; Ren, 2015; Chmiel and Schubert, 2018; Yang *et al.*, 2019)) to account for shifts in user interests by weighting the user feedback (e.g., ratings) using a nonlinear, time-based memory decay function. Yu and Li (2010) and Ren (2015) utilize the curve to design a novel collaborative filtering algorithm that accounts for shifts in user interests. Chmiel and Schubert (2018) use the Ebbinghaus forgetting curve to model drifts in user preferences in a music recommender system. Yang *et al.* (2019) use it to derive item embeddings in a collaborative filtering approach. They use the curve to divide user preferences into long-term and short-term preferences where recently rated items are weighted higher than dated items.

Models of human memory are sometimes part of broader *cognitive architectures*, which aim to draw a more holistic picture of how different cognitive domains work together to generate emergent phenomena, such as a coherent thought. For an overview of cognitive architectures, please refer to Chong *et al.* (2007). Sabater-mir *et al.* (2013) use the cognitive architecture Belief/Desire/Intention (BDI) as an intermediate between recommenders and their users. The cognitive architecture ACT-R (short for adaptive control of thought-rational) (Anderson *et al.*, 1997) has been employed in the context of recommender systems in several works (Maanen and Marewski, 2009; Kowald *et al.*, 2014; Trattner *et al.*, 2016; Kowald *et al.*, 2013; Kowald *et al.*, 2017b; Kowald and Lex, 2016; Stanley and Byrne, 2016)). ACT-R describes central cognitive operations of the human mind.

Figure 2.1 depicts the architecture of ACT-R. As illustrated in the figure and described in more detail in Kowald *et al.* (2020a), ACT-R differentiates between the working memory, and the declarative and procedural memory. Information is encoded using a sensory register (i.e., the ultra-short-term memory) and passed to the working memory, which interacts with the procedural and declarative memory. Information can be stored in and retrieved from the declarative memory. In the procedural memory, it can be matched to rules that describe actions. Thus, declarative memory stores factual knowledge and procedural memory stores action sequences. Most works that employ ACT-R in the context of recommender systems focus use the declarative memory,

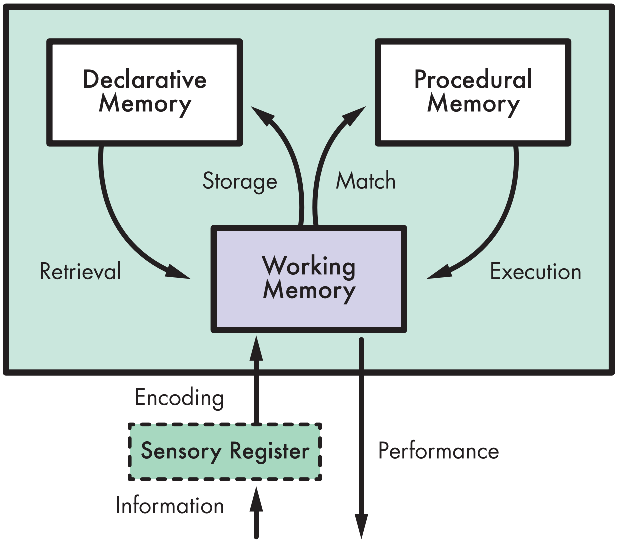

Figure 2.1: Schematic illustration of ACT-R (Kowald *et al.*, 2020a). Please note that the activation equation of the declarative memory module is used in a variety of recommender systems.

in particular, the activation equation of human memory. The activation equation determines the usefulness, i.e., the activation of a memory unit (i.e., in the case of a recommender system, a candidate item) for a user in the current context (Kowald *et al.*, 2020a).

According to ACT-R, the probability that a piece of information (i.e., a memory unit) will be needed to achieve a processing goal, i.e., will be *activated*, depends on its usefulness in the current context as well as a human's prior exposure to this information. This prior exposure can be quantified by two factors: recency and frequency of usage. In addition, the current context in which the information occurs also contributes to its activation. All factors are modeled using ACT-R's activation equation, as given in Equation 2.1.

$$A_i = B_i + \sum_j W_j \cdot S_{j,i} \tag{2.1}$$

where A_i denotes the activation level of a memory unit i, B_i is the base-level activation of i, j is a cue in the current semantic context,

W_j denotes the weighting of j, and $S_{j,i}$ is the strength of activation between j and i. B_i can be computed via the base-level learning (BLL) equation of ACT-R, i.e.:

$$B_i = ln\left(\sum_{j=1}^{n} t_j^{-d}\right) \tag{2.2}$$

where n is the number of times i was activated in the past, t_j is the time since the j^{th} activation of i and d accounts of the time-based decay of activation in memory.

The activation equation of ACT-R has been exploited in several recommender systems. Maanen and Marewski (2009) use it to provide researchers at scientific conferences with recommendations of which talk to attend. Here, the recommender system mimics a researcher's memory since it recommends a talk if words in the talk's abstract have occurred recently and frequently in the scientist's work. Kowald *et al.* (2017b) use the equation to model and explain how Twitter users apply hashtags. They find that almost two-thirds of Twitter users in their datasets reuse their hashtags or social hashtags (i.e., from their friends' network), following a time-based decay in the form of a power-law function, in line with Equation 2.2. Based on these findings, they introduce a novel hashtag recommendation approach that adapts the equation to account for individual and social hashtag reuse and which ranks a user's hashtags and the ones of her friends based on frequency and recency. In other works, Kowald et al. (Kowald *et al.*, 2014; Kowald and Lex, 2016; Kowald and Lex, 2015) and Trattner *et al.* (2016) use the BLL equation (i.e., Equation 2.2) to model tag reuse processes and to recommend items in social tagging systems. Please note that these implementations of the BLL equation are available in the open source recommender systems framework *TagRec* (Kowald *et al.*, 2017a). Stanley and Byrne (2016) combine the equation with a random permutation vector-based model to describe past tagging behavior in StackOverflow and Twitter. Kopeinik *et al.* (2016) use it to recommend learning resources and support collaborative learning with tag recommendations (Kopeinik *et al.*, 2017b). Besides, in (Kowald *et al.*, 2019; Lex *et al.*, 2020), the activation equation is utilized to model music listening behavior and recommend artists and genres, respectively. The latter works show that the resulting computational model can alleviate popularity bias in music recommender systems (Kowald *et al.*, 2020b). Please note that the algorithms based on the activation equation to model music listening behavior are available in the open-source recommender systems framework *TagRec* (Kowald *et al.*, 2017a). Furthermore, Zhao *et al.* (2014) use the activation equation to produce context-aware recommendations for mobile applications as they combine frequency and recency of application use into contextual information.

Finally, recommender systems can support memory processes, as is described in (Missier, 2014). Here, Schnabel *et al.* (2016) propose to support a user's short-term memory by creating a digital short-term memory in the form of shortlists, which contain the items a user is currently considering. Items on the shortlist represent implicit feedback that is exploited to generate additional training data for a recommender system. Additionally, Elsweiler *et al.* (2007) relate the task of supporting memory in retrieving objects to recovering from memory lapses. They show that building upon research on how people recover from memory lapses can help to create better personal information management tools. Other works suggest augmenting human memory via providing documentation of events gathered from external tools such as wearable sensors or cameras (Harvey *et al.*, 2016; Doherty *et al.*, 2012). Related to this, in (Gemmell *et al.*, 2002), the *MyLifeBits* project is presented, which aims to fulfill Vannevar Bush's Memex vision to generate a system that is capable of reminding users of their stored "bits" (e.g., documents or images). A similar initiative, the *Forget-me-not* project, was even already introduced in 1994 (Lamming and Flynn, 1994). Interestingly, the authors state the importance of context for retrieving memory cues, which is in line with the recommendation algorithms mimicking human memory access that have been proposed decades later (e.g., by Kowald *et al.* (2017b)).

2.1.3 Cognitive Models of Attention

Attention is a mechanism to selectively process information in an environment in the face of distraction. Attention is dynamic in nature and hence typically modeled using connectionist models. Connectionism is a research strand in cognitive science, which uses artificial neural networks to study cognition and to model cognitive processes (Buckner and Garson, 2019). In this vein, Seitlinger *et al.* (2013) use the connectionist human memory simulation model ALCOVE (Kruschke, 1992) to implement a novel tag recommendation algorithm termed 3Layers. Kowald *et al.* (2013) enhance the 3Layers algorithm with recency effects by combining it with the BLL equation mentioned before. Another connectionist model is used by Kopeinik *et al.* (2017a), who apply SUSTAIN (Love *et al.*, 2004), a connectionist model of human category learning and successor of ALCOVE, to recommend resources that fit to a user's current attentional focus. Please note that the resulting resource recommendation algorithm is publicly available in the open-source TagRec framework (Kowald *et al.*, 2017a).

The use of memory or attention mechanisms in deep learning-based recommender systems (see e.g. (Zheng *et al.*, 2019)) has gained traction in recent years. To the best of our knowledge, such works typically do not discuss underlying psychological constructs. Therefore, in the present study, such works are omitted. For an overview of deep learning-based recommender systems, see (Zhang *et al.*, 2019b), as well as the recent study by Xu *et al.* (2020).

2.1.4 Cognition and Case-based Reasoning Recommender Systems

Case-based recommender systems (Hammond, 2012; Kolodner, 2014; Riesbeck and Schank, 2013) employ case-based reasoning (CBR), a technique pioneered by cognitive scientist Janet Kolodner (Kolodner, 1992; Kolodner, 2014) to produce recommendations. CBR is a technique where a reasoner uses previous cases that are similar and uses them to solve new problems (Kolodner, 1992). Such systems constitute early examples of psychology-informed recommender systems as they employ a problem solving architecture designed by psychologists. The similarity metrics used by CBR systems were inspired by works in psychology on the basic features of similarity. Here, the similarity between two items is determined based on their common and distinctive features (Tversky, 1977). Since CBR recommender systems are based on learning from previous experiences, they require a knowledge base that contains well-

The version of record is available at: http://dx.doi.org/10.1561/1500000090

represented examples (Burke *et al.*, 1996).

CBR research examines the CBR process both as a model of human cognition and as an approach to build intelligent systems (Leake, 2001). In the context of recommender systems research, Burke employs CBR to generate recommendations in an e-commerce setting (Burke, 1999), and in Burke *et al.* (1996) to produce restaurant recommendations. Ricci et al. (Ricci and Werthner, 2001; Ricci *et al.*, 2002; Ricci *et al.*, 2006) utilize CBR in the domain of travel recommendations. Aguzzoli *et al.* (2002) combine CBR with CF to produce music recommendations, similar to Gong (2009), who combines CBR with item-based CF by first using CBR to fill missing entries in the user–item ratings matrix and then predicting items using CF. Yang and Wang (2009) designed an approach based on CBR to assist project managers in constructing new project plans based on previous projects. Wang and Yang (2012) introduce an extension to CBR to enable a hierarchical problem representation. Their approach considers multiple decision objectives on each level of hierarchical decision criteria; thus, problems can be identified more precisely. Musto *et al.* (2015) employ CBR to recommend personalized investment portfolios as an assisting tool to financial advisors. Bousbahi and Chorfi (2015) implement a CBR-based recommendation approach to assist learners in finding massive open online courses (MOOCs) that meet their personal interests.

CBR has furthermore been used to design explanation strategies for recommendations; see the respective chapter in the Recommender Systems Handbook for a concise overview of explanations for recommender systems (Tintarev and Masthoff, 2015); the review presented by Doyle *et al.* (2003) details the use of explanations in knowledge-based systems. McSherry (2005) explain recommendations along with the difference between query and case descriptions, whereas the query represents the user preferences. Sharma and Ray (2016) select the attribute with the highest weight in the similarity metric to find the similar cases that may be of interest to the user as an explanation of the recommendation.

Muhammad *et al.* (2015) describe a case-based recommender system for hotels whereas cases are extracted from the user-generated, textual reviews of users. In addition to cases, user profiles are created based on the reviews a user has submitted. Based on the profiles, a set of hotels are recommended and explanations for the candidates are produced and used to rank hotels. The explanations consist of hotel amenities enriched with sentiment extracted from opinions expressed in the reviews. Jorro-Aragoneses *et al.* (2019) introduce a CBR strategy to extract explanatory cases that are similar to recommended items, which are then used to interpret latent factors produced by matrix factorization recommendation algorithms.

Furthermore, critique-based recommender systems are a form of case-based recommender systems (Pu *et al.*, 2012). Critique-based recommenders produce recommendations by creating a dialogue, in which recommendations are offered and users give feedback to the recommendations in the form of critiques. A large body of research exists on critique-based recommender systems; for an overview, please refer to the respective chapter in the Recommender Systems Handbook (McGinty and Reilly, 2011). In this field, recent work by Contreras and Salamó (2020) introduces a cognitive user preference model that incorporates an adaptive clustering process into the user model. The authors use this user model in a critique-based recommender system. Here, the cognitive user preference model is generated from interactions with the user and adapts its content to the evolving requirements of the user, which are defined by the user's critiques. Also in recent work, Güell *et al.* (2020) introduce a cognitive-based assistant for a critique-based recommender system, whose reasoning process when recommending products employs the same cognitively-inspired clustering algorithm as Contreras and Salamó (2020).

2.1.5 Competence-based Recommender Systems

Competence can be understood as knowledge that is required to perform tasks in a particular domain (Fehling, 1993). In the context of recommender systems, competence is often used in learning and expert seeking scenarios. Bellandi *et al.* (2012) outline various design principles for competence-based recommender systems. The basis for such systems are competence profiles that help recommend expert advice or design teams. Chavarriaga *et al.* (2014) introduce a hybrid recommender system based on collaborative filtering and knowledge-based recommendations for students, which recommends activities and resources. The goal is to assist students to achieve certain competence levels in the context of an online or blended course. Prins *et al.* (2008) propose to support learners with personalized competence-based recommendations. The authors investigate the efficacy of using competence descriptions in personalized recommender systems. For a systematic review of competence-based recommender systems, refer to Yago *et al.* (2018).

Modeling competencies also plays an important role in the development of educational recommender systems (Pavlik and Anderson, 2008). An example is given by Mozer and Lindsey (2016), who follow a hybrid approach that integrates collaborative filtering and computational models of forgetting, such as a variant of the above described ACT-R activation equation. More specifically, they use collaborative filtering to infer a student's latent traits, such as the memory strength for a given item (e.g., vocabulary) or the individual time-based memory decay rate. They then exploit the activation equation to predict the student's knowledge state with respect to the item.

Thaker *et al.* (2018) present an approach to model dynamic student knowledge for online adaptive textbooks. Their model integrates student activities in a knowledge tracing framework (Corbett and Anderson, 1994), a framework based on ACT-R to model changes in knowledge states during the acquisition of skills. In the work of Thaker et al., students' current level of knowledge is derived from behavioral data and quiz activities.

A mathematically complementary approach can be found in educational recommender systems, which draw on the set-theoretical framework of Knowledge Space Theory (e.g., Falmagne *et al.* (2013)). Based on the observed problem solving behavior of a student, e.g., in the domain of mathematics, the probability distribution over the underlying subset of knowledge states (i.e., problems that can already be mastered) is estimated. These estimates serve as input for adaptive recommendations of learning objects, which are neither too easy nor too difficult.

2.1.6 Discussion

Incorporating cognitive models of human cognition to design and improve recommender systems is a promising research direction. In particular, a variety of human memory models have been applied to model user behavior and to improve recommender systems. The use of parts of the cognitive architecture ACT-R has put forth effective recommendation systems. The most compelling reason here is that the BLL equation formalizes fundamental time-based memory decay processes in a computationally efficient manner; additionally, its underlying psychological model is intuitive and contributes to a deeper understanding of user behavior. However, recommender systems based on the BLL equation foster interaction with content similar to what a user has already interacted with recently and frequently in the past (e.g., scientific content like in the work of Maanen and Marewski (2009)). Depending on the use case (e.g., recommending political news) this may lead to confirmation bias, i.e., the tendency to recall information that mostly confirms one's existing beliefs. Understanding the implications of such recommender systems from both the user and the system perspective is an open challenge for future research. One strand of research can look into the diversification of recommendation results to mitigate confirmation bias. For an overview of diversification in recommender systems, please refer to Castells *et al.* (2015). The topic of *counterfactual reasoning* (Hoch, 1985) can be another strand of research to alleviate confirmation, and in a larger context, information bias. Counterfactual reasoning is a core concept in human cognition that corresponds to thinking about a past situation and reflecting on alternative outcomes that might also have been. Galinsky and Moskowitz (2000) show in a psychological study that counterfactual reasoning can make study participants explore alternative explanations in situations in which they typically seek confirmatory information. Future work can explore how to develop counterfactual recommendations that help users explore alternative choices and their impact on user behavior.

CBR recommender systems, while being a category of recommender systems on their own, are also built on principles of cognition. In essence, they mimic how humans draw on previous learning episodes when solving new problems. One of their advantages is that they help generate recommendations in a transparent and explainable fashion. However, they require a knowledge base, whose creation is often labor intensive. More research is needed to devise efficient techniques to create and maintain such knowledge bases.

Furthermore, we reviewed works that incorporate a user's attention into the recommendation model. While the success of deep learning has spawned a range of attention-based approaches, we are not aware of any works that discuss underlying psychological models and theories of attention. Here, we see potential for future work to investigate attention-based approaches in light of underlying psychological constructs. That can foster the transparency and interpretability of the inner workings of such algorithms.

Finally, there is also untapped potential in the study of the connection between utilizing human memory processes to design and improve recommender systems and using recommender systems to support human memory in retrieving objects. While both strands of research agree on the relevance of context cues for determining the importance of objects in human memory, to date, research that addresses both aspects simultaneously is scarce.

2.2 Personality-aware Recommender Systems

Personality is a fundamental human characteristic, which has been studied in psychology for decades. Personality traits are human characteristics that are stable over the years. In contrast to mood or emotion, which change frequently and are context-dependent, personality traits do not depend on a particular context or stimulus. Personality traits are known to be significantly correlated with user characteristics that recommender systems exploit, such as music preferences (Tkalcic and Chen, 2015a; Ferwerda *et al.*, 2017b), or preferences for movies (Golbeck and Norris, 2013) or books (Rentfrow *et al.*, 2011); or the need for diversity in recommendation lists (Chen *et al.*, 2013b; Wu *et al.*, 2013). Nguyen et al. (Nguyen *et al.*, 2018) find, in a user study with over 1,800 subjects, that personality traits of users can also help infer the users' preferences for recommendation diversity, popularity, and serendipity. They also show that user satisfaction increases when personality traits are incorporated into the recommendation process. The correlation between user preferences and personality traits is also confirmed in the work of (Karumur *et al.*, 2018). In a user study conducted on the MovieLens dataset,[1] the authors identify user behavior that is related to the recommender system (i.e., user retention and engagement, preferences, and rating patterns), and show that the users' personality traits correlate significantly with their behavior.

The most common motivations for considering personality in the recommendation process are to alleviate cold-start situations (in particular for new users) and to improve the level of personalization (e.g., to increase recommendation list diversity). The correlation between user preferences and personality traits is also confirmed in the work of Karumur *et al.* (2018), who go beyond this research as their aim is to identify specific areas where personality can contribute to recommender systems. To that end, they study category-by-category variations in preference (rating levels and distribution) across different personality types.

2.2.1 Elicitating Personality Traits

While a variety of models exist to describe human personality traits, the least disputed and most commonly used model in the context of recommender systems research is the *Five Factor Model* (FFM), which is also known as the *Big Five* model or the *OCEAN* model (McCrae and John, 1992). Please note that other personality models are the Thomas-Kilman conflict mode personality model (Thomas, 1992), which is used to model dynamics in groups (Felfernig *et al.*, 2018d), or the vocational RIASEC model (short for Realistic, Investigative, Artistic, Social, Enterprising, and Conventional) model (Holland, 1997), which is used to deliver personalized recommendations in an e-commerce setting (Bologna *et al.*, 2013), as well as the Bartle model (short for Killers, Achievers, Explorers, and Socializers) (Stewart, 2011), which is used to provide recommendations in gamified learning settings (Konert *et al.*, 2013; Paiva *et al.*, 2015).

[1] https://grouplens.org/datasets/movielens

The most commonly adopted FFM describes personality along the five dimensions of openness to experience (conventional vs. creative thinking), conscientiousness (disorganized vs. organized behavior), extraversion (engagement with the external world), agreeableness (need for social harmony), and neuroticism (emotional stability). Various instruments have been developed to elicit personality traits, with questionnaires being a common choice. Each personality dimension is then described along a given multi-point rating scale, e.g., between 1 and 5. To this end, the responses/ratings to the questions are linearly combined using a fixed combination for each trait.

A comprehensive resource for such instruments is the International Personality Item Pool (IPIP),[2], which contains a wealth of measures and scales (Goldberg *et al.*, 2006).

The most commonly used instruments to elicit personality traits according to the FFM include the *Ten Item Personality Inventory* (TIPI) (Gosling *et al.*, 2003) and the *Big Five Inventory* (BFI) (John and Srivastava, 1999). The former asks users to fill in 10 questions on a 7-point scale from "disagree strongly" to "agree strongly" (e.g., "I see myself as anxious, easily upset."). The latter, sometimes also referred to as BFI-44, uses 44 questions. Both linearly combine the answers to result in a final score for each of the OCEAN dimensions.

Please note that several approaches exist, which infer personality traits not based on questionnaires; including extracting personality information from eye tracking data (Berkovsky *et al.*, 2019), communication behavior in Web-based learning Systems (Wu *et al.*, 2019), visual and content features from Instagram pictures (Ferwerda and Tkalcic, 2018), or social media content (Golbeck *et al.*, 2011a; Golbeck *et al.*, 2011b; Golbeck, 2016).

2.2.2 Personality Traits in Recommender Systems

Since personality traits are human characteristics that are stable over years and do not depend on a certain context or stimulus, in contrast to mood or emotion, respectively, they can be used to create personalized recommender systems. The most common motivations for considering

[2] https://ipip.ori.org

personality in the recommendation process include to alleviate *cold-start* situations (in particular for new users) and to improve the level of *personalization* (e.g., to increase recommendation list diversity). In the following, we present a selection of very recent work; for a review of earlier research, please consider Tkalcic and Chen (2015b).

Asabere et al. propose a recommender system for *conference attendees* that integrates personality traits and social ties of attendees (Asabere *et al.*, 2018). Personality is described using the OCEAN model, social ties using contact duration and frequency of conference attendees (they were equipped with smartphones). User similarity in terms of personality is computed using Pearson's correlation between two persons' OCEAN scores treated as a vector. The similarity between two attendees concerning social ties is computed as a product of their contact frequency and duration. Based on these two kinds of similarity, the authors present a hybrid system that linearly combines the personality and social tie similarities between users. The system alleviates cold start for users with low social tie strength (e.g., users who just arrived at the conference) by resorting to using personality only.

Yang and Huang propose a personality-aware recommender for *computer games* (Yang and Huang, 2019). They predict players' OCEAN traits from their social media posts employing methods of personality recognition from texts, in particular, natural language processing techniques. Games are also assigned personality scores based on the personality of their players and based on results of personality recognition applied to game reviews. The target user is then recommended games that are played by users with a similar personality, an approach that resembles memory-based collaborative filtering where similarities are computed over personality trait vectors rather than rating vectors. Alternatively, the target user is recommended games similar to the games the user interacted with, which resembles content-based filtering where game content is modeled by predicted "personality" of the game.

Adaji et al. present a graph-based approach for recommending *recipes* using personality information of users of an online social networking site for cooking (Adaji *et al.*, 2018). The authors extract OCEAN scores from users' reviews and describe each recipe by the dominant personality trait of its reviewers. A graph is then constructed in which nodes (recipes) are connected by edges indicating that the same user has reviewed them. Recipes are weighted by the number of reviews received; edges are weighted by the number of users who reviewed both recipes the edge connects. The authors propose to alleviate cold start by first creating a recipe subgraph that only contains the recipes whose dominant "personality" matches that of the new user. Recipes are then recommended starting at the node with the highest weight and traversing the graph in decreasing order of edge weight.

Nalmpantis and Tjortjis present a simple method to include personality into a *movie* recommender system (Nalmpantis and Tjortjis, 2017). Based on the OCEAN traits of the target user, the authors compute the Manhattan distance between the user's traits and the traits assigned to each genre in a list of movie genres with personality annotations created by (Cantador *et al.*, 2013). The proposed system, which is based on a nearest neighbor collaborative filtering approach, then predicts ratings as a linear combination between the movie ratings predicted by the CF component and the user's personality-based genre distance to the movie's genre under consideration.

Gelli et al. integrate personality information into an *image* recommender system, framed as the task of predicting interactions of users with images shared on Twitter (Gelli *et al.*, 2017). To this end, the authors propose a context-aware factorization machine that integrates both sparse features (user–item interactions) and dense feature vectors, such as multimedia content descriptors or user side information. As dense features, they include the users' OCEAN scores and visual concept vectors of the images under consideration into the model, to learn a joint representation. Personality scores of the Twitter users are extracted from their shared posts using the Apply Magic Sauce API.[3]

Personality information is often considered in recommender systems to tailor the level of *diversification* of recommended items to the user's needs, relying on studies that show that personality is correlated with a preference for diversity, e.g., (Tintarev *et al.*, 2013; Wu *et al.*, 2018; Ferwerda *et al.*, 2017a). For instance, Lu and Tintarev propose a *music* recommendation system that adapts to users' personality factors and

[3] https://applymagicsauce.com

their diversity needs on music preferences (Lu and Tintarev, 2018). They rerank results of a collaborative filtering approach by linearly combining the original rank of each item (song) produced by collaborative filtering and the degree of diversity that the item contributes to the recommendation list, integrating personality as a weighting term into the objective function used for reranking. The authors describe users' personality according to the OCEAN model and define diversity as intra-list diversity, i.e., averaged pairwise distance between all items in the recommendation list. These distances are computed on item features, namely music key, genre, and the number of artists. In a pilot study, the authors found these three features to be most correlated to personality traits. For instance, extraversion was correlated with diversity in terms of music key, as well as agreeableness and diversity in the number of artists. Based on such correlations, Lu and Tintarev then map each personality factor to a desired level of diversity and integrate this as a weighting term into the objective function used for reranking.

Wu et al. propose an approach for recommending *interest groups* to join for users of an online social network (Wu *et al.*, 2018). The approach tackles cold start and tailoring recommendations to the user's desired level of diversity by integrating personality information into a user-based CF system. The authors elicit OCEAN scores and linearly combine user similarity in terms of item ratings and personality-based user similarity to alleviate cold start. The personality-based similarity is defined as the Euclidean distance between two users' personality scores. Adjusting diversity is achieved by integrating findings of a pilot study in which the authors use OCEAN traits to predict diversity preferences of users of a Chinese social network site. Thereby, diversity of a user is measured as entropy over categories of interest groups (e.g., sports or culture) the user joined on the site. The recommender system then adjusts the level of item diversity in the recommendation list so that it best matches the diversity level desired by the target user (as estimated from his or her personality traits).

Fernandez-Tobias et al. propose a personality-aware recommender system, which they evaluate for recommending *books*, *movies*, and *music* (Fernandez-Tobias *et al.*, 2016). Among other contributions (e.g., on active learning and cross-domain recommendation), the authors extend the classical matrix factorization approach commonly used in model-based collaborative filtering by integrating a user latent factor that describes their personality in terms of the five dimensions of the OCEAN model. The proposed personality-based matrix factorization approach can deal with implicit feedback data, i.e., information on user-item interactions beyond explicit ratings, such as clicks, purchases, or the frequency of item consumption.

2.2.3 Personality Traits in Group Recommender Systems

Personality can also be taken into account in group recommendation scenarios to improve the quality of group decisions and increase user satisfaction. In groups of users, especially heterogeneous groups, a conflict situation may arise quickly since group members have different personality traits, which leads to contradicts in terms of the preferences of group members (Recio-Garcia *et al.*, 2009). Thereby, generating group recommendations by solely aggregating group members' preferences, using standard social choice functions (Felfernig *et al.*, 2018a; Masthoff, 2011), might not reflect the overall satisfaction of a group (Quijano-Sanchez *et al.*, 2010).

More recently, some novel methods have been proposed to create group recommendations considering different types of group members' personalities. For instance, Rossi and Cervone (2016) propose a group recommendation approach that considers the *agreeableness* factor. The authors argue that in choosing an item in a group of close friends, agreeableness, being related to *altruistic behavior* (Costa and McCrae, 1995), plays a crucial role. An agreeable person tends to compromise and avoid items that are not in the interest of others. Based on this idea, instead of defining a specific social choice function that considers the agreeableness factor, the proposed solution uses the definition of an individual *utility function* to evaluate the item rating of each group member. The underlying idea of this function is *"the user satisfaction if the recommender system chooses that item for the group"*. This function conforms to the model proposed by Charness and Rabin (2002) that maximizes the social welfare and increases the sum of group members' payoffs. The utility function measures how much a group member likes to increase social surplus, caring about helping himself/herself and others with low payoffs. In another work, Delic *et al.* (2017) conduct a user study in the travel destination domain to explore the satisfaction levels of individual group members with the final group decision. The authors find out that group members are highly satisfied with the outcome of group negotiations when the final group decision matches their initial preferences. Besides, they indicate that individual satisfaction is correlated with the Big Five personality traits of group members. The satisfaction with the final group decision is positively correlated with the traits *agreeableness* and *conscientiousness* and negatively correlated with the trait *neuroticism*.

Personality traits of group members can also be exploited in group recommender systems to resolve conflict situations in group decisions. Nguyen *et al.* (2019), Quijano-Sanchez *et al.* (2010), and Recio-Garcia *et al.* (2009) characterize the personality of group members using the *Thomas-Kilmann Conflict Mode Instrument* (TKI) model (Thomas and Kilmann, 1974). This model describes a group member's behavior in conflict situations according to two dimensions: *assertiveness* and *cooperativeness*. These dimensions are the extent to which an individual attempts to satisfy his/her own (assertiveness) and other people's preferences (cooperativeness) (Nguyen *et al.*, 2019). The dimensions can be used to define five personality modes of conflict resolution: (i) *competing* (assertive and uncooperative), (ii) *collaborating* (assertive and cooperative), (iii) *avoiding* (unassertive and uncooperative), (iv) *accommodating* (unassertive and cooperative), and (v) *compromising* (moderately assertive and cooperative) (Nguyen *et al.*, 2019; Recio-Garcia *et al.*, 2009). Although these studies share the common idea of exploiting the personality of group members for conflict resolution, they show different points of view in modeling the dimensions *assertiveness* and *cooperativeness*. Nguyen *et al.* (2019) model *assertiveness* as the probability that group members propose items to the discussion that are highly related to their preferences. Thereby, the probability increases if a group member is assertive and decreases otherwise. In contrast, the authors model *cooperativeness* with the probability that a group member gives positive and negative evaluations to items proposed by other group members. A group member with a *high cooperativeness* tends to have a higher probability of giving positive feedback and a lower probability of giving negative feedback. Quijano-Sanchez *et al.* (2010) and Recio-Garcia *et al.* (2009) estimate the *assertiveness* and *cooperativeness* of a group member based on the sum of the coefficients of his/her personality modes specified by the TKI model (i.e., *competing, collaborating, avoiding, accommodating* and *compromising*). These two dimensions are combined to estimate a *Conflict Mode Weight (CMW)* indicating how selfish or cooperative a group member is. The CMW value is in the range of [0..1], where *"0"* reflects a very cooperative person and *"1"* reflects a very selfish one. The rating of a group member u for a specific item can then be predicted by considering the difference between $CMW(u)$ and any other user v in the group ($CMW(v)$), e.g., in a simple user-based CF fashion. Recio-Garcia *et al.* (2009) also apply a CF approach to first recommend the best items for each group member (we assume $Best_u$ consists of the best items recommended to a group member u using the CF approach). After that, the preferences of individual group members for each item in $Best_u$ are merged using the *minimization misery procedure* (O'Connor *et al.*, 2001). The general idea of this procedure is to minimize as much as possible the misery within the group. For further details of this recommendation approach, we refer to (Recio-Garcia *et al.*, 2009).

2.2.4 Discussion

As illustrated by the reviewed works, personality has a significant impact on user preferences and behavior. The use of personality traits in personalized recommender systems helps alleviate cold-start problems and bears the potential to improve the level of personalization, also in terms of diversification of recommendation results. However, to date, it is not well understood to which extent personality influences perceived recommendation quality; neither is the variability of this extent between users. For some users and domains, tailoring recommendations to personality traits might be valuable to recommend items that fit their personality; for others, personality could be an irrelevant signal, which could even be perceived as invasive concerning privacy and ethics. Incorporating personality in a privacy-aware fashion is an open issue.

Also, current approaches integrate personality in quite simplistic ways, e.g., by linearly combining a content-based similarity with a personality/user-based similarity metric. Only in a very recent article, Beheshti *et al.* (2020) incorporate personality information as features in a neural embedding framework in the larger context of a so-called cognitive recommender system.

Furthermore, manifold instruments and frameworks exist to elicit personality traits. However, the question of when to use which and what quality can be achieved is still the subject of more detailed investigation. The same holds for the willingness of users to fill out a questionnaire containing tens or even hundreds of questions.

Finally, how to model the "personality" of an item is still an under researched question. More sophisticated methods to derive personality traits on the item level are required. One recent example in this vein is the approach by Sertkan *et al.* (2019).

2.3 Affect-aware Recommender Systems

Affect plays a crucial role in human life. Human affect is commonly categorized into *mood* and *emotion*. Mood refers to an affective experience of longer duration (minutes to hours) but lower intensity, emotion to an affective response of shorter duration (seconds to minutes) to a particular stimulus. Like personality, both mood and emotion are fundamental human characteristics and have been in the focus of psychological research for a long time. They are known to influence our decision making and preferences (Shiv and Fedorikhin, 1999), for example in the domain of videos (Orellana-Rodriguez *et al.*, 2015), fashion (Piazza *et al.*, 2017), music (Ferwerda *et al.*, 2017b), movies (Golbeck and Norris, 2013), or books (Rentfrow *et al.*, 2011); or the need for diversity in recommendation lists (Chen *et al.*, 2013b; Wu *et al.*, 2013) and reading choices in online news (Mizgajski and Morzy, 2019). In addition, consumption of media items plays a vital role for human mood regulation. In the context of music, mood regulation was even identified as one of the main purposes why people listen to music (Schäfer, 2016).

It has also been shown that humans with different personality traits perceive different emotions when listening to the same piece of music (Schedl *et al.*, 2018). Emotion is a well-explored contextual factor in context-aware recommender systems (e.g., (Zheng, 2013)).

2.3.1 Modeling Affect

Focusing on describing emotions, we can distinguish between *categorical* models and *dimensional* models. The former describes emotions using a predefined vocabulary of basic emotion terms (e.g., happy, sad, angry, or relaxed) or secondary emotions that are reactions to primary ones (e.g., energetic, lonely, confused, or hopeful). Dimensional models, in contrast, describe emotions by assigning them values in a continuous space, which is most commonly spanned by the two dimensions *valence* (V) and *arousal* (A), according to Russell (1980). Valence refers to the level of the pleasantness of emotion (positive vs. negative), while arousal refers to the emotion's intensity (high vs. low). The V/A space is sometimes complemented by a third dimension that describes how much in control of the respective emotion a person is (dominant vs. submissive). This dimension is commonly called *dominance* by Mehrabian (1980), *potency*, or *control* according to Fontaine *et al.* (2007). An illustration of the valence–arousal plane with several affective terms mapped to it can be found in Figure 2.2.

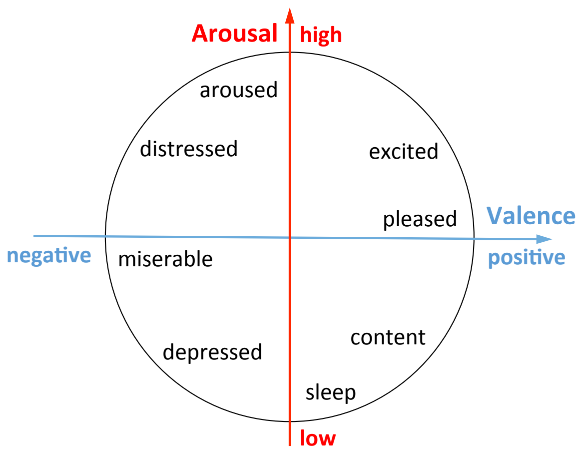

Figure 2.2: Some categorical affective terms mapped to valence–arousal plane (Knees *et al.*, 2019).

2.3.2 Affect in Recommender Systems

To create affect-aware recommender systems, we need to infer the mood or emotion of the user, identify relationships between the user's affective state and item preferences, and finally match users and items constrained to some function that describes affective relationships (Tkalcic *et al.*, 2011). Most often, both users and items are represented in the same affective space to enable direct computation of similarities between users and items.

Ravi and Vairavasundaram (2017) present a recommender system for *locations* that leverages users' emotions, and their locations shared in a location-based social network. To establish associations between locations and emotions as well as users and emotions, the authors adopt a lexicon-based approach to identify emotion words in user posts shared at a particular location. Emotions are described using a categorical model of positive emotion categories (happy, like, and surprised) and negative categories (angry, sad, fear, and hate). As a result, each user and each location is described by an emotion vector, which allows computing emotion similarity between users and items. The authors propose adaptations of user-based and item-based collaborative filtering to make recommendations. The user-based collaborative filtering model recommends locations to the target user u based on the product of two components: overall emotional similarity to other users v (irrespective of location) and similarity between u's current emotion and the emotion v expressed when visiting the location under consideration. The proposed item-based collaborative filtering model uses the emotionally most similar locations to those locations l already visited by the target user u and weighs them with the similarity between u's current emotion and u's emotion when visiting l. Cosine similarity is used for all similarity calculations. A hybrid system is also proposed, as a simple linear combination of the user-based and items-based prediction scores.

Deng *et al.* (2015) propose a similar approach while using other resources and targeting another recommendation domain, i.e., *music*. The authors extract emotion information and music listening information from a popular Chinese microblogging service. They adopt a lexicon-based approach using various Chinese text resources and emoticons to infer emotions of microblogs. Emotions are described using different categorical models of varying granularity (from 2 to 21 emotion categories). To be able to compute similarities, a user's emotional context is then defined by a vector representation over the dimensions of the applied emotion model, where each dimension contains the frequency of terms belonging to the respective emotion category in the user's most recent microblogs. Contextual relationships between emotions and songs for a given user are established by considering the emotions reflected in the user's posts directly before his or her posting of a music listening event. This way, each pair of user and song (listened to by the user) is assigned an emotion vector. For recommending songs, the authors define a user-based collaborative filtering model, an item-based collaborative filtering model, a hybrid of the two, and a random walk model. The former three are almost identical to Ravi and Vairavasundaram (2017), but use songs instead of locations as items. For the random walk approach, the authors construct a bipartite graph of users, emotional contexts (merged by clustering), and songs. They adapt a variant of PageRank to traverse the graph and effect recommendations.

Ayata *et al.* (2018) propose a framework for emotion recognition that can be integrated into *music* recommender systems. The authors gather various physiological signals through wearable sensors (measuring, for instance, skin conductance or heart rate). From the sensor data, several features are computed using different statistical summaries of the physiological measurements (e.g., min, max, mean, variance, median, skewness, and kurtosis) within time windows. These features are used to predict the user's emotional state, where emotions are described using the V/A model. The authors then conceptualize a music recommendation architecture that integrates the affective response of the previous recommended song on the user and adapts future recommendations based on this response.

2.3.3 Discussion

The discussed works show that both emotion and mood are beneficial in context-aware recommendation scenarios, such as location-based recommendations, and in scenarios in which recommended items have a strong affective impact on users, such as music recommender systems. As shown by the literature, users' affective states can be exploited to tailor recommendations to the needs of an individual.

A shortcoming of current research is that it largely neglects dynamic changes in mood or emotion during item consumption. We see further potential to research on detecting such changes and integrating affect dynamics into recommender systems. Besides, as in the case of personality, to which extent a user's mood or emotion influences the perceived recommendation quality is not well understood either and another challenge for future research.

An additional limitation of current work on affect-aware recommenders is that they assign one affective state to the user, neglecting the differences between expressed, perceived, and induced emotion. This is in contrast to psychological literature, which makes a clear distinction between those kinds of emotions. This distinction is particularly important for recommenders in the entertainment domain, with typical strong emotional attachment of users. Expressed emotion refers to the emotion the creator of an item, such as a photographer or composer, intended to express when creating the item. Perceived emotion refers to the emotion the user (e.g., viewer or listener) perceives when exposed to the item. Induced emotion is the emotion truly experienced or felt by the user. Since these three categories of emotions may be very different (Juslin and Laukka, 2004; Schedl *et al.*, 2018), an emotion-aware recommender system should be able to distinguish between them and incorporate them in multifaceted ways.

Finally, mood and emotion constitute sensitive information. Therefore, more research is needed to make emotion detection and inclusion of emotion as a contextual factor in recommender systems privacy-aware.

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3

Recommender Systems and Human Decision Making

So far, in this survey, we focused on recommendation techniques and systems that use psychological features of the user in the recommendation process. In this section, we discuss works that investigate how recommender systems influence human decision making. In addition to helping users make decisions, recommender systems also persuade users (Yoo *et al.*, 2012) and influence human choices. Here, several psychological mechanisms should be taken into account. In the following, we review works that discuss such mechanisms in light of recommender systems research.

When users interact with a recommender system, they make decisions; for instance, they choose an item from the recommendation list (Chen *et al.*, 2013a). Decision making is a fundamental cognitive process that has been studied for decades by renowned psychologists such as Kahneman (Kahneman, 2011), Stanovich (Stanovich and West, 1998), Loewenstein (Loewenstein and Lerner, 2003), Gigerenzer (Gigerenzer and Gaissmaier, 2011), Thaler (Thaler, 1980), or Tversky (Tversky and Kahneman, 1974), who describe the process of users' decision making as being not completely rational (Stanovich and West, 1998; Kahneman, 2003), in cases guided by affect (Loewenstein and Lerner, 2003), influenced by biases and heuristics (Tversky and Kahneman, 1974), and anchor effects (Tversky and Kahneman, 1974), or subject to bounded rationality (Simon, 1966), which means that cognitive limitations of the decision maker impact rational decisions.

Such factors can lead to sub-optimal decision outcomes. The reason for this is that users frequently do not try to optimize a decision outcome, but instead apply decision heuristics (Payne *et al.*, 1993). Bettman *et al.* (1998) describe that while users' preferences evolve in the course of a decision process, they typically cannot state these from the very beginning. Thus, human decision making is more focused on *constructing* preferences than on *eliciting* preferences. Correspondingly, in the case of recommender systems, users often do not know their preferences beforehand but construct and frequently adapt these within the scope of the recommendation process (Mandl *et al.*, 2011). Please note that the Recommender Systems Handbook dedicates a chapter to human decision making and recommender systems (Jameson *et al.*, 2015). Besides, Teppan and Zanker (2015) present an empirical study of several decision biases in recommender systems. They investigate three types of biases, i.e., decoy effects (Teppan and Felfernig, 2009a; Teppan and Felfernig, 2009b), serial position effects (Felfernig *et al.*, 2007), and framing (Tversky and Kahneman, 1981). Adomavicius *et al.* (2013) discuss anchoring effects (Tversky and Kahneman, 1974; Chapman and Johnson, 2002), which influence the decisions of users if they are presented with an initial proposed value for available options.

Furthermore, decision making behavior varies between users. The work of Jameson *et al.* (2015) describes a variety of choice patterns observed in users and outlines how recommender systems can support such patterns. Karimi *et al.* (2015) investigate the variance of user decision making behaviors on the basis of analyzing four archetypes of online customers. The authors find that the decision making behavior of users significantly differs depending on the nature of the decisions (i.e., number of cycles, duration, number of alternatives and number of criteria). Jugovac *et al.* (2018) present a study on how to adapt recommender systems to such different decision-making styles.

In the next sections, we summarize research efforts on relevant factors that influence decision making and which can impact the likelihood of recommended items being selected by a user. Besides, we discuss further aspects of counteracting decision biases. Please note that, we focus on approaches to mitigate *decision biases* that occurred in users' interactions with recommender systems. The discussed solutions are user-interface oriented, which help to minimize the impact of decision biases at the rating collection time. In the current literature, there exist various approaches to eliminate biases in datasets, algorithms, and recommendation results; however, they are not our primary focus. For further related details of these approaches, we refer to Chen *et al.* (2020) and Huang *et al.* (2020).

3.1 Decoy Items

One decision bias results from users making decisions depending on the way decision alternatives are presented to them. A frequent decision heuristic in this context is an attribute-wise comparison between items (Payne *et al.*, 1993). For example, the inclusion of items that are entirely inferior to other items in a list of alternatives can trigger changes in choice behaviors. Such inferior items are denoted as *decoy items (D)* (Huber *et al.*, 1982), which can be used to increase the selection probability of a *target item (T)* and potentially decrease the selection probability of the *competitor item (C)*. Such an effect is called *context effect* (or decoy effect). An illustration is provided in Figure 3.1. A target item T is regarded as a *compromise* between D and C if it is, for example, significantly less expensive than the decoy item and only has a slightly lower quality. *Asymmetric dominance* is given if the target item dominates the decoy item in all dimensions, whereas the competitor item dominates the decoy item in only one dimension. Finally, an *attraction effect* is triggered if the target item, for example, has a significantly higher quality and is only marginally more expensive.

A detailed analysis of different types of context effects in recommender systems is given in Teppan and Felfernig (2012) and Teppan and Zanker (2015). Here, the authors show that decoy items can be applied to increase the selection share of target items, which raises several ethical issues. Being able to identify decoy items in a result set also enables to de-bias the result set by simply omitting decoy items. Decoy

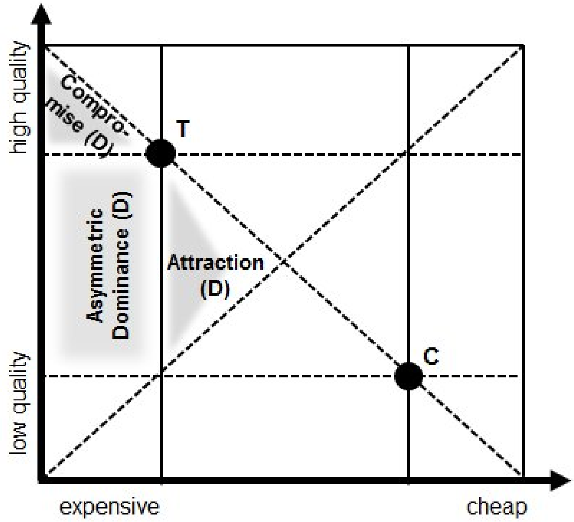

Figure 3.1: An overview of decoy effects. Figure from (Felfernig, 2014).

items can also be used to generate explanations in knowledge-based recommendation scenarios, e.g., via an attribute-wise comparison that led to the recommendation of specific items.

3.2 Serial Position Effects

Serial position effects can occur in settings where humans are presented with a list of items. These effects have been observed in the context of human memory research (Deese and Kaufman, 1957; Glanzer and Cunitz, 1966) to describe a person's tendency to more likely remember items at the beginning and end of a list (Ranjith, 2012). Figure 3.2 illustrates the effect.

Murphy *et al.* (2012) show such effects in the context of user link clicking behavior. In their study, links at the beginning of a list were clicked more often than items in the middle of a list, which is called *primacy effect*. Furthermore, there was an increased tendency to click on the links at the end of the list. That is described as the *recency effect*. Primacy and recency effects can also be observed in human

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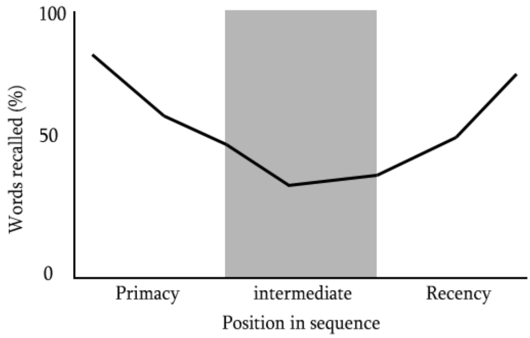

Figure 3.2: This plot (Commons, 2020) shows a U-shaped serial position curve that results from a serial position effect. The effect occurs when a list of words is recalled and words from the start and the end of the list are more likely recalled than words in the middle of the list (Ranjith, 2012).

memory. Cognitive psychologists showed in memory tests that items at the beginning of a list (primacy) are more easily memorized (Crowder, 2014) since first items having an advantage over later items because memory capacity is limited (Waugh and Norman, 1965). The last items in a list (recency) are also more easily remembered since they may be still in the short-term memory during the memory test. Felfernig *et al.* (2007) discuss primacy/recency effects in the context of dialogs in knowledge-based recommendation scenarios. They found that product attributes presented to a user at the beginning and the end of a dialog are recalled more often than items in the middle of a list. These attributes are also the preferred criteria when selecting items from a recommendation list. This still holds in situations where unfamiliar product properties are presented at the beginning and the end of a recommendation dialog. Schnabel *et al.* (2016) present a recommendation interface that enables the user to create shortlists of items that the user is currently considering. A user study reveals that the interface helps users memorize and compare choices and that many users explore more instead of being satisfied with the first good item.

Stettinger *et al.* (2015a) analyze the existence of serial position effects in the context of restaurant reviews. The authors show that the same arguments arranged in different orders can lead to significantly different perceptions of restaurant attractiveness. Similar to decoy effects, serial position effects can be used to influence the selection behavior of users. Serial position effects are also investigated in the context of group decision making. Tran *et al.* (2018) investigate serial position effects in scenarios where the same group of users has to solve a series of decision making tasks in different item domains (*low-* and *high-involvement* item domains). The authors examine whether the order of decision tasks result in different decision making behaviors of group members. Related empirical results show that the group recommendation strategy applied in decisions with high related decision efforts tends to be re-used by group members in the follow-up decision with low related decision effort.

Hofmann *et al.* (2014) explore position bias (Joachims *et al.*, 2017) in light of click-based recommender systems evaluation. Position bias is a problem in click-based evaluation, since the probability that an item will be clicked is influenced by its relevancy and its position in the recommendation list. Related work finds that the probability that an item of a top-N list is clicked decays with its rank (Craswell *et al.*, 2008). Hofmann *et al.* (2014) find that if no position bias is present, user behavior (i.e., items a user will click) can be predicted based on historic rating data and using error-based metrics such as precision. However, if position biases exist, the performance of the recommender systems can be wrongly estimated if a performance metric is chosen that does not well reflect the actual user behavior.

In order to counteract serial position effects in group decision making, Stettinger *et al.* (2015b) proposed a solution that allows group members to evaluate items based on MAUT (*Multi-Attribute Utility Theory*) dimensions (Dyer, 2005). With this approach, a group member evaluates an item by articulating his/her preferences for different dimensions that describe the item. The authors conducted a user study in the restaurant domain, where a restaurant was evaluated based on the following dimensions: *"ambience", "price", "quality",* and *"location"*. A MAUT-based group recommendation for a specific item is the sum of *individual MAUT values* of group members in the group decision task. The individual MAUT value of a group member is a weighted average of all personal ratings of an item's dimensions. In the user study, participants were shown a list of restaurants. Each restaurant was described by a list of arguments describing the restaurants. The arguments were tailored in two types: (1) the *negative salient description* where the negative arguments of the restaurant were placed at the beginning and the end of the description, and (2) the *positive salient description* where the positive arguments of the restaurant were placed at the beginning and the end of the description. The participants were asked to evaluate the restaurant based on the aforementioned dimensions. The user study aimed to examine if the participants' item evaluations were different according to the description type. The experimental results show no significant differences in terms of evaluation values between the two description types. In other words, adopting the MAUT strategy in the item evaluation phase can help to counteract position effects in group decision making.

3.3 Framing Effects

Framing corresponds to the principle that human decisions are influenced by the way options are presented through different wordings, settings, and situations (Tversky and Kahneman, 1981). Decision behavior is often evaluated in terms of gains and losses, which is described in the prospect theory (Tversky and Kahneman, 1992). According to the theory, it is more critical to avoid loss than to ensure gain. The paper by Mandl *et al.* (2011) gives a concise overview of the use of different types of framing effects in recommender systems.

3.4 Anchoring Effects

Anchoring effects are a cognitive bias that makes users rely on the first piece of information (i.e., the anchor) they receive when making decisions. As pointed out in different social psychology studies, early preference visibility can harm the quality of a decision outcome (Mojzisch and Schulz-Hardt, 2010). Adomavicius *et al.* (2011) find evidence for the anchoring effect in a collaborative filtering scenario. Specifically, they show that anchoring effects can be triggered by disclosing the average rating of similar users. This is verified in a user study presented by Zhang (2011). Köcher *et al.* (2019) provide evidence for a so-called attribute-level anchoring effect that can bias the choices of users towards numerical attributes of product recommendations. Adomavicius *et al.* (2014) also present an approach to de-bias ratings to mitigate anchoring effects using a post-hoc algorithm, as well as a user interface to minimize anchoring biases already when ratings are collected.

Anchoring effects can also be triggered in group recommendation scenarios when one group member's evaluations for items are influenced by the evaluations articulated earlier by other group members. Social-psychological studies point out the correlation between anchoring biases with *confirmation biases*, in which group members tend to focus on discussing available information rather than exploring and sharing new decision-relevant information (Felfernig *et al.*, 2018b). To investigate the impact of anchoring effects in group decision making, Stettinger *et al.* (2015a) conducted a user study in the requirements engineering where groups of stakeholders had to decide on which requirements should be implemented in their software project. The authors showed that the occurrence probability of an anchoring effect increases if individual group members' preferences are disclosed to others in the early phase of the group decision making process. This brings the idea of counteracting anchoring effects that the preference disclosure should be performed after group members have articulated their preferences for items. The authors also proved that a late preference disclosure helps to increase the group decision performance in terms of user satisfaction, the perceived degree of decision support, the understandability of group recommendations, and the consideration of individual group members' preferences.

3.5 Nudging

Nudging is a concept from behavioral economics to influence human behavior via suggestions towards choices in the users' and societies' long-term interests (Thaler and Sunstein, 2009). *Nudges* are interventions that aim to predictably influence human behavior without limiting any options or significantly changing people's economic incentives (Thaler *et al.*, 2013). Several psychological effects are exploited in nudging that impact decision making, such as those discussed in this chapter, including decision heuristics, the anchoring effect, decoy effects, framing, or the availability and similarity heuristics (Tversky and Kahneman, 1974). Given such effects, a choice architecture, i.e., an environment in which people make decisions (Thaler and Sunstein, 2009), is designed that guides people to decisions that are to their and society's advantage (Jesse and Jannach, 2021). Various such effects are described, and the survey paper by Jesse and Jannach (2021) gives a comprehensive overview of the underlying psychological phenomena of nudging.

Recommendations can be seen as a form of nudging, where the aim is to recommend items that support the nudging goal (Karlsen and Andersen, 2019). Please note that the paper by Jesse and Jannach (2021) gives a structured review of the state-of-the-art of nudging with recommender systems, for a review of nudging in human-computer interaction research, see Caraban *et al.* (2019).

Karlsen and Andersen (2019) present an architecture for nudging recommender systems. As an illustrative example, the authors define the use of nudges to convince people to use environmentally friendly transportation. They introduce a nudge-driven filtering technique that recommends activities to a nudging goal (e.g., use environmentally friendly transportation). The activity is recommended based on a user profile that contains user characteristics and their history of previous activities and behaviors, the user's current context, and the next planned activities. To present the nudges to the user, the authors exploit several decision biases, i.e., framing, anchors, reminders, or social norms (e.g., showing how many others have chosen a particular option (Starke *et al.*, 2020)). Elsweiler *et al.* (2017) aim to nudge people to make better health decisions by recommending them healthy content. In this work, the authors investigate if food recommender systems can nudge users of an online recipe platform towards selecting healthier meals. First, they study if meals in the platform can be replaced with similar but healthier options (in terms of fat content) that also receive high ratings. Then, they conduct a user study to identify if users can distinguish between unhealthy and healthy dishes and find that many cannot tell the difference, still users tend to select the unhealthier option. In addition, they examine how cues such as recipe title, an image of the meal, and a list of ingredients influence users when selecting recipes and show that users can be nudged to choose healthy over unhealthy recipes; this works particularly well based on visual cues. Esposito *et al.* (2017) introduce nudges to prevent customers in a digital marketplace to purchase incompatible products. In a user study, they evaluate different types of nudges and find that nudges in the form of emotive warning messages and incompatibility information at the checkout page reduce the number of incompatibility purchases. Turland *et al.* (2015) aim to nudge users towards selecting more secure public wireless networks by recommending more secure network alternatives. They found evidence for a decoy effect that nudged users in choosing a secure network.

3.6 Discussion

As pointed out by Teppan and Zanker (Teppan and Zanker, 2015), current recommender systems typically cannot control decision biases, and more research is needed in this direction. From a user perspective, the awareness of the existence of decision biases is essential to make more informed decisions when interacting with a recommender system. Psychology-informed recommender systems that are aware of decision biases can help educate users and make them aware of their own biases in decision making, e.g., via explanations. Another possibility for future research is to study how biases change over time and how these changes impact a user's preferences and behavior.

System-induced biases such as popularity biases (Cremonesi *et al.*, 2010) can be reinforced when already popular items are always put on top of a recommendation list (i.e., exploiting serial position effects). Future research can investigate whether different user groups experience different recommendation utility due to biases such as popularity and demographic biases (Ekstrand *et al.*, 2018). Also, while most related work has been on detecting decision biases in recommendation scenarios, we need more research on proactively preventing or minimizing such biases.

Furthermore, commercial recommendation platforms often actively exploit decision biases of humans to nudge users to adopt a specific behavior or to persuade users to make particular decisions, e.g., what to buy or what to read. This can be beneficial to the user, e.g., when a relevant recommended item is presented prominently. However, it can also be harmful, e.g., in case of decision manipulation (Tran *et al.*, 2019b) and since not all nudges and persuasive mechanisms are helpful and to the user's advantage. For example, marketers may employ nudges to guide consumers towards non-essential options (Schneider *et al.*, 2018). Consequently, ethical concerns and discussions around the concept of nudging and persuasion have emerged (Sunstein, 2015). These discussions gave room for a competing framework termed *boosting* by Grüne-Yanoff and Hertwig (2016). Boosting attempts to help users improve their competencies in decision making instead of nudging them (Hertwig and Grüne-Yanoff, 2017). Grüne-Yanoff *et al.* (2018) distinguishes between boosting and nudging in two aspects: firstly, boosting aims to expand people's competencies by overcoming human cognitive limitations rather than exploiting them. Secondly, a nudge intervenes in a person's choice environment and exploits specific decision heuristics to guide behavioral change, boosting intervenes on people's decision heuristics and expands their decision competencies to foster a specific behavioral change. While, to the best of our knowledge, boosting has not yet been explicitly employed in recommender systems research, there exist related examples in the information retrieval community - e.g., Zimmerman *et al.* (2020) and Ortloff *et al.* (2021) employ boosting to boost users' competencies in searching while preserving their privacy. Bateman *et al.* (2012) provide a search dashboard to make users reflect on their search behavior by comparing it to the behavior of expert searchers. Moraveji *et al.* (2011) boost the search skills of participants in a user study by offering them tips on conducting optimal searches. In a follow-up study, the authors find that the study participants retain their improved search skills compared to a control group also in the absence of search tips.

We believe that boosting is a promising research area for the recommender systems community. For example, boosting can be applied to improve user knowledge about decision biases and underlying mechanisms of the recommender systems, including the implications of users' behavior on the prediction quality. An advantage would be that some of the ethical concerns that come with nudging and persuasion in recommender systems could be alleviated as well.

4

User-centric Recommender Systems Evaluation

This chapter discusses research works that investigate recommender systems' evaluation with a particular focus on the user perspective. In addition, we review factors that influence how users experience and engage with recommender systems. In the next paragraphs, we, nevertheless, briefly summarize core concepts of classic evaluation metrics and strategies.

Recommendation evaluation has traditionally centered on the accuracy of algorithms (Pu *et al.*, 2012) by quantifying the relevance of recommendations to a user's preferences. To that end, typically, metrics of accuracy are employed such as precision, recall, or normalized discounted cumulative gain (Herlocker *et al.*, 2004). Please note that the survey of Gunawardana and Shani (2009) provides a detailed discussion of accuracy metrics in recommender systems research.

Classic recommender systems evaluation employs either offline, online evaluation (i.e., A/B testing), user studies, or a combination of these methods. In offline evaluation, a pre-collected dataset consisting of user-item interactions is leveraged to simulate users' behavior interacting with a recommender system (Shani and Gunawardana, 2011). Online evaluation corresponds to observing user behavior in real-world, deployed systems (Shani and Gunawardana, 2011). User studies denote an evaluation scenario where small groups of users interact with the recommender system and report their experience (Shani and Gunawardana, 2011). Please note that the respective chapter on evaluation in the Recommender Systems Handbook gives a concise overview of both recommendation evaluation metrics and commonly adopted evaluation strategies (Shani and Gunawardana, 2011).

Related work has discussed that accuracy as a sole metric is not sufficient to assess a recommender system's quality as accurate recommendations might not be perceived as the most useful recommendations (McNee *et al.*, 2006a; Herlocker *et al.*, 2004; Konstan and Riedl, 2012). As a remedy, a variety of so-called beyond-accuracy metrics have been introduced to quantify aspects beyond algorithmic performance. These metrics include *diversity* (Ziegler *et al.*, 2005), *coverage* (Herlocker *et al.*, 2017), or *novelty* and *serendipity* (Herlocker *et al.*, 2004). The latter quantifies how interesting, yet unexpected recommendations are for a user (McNee *et al.*, 2006a). Please note that the survey by Kaminskas and Bridge (2016) gives a concise overview of standard beyond-accuracy metrics used in recommender systems research.

4.1 Psychological Aspects of User Experience

Recommender system evaluation from the user perspective requires a systemic approach beyond the investigation of single actors such as algorithms or users and aims to capture the actors' inter-relations and emerging phenomena, such as user experiences (Ekstrand and Willemsen, 2016; Knijnenburg *et al.*, 2012a; McNee *et al.*, 2006b). Given that recommender systems' providers aim to motivate users to return to the system, users must build trust and have a positive perception of the system and its outcomes (Chen and Pu, 2005). Hence, the *user experience* with a recommender system has become the subject of research. User experience is defined by Konstan and Riedl (2012) as the delivery of recommender system outputs to users and the interactions of users with recommendations. In studying the user experience, crucial aspects of recommender systems can be unveiled, such as recommender systems' use and perceived value, and factors related to items, users, user-item interactions, which influence the users' decision-making processes (Xiao and Benbasat, 2007). Such factors include users' attitudes and motivations, their perceived trust in the algorithms, and issues related to the perception of recommender systems in general (Shin, 2020).

Related work investigates the user experience of recommender systems in light of various tasks, e.g., to improve preference elicitation (McNee *et al.*, 2003), increase user satisfaction (Ziegler *et al.*, 2005), study user engagement (O'Brien and Toms, 2008), inspire trust in the system (Pu and Chen, 2006), improve recommendation interfaces (Cosley *et al.*, 2003), or quantify how likely a user will return and recommend a novel system (O'Brien and Toms, 2010).

From a psychological perspective, several factors influence how users experience and engage with recommender systems, such as cognitive dissonance (Festinger, 1954), the persuasiveness of the systems (Fogg, 2002; O'keefe, 2015), perceived system qualities related to interaction and interfaces (Pu *et al.*, 2011; Jugovac and Jannach, 2017), or several attitudes and beliefs (Pu *et al.*, 2011). In the following, we discuss these factors in more detail.

4.1.1 Cognitive Dissonance

Cognitive dissonance denotes a cognitive-affective response to being exposed to information that contradicts one's beliefs and values (Festinger, 1954). Users of recommender systems may experience dissonance after reevaluating a choice they made because they followed a recommendation (Surendren and Bhuvaneswari, 2014) or when being confronted with a recommendation inconsistent with their preferences (Schwind *et al.*, 2011). Dissonance is an aversive cognitive-affective state that users attempt to avoid (Surendren and Bhuvaneswari, 2014) and may make them lose trust in the system (Kuan *et al.*, 2007). Schwind *et al.* (2011), however, explore potential benefits of dissonant recommendations. Concretely, they study if recommending dissonant information for controversial issues helps mitigate confirmation bias. In an online user study conducted on Mechanical Turk, they investigate if users select dissonant or consonant recommendations and assess cognitive and affective reactions to these recommendations. In the first experimental condition, the study participants are recommended an argument on a specific topic that is consonant with the participant's view. In the second condition, they receive a recommendation with an argument that is inconsistent with their belief. The results show that when a consonant argument is recommended, more users select the consonant argument, and a confirmation bias can be observed. When a dissonant argument is recommended, however, users less frequently select the argument. Also, the consonant recommendations receive better evaluations in terms of cognitive and affective states. In later work, Schwind and Buder (2014) show that dissonant recommendations can help de-bias information selection. However, offering dissonant recommendations might also strengthen people's initial beliefs, mainly when the recommendation falls outside the boundaries of what users consider acceptable (Nguyen *et al.*, 2007). Here, future work can investigate the relationship between cognitive dissonance, boosting (see Section 3.6), and *counterfactual thinking* (Roese, 1997). In the case of counterfactual thinking, consumers reflect on how outcomes could have been different if they had made different decisions (Wang *et al.*, 2017).

4.1.2 Persuasion

Persuasion is a communication process in which a person seeks to convince other people to adapt their behavior and attitudes (Fogg, 2002; Perloff, 2020). Persuasion and the earlier described communicative process of nudging (see Section 3.5) are related concepts, which have originated in different communities, persuasion in social psychology (McGuire, 1969), and nudging in economics (Thaler and Sunstein, 2009), and with slightly different aims. While nudging aims to influence a user's behavior in a particular setting, persuasion aims to influence a person's attitude or behavior; for a more detailed comparison of both concepts, please refer to Meske and Potthoff (2017).

Yoo *et al.* (2012) describe a recommendation as being persuasive when it results in a change of the user's behavior or attitude. The authors elaborate that user interactions with a recommender system correspond to a communication process, in which the extent to which a user is influenced depends on four components: (i) the recommender system itself (source), (ii) the recommendation (message), (iii) the user (target), and (iv) the context in which the recommendation is offered. Multiple factors in the components impact if a user is persuaded and changes their behavior or attitude. As Gretzel and Fesenmaier (2006) show, persuasion can happen already during preference elicitation since transparent and short elicitation phases positively influence user satisfaction and perceived fit of later recommendations (Jugovac *et al.*, 2018).

Many studies investigate what makes a recommender persuasive. Related work finds the credibility of recommender systems (Yoo and Gretzel, 2011) is a decisive factor in a recommender system's persuasiveness. Nanou *et al.* (2010) observe that the presentation of recommendation lists in the context of movie recommendations influences persuasiveness. They compare top-N recommendation lists with a structured overview of recommendations, in which recommendations are organized by movie genre and are presented either as purely textual recommendation lists or as a multimodal representation of recommendations (text, images, video). The authors measure persuasiveness in terms of users selecting a recommendation. A small-scale user study with 20 users gives evidence that a structured overview of multimodal recommendations is more persuasive and results in higher user satisfaction in their domain than a textual recommendation list. Cremonesi *et al.* (2012) observe that the perceived novelty of recommendations has higher persuasive power than the perceived accuracy of recommendations (Jugovac *et al.*, 2018). Felfernig *et al.* (2008a) report that the attractiveness of items contributes to a recommender system's persuasiveness and that the use of attraction decoy items can influence a user's decision-making process. Related work also shows that offering explanations to recommendations can make recommendations persuasive (Herlocker *et al.*, 2000; Tintarev and Masthoff, 2012).

From an ethical perspective, persuasive technology raises several questions (Berdichevsky and Neuenschwander, 1999), naturally, also if applied to recommender systems (Milano *et al.*, 2020). Recommender systems providers may offer persuasive recommendations to maximize some business value, which, from a consumer perspective, might be less transparent (Jesse and Jannach, 2021) and hard to resist (Smids, 2012). According to a standard definition of persuasive technology (Fogg, 2002), persuasion is about voluntary change and needs to function without deceiving the user.

4.1.3 Interaction Methods

Several *perceived system qualities related to interaction and interfaces* influence the user experience of recommendations. Knijnenburg and Willemsen (2015) find that the way lists of recommendations are composed and presented to the user strongly impacts user experience. Knijnenburg *et al.* (2011) construct five interaction methods: (i) a top-N recommendation list, (ii) a sort method that lets users sort recommendations by their preferred attribute, (iii) an explicit method that allows users to assign weights to attributes and thus, directly express their preferences, (iv) an implicit method that automatically weights attributes based on the user's browsing history, and (v) a hybrid combination of the explicit and implicit method. In a user study, the authors compare the five interaction methods and assess user interface satisfaction, trust in the system, system effectiveness, understandability, perceived control, and choice satisfaction. They find that most users prefer the hybrid method, which gives them some control over the system.

Bollen *et al.* (2010) finds that users, when presented a list of recommendations, tend to inspect only the first few items on the list due to the earlier mentioned primacy effect (see Section 3.2). Chen and Pu (2010b) find that presenting recommendations in the form of a grid can mitigate this issue; however, the authors do not discuss the underlying reasons for that. Another work by Chen and Pu (2010a) suggests a category-based interface, in which a user's top-N recommendations are shown as the main category, while other categories contain items that help find trade-offs. As shown by Hu and Pu (2011), an interface where recommendations are grouped into categories, which represent trade-off properties among items, can increase perceived recommendation diversity and improve user satisfaction. Ekstrand *et al.* (2014) present a user study in which each user is provided a recommendation list produced by three variants of collaborative filtering (i.e., item-based, user-based, and an SVD-based variant). The users are asked about their perceptions along five dimensions of interest, i.e., accuracy, personalization, diversity, novelty, and overall satisfaction with the recommendations. Then, they pairwise compare algorithms based on a first-impression preference and a subjective assessment of the recommendation lists for the five dimensions. Also, the users select their preferred algorithm for future use. The authors find that novelty of recommended items negatively influences the perceived usefulness of the recommendations. The diversity of recommendations positively influences if a user chooses a recommendation algorithm. Please note that Jugovac and Jannach (2017) give a detailed overview of relevant work on user interaction in recommender systems.

4.1.4 Attitudes and Beliefs

User-centric factors such as *attitudes and beliefs* also influence how users evaluate recommendations. Attitudes correspond to the perceived overall perception of the recommender system in terms of user satisfaction and trust, while beliefs describe the user's perception of the usefulness, ease of use, and control of the system (Cremonesi *et al.*, 2011a; Pu *et al.*, 2011). Swearingen and Sinha (2002) find that showing familiar recommendations can increase users' trust in the system. The familiarity principle (Zajonc, 1968) is a psychological effect that causes users to prefer items they frequently see. Bollen *et al.* (2010) present a user study to understand users' perception of recommendation set attractiveness, choice difficulty, and satisfaction with the selected recommendation. Participants answer 29 questions on a 7-point scale, and in addition, their clicks are logged. The authors fit a structural equation model (Ullman and Bentler, 2003) to the data to understand the interplay between recommendation set attractiveness, choice difficulty, and satisfaction with the chosen item. Please note that structural equation modeling techniques are statistical methods that enable to study relationships between independent variables and dependent variables. Bollen *et al.* (2010) find that user satisfaction depends on the attractiveness of the recommendation set and on the difficulty of choosing from this set.

Attractiveness is high if the items in the set vary. A low choice difficulty positively influences satisfaction. However, if the user is presented with more attractive sets, the choice difficulty becomes higher. Willemsen *et al.* (2016) investigate the influence of diversity of the item set on choice overload that arises when users have to select from many items. They find that small but diverse item sets help reduce choice overload and result in similar user satisfaction as top-N recommendations. Jin *et al.* (2019) examine the influence of user control over contextual factors incorporated in the recommendation process on perceived quality, diversity, effectiveness, and users' cognitive load. In a user study, they test two conditions: either the participants have no control over a music recommendation algorithm, or they can choose a particular context, i.e., mood, weather, and location, to which recommendations should be tailored. The study results show that users perceive the utility of recommendations differently when they can select a context. In particular, tailoring recommendations to a user's mood positively impacts recommendation quality and diversity.

4.2 Designing User Studies for Recommender Systems and Existing Evaluation Frameworks

Many research works in recommender systems employ offline evaluation studies, which retrospectively analyze available datasets for certain model-based predictions. While offline evaluation helps assess the internal validity of the recommendation model, it only allows for speculations about the actual user experience. Thus, offline evaluation needs to be complemented by methods that also enable insights into (i) latent user states (e.g., a user's perception of the system) and (ii) the ecological validity of the evaluation results. Both aspects can be addressed by user studies, which we outline next.

When running user studies, it is essential to consider principles of psychological measurement theory (Allen and Yen, 2001) and its application to construct reliable and valid self-report scales (McCroskey *et al.*, 1984; Yannakakis and Hallam, 2011). Self-reports are tests and measures that require individuals to report on their behavior, beliefs, or attitudes. Self-reports are beneficial to elicit key aspects of user experiences, such as engagement (e.g., O'Brien and Toms, 2008), which has been shown to reliably predict perceived usability and endurability, i.e., how likely a user is to return to and recommend a novel system (O'Brien and Toms, 2010). The construction of self-report scales requires representative samples of participants and latent factor analysis. Here, a classic choice is to perform an Exploratory Factor Analysis (EFA) (Goretzko *et al.*, 2019) to group inter-item correlations into distinct dimensions (for a review and guideline of how to apply an EFA in the context of recommender systems, see, e.g., O'Brien and Toms, 2010). Subsequently, a Confirmatory Factor Analysis can be run on an independent dataset (gathered from additional user studies) to validate the previously explored factor structure.

For the systematic planning of user studies of recommender systems, Knijnenburg and Willemsen (2015) present a framework that facilitates the design of user studies. In particular, the framework describes how *objective system aspects* such as the algorithm or a presentation layout are perceived by the user and how the user's *perception* – denoted *subjective system aspects* (e.g., perceived recommendation quality and variety), in combination with *personal* and *situational characteristics*, influence the *user experience* and *interaction* with the recommender system. The situational and personal characteristics help account for context-relevant information (e.g., the user's current information goal) and individual variables (e.g., personality traits; see Section 2.2.2).

Similarly, Pu *et al.* (2011) introduce the *ResQue* framework to assess the perceived recommendation quality (e.g., attractiveness, novelty, diversity, and perceived accuracy of recommended items), usability, interface adequacy (e.g., information sufficiency and layout clarity), interaction quality (e.g., preference elicitation and revision), and the overall user satisfaction with the recommender system, as well as the influence of these aspects on the user's intention to buy recommended products and to revisit the system.

To conclusively explain observed effects such as perceived quality differences between algorithms, behavioral data such as user's interactions with recommendations can be triangulated with self-report data. For example, Knijnenburg *et al.* (2012b) demonstrate that two types of matrix factorization algorithms have the same effects on certain experience variables (e.g., perceived system effectiveness) but are mediated by different subjective system aspects (e.g., different dynamics between perceived diversity and quality). Such study outcomes are essential for the design and improvement of user interfaces, but can only result from the triangulation of behavioral and self-report data.

Due to its high degree of abstraction, the Knijnenburg et al. framework can help guide the systematic planning of research designs. Also, the framework provides a scheme for the formulation of experimentally testable research questions, and it provides guiding information for implementing and analyzing the planned research design, including the operationalization and measurement of the variables to be investigated (e.g., constructing new or using existing questionnaires) and a comprehensive data analysis (e.g., applying structural equation modeling techniques (Ullman and Bentler, 2003)).

4.3 Discussion

The reviewed works show that many factors influence how users experience and engage with recommender systems. One of them is cognitive dissonance. While dissonant recommendations that are inconsistent with the users' attitude could make them lose trust in the system, Schwind and Buder (2014) find that dissonant recommendations can help de-bias information selection. Future work can take a cognitive-computational perspective on biased information behavior (e.g., inspired by self-directed search (Dubey and Griffiths, 2020)) to design recommender systems that help explore non-confirmatory information. Here, the relationship between experienced novelty and curiosity can be explored (e.g., Dubey and Griffiths (2020)): If novelty is perceived as either very high or rather low, an information seeker's curiosity drops; the optimal level of novelty – the sweet spot on the continuum – arises primarily at a moderate level (see also Berlyne (1966)). Future work can therefore investigate, whether a recommender system, drawing on these cognitive-computational accounts of information behavior, can identify the sweet spot of novelty for a given user-subject combination and help identify resources that make the user curious about and willing to tap into them. Another strand for future research lies in exploring boosting in recommender systems to foster counterfactual thinking to de-bias information selection.

Jannach *et al.* (2019) state that research in recommender systems should strive towards *impact-oriented algorithms* that address the intended purpose of a system. The impact can be, e.g., to help users make better decisions and to increase user satisfaction. As the authors describe, persuasion can help achieve this goal. However, persuasion in recommender systems can decrease the user's possibility to develop their taste since humans tend to take the default setting if one is offered (Knijnenburg *et al.*, 2016).

In their work, Knijnenburg *et al.* (2016) call for personalized systems that aim to not just recommend the most relevant items to the user but to help users develop, explore, and understand their personal preferences. To that end, they suggest several recommendation lists that contain only items unrelated to the top-N, which means they are not "good" recommendations (e.g., items that the algorithm predicts a user will dislike or unrated items). Their intuition is that such recommendations will help the user learn about their taste and preferences. Including unrelated recommendations to increase the user's awareness of their preferences can lead to effective feedback mechanisms for recommender systems. On a more general note, such mechanisms can help users understand what assumptions the algorithm makes about them and enable them to correct such assumptions.

The way recommendations are presented also influences whether users are satisfied with a recommender system and the level of control users have in the process. Studying these questions in the context of psychological theories is still a largely unexplored field and requires more interdisciplinary research efforts.

In this chapter, we also discussed the design of studies for user-centric evaluation. From a methodological perspective, user-centric evaluation entails designing questionnaires and conducting user studies that help uncover intrinsic properties and characteristics of subjective user experiences. User studies are a standard evaluation methodology in psychology that help investigate the impact of system changes under natural conditions and access (latent) user states.

Conducting such studies can be challenging, though. In particular, it can be difficult to gather a sufficiently large sample of participants that allows for drawing significant and meaningful conclusions with a high ecological validity. Ecological validity, in psychology, measures whether we can generalize from behavior observed in an experiment to behavior in real-world settings (Schmuckler, 2001). One issue in recommender systems research is that ecological validity can be low (Sinha, Swearingen, *et al.*, 2001), particularly in field studies, where filling out questionnaires can be time-consuming and a burden for the respondents. The challenge is to design the study so that enough reliable data can be collected and respondents participate, which often requires tending towards simplicity in the user-centric evaluation (Fazeli *et al.*, 2017).

To facilitate the design and conduction of user studies, the research community has introduced several evaluation frameworks, as well as beyond-accuracy metrics that quantify more user-centric aspects of recommender systems, such as novelty, serendipity, or diversity. Optimizing a recommendation system for such metrics can help increase user satisfaction, as in the case of diversification of recommendations.

Furthermore, investigating user experience requires access to a deployed system and users interacting with the system over some time (Konstan and Riedl, 2012). That is particularly challenging as academic research often has limited access to such systems. As a remedy, the research community has put notable efforts to help academics build real-world systems via initiatives such as GroupLens (Resnick *et al.*, 1994), or LensKit (Ekstrand, 2020).

5

Conclusion and Suggestions for Future Research

A substantial amount of research on psychology-informed recommender systems has been conducted in the past years. In this paper, we reviewed such recommender systems along three categories: i.e., *cognition-inspired*, *personality-aware*, and *affect-aware* recommender systems.

As shown by the reviewed works on **cognition-inspired recommender systems**, cognitive models help design and improve recommender systems in various domains. One advantage is that these algorithms are interpretable and transparent. Also, they can give further insights into user behavior grounded in human cognition.

While many works in cognition-inspired recommender systems utilize human memory processes to model and predict user behavior, there is untapped potential in the study of the connection between utilizing human memory processes to design and improve recommender systems and using recommender systems to support human memory in retrieving objects. While both strands of research agree on the relevance of context cues for determining the importance of objects in human memory, to date, research that addresses both aspects simultaneously is scarce.

Furthermore, we reviewed works that incorporate a user's attention into the recommendation model. While the success of deep learning has spawned a range of attention-based approaches, we are not aware of any works that discuss underlying psychological models and theories of attention. Here, we see potential for future work to investigate attention-based approaches in light of underlying psychological constructs.

As illustrated by the reviewed works on **personality-aware recommender systems**, personality has a significant impact on user preferences and behavior. The use of personality traits in personalized recommender systems helps alleviate cold-start problems and can improve the level of personalization and diversification of recommendation results both in single-user and group recommendation scenarios.

However, it is not well understood to which extent personality influences perceived recommendation quality; neither is the variability of this extent between users. For some users and domains, tailoring recommendations to personality traits might be valuable to recommend items that fit their personality; for others, personality could be an irrelevant signal, which could be perceived as invasive concerning privacy and ethics. Incorporating personality in a privacy-aware fashion is an open issue. Also, current approaches integrate personality using quite simplistic ways, e.g., by linearly combining a content-based similarity with a personality/user-based similarity metric. Only in a very recent article, Beheshti *et al.* (2020) incorporate personality information as features in a neural embedding framework in the larger context of a so-called cognitive recommender system. Furthermore, how to model the "personality" of an item is still an under-researched question. More sophisticated methods to derive personality traits on the item level are required. One related example is the approach by Sertkan *et al.* (2019).

In the context of **affect-aware recommender systems**, our survey shows that incorporating users' affective states can help improve personalization. Both emotion and mood are beneficial in context-aware recommendation scenarios, such as location-based recommendations, and in scenarios in which recommended items have a strong affective impact on users, such as music recommender systems. As in the case of personality, to which extent a user's mood or emotion influences the perceived recommendation quality is, to date, not well understood. Nor is the importance of mood or emotion changes during item consumption. We see further potential to research detecting such changes and integrating affect dynamics into recommender systems. Finally, mood and emotion constitute sensitive information. Therefore, more research is needed to make emotion detection and inclusion of emotion as a contextual factor in recommender systems privacy-aware.

On a more general note, existing methods in personality- and affect-aware recommender systems are relatively simple extensions of standard collaborative filtering or content-based filtering algorithms. We see further potential to study how information about personality, mood, and emotion can be integrated into current state-of-the-art deep learning methods (e.g., (Zhang *et al.*, 2019a; Schedl, 2019)).

Finally, most works discussed in this paper employ standard performance metrics from information retrieval and machine learning for evaluation. Future work can explore what metrics psychology-informed recommender systems can improve beyond accuracy, such as algorithmic fairness or transparency. Here, frameworks like the one presented by Deldjoo *et al.* (2021a) could be applied to evaluate user and item fairness and to devise suitable metrics. More research is also needed on the online performance of psychology-informed recommender systems to better understand whether their recommendations result in higher user satisfaction.

In this paper, we have also discussed the relationship between **human decision making and recommender systems**. A range of decision biases are described in the literature, which influence how users interact with a recommender system. Recommender systems can exploit and strengthen such biases to provide more useful recommendations, or to nudge and persuade users. Such effects require a level of control, in particular when they lead to sub-optimal outcomes. While most related work has focused on detecting decision biases in recommendation scenarios, we need more research on proactively preventing or minimizing such biases.

Also, the ethical concerns and discussions around the concept of nudging and persuasion gave room for *boosting* as a competing framework. Since the aim of boosting is to help users improve their competencies in decision making and overcome human cognitive limitations, we believe that boosting is a promising research area for the recommender systems community. For example, boosting can be applied to improve user knowledge about decision biases and underlying mechanisms of the recommender systems, including the implications of users' behavior on the prediction quality.

In this paper, we also discuss the **user-centric evaluation of recommender systems** and factors that influence how users experience and engage with recommender systems. One of them is cognitive dissonance, which, on the one hand, recommender systems designers should avoid as it can make users lose trust in the system. On the other hand, it can help de-bias information selection. We see potential for future work to take a cognitive-computational perspective on biased information behavior to design recommender systems that help explore non-confirmatory information. Here, the earlier mentioned boosting could help foster such exploration via dissonant recommendations that spark counterfactual reasoning.

Finally, in this paper, we discussed the design of **user studies for recommender systems evaluation**. Here, psychology has strongly influenced recommender systems research since methodologically, user-centric evaluation employs questionnaires and other instruments to uncover intrinsic properties and characteristics of subjective user experiences.

Conducting such studies with ecological validity in mind can be challenging, in particular, to gather a sufficiently large sample of participants that allows for drawing significant and meaningful conclusions. Here, the community could benefit from increased interdisciplinary cooperation between computer science and psychology to benefit from the rich knowledge in the psychological community on designing user studies that do not overburden users and still result in sufficiently large amounts of data.

To facilitate the design and execution of user studies, the research community has introduced several evaluation frameworks. Nevertheless, such user-centric evaluations require access to real-world systems and the ability to observe long-term user behavior. To mitigate this issue, the research community has put notable efforts to help academics build real-world systems via initiatives such as GroupLens (Resnick *et al.*, 1994).

All in all, even though the past few years have witnessed an increasing awareness of psychological considerations in recommender systems research, we are still far away from considering the recommendation task as a multi-perspective endeavor. While historically, recommender systems research has been tied to business (informatics) and computer science, we argue that it should be similarly intertwined with sociological and psychological research.

Our vision for future recommender systems research is, therefore, to draw from the decent knowledge of these disciplines in the entire workflow of creating and evaluating recommender systems. Corresponding systems should, as a result, holistically consider extrinsic and intrinsic human factors; corresponding research should adopt a genuinely user-centric perspective.

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