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Considering Temporal Aspects in Recommender Systems: A Survey

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Abstract The widespread use of temporal aspects in user modeling indicates their importance, and their consideration showed to be highly effective in various domains related to user modeling, especially in recommender systems. Still, past and ongoing research, spread over several decades, provided multiple ad-hoc solutions, but no common understanding of the issue. There is no standardization and there is often little commonality in considering temporal aspects in different applications. This may ultimately lead to the problem that application developers define ad-hoc solutions for their problems at hand, sometimes missing or neglecting aspects that proved to be effective in similar cases. Therefore, a comprehensive survey of the consideration of temporal aspects in recommender systems is required. In this work, we provide an overview of various time-related aspects, categorize existing research, present a temporal abstraction and point to gaps that require future research. We anticipate this survey will become a reference point for researchers and practitioners alike when considering the potential application of temporal aspects in their personalized applications.

Keywords Recommender Systems · User Modeling · Temporal Aspects · Dynamics · Long-term Preferences · Short-term Preferences · Survey

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1 Introduction

Personalization is a key feature of many of today's online services. From entertainment and product recommendations to personalized medicine, in many cases nowadays services are tailored to the individual needs and preferences of their users (Schork, 2015). An essential component that is needed to support such a personalization process is the *user model*—a representation of the user and her characteristics, including in particular interests and preferences in the specific domain of interest (Kobsa, 1993). Whether it is a recommendation about a product, a route to a destination or a medical treatment, all must take the user characteristics into consideration (Lu et al., 2009).

Naturally, the user model needs to be adapted over time, as new information is acquired by the system and irrelevant or outdated information needs to be removed. This is the role of the *User Modeling Component* of a personalized system (Kobsa, 1993). The need to continuously update the user model arises whenever new information becomes available about the user that reflects changes in the users' characteristics, interests and preferences. Naturally, users acquire new skills, gain experience, and their tastes, preferences and goals may change over time as well as their physical and medical characteristics. As a result, there is a strong temporal aspect that must be considered in user modeling.

The literature shows that considering temporal aspects can increase the effectiveness of a personalized service. One well-known example is the Netflix prize competition, where temporal aspects, when considered for product recommendation, helped to improve the accuracy of the recommendations to ultimately win the prize (Koren, 2009). Additional recent studies include—but are not limited to— predicting sequences of interaction events (Borisov et al., 2018), combining user's past consumption patterns with the current temporal context via recurrent neural networks (RNN) to predict next track to listen to in the session (Hansen et al., 2020), disease count time-series prediction (Talaei-Khoei and Wilson, 2019), next basket recommendations that capture users' shopping patterns (Faggioli et al., 2020) and many more.

Temporal aspects in these studies were shown to be helpful in modeling individual users' behavior and to improve the accuracy of the recommendations. Still, many challenges in considering temporal aspects remain. This may include, for instance, the fact that the personal information used for user modeling may have an expiration date; or that their lifetime may be different across application domains, e.g., very short for seasonal shopping and very long for knowledge or education.

Despite the importance of the topic, no recent structured review about temporal aspects in recommender systems is available today. Hitherto studies about concept drift (Gama et al., 2014) can be considered highly relevant to user modeling in recommender systems, as changes in the user model can be considered as a concept drift.[1] These studies however focus on what we consider a certain subproblem in temporal user modeling. We therefore believe that the still growing and wide-spread use of temporal aspects in recommender systems requires an updated reference point for researchers and practitioners that consider integrating temporal aspects in their personalized systems. To the best of our knowledge, there was also no previous literature review on the evaluation of short-term and long-term user's preferences in recommender systems domain, except by Campos et al. (2014), where different evaluation protocols for time-aware recommender systems were reviewed. Therefore, the discussion of evaluation aspects of time-aware recommender systems—which is already covered in depth by Campos et al. (2014)–is beyond the scope of our survey. Instead, we focus on the modeling of user characteristics and preferences and their evolution over time in a variety of domains. As one further main contribution, we provide an abstraction of temporal aspects in user modeling and recommender systems. Specifically, in our study, which focuses on recommender systems as a highly relevant use case of personalized systems, we address the following questions:

RQ1. How can we categorize temporal aspects in recommender systems and what abstractions are possible?

RQ2. How are temporal aspects of recommender systems considered in different domains?

The paper is organized as follows. First, we describe our review method and then discuss aspects of temporal reasoning in recommender systems. In Section 3, we provide a landscape of existing research in a structured way—we present a novel taxonomy of time-dependent aspects in recommender systems (RQ1). Afterwards, we provide an analysis of time-dependent user preferences in different domains based on the previously defined abstraction and the idiosyncrasies of the individual domains (RQ2). Finally, we raise open questions in the temporal aspects-aware recommender system research and point to the future directions.

2 Research Method

We adopted a semi-systematic literature review process for our survey, applying principles proposed by Kitchenham et al. (2009). First, we defined the scope: peer-reviewed venues (conferences and journals) related to recommender systems or those that have related tracks. Since the topic is relatively narrow, we started with manually scanning the proceedings of the ACM RecSys conference[2] series, scrutinizing their abstracts and methods sections, pursuing two goals: (i) finding papers that are relevant to our survey; (ii) finding patterns to be used as search queries. Then, a manual search was done using the following query to Google Scholar: "(time OR temporal OR

[1] Gama et al. (2014) defined *concept drift* as changes in the conditional distribution of the output given the input.

[2] https://recsys.acm.org/

dynamic OR evolve/evolution OR drift OR adapt) AND (recommend)" in primary conferences proceedings, including but not limited to WWW (The Web Conference), User Modeling, Adaptation and Personalization (UMAP), Intelligent User Interfaces (IUI), Research and Development in Information Retrieval (SIGIR), Knowledge Discovery and Data Mining (KDD), International Joint Conference on Artificial Intelligence (IJCAI), Association for the Advancement of Artificial Intelligence (AAAI) and Web Search and Data Mining (WSDM) conferences, as well as in leading journals, including User Modeling and User-Adapted Interaction (UMUAI), Information Processing & Management(IP&M) and Expert Systems with Applications (ESWA). Let us remind the reader that our goal is not to provide an exhaustive list of papers. Figure 1 shows the list of the most popular venues (with more than six papers found per venue) and the number of publications found in each of them. We considered works on user modeling and recommender systems appearing between 2007, when the ACM Conference on Recommender Systems series began, and 2020.

After identifying and scrutinizing relevant papers, we applied a snowballing procedure, where the papers' references list as well as the papers citing them were examined and considered (Wohlin, 2014). Altogether, around 400 papers were reviewed and analyzed according to the following criteria: temporal aspects that are discussed in the paper, domain to which the paper belongs, data sets that are used in the paper, technical approaches, evaluation techniques and whether short-term, long-term or dynamics/evolution are considered in the paper[3]. Looking at the initial results, it seems that in recent years there was a growing research interest in these aspects until 2017, after which many of the related papers focus on sequences and feature embeddings in various deep neural network architectures (see Figure 2).

3 Temporal Abstractions in User Modeling

In this section we present a novel taxonomy for temporal aspects in user modeling. To create it, we first identified a small set of abstract concepts related to temporal aspects, including long-term and short-term user preferences, contextual aspects and the evolution of user's interests over time. These abstract concepts were already noted in early days of personalization and user modeling research. In the early three-dimensional user model by Rich (1983), the third dimension is a temporal one: *short-term vs. long-term*. Here, long-term models relate to the long-term user preferences (long-term facts) like areas of interest or expertise, while short-term models refer to the current problem that the user is trying to solve, like finding a suitable item in the current purchase session (short-term facts). Billsus and Pazzani (1999) later linked short-term interests to "hot events", while referring to long-term interests as to the actual reflection of the real user's interest.

[3] We share the raw data that was collected in this process online: `https://github.com/sveron/TempAspectsSurvey`

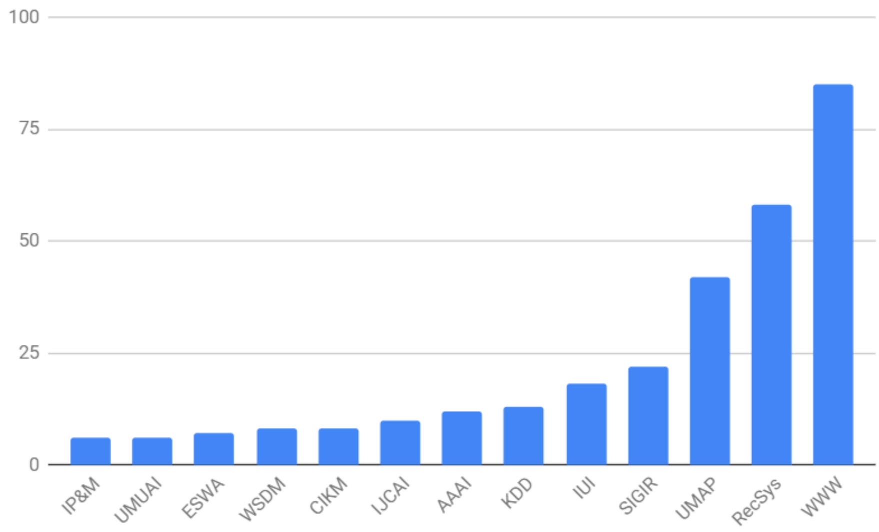

Fig. 1 Number of relevant papers per venue

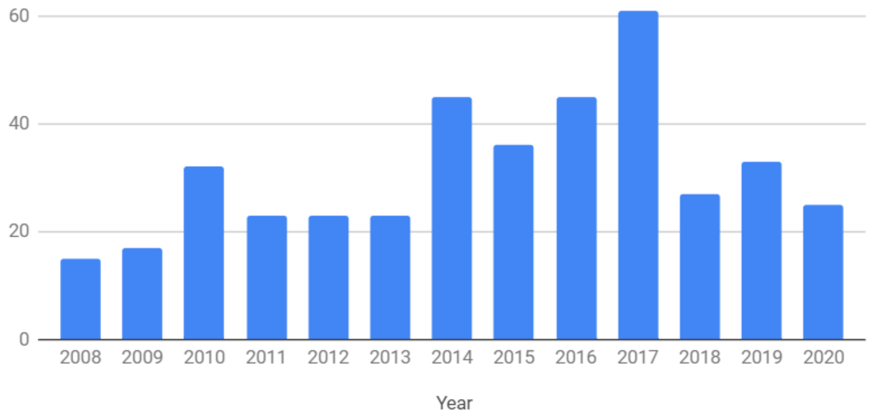

Fig. 2 The number of studies per year that addressed temporal aspects for modeling users (from the above sources).

In this review we follow Rich's definitions (Rich, 1983) of short-term and long-term characteristics. For the sake of brevity, we use the term *preferences* as an abstraction of various types of user characteristics, including the various *underlying factors* that may have led to the observed actual expressed or implicit preferences (e.g., personality traits, interests, preferences, needs, constraints etc.).

In our study, we identified commonalities and variability in the way temporal aspects were addressed in works in different domains. The main domains of application we found in our work include news, e-commerce, tourism, learning/tutoring, entertainment (music, movies, books) and health. Figure 3 shows the number of papers per domain. Naturally, these domains may have different characteristics that impact the way temporal aspects are incorporated in the corresponding recommender systems.

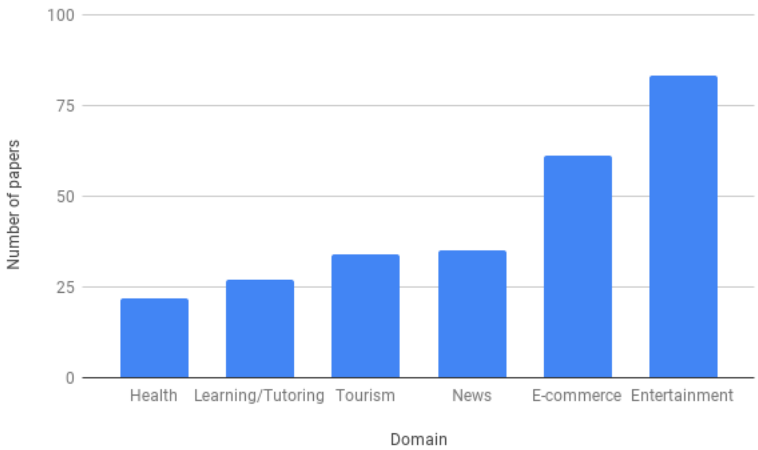

Fig. 3 The number of studies per chosen domains.

3.1 Long-term User Preferences

Long-term preferences represent steady preferences that do not change or change slowly over time. Li et al. (2014) demonstrates the difference between long-term and short-term preferences as follows, where long-term preferences often refer to something more general and short-term preferences are often much more specific. Consider a user that is interested in sports and politics: she may prefer sport-related news to other topics in general (long-term preferences), while in the short-term she may hop between "Cycling World Championships", "Baseball World Championships" and so on. However, in the short-term she might also be interested in other areas, such as celebrity news that are not part of the long-term model. Hence, the short-term model therefore could also include uncommon, novel or serendipitous areas of interest.

According to Kobsa (1993), long-term preferences may also be more "personal" than the short-term ones. Therefore, they evolve slowly over time. Such characteristics relate to demographics (age, gender, place of birth and living), physical characteristics like height (Kay and Kummerfeld, 2019), education, previous knowledge about the application domain (Fink and Kobsa, 2002) and personality (Gosling et al., 2003; Cantador et al., 2013). Personality affects users' decision making and is strongly correlated with user preferences (Tkalcic and Chen, 2015). One of the most known models for measuring personality traits is the Big Five model that distinguishes five personality factors for describing a human's nature: neuroticism, extraversion, openness to experience, agreeableness, and conscientiousness (Goldberg, 1993; Costa Jr and McCrae, 2008). Cantador et al. (2013) showed relations between such personality traits and user preferences in four leisure sub-domains: movies, TV genres, books and music. For example, people with a high degree of openness often preferred poetry and science fiction books, while those with a low degree of openness preferred drama, scary and crime books. Tkalcic and Chen (2015) claimed that the former are open to novelty and new experience, as well as to diversity, and such relations should be taken into consideration for user modeling in recommender systems. Chorley et al. (2015) found positive correlation between conscientiousness and location-based social networks usage. Openness mainly correlated with popularity of the venue and the number of check-ins at social media sites, such as Foursquare. Neuroticism showed negative correlation with the number of visited venues.

In order to model user preferences in the long run, including the users' past behavior and activity patterns, different techniques were used in the literature, e.g., Latent Dirichlet Allocation (LDA) approaches (Kowald et al., 2013; Li et al., 2014), deep learning techniques (Song et al., 2016), reinforcement learning (Wang et al., 2014), non-negative matrix factorization (NNMF) (White et al., 2010), random walk (Hong et al., 2012) and temporal similarity (Tran et al., 2015). Such techniques can be used in various domains, like tourism or entertainment. Some long-term preferences, especially those characterizing a user's past behavior, tend to differ from domain to domain. In health, the patient's medical history and her family medical history are very important for diagnostics and predictions, where often collaborative filtering and general machine learning techniques, such as Naive Bayes, Support Vector Machine and Decision Tree are used (Davis et al., 2010; Gonsalves et al., 2019). In domains where the users' interaction with the systems is characterized by sessions or sequences, including news, e-commerce, tourism (points of interest – POIs) and music (playlists), long-term preferences refer to the users' past (historical) behavior in sessions (Jannach et al., 2015) and should be modelled accordingly, applying sequence-related techniques that are able to capture sequential information in the actions, e.g., Markov Chains (He et al., 2016; Klingler et al., 2016), RNN-based (Recurrent Neural Network) architectures (Yu et al., 2016; Liu et al., 2016; Quadrana et al., 2017) or Transformers (Kang and McAuley, 2018; Sun et al., 2019).

3.2 Short-term Preferences

We extend Rich's definition of short-term preferences: "the current problem that a user is trying to solve" and add the user's context as a constraint or trigger to be part of modeling the users' short-term preferences. According to Fling (2009), there are two relevant definitions of context to be considered here. On the one hand, context is "an understanding of circumstances, the mental model, which enhances user experience and awareness of the surroundings". On the other hand, "it is the mode, medium or environment, where a task is performed". Fling distinguishes between three types of contexts: (i) a *physical/environmental context*, (ii) *a media context* (present device access) and (iii) the user's present *state of mind*. When considering short-term user preferences, we can see that they are often influenced by such contextual aspects, as we show below.

A physical context is related to the physical environment of the user and its constraints. It dictates how the information is accessed and, as a result, how the user's actions might be influenced by it. This context can be important for user modeling in domains like tourism and entertainment, where location, weather, activity, crowdedness and time (weekend/weekday, part of the day, opening hours) should be taken into account when recommending users POIs to visit. For example, if a place is very crowded in the afternoon, but closed in the evening, then morning hours may be considered best for visiting. Or, if the weather is stormy, a hike on the Dolomites should be postponed to another, more appropriate day (Braunhofer et al., 2013). What music to listen to during various daily activities may also depend on the activity-related context (working, studying, running, sleeping, walking or shopping) (Wang et al., 2012). *Social context* is also considered as part of the physical context. Whether a user is alone or a part of a group, this may impact the system's behavior or recommendations (Masthoff, 2011). For example, what movie should a user watch in the evening? In case of a group watching (with kids or with friends) the final choice may be different, depending on other group members' preferences (Masthoff, 2004).

Media context refers to the specific device in use. User experience and expectations differ between mobile and desktop devices. With mobile applications, POI recommendations with a map may be more suitable and more dynamic. Since the user can actually see herself moving on the map towards the relevant POI and discover other POIs around on the map.

The user's present state of mind can be a more complicated factor and relates to aspects such as mood, intent, experience and cognitive capabilities, that affect users' decision making. Whether to purchase something now or add to the shopping cart and wait for a price reduction? What kind of music may fit the current mood (Schedl et al., 2015)? What online course should be taken now and which one afterwards?

After having discussed short-term preferences and what may affect them, we review examples of how they can be modelled, which can be done in different ways. Time-stamped information provided by the system (e.g., as transaction logs) usually represents a starting point for many further analyses: sequences of clicks (user-item interaction) within sessions and additional temporal factors such as hour of the day, day of the week, day of the month, month of the year are considered with the help of various techniques, such as DBSCAN clustering (Cai et al., 2018), Temporal Deep Semantic Structured Models (Song et al., 2016), auto encoders as a part of the temporal module that embeds the sequential behaviors with timestamps into dense vectors (Ye et al., 2020), or attentive deep models (Shen et al., 2020). Moreover, item characteristics that vary over time can be considered as well, such as item trendiness (Bogina et al., 2016), new trends (Lommatzsch et al., 2017; Jannach et al., 2017), freshness/recency (Chu and Park, 2009; Garcin et al., 2013; Kille and Albayrak, 2017; Jannach et al., 2015; Gulla et al., 2016; Wang et al., 2016; Chakraborty et al., 2017; Kowald et al., 2017), seasonality (Xiong et al., 2010; Rokicki et al., 2017) and promotions (Luo et al., 2016). All of them may affect a user's short-term preferences. Note that these factors may provide a starting point to address cold-start problems (Schein et al., 2002) of user modeling as well, as they may provide some initial information about what items are generally preferred by users at the moment. Next, we review more examples for short-term user modeling from the literature, including approaches that consider periodic signals.

1. *Popularity/Trendiness.* An item's popularity may last only for a certain period of time, depending on the domain. In e-commerce and news, for example, this period can be shorter than in the movies domain (Garcin et al., 2013; Tsur and Rappoport, 2012; Yang and Leskovec, 2011; Lerman and Hogg, 2010; Brenner et al., 2010). This may mean that a "popularity window"[4] should be determined based on the specifics of the domain and, probably, this window may even be dependent on an item's category.
2. *Seasonality.* There are items that are relevant and available only for a short period of time and may have a repetitive cycle (every winter, every year, once per four years), while they are consumed less frequently off season. Seasonality in the news domain is for example reflected in specific periodic news on topics such as soccer world cup, Olympics, or presidential elections (Gulla et al., 2016; de Souza Pereira Moreira et al., 2018; Kramár and Bieliková, 2014; Keerthika and Saravanan, 2020). In the e-commerce domain, the users' behavior may likewise vary during a year: they buy turkey and pumpkin for specific holidays, or watermelon and avocado only when they are available (Xiong et al., 2010; Ma et al., 2019; Lonlac et al., 2020; Trattner et al., 2019). It is worth noting that Pagano et al. (2016) relates to seasonality also as a context.
3. *Freshness/Recency.* When a new item is released—including new versions of existing items, such as mobile phones—it is considered to be fresh or recently updated. The same is true when considering dynamic content (e.g., news articles) (Chu and Park, 2009; Garcin et al., 2013; Kille and Albayrak,

[4] Such a window may for example express that items that were most popular in the last n days should be considered to be particularly relevant.

2017). In many domains, freshness is important for user modeling. In digital games, for example, most of the players join the new game in the first few weeks after it was released (Wu et al., 2019). In a different domain, Lehmann et al. (2012) showed that the recency of tags has a positive effect on their recurrence probability. Garg et al. (2019) finally considered the recency of the past session with respect to the current session in session-based recommendations.
4. *Recurrence.* Recurrence refers to the repeated consumption of an item (Ren et al., 2019). Reminders about items that were purchased before or discounts may be a trigger for item re-consumption (Jannach et al., 2017). Bai et al. (2019) proposed a Demand-aware Hawkes Process framework that captured long-term user demands (repeated purchase) and short-term demands (complementary purchasing[5]) using RNNs. Benson et al. (2016) identified two patterns of user behavior with respect to repeated consumption: (i) the related items have a limited lifetime span; (ii) towards the end of their lifetime users tend to consume them less in comparison with the beginning of their lifetime, e.g., because the users may become bored with them.
5. *Temporal Availability.* This concept refers to the question if an item is available at a specific point in time for a user. For example, TV programs that are scheduled to be broadcast at different times throughout the day are not always available to be recommended (Oh et al., 2012; Turrin et al., 2014; Bogina et al., 2020). Another example are the opening hours of POIs in tourism or other factors, such as weather, that may affect temporal availability (Trattner et al., 2016). Even queuing times might be considered here, i.e., when an item is not immediately available, a user may not be willing to wait for it to open (Lim et al., 2017).

From our analysis it appears that short-term aspects in most of the cases were acquired implicitly, through the user's current interaction with the item: clicks on items in the current session, implicit feedback, brand and category information of recently viewed items. These aspects are frequently considered in recommendations of news and tourism destinations, as well as in e-commerce.

3.3 Combined Approaches

In many application cases, both long-term aspects and short-term aspects have to be considered, possibly in combination with contextual aspects. This leads to combined approaches. Such work was done in time-aware, session-aware and sequential settings. Yu et al. (2019), for example, proposed an attention-based framework to combine both short-term and long-term user preferences to represent users with respect to the relevant context. In fact, various researchers considered both long-term and short-term aspects in different domains, since such a combination often leads to better results. Such approaches

[5] Complementary purchasing is the purchasing of items that are consumed in combination with this specific item and add some value one to another (cereal and milk)

are frequently used in e-commerce applications, in particular in session-based recommendation, to combine short-terms user intents (within session) with reminders from their historical interactions (Jannach et al., 2017), to consider preference changes in the long-term and short-term purchase patterns (promotions) (Luo et al., 2016), or to find trade-off between them. Devooght and Bersini (2017), for example, combined them in a neural network, applying an attention mechanism to weight different aspects. Another relevant domain is news, where researchers combined long and short-term user profiles (Billsus and Pazzani, 1999; Li et al., 2014; Symeonidis et al., 2020; Hu et al., 2020). Li et al. (2014) proposed to model the readers' temporal interests considering both a long-term interests profile—which changes slowly over time—and a short-term one, which may change rapidly. Symeonidis et al. (2020) also suggested applying random walks on dynamic heterogeneous graphs of session nodes using a sliding time window for personalized news recommendations. Zhu et al. (2017) proposed to use Time-LSTM, that considered time intervals between users' actions, to capture both long-term and short-term preferences in the next item prediction. The combination of long-term and short-term models is also relevant in *tourism*, especially in modeling route recommendations. Short-term preferences revealed that user's interests in some venue affected by the recently visited places, while long-term preferences - from the historical trajectories (Lim et al., 2015; Sun et al., 2020; Lim et al., 2020; Zhao et al., 2020; Liu et al., 2020). A recent performance comparison of neural and non-neural techniques to consider long-term user information in session-based recommendation scenarios can be found in (Latifi et al., 2021), highlighting the need for more effective methods to better leverage longer-term user preference information in such scenarios.

3.4 Evolution and Dynamics

The evolution of user preferences over time is a common phenomenon. As time passes, we change: we become older, change our family status, change jobs, acquire more knowledge, become experts in different areas, change our residency etc. As a result of such developments, our preferences may change as well. Sometimes these changes happen rather abruptly, e.g., due to marriage or a new baby. Sometimes they happen more gradually. However, there is almost always a noticeable trigger for a change. In this paper we distinguish between two main concepts: we refer to *Evolution* as a gradual (slow) change over the time, while we consider *Dynamics* as a quick change in the current, short time-window, e.g., a shopping or music listening session.

Webb et al. (2001) emphasized the importance for machine learning algorithms to adjust quickly to user characteristics change over time. As stated by Gama et al. (2014) concept drift primarily refers to an online supervised learning scenario when the relation between the input data and the target variable changes over time. Therefore, changes in the user model can be considered as a concept drift. Although there might be differences across domains.

Here, we look at the temporal abstraction of user preferences discussed above through the Four-Phase Model of Interest Development. In this model, interest refers to an individual's psychological state during engagement with some content (Hidi and Renninger, 2006), which in our case may for example be a recommendable item. The model includes four sequential phases that evolve into each other:

1. A triggered situational interest;
2. A maintained situational interest;
3. An emerging individual interest;
4. A well-developed individual interest.

The length and character of such phases are affected by an individual's experience and personality. *Situational interest* is triggered by the current context and may not last long. It may be supported by the meaningfulness of the task or personal involvement. *A triggered situational interest* is a result of short-term changes. *Maintained situational interest* refers to a psychological state of interest that lasts longer and persists over an episode in time and/or reoccurs. *Individual interest* refers to a person's tendency to re-tolerate certain content over time. *An emerging individual interest* assumes seeking repeated re-engagement with some content over time. *A well developed individual interest* assumes re-engagement with the specific content over time. The Four-Phase Model of Interest Development describes two phases of situational interest: triggered and maintained, as well as two phases of individual interest: emerging and well-developed. The former two are externally supported, while the latter two are self-generated (Hidi, 1990).

3.5 Taxonomy of Time-Dependent Aspects in Recommender Systems

When analyzing the literature, we identified a variety of temporal aspects related to recommender systems. Here, we present a novel taxonomy of time-related entities when considering personalization services. In this taxonomy, shown in Figure 4, the main entities are: a user model that is created based on (i) short-term, long-term, or a combination of preferences or their evolution and dynamics, (ii) domains, (iii) the way the data is acquired (implicit/explicit) and (iv) factors that affect user preferences (slowly/rapidly changing, user/item related). For example, item-related context affects suitability/attractiveness of items, including seasonality, while user-related context affects preferences of users, internal factors.

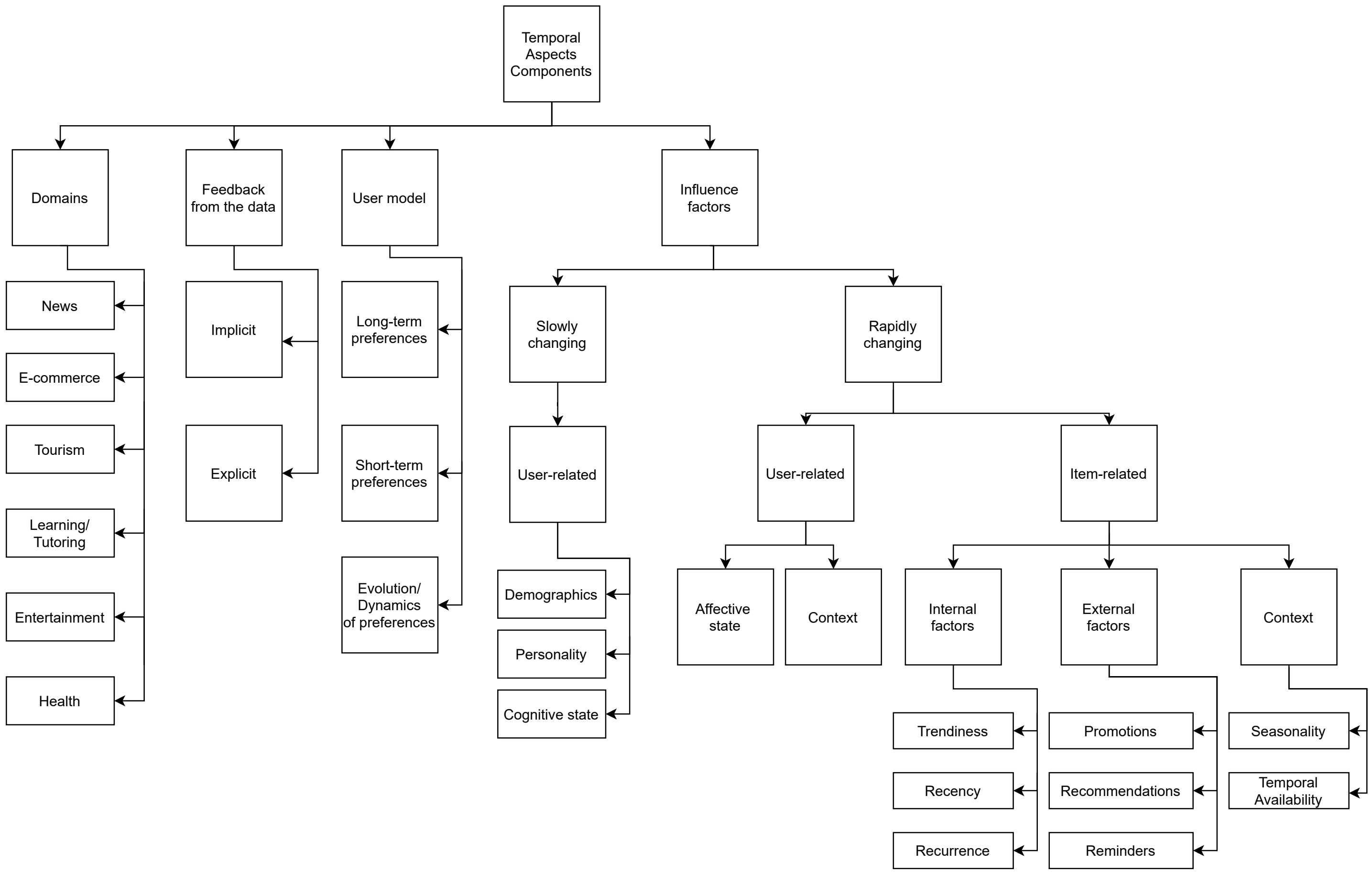

Fig. 4 Temporal aspects taxonomy in recommender systems: Reviewed domains (left), Feedback types (2nd from the left), User modeling component (2nd from the right) and Influencing factors (right).

Given the importance of recommender systems as representatives of personalized applications that involve user modeling, we created an abstraction to which most traditional recommender systems related user models can be mapped, shown in Figure 5. The figure contains two parts separated horizontally by a timeline that illustrates the temporal progression and the two schematic user model components: a long-term one and a short-term one that continuously evolve and are used for episodic recommendation, as needed. Note that the border between them may be blurry and that “old” information may be forgotten. Under the timeline we see the variety of components that may be used for long-term and short-term user modeling and the possible mechanism used for that. There are slowly changing influence factors, such as user-related factors including demographics or personality; on the other hand, we see more rapidly changing influence factors, such as user-related context or item-related aspects. These include trendiness and recency as well as context or external item-related factors such as promotions. Both implicit and explicit signals may be used.

The part of the figure above the timeline shows how item- and user-dependent information, as captured by the models, may be used by a recommender system (e.g., how at a certain point of time the long-term and short-term user models are integrated in order to provide an episodic user model to be used for recommendation). The user model itself may evolve over time and consists of long-term and short-term components. The model is either based on learning from observations (ratings/augmented implicit feedback) or based on explicitly encoding additional time-related knowledge. Figure 5 also shows how item- and user-dependent information is either directly used by the models (e.g., about user personalities or item trendiness) or is indirectly inferred from the observed interactions, which are in turn the result of the influencing factors. Such factors can be user-related or item-related and may change slowly or rapidly. The item-based context is any relevant information that can characterize the item’s situation, such as with what other items this item is purchased with or when this item is available. The item-based context affects suitability/attractiveness of items, incl. seasonality. The user-based context affects preferences of users, internal factors. The user-based context is any relevant information that can characterize the current users’ situation. An example for user-based context is social context (whom the user is with at the current moment) or user’s current location (where the user is).

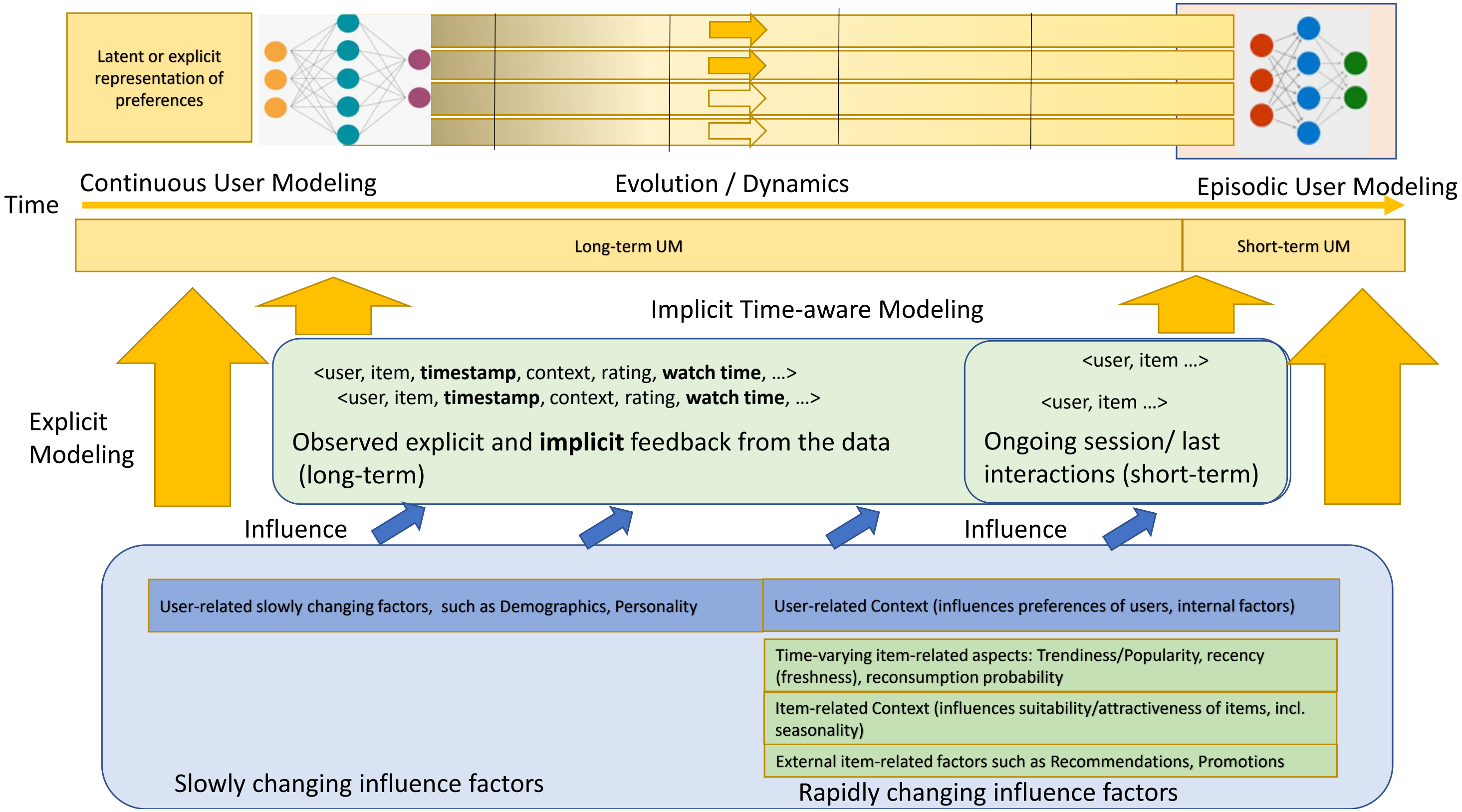

Fig. 5 Temporal aspects in building and using a user model for recommendation.

To further elaborate on this abstraction, consider how to map different traditional recommender systems approaches in this picture. For time-aware models, we would, for example, consider the observed interactions and probably only one time-aware user model. For session-based models, only the observed short-term interactions are available; for session-aware models[6] also the long-term history can be used (probably without explicit evolution as well). Works that focus on model evolution (e.g., through forgetting) would be positioned on top of the figure, where the user model evolves and some old information may be forgotten.

Next, in Section 4, we provide the results of our analyses of temporal abstractions in the context of recommendations per application domain. Specifically, we present commonalities and variabilities in the following domains: news, e-commerce, tourism, learning/tutoring, entertainment (music, movies, books) and health.

4 Time-Dependent User Modeling: A Domain-specific Analysis

In this survey, as noted in Section 3, we focus on the following domains: news, e-commerce, tourism, learning/tutoring, entertainment (music, movies, books) and health. In these domains, personalization is crucial and plays a key role in providing effective recommendations and support to users. Movies, books and music may be grouped together as entertainment, since they are similar in their nature, i.e., they follow the same goal of entertaining the user (Winoto and Tang, 2008). Moreover, this is the way they are referred to in the recommender systems domain.

The specific challenges may however be somewhat different in some cases. Moreover, Sahebi and Brusilovsky (2015) examined different domains for cross-domain recommendation and found that the similarity of two domains may depend on both: their common characteristics and on shared information. In the following sections we discuss these domains through the lens of relevant temporal aspects.

4.1 News Recommendation

News is an interesting and challenging domain for various reasons. News spans a large variety of topics and they have a large variety of "time to live". Some appear and disappear shortly; some stay and evolve over long periods of time. Hence, it is understandable why news recommendations attracted strong research attention over the years, as demonstrated by several recent surveys that reviewed the domain (Özgöbek et al., 2014; Karimi et al., 2018).

Özgöbek et al. (2014) analyzed challenges in news recommender systems considering content-based filtering, collaborative filtering and a combination

[6] See (Quadrana et al., 2018) for a categorization of sequence-aware recommendation models into session-based and session-aware ones.

of them (combined approaches). They considered several challenges, including the well-known cold start problem, recency—which is highly important in this domain almost by definition—and also covered trendiness and popularity aspects of the item. Recency is often dealt with by applying different decay functions (Lee and Park, 2007). Moreover, the use of implicit feedback and changing user's interests are critical factors that should be considered by news recommenders.

In their survey Özgöbek et al. (2014) found that in almost all examined studies recency was dealt with by either considering temporal aspects (Lee and Park, 2007; Wen et al., 2012; Tavakolifard et al., 2013) or changing user preferences (Lee and Park, 2007; Saranya and Sadhasivam, 2012) or the current popularity of the articles (trends) (Liu et al., 2010; Tavakolifard et al., 2013). Implicit feedback was mostly collected from the users' traces, e.g., by analyzing logs of click histories or the user navigation data in the system (Yeung and Yang, 2010; Garcin et al., 2013; Tavakolifard et al., 2013). Most of the data sets that are available for research in the news domain contain such type of information. In about half of the studies, the authors addressed changes of user interests, often by proposing a combination of static and dynamic user profiles (Saranya and Sadhasivam, 2012), combining short-term and long-term user profiles (Lee and Park, 2007), click distribution analysis (Yeung and Yang, 2010) and so on. Here we focus specifically on the temporal factors that were used in news recommendations.

In another survey, Karimi et al. (2018) analyzed papers on news recommendations during the previous decade and discussed domain specific challenges. One of them is the unceasing change in the users' interests that may depend on the users' context, such as time of the day, location or the platform the users use to access news from (mobile vs desktop). Recency and freshness were also identified as important aspects to be considered in news recommendation algorithms. Aside from these topics, Karimi et al. (2018) also discussed questions of serendipity, diversity, and scalability; these topics are however out of scope in this survey.

After analyzing recent papers on news recommendation, we found the following components from our taxonomy in Figure 4 to be frequently in the focus: short-term preferences, long-term preferences and evolution of preferences.

Short-term preferences in news recommendation can be modeled through various temporal factors. Timestamps attached to news items represent a starting point for further analysis. Sequences of user clicks within sessions and temporal factors such as hour of the day, day of the week, day of the month, month of the year were for example considered in deep learning techniques (Song et al., 2016; Zhang et al., 2019). Moreover, trendiness, trends, popularity and recency are also important factors in news recommendations, that may serve as a basis to address the cold-start problem (Montes-García et al., 2013; de Souza Pereira Moreira et al., 2018; Gabriel De Souza et al., 2019). When providing recommendations within sessions, researchers often considered the current user's interests that were modeled from the previously viewed items, combining them with the popularity/recency/context features (de Souza Pereira Moreira et al., 2018; Gabriel De Souza et al., 2019).

Long-term preferences are often based on traces that users leave during previous consumption sessions, on the users' general habits and on demographics (age, education, place of birth, current residence and so on). In order to model user interests in the long run, LDA approaches (Li et al., 2014), deep learning techniques (Song et al., 2016; Symeonidis et al., 2020) and temporal similarity (Tran et al., 2015) were used among other techniques in the surveyed studies.

The evolution of user preferences over time is a common theme in news recommendations. However, not only the interests, but also the news themselves change rapidly. Furthermore, during our analysis we identified a few sub-dynamics: dynamics of reading behavior, dynamics of content pools, user preference dynamics and emotion dynamics towards news. The most popular methods considered for addressing these aspects are Markov Processes, Contextual Bandits and Deep Neural Networks. Garcin et al. (2013) represented sequences of articles or sequences of topic distributions as a node in a context tree that was used to estimate Variable-order Markov Models (VMM). Qin et al. (2016) proposed to use contextual bandits for periodical recommendations, based on features hashing. Epure et al. (2017) modeled the dynamics of user interests in news consumption by a discrete First-order Markov Chain over news categories. They in particular discovered breaks, which are stable periods in the user's behavior, e.g., January-March, April-July and August. He et al. (2018) suggested using a temporal smoothness framework that should smooth the learning results over time. Their framework consisted of a neural network with evolving classifiers, where time is sliced into a sequence of steps. At each time step different features are extracted and then fed into the deep diachronic connections, considering both the historical impact and currently learned features. Finally, this neural network's output layer yields a probability to belong to the predicted topic label. This way a trade-off between the long-term evolution of news topics and their short-term fluctuation is considered.

Considering the studies analyzed so far, the two main challenges of news recommendation are how to combine short term and long-term user interests and how to identify concept drifts. Many commercial portals try to get user information from browser cookies. However, since readers oftentimes prefer not to authenticate themselves, building a long-term profile for news recommendation can remain challenging.

4.2 E-commerce

In e-commerce, temporal aspects like seasonality, popularity and trendiness play a major role in recommendations (where the last two tend to evolve over time). The users' behavior can be modelled within a specific session or between sessions. Individual sessions are usually short, averaging between two to three clicks, when a user comes with a specific purpose to purchase something

(Mokryn et al., 2019). Long-term models consider the user's history and evolution patterns and may provide richer user profiles (Jannach et al., 2017). Still, such historical data is not always available. This can explain why the majority of research works in e-commerce recommendations focuses on modeling users within sessions and using sequences of clicks for creating user profiles, e.g., (Hidasi et al., 2016; Jannach et al., 2015). Given the available data sets that contain sequences of user activities without any additional user information, this can be referred to as within-session modeling of anonymous users (Bogina et al., 2016).

Another related aspect is reminders. Lerche et al. (2016) proposed to remind users about items purchased in the past that may still be relevant in the future. They discovered that even though reminders do not lead to the discovery of new items, they can still be valuable. In an online evaluation they found that many customers accepted what they termed *recominders*—reminders in the recommendation list. In such cases user models should be built upon past user sessions and preferences towards various items, as well as a long-term and a combination of both short-term and long-term models (Devooght and Bersini, 2017; Guo et al., 2019a; Luo et al., 2016; Yu et al., 2019).

One more research direction in e-commerce is to try, identify, and model the user's intent when she visits an e-commerce site. A user's intent can change rapidly or gradually and promotions, reminders and recommendations can affect it. For such tasks, different deep learning networks were used. Mokryn et al. (2019) aimed to predict the intent of purchasing of anonymous visitors: whether the session is going to end with purchase or not. They considered item trendiness—modeled over different window sizes—together with the month, day of the week and dwell time as input to the classifiers. At the same time, they used RNNs for in-session intent prediction. The F1 measure was used to assess the success of such an approach. Guo et al. (2019b) suggested using an attention-based neural network to predict the user's real intent during an e-commerce session: whether the user is going to browse or buy. The duration of the action and the time gap between two actions were used as features in their deep intent prediction network.

4.3 Tourism

Tourism is another domain where temporal aspects play a major role. These aspects may include the time of the day, the opening hours of an attraction, the month, season (in particular when the same site can offer different activities for winter and summer), temporal users' states (e.g., working time vs. leisure time) (Rahmani et al., 2020), time constraints when planning the route, visitors' viewing times at exhibits (Bohnert and Zukerman, 2014), journey duration and the time it takes to go from one POI to another (Borràs et al., 2014) and even the "silence"—periods of time when no visit was made (Kim et al., 2017). Users may also have temporal constraints: when to start, when to finish, how much time they may spend in the area, when to have a break at some restaurant that should be open at this specific time, queuing times etc. (Lim et al., 2017). This is another temporal dimension that relates to the user context that may involve recommending a point in time to consume an item.

Since users usually want to plan a whole day of activities (e.g., POIs to visit in travel itineraries), many recommender systems predict the next sequence of POIs to visit and not only the next POI. De Choudhury et al. (2010) proposed an algorithm for itinerary planning, recommending a sequence of POIs, including recommending visiting times and approximate transit times between POIs. The temporal data was generated using Flickr photos that contain timestamps of when such photos were taken and uploaded. After mapping photos to POIs, time paths were constructed for further itinerary recommendations. Lim et al. (2017) suggested a personalized recommendation algorithm for itineraries that takes into account not only attractions' popularity and user interests, but also time-varying item features (e.g., queuing times). An objective function based on Monte Carlo Tree Search that maximizes the popularity and interest, while minimizing the attractions' queuing times, was used as a reward function in their algorithm. Kumar et al. (2017) predicted the next sequence of activities of a user during weekdays only, since user activities during the weekends are different. In their approach they relied on the context (such as time of day, location or weather) and previous activity patterns: past timelines that have patterns that are similar to the user's current timeline. By calculating the distance between two timelines they were able to find similar timelines which were used to recommend the next set of activities to perform.

We believe that such temporal aspects should be combined with additional contextual aspects. Location and weather can determine whether a user is going to visit an outdoor activity or not; social context is defined by with whom the user is going to perform a specific tourist activity. Such contexts are dynamic, they change over time, varying also in time granularity. The weather can change over a few minutes (sunny/rainy), while the social context can change daily or hourly, depending on the routes (museum visits vs. nature track).

4.4 Learning/Tutoring

In the learning/tutoring domain, temporal aspects are often used to identify the strategy of learners by finding sequential patterns in the users' learning activity (Maldonado et al., 2010; Doko et al., 2018; Wong et al., 2019; Uto et al., 2020). Some researchers, for example, consider the time it took for a student to solve a problem (Shen and Chi, 2016). Others try to identify the next task to recommend to a learner using system dynamics (Sanz et al., 2017). Student modeling using Kalman Filters was proposed in (Schatten and Schmidt-Thieme, 2016). Finally, Xing et al. (2016) used a temporal modeling approach to predict student dropouts based on their history, with features including the last week the student visited the course, the number of days the student interacted with the course each week, etc.

Temporal features were not only used for the prediction of student success, but also for discovering cheating in online education platforms. Ruiperez-Valiente et al. (2017) used temporal aspects in the user behavior to identify "multiple account" cheating in online platforms. In such scenarios, "harvesting" accounts are used to discover the correct solution to a question, to submit it to the master account and earn a certificate. The researchers found that the student's features are more important than the problem's features when classifying such accounts using Random Forest. Among the student features, the following time-related ones were considered: the total time students spent watching the videos, the average time required to submit the correct answer by the student (the most effective in identifying cheaters according to the variables analysis) and the total amount of time the student spent on the course page (this feature was removed later on because of the correlation with other student features). Alexandron et al. (2020) continued with similar ideas for identifying fake learners in Massive Open Online Courses (MOOCs). They defined fake learners as users "who apply unauthorized methods to improve their grade". In their research, the average time students spent on the task and the change in performance from the previous week were two temporal features used to differentiate between fake and true learners. They found that fake learners spent less time on the explanations, videos and pages related to homework items. However, they were better on the weekly improvement and they tended to improve during the course.

Barua et al. (2011) established theoretical foundations for considering forgetting in user modeling, that is of high importance in the learning domain, especially when designing user interfaces for such platforms. Several forgetting forms should be considered while building user models for long-term goals, including decay processes, forgetting during learning and forgetting during rehearsal (where some information will be replaced by updated one).

4.5 Entertainment

The entertainment domain includes leisure activities such as consuming shows, music, movies, TV shows, books etc. User modeling in the movies domain attracted a lot of research attention in the past, due to the availability of data sets like MovieLens and also the Netflix prize, when Koren (2009) took into consideration two important temporal factors when predicting future movies ratings: (i) an item's popularity may change over time and (ii) a user's ratings scale may change over time.

Research in this domain concentrated on rating predictions. Most of the studies applied time-enhanced collaborative filtering techniques, e.g., timeSVD++ (Liu and Aberer, 2014), Tensor Factorization, where time is considered as an additional tensor (Gantner et al., 2010), time-based KNN (Campos et al., 2014) and Hidden Markov Models (HMM) (Sahoo et al., 2010). All of them implicitly considered temporal aspects such as the affinity between group members (that relates to our taxonomy's user-related "rapidly changing" affective states) and its evolution over time (Amer-Yahia et al., 2015), item popularity (Gantner et al., 2010), or the temporal evolution of an item (Brenner et al., 2010). The prediction of TV shows to watch is often considered to be related to the movies domain. The biggest challenge here is that items are scheduled at specific times. Therefore, there is a limited set of programs that can be recommended to the user based on her profile (Oh et al., 2012; Turrin et al., 2014; Bogina et al., 2020). Moreover, watching TV is often a group activity. Since the household owns a limited number of TV sets and such recommendation and prediction can be considered as group related, hence the viewing habits can widely vary not only between weekends and weekdays, but also during the day (morning vs. evening patterns) (Bogina et al., 2021).

As can be seen, past research was often built on usage patterns that seem outdated now and more research is required. In real life everyone watches TV on their devices, while most channels stream their programs. Alas, data sets that contain data about programs streamed on TV channels are not publicly available.

The books domain is similar in a number of ways to the movies domain (Winoto and Tang, 2008). Usually, books are recommended by applying collaborative filtering techniques. For example, in (Vaz et al., 2013) a temporal decay is embedded into the Pearson similarity metric between two items. Quite differently, Zhang et al. (2015) suggested considering book borrowing sequences together with book circulation time in a digital library for books recommendations.

In contrast to movies and books, in the music domain there are two main research tasks: (i) next song recommendation; (ii) personalized playlist generation (Chen et al., 2018; Bonnin and Jannach, 2015). The former is similar to the previous domains, movies and books. Similar CF techniques are often used in these domains, relying on the historical listening patterns of the users and implemented through variations of Matrix Factorization techniques (Baltrunas and Amatriain, 2009; De Pessemier et al., 2010; Koenigstein et al., 2011; Yang et al., 2012) and Markov Processes (Ji et al., 2015; Sahoo et al., 2010). The second task is different since a playlist is a sequence of tracks. Therefore, the analyses and the algorithms applied are different (Bonnin et al., 2009). However, recently, movie watching sequences are also interpreted as sessions, making the problem similar to music playlist generation. In such scenarios various architectures related to RNN are used. One main question here is how to slice the users' sessions (Anelli et al., 2017). Hansen et al. (2020) suggested combining a user's past consumption patterns with the current context (consisting mostly of time and device context) in an RNN to predict which track the user will listen to during the session.

Another direction in the music domain is psychological approaches in music recommendations. Kowald et al. (2020) leveraged a user's prior exposure to the genre inspired by the "Adaptive Control of Thought–Rational" (ACT-R) architecture, which defines cognitive operations in the human mind. Such a mechanism differentiates between short-term and long-term memory modules. For predicting the next music genre—in their case using a data set from

Last.fm—the authors followed two approaches: the first considered popularity and recency, while the second one is context. They embedded it into the activation function of linear regression.

A few researchers evaluated their models on both the music and movies domains (Sahoo et al., 2010; Kaya and Bridge, 2019; Song et al., 2019). Sahoo et al. (2010) considered concept drift and dynamic user behavior modeling by using HMMs in order to recommend the next item to consume in both domains (music/movie). Song et al. (2019) suggested to use a dynamic graph attention model based on RNNs to recommend items to users in the online community. In their model they combined both users' dynamic interests and context-dependent social influences for such recommendations.

Generally, we assume that music, movies, books and TV shows domains can be merged into an entertainment domain, at least with respect to how temporal factors are considered in user modeling. Some specific challenges and context factors to be considered may however be unique to individual domains.

4.6 Health

Health differs from all previous domains both in terms of recommendations and of user modeling. Recommending the wrong movie to watch will not harm anyone much but recommending the wrong medical treatment certainly will. Therefore, many additional challenges as well as ethical and privacy concerns are involved in this domain (Valdez et al., 2016). We can distinguish between three different research directions in this domain: well-being (ongoing), rehabilitation, and medical records (diagnoses). With respect to diseases, the main temporal factor is the season. The flu epidemic is typical for late autumn and winter. With the hype of social media, analyzing harmful user behavior becomes a popular topic (Hossain et al., 2016; Dyson et al., 2016). De Choudhury et al. (2013) found that people in depression are more active at late night, while being inactive during the day. Moshtaghi et al. (2015) focused on atypical long time periods of inactivity in the elder population that can be used later on to foresee the falls and unsafe movements at home. Suhara et al. (2017) incorporated the day-of-the-week into an RNN to predict depression based on historical records. A few studies attempted to create systems that encourage people at risk (with diabetes) to perform physical activities; an example of that work using reinforcement learning is (Yom-Tov et al., 2017).

Moreover, when considering food related aspects, numerous aspects, such as recipes, diets, nutrition consumption are considered in the literature (West et al., 2013). Kusmierczyk et al. (2016) showed that in online recipe creation the popularity of different ingredients and food types follows seasonal and weekly trends. Obesity is also part of this domain, where user modeling is applied. Trattner et al. (2017) showed that temporal factors, when incorporated into the model, help to explain variance in obesity.

5 Discussion and recommendations

After proposing a novel taxonomy of temporal aspects in user modeling and discussing it with respect to various domains, we make practical recommendations in this section on how to consider temporal aspects in personalized systems. When designing a personalized system or a service, researchers should understand first what data may be available for user modeling. Then, it is important to understand the temporal characteristics of the domain. Finally, the technology to be used for representing and reasoning on the temporal aspects has to be considered in light of the available data and the domain characteristics.

What data is available is of utmost importance, especially the question if users are uniquely identified or not. User identification enables us to build rich user profiles over time by reasoning about their explicit and implicit behavior. Another aspect is whether there is any external information about the user. Of similar importance is the information about the items and about domain-specific temporal characteristics. Therefore, we distinguish between different types of data (modules) that can be used for temporal reasoning. These modules can be linked to the “influence factors” entity in our taxonomy, either to user-related or item-related context, depending on the available information.

1. *User Identification:* The availability of a user ID and recurring interactions enables the development of a long-term user profile. Depending on the availability of data, a comprehensive model may be built. Without it, only “within session” personalization may be considered. Such a model can be linked to the “influence factors” block in our taxonomy, specifically to the user-related entities (see Figure 4).
2. *Long-term preferences:* The availability of long-term user characteristics in the data set such as: demographics, education, as well as previous interaction histories with the system. This module can be linked to long-term preferences in our taxonomy (see Figure 4).
3. *Short-term preferences:* The availability of short-term preferences of the user represents the latest interaction(s) with the system. In most cases this information is represented in usage sessions and can be seen as an interaction between the user and the items. Such a module can be linked to the short-term preferences in our taxonomy (see Figure 4).
4. *Item information:* The availability of various item features such as ID, category, description and additional information that can be extracted from external sources (like IMDb for movies or Wikipedia for people). Such information may be useful for better understanding the consumer’s preferences. This module is related to the “influence factors” or to the item-related block, depending on the available item’s features (see Figure 4).
5. *Context:* When contextual information is available, relevant context-related temporal aspects may be considered. Examples for explicitly available contextual data include the location, the weather, promotions, the time of day, companions or the device from which the application was accessed.

Furthermore implicit contextual signals may be extracted from the given data, e.g., crowdedness, intent, month, weekday/weekend etc. This module can be linked to the "influence factors" entity in our taxonomy, either to user-related or item-related context, depending on the available information (see Figure 4).

6. *Item sequences:* Sequences of consumed items that can be extracted from the data set, either directly from the order in the logs or from timestamped interactions. This information is relevant for session modeling in domains like news, e-commerce or ads. Such a module can be linked to "evolution/dynamics of user preferences" in our taxonomy (see Figure 4).
7. *Domain:* As we saw in Section 4, different domains have different temporal constraints that should be taken into consideration while providing recommendations or performing predictions. This module is linked to the "domains" entity in our taxonomy (see Figure 4).

Generally, depending on the format in which the data is provided and how different features are derived, the information may be linked to the "explicit" or "implicit" data feedback in our taxonomy in Section 3, Figure 4.

Next, we elaborate on how different combinations of such modules can be juxtaposed, following examples from the surveyed papers, together with the data sets used for such cases.

If only information about item consumption (e.g. *user* id and *item* id) are given, collaborative methods may be applied (even though item features may be extracted from external sources, as suggested by Berkovsky et al. (2008) and may be used for personalized predictions (ratings, items) (Koren, 2009). Such cases are however not too relevant to our survey, since no temporal data is available, unless sequences of items per user are given.

Combining *user*, *item* and *context* modules might help in item recommendations. Tensor factorization techniques relate to N-dimensional models, where the two mandatory dimensions are user and item. Data sets that contain user, item and their interaction information are MovieLens 1M, MovieLens 20M[7], Yelp[8], Pinterest[9], and the Taste Profile[10] Subset.

Given *item sequences*, session-based techniques, or more generally, sequence-aware techniques, may be considered. If the user's identity is known, session-aware recommenders are relevant, where information from the previous sessions can be used. Quadrana et al. (2017) provided personalized session-based recommendations by training an RNN on a data set that contained both users IDs and items sequences of items that were consumed by these users in different sessions. A recent performance comparison of session-aware algorithms can also be found in (Latifi et al., 2021). They found that simple approaches, such as nearest neighbours, outperformed neural networks. In addition, they do not outperform other techniques that do not consider long term user pref-

[7] https://grouplens.org/datasets/movielens/20m/
[8] https://github.com/hexiangnan/sigir16-eals
[9] https://sites.google.com/site/xueatalphabeta/academic-projects
[10] http://millionsongdataset.com/tasteprofile/

erences. Hidasi et al. (2016) dealt with sequential data: sessions with item sequences but without user identity, via RNN to predict the next item to be consumed. Data sets that are available for session-aware recommendations include Ta-Feng[11], Taobao[12] (Bai et al., 2019); for session-based recommendation, common data sets are Yoochoose (Ben-Shimon et al., 2015), Spotify with playlists as sessions[13] and Diginetica[14] (Liu et al., 2018).

Steck (2018) used items and user long-term preferences for calibrated recommendations[15], demonstrating it on the MovieLens 20M data set. Combining short-term and long-term user preferences allowed the authors to capture both and provide better personalized recommendations to the user. Devooght and Bersini (2017) proposed a modified RNN for finding a better trade-off between short-term and long-term user profiles and improved recommendations with respect to recall. They conducted experiments using three data sets: MovieLens, Netflix and Yoochoose.

In some cases, when not all modules are available in the data set, the missing modules can be extracted from the available ones. When user, items or item sequences (user-item interactions) are provided in the data set, user short-term preferences can be retrieved. Having user, item and the timestamps of consumption, Pereira et al. (2019) created the sequences of items (songs) per user, also including other relevant features, derived from datasets from Last.fm, Spotify and MusicBrainz, and performed online learning for personalized ranking.

Finally, we provide a list of *data sets* that are freely available for experimentation, marking relevant dimensions that may be used for research in Table 1. Moreover, temporal aspects that were used in the previous researches were added per data set, as well as approaches used to deal with them and metrics to evaluate such approaches. It can be seen that when dynamics/evolution/sequences/sessions are being involved, sequence related neural networks are used (LSTM, RNN) with recall/precision evaluation metrics accordingly. However, for more simple temporal aspects, such as recency, seasonality, popularity, and recurrence, collaborative filtering (CF) techniques are applied.

[11] http://www.bigdatalab.ac.cn/benchmark/bm/dd?data=Ta-Feng

[12] https://tianchi.aliyun.com/dataset/dataDetail?dataId=649&userId=1

[13] https://www.aicrowd.com/challenges/spotify-million-playlist-dataset-challenge

[14] https://cikm2016.cs.iupui.edu/cikm-cup/

[15] Roughly speaking, in what Steck named “calibrated recommendations” in (Steck, 2018), the distribution of item properties in the recommendation list correlates with the distribution of the items in the user profile. See also (Jugovac et al., 2017) for an analysis of earlier related methods.

Table 1 Collection of available research data sets

DataSet	Domain	User ID	Item ID	User/item interaction	Sessions	Context	Temporal factors	Approaches	Evaluations
Diginetica	E-commerce	v	v	v	v	v	long-term, long sessions, browsing history, recency, popularity, recurrence	GRU4REC, FPMC, session-based KNN	recall@k, MRR@k, precision@k
Taobao	E-commerce	v	v	v	v	v	The behavior history of each user via bundles, different time buckets	LSTM, MF, self-attention neural networks	recall@k, MRR, NDCG, AUC
YooChoose	E-commerce		v		v	v	temporal order, short-term, trendiness, recency, recurrence, sequences	GRU4Rec, FPMC, LR, Bagging,	recall, precision, MRR
Ta-Feng	E-commerce	v		v			dynamics, sequential features	MF, LSTM, RNN	NDCG, recall
Amazon	E-commerce	v	v	v		v	users' history, user's evolution	Hypergraph Convolution Network, Attentive network, CF, LSTM	NDCG@k, MRR, Hit@k, AUC
Dunnhumby	E-commerce	v	v	v	Baskets	v	recurrence, popularity, recency, seasonality	CF (MF)	NDCG, recall
Instacart	E-commerce	v	v	v	Baskets	v	recurrence, popularity, recency	CF	NDCG, recall
MovieLens	Entertainment	v	v	v		v	dynamics, similarities among users over time	CF, CNN, RNN (GRU), time decay	DCG, recall, item coverage, MRR
MovieLens20	Entertainment	v	v	v		v	dynamics, popularity	CF , genre distribution, self-attention based sequential model	KL divergence, Hit, NDCG
Netflix	Entertainment	v	v	v			dynamics, historical ratings	RNN(GRU), CF, cos measure with temporal relevance, time decay	recall, RMSE, MAP
30Music	Music	v	v	v	v		songs sequences in the playlists, popularity	RNN, KNN, CF, ItemKNN	MRR, Hit, MAP,precision, NDCG
LastFM	Music	v	v	v			time intervals between actions ,recurrence	CF, ItemKNN, LSTM	MAP, NDCG, precision, recall
Spotify MPD	Music		v		Playlist	v	playlists (sequences of songs)	CF, String matching (name),	precision, NDCG, clicks
MSSD/Taste Profile	Music		v	v	v		time of the day, week day, long-term taste (personality) and short-term preference (emotion)	Neural Networks	NDCG, Hit
Trivago	Tourism	v	v	v	v	v	recency, short-term interests, dwell time, the time difference between the click-outs	gradient boosting related (LGBMRanker, GBDT)	MRR, NDCG
Yelp	Tourism	v	v	v		v	checkins and reviews history, popularity, ratings recurrence	clustering, regression, CNN	Hit@n, NDCG@n
Foursquare	Tourism	v	v	v		v	temporal intervals between checkins, dwell time	LSTM, CF with time similarity	Accuracy, MAP, precision, NDCG

6 Conclusions and Open Questions

Temporal aspects are an integral part of user modeling and should be considered when designing a user model for any personalized service or system. This survey presented the diversity and complexity of these aspects. Obviously, their application was found to be different in different domains, as we presented in the review of the individual domains. Hence, we presented an abstract model of these aspects, proposed a taxonomy for such aspects.We emphasized the critical role of the data, as the personal-temporal information that may be available limits the opportunities and dictates what aspects may be considered to be used in an application. In spite of the fact that up till now—regardless of the efforts invested in research that considers temporal aspects in user modeling in various domains—there remains a certain lack of standardization in the treatment of temporal aspects. This may drive application developers to "reinvent the wheel" every time. Suggesting a terminology that may be commonly agreed and accepted may provide a starting point towards the solution of this challenge and hopefully this work contributes to this direction.

In recent years the main direction in using temporal aspects in recommender systems is the temporal order of the items and the use of such sequences as input to deep networks. However, less attention is given to aspects such as: recency, forgetting, seasonality, dynamics of user preferences etc. These are rapidly changing factors that are dealt with as something static for the sake of simplicity. Moreover, the temporal aspects are temporal not due to time itself but since time is a proxy variable, as can be seen from the taxonomy.

We should not forget that still, when considering temporal aspects of user modeling, numerous challenges exist. Here we list a few of them as an example of ideas for future research:

Proactive recommendations. One main future direction in our view is the problem of proactive recommendations (Rook et al., 2020). Many users receive news via social media like Facebook, Twitter and so on. In case the user is not available at the time when an event occurs, the question would be whether or not to send her news about the event when she becomes available (as news gets outdated quickly), and how to define a news event validity period per each user. In the suggested taxonomy we considered the temporal availability of items for the consumer. However, in this case user availability is the important context-related factor that needs to be taken into consideration when recommendations are made.

Time-dependent evaluation. Various open questions remain with respect to the appropriate research methodology for data-based experiments. How should the data be split into training and testing sets so that the evaluation is as realistic as possible? Random data splits are common in recommender systems evaluation, but they lead to the problems that (i) sometimes future data points are used for prediction and (ii) that time-related aspects cannot be properly taken into account. Moreover, there are open questions mentioned by

Campos et al. (2014), which have not been fully addressed yet in the context of time-aware recommenders: (i) the relation between data set characteristics and evaluation conditions, (ii) whether improved offline evaluation results actually translate into better systems in practice and (iii) the lack of user-based online evaluations.

Time-dependent explanations. To address General Data Protection Regulation (GDPR)[16], privacy and transparency concerns, explanations are required. Explanations attracted significant attention (Tintarev and Masthoff, 2015), however, various kinds of explanations do not consider temporal aspects (recency, seasonality, temporal availability etc.). Another direction might be dynamic explanations, even if the system output (e.g., recommendation) remains the same, the context may change and explanations may need to be adapted accordingly. For example, in the tourism domain a restaurant recommender might—depending on the season—either emphasize the nice terrace of the location (in summer) or some food-related aspect (in winter).

Forgetting and relevance expiration. Forgetting, as discussed above, has been explored in the literature as a means to obtain more accurate user models. But also items may become more and more irrelevant over time in general, and sometimes these items should not be considered anymore by a recommender system. This issue becomes more relevant with regards to GDPR compliance. It raises questions that need to be considered by developers. For example, is it enough to use only recent data? Should all data be kept? What is an optimal period of time that will allow providing decent recommendations? With respect to the relevance expiration one main question here is: "How can we determine if an item is still relevant to a given user?".

Cognitive and affective user aspects. As our taxonomy depicts, cognitive aspects are part of the user-related and slowly changing path. In contrast, affective aspects, such as emotions, may change rapidly. Here there is no definite suggestion at the moment, but a need for further research. The future direction would be to discover how they evolve over time, how they affect data and recommendations in different domains. In what domains they might get more attention (entertainment?). When should cognitive aspects be considered more seriously than affective ones?

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