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How to Design More Empathetic Recommender Systems in Social Media

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Completed Research Paper

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Abstract

Social media's value proposition heavily relies on recommender systems suggesting products to buy, events to attend, or people to connect with. These systems currently prioritize user engagement and social media providers' profit generation over individual users' well-being. However, making these systems more "empathetic" would benefit social media providers and content creators as users would use social media more often, longer, and increasingly recommend it to other users. By way of a design science research approach, including twelve interviews with system designers, social media experts, psychologists, and users, we develop user-centric design knowledge on making recommender systems in social media more "empathetic." This design knowledge comprises a conceptual framework, four meta-requirements, and six design principles. It contributes to the research streams "digital responsibility" and "IS for resilience" and provides practical guidance in developing socially responsible recommender systems as next-generation social media services.

Keywords: Recommender System, Social Media, Design Science Research, Resilience, Empathy

Introduction

In 2021, 70 percent of US adults used social media every day (Pew Research Center 2021). Acknowledging that individuals even use social media to adjust to disruptions (such as bereavements or natural crises) and overcome them (Eriksson Krutrök 2021; Mirbabaie et al. 2020) has motivated numerous calls for contributions in prime IS outlets on *digital responsibility* (Recker et al. 2022) or *information systems (IS) for resilience* (Cheung et al. 2021). In their calls, IS scholars pinpoint that "with great power comes great responsibility" (Recker et al. 2022, p. 1) and to transfer this awareness to the design of our systems such as social media recommender systems which are at the core of social media. Recommender systems refer to *"software agents that elicit the interests of preferences of individual users for products […] and make recommendations accordingly"* (Xiao and Benbasat 2007, pp. 137-138). They are anticipatory agentic IS that proactively search, filter, and compile digital content (Baird and Maruping 2021). YouTube already reported more than a decade ago that 60 percent of the clicks on its starting page were generated thanks to recommender systems (Davidson et al. 2010). Also, Netflix's business value, rooted in personalization and recommendations to have its users attracted and engaged with the content, was put at over one billion US dollars in 2015 (Gomez-Uribe and Hunt 2016). Those figures are certain to increase, and significantly so, as aspects of human life increasingly partake in digital spheres.

These spheres are hailed as great opportunities with numerous benefits for users (e.g., more relevant content for the individual user) and social media providers (e.g., the continuous attraction of users to the platform). However, recommender systems may not always act in users' best interest but rather serve the providers' aims (Jeckmans et al. 2013; Xiao and Benbasat 2007). Research pinpoints that commercial recommender systems prioritize profit maximization over users' benefits and circumstances (Zhang et al. 2021). In social media, providing users with certain recommendations, such as content concerning controversial political issues (Golbeck 2019) or the self-presentation of others (Fan et al. 2019; Steers et al. 2014), can even decrease their well-being. Similarly, recommending other types of content may also adversely affect well-being. For example, a user whose engagement broke off might continue to see posts from influencers about weddings in their social media feed, further reminding them of the allegedly sad occasion. In a current US study including 1,875 participants, over 94 percent of social media users reported they would appreciate social media content created to improve their well-being (Golbeck 2020a).

Introducing an "empathetic" lens to recommender systems could help prevent negative impacts on social media users' well-being. Empathy is *"the process associated with the capability of perceiving and reacting to another's emotional state"* (Paiva 2019, p. 1). Although empathy is a human ability, the concept might serve as a template for the behavior of agentic IS such as recommender systems. To this end, previous studies have already investigated recommender systems in social media (e.g., Jaywant et al. 2016; Wu et al. 2017), considered users' state of mind to generate suitable recommendations (e.g., Polignano et al. 2021; Yousefian Jazi et al. 2021), and showed that social media affects users' well-being (e.g., Weinstein 2018; Mackson et al. 2019). These studies do a great job in their respective research streams. However, they focus on technical feasibility or social media's user impact rather than addressing the problem of "unempathetic" recommender systems in social media from a comprehensive sociotechnical perspective. An exception is a study from Golbeck (2020a), who examines recommender systems in social media and indicates that users who actively search for content in social media to increase their well-being can benefit from such systems. We follow this research and occupy the intersection between social media recommender systems, recommender systems building on users' state of mind, and research on social media users' well-being. Thereby, to make empathetic social recommender systems in social media applicable, we aim at a comprehensive view of users' well-being and ancillary conditions such as user acceptance, provider interests, or legal conditions. Thus, we state the research question *"How to design more empathetic recommender systems in social media?"* To answer this question, we adopt a design science research (DSR) approach and set the following design objective.

Design Objective: We aim for user-centric design knowledge on empathetic recommender systems (ERS) to help overcome the problem that current recommender systems in social media do not sufficiently focus on users' well-being. In line with Sarker et al. (2019) and Lee et al. (2015), we define ERS as sociotechnical systems consisting of (1) a social component, that is, an interplay of social media users, a social media platform, and related key stakeholders and (2) an IT artifact, specifically, a recommender system that captures the user's state of mind to generate appropriate recommendations. These recommendations serve to increase users' psychological and subjective well-being. Thus, the ERS acts empathetic toward them. The design knowledge we aim for focuses on a comprehensive view that considers users' needs and aligns them with key stakeholders' needs to ensure applicability in a commercially driven environment such as social media. Since ERS are a new class of systems, there is not yet a direct benchmark from research or practice against which to measure ERS' effectiveness. However, studies from existing research streams on social media recommender systems, recommender systems building on users' state of mind, and research on social media's effects on users' well-being can serve as a foundation for evaluating ERS.

To achieve the above-stated design objective, we apply the first two design activities of the DSR approach by Sonnenberg and vom Brocke (2012) alongside two evaluation episodes. As part of the first evaluation episode, we conduct a structured literature review on emotion-based recommender systems, social media recommender systems, and the IS discipline's empathy research. We further conduct six expert interviews with psychologists, system designers, and social media experts as part of the first evaluation episode. As part of the second evaluation episode, we conduct another six interviews with a system designer, a social media expert, a communications psychologist, and three social media users. Further, we conduct an applicability check to ensure the relevance of our research to practice (Rosemann and Vessey 2008) as part of the interviews of both evaluation episodes.

Our design knowledge for ERS in social media resulting from our design activities and evaluation episodes comprises three artifacts: a conceptual framework, four meta-requirements, and six design principles. With ERS, we introduce a new class of digital products to social media with novel features specific for generating empathetic recommendations. In theoretical terms, our work further addresses challenges of our digital society, such as the negative impact on younger users by social comparison (Fardouly et al. 2015; Mackson et al. 2019) or echo chambers (Kitchens et al. 2020; Markgraf and Schoch 2019). Our research adheres to the streams digital responsibility (Recker et al. 2022) and IS for resilience (Cheung et al. 2021) and aims to extend these research streams by viewing recommender systems from a different, more empathetic angle. In practical terms, our research guides how social media providers can make the platforms more social and try to increase users' well-being by adhering to our design knowledge on ERS.

Theoretical Foundations and Related Work

Recommender Systems in Social Media

Recommender systems are anticipatory or proactive agentic IS (Baird and Maruping 2021) because they serve to anticipate users' needs. They originate from the intention of tackling information overload that mainly occurs in the digital realm (Yousefian Jazi et al. 2021). In this vein, two design paradigms exist for recommender systems: *content-based* and *collaborative* filtering. *Content-based* filtering generates recommendations based on a similarity between content characteristics and user preferences according to content that the user has previously liked or interacted with (Lops et al. 2011). *Collaborative* filtering generates recommendations based on ratings by an existing community of users (Jannach et al. 2010). Therefore, a recommender system using collaborative filtering does not need to know anything about the contents it recommends to its users. In addition, other paradigms evolved, such as *utility-based recommendations*, where a utility score is assigned to content (Elahi et al. 2016), or *knowledge-based recommendations*, where constraints (e.g., minors cannot receive recommendations on content related to alcohol or tobacco) are applied (Felfernig et al. 2015). In practice, *hybrid approaches* often occur (Burke 2002; Jannach et al. 2010), combining the benefits of different recommendation paradigms. For example, the monolithic hybrid recommender system "Predictory" combines content-based filtering, collaborative filtering, and knowledge-based recommendations for movie recommendations (Walek and Fojtik 2020).

It is essential to consider contextual information in recommender systems to increase the quality of recommendations generated through employing the presented traditional recommendation paradigms (Adomavicius et al. 2011; Adomavicius and Tuzhilin 2011). For example, the relevance of restaurant recommendations may vary strongly with users' location. Other contextual factors for recommendations besides location might be time, the user's activity, state of mind, or mood (Adomavicius et al. 2011). Much of this contextual information about users is known to social media providers. They can therefore exploit this information to generate recommendations. Previous research has dealt with using context-based recommender systems in social media in various ways. One example is "Kaleido," a prototypical recommender system generating media content recommendations toward users based on their affective pulse, social network, and location data (Wu et al. 2017). Another example is "HappyMovie," a prototypical recommender system for Facebook which generates movie recommendations using trust between group members as a contextual factor (Quijano-Sanchez et al. 2014). A third example is a digital identity-based recommender system using behavioral data from Twitter to provide social media users with recommendations for financial services (Jaywant et al. 2016).

When considering the target variables to achieve our design objective of deriving design knowledge for ERS, emotion as part of a user's state of mind is an important contextual factor for generating recommendations. Several studies deal with the consideration of user emotions in emotion-aware recommender systems, of which many focus on music recommendation. For example, users' emotions can be estimated through device operation behavior and subsequently used to provide music recommendations (Yousefian Jazi et al. 2021). The music recommender system "EMRES" (Polignano et al. 2021) demonstrates that emotion-aware recommender systems can also estimate users' affective states by exploiting their social media posts. One can further derive emotion-aware recommendations by analyzing physiological signals such as electrodermal activity or cardiac activity to determine the contextual factor of users' emotions (Ayata et al. 2018). While many studies dealing with emotion-aware recommender systems do not focus on a social media context, we can still apply the referenced approaches to social media because the content these systems recommend, such as music or movies, typically also occurs on social media.

Empathy and Well-Being in Social Media

Empathy refers to a person's cognitive or emotional reaction to observed experiences of another person (Davis 1983) and is considered a significant element in human social interaction (Paiva 2019). In the digital age, however, the construct of empathy is no longer limited to interactions between humans. Instead, research develops empathetic software agents for different purposes, such as increasing believability towards the user or increasing user engagement (Rodrigues et al. 2009). One example of such a software agent is the "Empathic Companion," which accompanies users in a virtual job interview by addressing users' affective states through empathetic feedback (Prendinger and Ishizuka 2005). Another example is the empathetic chatbot "Rose," which can raise the mood of socially excluded users by providing empathetic responses (Gennaro et al. 2019).

Well-being is a complex multidimensional construct with two parts we both target with our design knowledge: psychological and subjective well-being. Individuals have high *psychological* well-being if they accept themselves, see purpose in life, experience personal growth, have positive relations with others, master their environment, and act autonomously (Ryff and Keyes 1995). Individuals have high *subjective* well-being if they experience general satisfaction in life, the presence of pleasant emotions, the absence of unpleasant emotions, and satisfaction in specific life domains such as family, work, or health (Diener 1984; Diener et al. 1999). Psychological well-being is associated with the health of the body and mind (Ryff and Singer 1998). It encompasses a longer-term process of goal attainment, whereas subjective well-being rather defines temporal feelings of happiness (Hall 2015). Psychological well-being thus represents eudaimonic living, whereas subjective well-being describes a hedonic perspective (Ryan and Deci 2001).

Social media can both positively and negatively impact users' psychological well-being. Prior research shows that user interaction on social media can increase psychological well-being independent of the social media platform (Oh et al. 2014). However, research also suggests the opposite. For example, the use of Facebook negatively affects women's self-assessment and well-being due to social comparison (Fardouly et al. 2015). If social media contacts present themselves as happier than they are in fact, this presentation can be detrimental to users' well-being (Steers et al. 2014). Similar research showing that social comparison can lead to decreased psychological well-being exists for Instagram (Mackson et al. 2019). However, the same study indicates that Instagram users have higher psychological well-being than non-users because social media use enables users to receive positive feedback and reduces loneliness (Mackson et al. 2019). Whether social media is detrimental to psychological well-being depends on the way of using it. If users only browse content, their psychological well-being benefits, but if they start broadcasting and comparing themselves, they might experience harm to their psychological well-being (Yang 2016).

Similarly, social media can positively and negatively influence subjective well-being (Weinstein 2018). Facebook use reduces subjective well-being over time (Kross et al. 2013). Through upward comparison, others' self-presentation may reduce social media users' subjective well-being (Fan et al. 2019). However, social media can increase subjective well-being, for example, by showing users dog pictures or content considered generally funny (Golbeck 2019). A survey among US teenagers showed that the majority of interviewees associated a positive sense of well-being with using social media, such as Instagram or Snapchat (Weinstein 2018).

In our ERS context, we consider each content recommendation as a reaction toward the user, and we aim for these recommendations to be empathetic. There are positive effects of empathetic behavior on the recipients' well-being, which have been proven, for example, in organizations (Scott et al. 2010) and medicine (Decety and Fotopoulou 2014). Taking this connection as a model, we define the empathetic nature of ERS by their ability to increase social media users' well-being.

Empathetic Recommender Systems in Social Media

Looking at state of the art, three research streams that are suitable to inform ERS exist: (1) research on recommender systems in social media (e.g., Wu et al. 2017; Quijano-Sanchez et al. 2014), (2) research on recommender systems building on users' state of mind as a contextual factor (e.g., Yousefian Jazi et al. 2021, Polignano et al. 2021), and (3) research showing that social media can affect users' well-being both positively and negatively (e.g., Mackson et al. 2019; Weinstein 2018). According to our definition, ERS lie at the intersection of these research streams.

Research streams 1 and 2 provide an architecture-based means to inform ERS design and prospectively evaluate ERS system characteristics compared to state of the art. Research stream 2 further offers a basic measure of how empathetic recommender systems are already. Research stream 3 offers a content-wise perspective to inform ERS as a tool to increase social media users' well-being. Factors that lead to increased user well-being are receiving positive feedback and enjoyable content. The main factor leading to a decrease in user well-being is social comparison. Research stream 3 reveals how empathetic social media acts toward users to date and, thus, affords a benchmark for ERS' future success in increasing users' subjective and psychological well-being. The degree of empathy with which ERS act toward their users can be measured by proxy through scales of subjective well-being (e.g., Watson et al. 1988) or psychological well-being (e.g., Ryff and Keyes 1995).

No research to date merges the presented research streams to conceptualize ERS. Building on the research streams to inform and evaluate ERS design, we set off to answer our research question: "How to design more empathetic recommender systems in social media?" To this end, we occupy the intersection between the three research streams and develop design knowledge for ERS.

Method

To achieve our design objective and establish design knowledge for ERS in social media, we adhere to the design science paradigm (Gregor and Hevner 2013; Gregor and Jones 2007; Hevner et al. 2004). We adapt the iterative approach by Sonnenberg and vom Brocke (2012), which includes four design activities: *Identify Problem*, *Design*, *Construct*, and *Use*. Each design activity follows an evaluation activity termed *Eval 1-4*. To derive our design knowledge, we focus on the design activities Identify Problem and Design and the associated evaluation activities Eval 1 and Eval 2. Within this focus, we combine deductive and inductive reasoning, which is central to the theory-building phase of DSR projects (Gregor 2009). Figure 1 visualizes the focus of our research following Sonnenberg and vom Brocke (2012), our design outcomes, and evaluation tools.

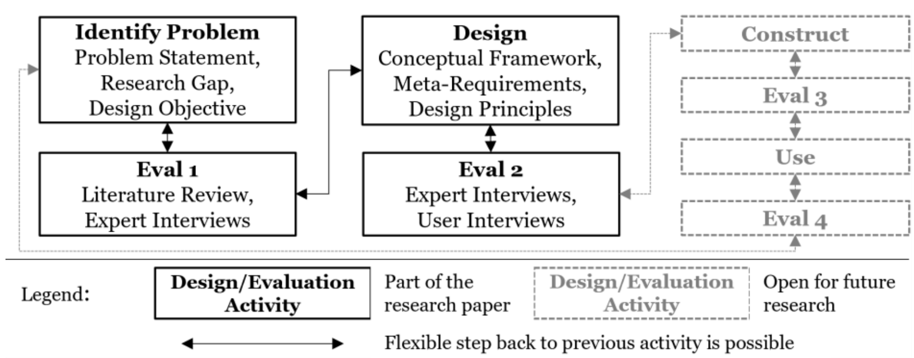

Figure 1. Research Methodology Adapted from Sonnenberg and vom Brocke (2012)

Identify Problem and Subsequent Evaluation (Eval 1)

As part of the design activity Identify Problem, we defined the problem statement, research gap, and design objective of our research (see Introduction). Subsequently, we conducted a structured literature review guided by the criteria of Webster and Watson (2002) and vom Brocke et al. (2009) as part of the first evaluation activity Eval 1. This literature review served to validate and scope the identified problem, the research gap, and our design objective. The literature review further informs the second design activity, Design. We conducted a title search in the following scientific databases: AIS eLibrary, Web of Science, IEEE xPlore, ACM Digital Library, and APA PsycInfo. We additionally conducted an abstract search in the AIS eLibrary, since it is essential for IS research, and the title search yielded very few hits. For all searches, we used the following search string:

("recommender system" AND (empath* OR emot*)) OR ("recommendation system*" AND (empath* OR emot*)) OR ("information system*" AND (empath* OR emot*)) OR ("social media" AND (empath* OR emot*)) OR ("social media" AND ("recommender system*" OR "recommendation system*"))*

The searches resulted in 785 overall hits. Abstract screenings and removal of duplicates reduced the number of relevant hits to 67. We screened these hits for articles that design or explore IS at the intersection of recommender systems, social media, and well-being and empathy. To this end, we specifically included articles dealing with recommender systems or similar IS building on users' state of mind as a contextual factor, articles specifically dealing with recommender systems for social media, and articles investigating well-being and empathy in IS design. We excluded articles dealing only with the effects of social media on users' well-being or empathy and articles from a merely medical context. As a result, we identified seven papers to validate our research question and the connected design objective and inform our design knowledge. Additional forward, backward, and complementary searches based on these results and the above-listed inclusion and exclusion criteria yielded another 18 relevant articles. We used the selected articles to review whether and how we needed to adapt our problem statement, research gap, and design objective. Please refer to our Supplementary Material[1] A for details on the literature review results.

In addition to the literature review, we evaluated the problem statement, research gap, and our design objective in six expert interviews (also part of Eval 1). As our research is at the intersection of recommender systems, social media, and well-being, we aimed to combine different perspectives for recruiting interviewees. To cover the perspectives of this intersection, we interviewed three system designers, one social media expert, and two psychologists. For details on the Eval 1 interviewees, please refer to Supplementary Material B. We conducted all interviews in our research project in German in a one-on-one setting via video chat. The interviews were semi-structured with 18 questions to evaluate our research's importance, accessibility, suitability, novelty, feasibility, and applicability. For the Eval 1 interview guide, please refer to our supplementary material C. We chose these evaluation criteria according to the suggestion of Sonnenberg and vom Brocke (2012). The first three of these evaluation criteria form an applicability check of our research following Rosemann and Vessey (2008) to validate the relevance of our research for practice. We coded the interview results using the problem statement, research gap, and design objective as themes following our interview guide. We used the interview results to evaluate our problem statement, research gap, and design objective (see Introduction) and as an inductive reasoning step to explore insights for the design of ERS.

Design and Subsequent Evaluation (Eval 2)

The activity Design built upon the results of our literature review (i.e., deductive reasoning) and the insights of the first interview round (i.e., inductive reasoning). This knowledge enabled us to develop a conceptual framework and derive meta-requirements and design principles guiding the design of ERS in social media. To evaluate these components of our design knowledge for ERS, we conducted a second round of interviews, including six participants, as part of the evaluation activity Eval 2. Again, we aimed for different perspectives on the topic in recruiting our interviewees. To cover the different fields of expertise at the intersection of our research mentioned above, we recruited one system designer, one social media expert, and one communication psychologist. To complement the expert perspective and focus on a user-centric DSR approach, we recruited three social media users to evaluate our design knowledge from a user perspective. For details on the Eval 2 interviewees, please refer to Supplementary Material B.

The interviews in Eval 2 were semi-structured and followed an interview guide comprising 13 questions about the conceptual framework, the meta-requirements, and the design principles. For the Eval 2 interview guide, please refer to our supplementary material C. The questions targeted the following

[1] https://doi.org/10.6084/m9.figshare.20936911

evaluation criteria: clarity and accessibility, suitability, completeness, level of detail, applicability, and feasibility of the design knowledge. These evaluation criteria, too, originate from the design-evaluation process by Sonnenberg and vom Brocke (2012). The first two criteria re-evaluate our research's relevance in the applicability check, as mentioned above (Rosemann and Vessey 2008). We coded the results of the second interview round by using the respective design artifacts (i.e., conceptual framework, meta-requirements, design principles) to which the responses referred as themes. As a result of the evaluation, we conducted a second design cycle and revised the design artifacts.

Design Knowledge and Evaluation

Conceptual Framework

From the insights of our first round of expert interviews and the literature review results, we created a conceptual framework mapping the stakeholders involved in the research problem and their needs in the realm of ERS. This framework provides the scope for our design objective, which is creating design knowledge for ERS and is part of that design knowledge. Figure 2 depicts the conceptual framework.

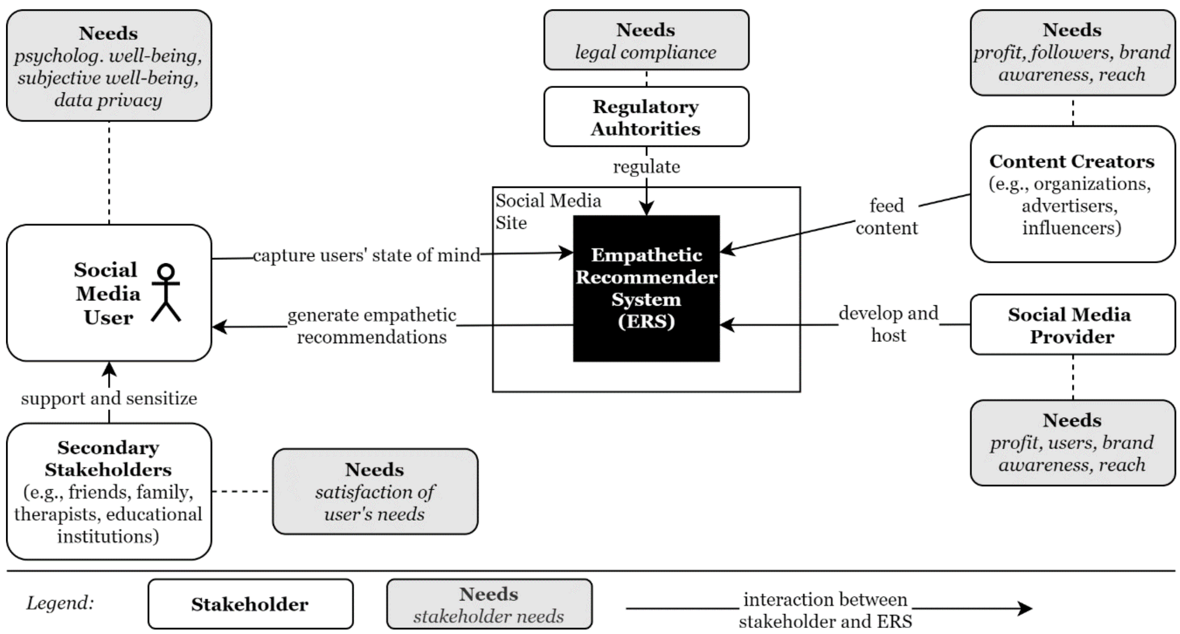

Figure 2. Conceptual Framework for Empathetic Recommender Systems

Figure 2 maps their needs in the context of the design objective in gray boxes for each stakeholder. Social media users' needs are psychological well-being (Ryff and Keyes 1995), subjective well-being (Diener et al. 1999), and data privacy. The needs of the social media provider and the content creators are very similar business-related goals: high profit, high user or follower numbers, brand awareness, and a high reach. These are just a selection of the most prominent needs, which is not exhaustive in the context of social media or designing ERS. Users' secondary stakeholder needs are supporting and sensitizing them to their social media use. Regulatory authorities have only one need: legal compliance. Figure 2 depicts the conceptual framework.

In the second round of interviews with experts and social media users as part of Eval 2, we evaluated the first draft of the conceptual framework. Overall, the interviewees found the framework clear, complete, and sufficiently detailed. We made minor changes, such as consolidating the secondary stakeholders to the social media user or content creators into one stakeholder group (i.e., one white box in Figure 2) as part of the second design cycle.

Meta-Requirements

The conceptual framework of Figure 2 above defines the embedding of the ERS in a social media context. We now zoom in to define the inner structure of the ERS, which we purposefully displayed as a "black box" in Figure 2. In addition to confirmatory questions for evaluating the research problem, research gap, and design objective (Eval 1), the first round of our expert interviews included exploratory questions related to a possible design of ERS. Further, we collected possible design characteristics for ERS from analyzing the three identified literature research streams. In the research team, we clustered all possible characteristics until three meta-requirements emerged (named individualization, stakeholder acceptance, and responsibility). With these three meta-requirements, we started the evaluation phase Eval 2. As a result of the evaluation, an additional fourth meta-requirement concerning data privacy emerged. Table 1 briefly describes the four final meta-requirements for ERS termed MR1-4 in the order which best suits our logical reasoning. In the following, we elaborate on the evolvement of these meta-requirements.

	Title	*Brief Description*
MR1	Stakeholder Acceptance	ERS in social media require the acceptance of all stakeholders. Since the needs of different stakeholders may conflict, one must align them by making trade-offs.
MR2	Individualization	ERS in social media must consider each user individually. In this way, ERS can address the high dynamics of changes in users' needs and interests.
MR3	Data Privacy	ERS in social media must ensure data privacy. This requirement allows ERS to process sensitive user data to generate empathetic recommendations.
MR4	Responsibility Towards Users	ERS in social media must minimize risks for users. Thus, ERS must not cause users to fall into filter bubbles or censor content.

Table 1. Meta-Requirements for Empathetic Recommender Systems in Social Media

MR1 – Stakeholder Acceptance. Designing applicable ERS in social media requires the acceptance of all stakeholders. These stakeholders include (1) the user as the focus of our design knowledge; (2) secondary stakeholders affiliated with the user such as family, friends, therapists, or educational institutions; (3) the social media provider; (4) content creators such as organizations or influencers; (5) regulatory authorities such as data protection authorities. Only if ERS address stakeholders' needs it will yield acceptance. Users, for example, will particularly accept an ERS if it generates recommendations that fit their state of mind (Ayata et al. 2018; Polignano et al. 2021). The secondary stakeholders support users in using social media and sensitize them to this use. Therefore, their needs in the context of our research correspond to those of the users. Social media providers and content creators will particularly accept an ERS if it meets their commercially justified needs such as profit, high user or follower numbers, brand awareness, or reach. Regulatory authorities will particularly accept and approve an ERS if it is legally compliant.

These stakeholder needs may conflict. For example, recommending content such as edited and staged photographs of influencers may be financially profitable for content creators and social media providers. However, consuming this content might not be in the user's best interest and decrease their well-being. This effect can lead to users leaving the social media platform and no longer being available as customers to meet the needs of the business-driven stakeholders (i.e., content creators and the social media provider). Trade-offs in aligning the needs of stakeholders can avert such negative loops. Partially deferring profit interests recommending to users only content that benefits them can pay off in other needs such as increasing user numbers and positive effects on brand awareness.

Eval 2 resulted in putting this meta-requirement in a prominent first position. The interviewees pinpointed that it represents a fundamental prerequisite for the following meta-requirements and applies to all stakeholders. Further, as we focused too strong on user acceptance in the first version of this meta-requirement, we have revised the description in a second design cycle to consider the acceptance of all stakeholders.

MR2 – Individualization. ERS' essential characteristic is the empathetic nature of the recommendations they generate. ERS must consider each user individually to generate tailored recommendations that increase users' well-being to fulfill this quality. Although context-awareness is a well-known design property of recommender systems (Adomavicius et al. 2011; Adomavicius and Tuzhilin 2011), interviewees in our Eval 1 and Eval 2 interviews reported receiving many static, infrequently adapting recommendations in their social media environments. To overcome this deficiency and make more dynamic recommendations, ERS must capture the user more dynamically. One can achieve dynamic and thus more usable recommendations by exploiting existing data and knowledge (Jannach et al. 2010). For example, users' preferences and emotions change depending on the day of the week (e.g., workday or weekend) or time of day (e.g., morning or evening). So should dynamic recommendations. Additional personal data about the user, which is regularly updated, help individualize recommendations. These data include values (e.g., environmental awareness or social awareness), emotions (e.g., happiness or sadness), or current life circumstances (e.g., single student or working mother). However, obtaining this data is challenging because it is highly individualized whether users share such data on social media (Beasley et al. 2016). Overall, making individual recommendations may positively affect users' well-being and other stakeholder needs, such as more profit for content creators due to higher customer fit. Individualization thus holds the potential to affect stakeholder acceptance (MR1) positively.

This meta-requirement initially took the first position in the very first version of our meta-requirements. Based on expert and social media feedback in Eval 2, we now list the requirement second because it is not as overarching as MR1. We also have revised its level of detail alongside the second design cycle. In the final version of the meta-requirement, we provide an example to illustrate that recommendations in current recommender systems are often too static. We explain what it means to make recommendations more dynamic, and we include the current life circumstances as part of a more individualized user experience.

MR3 – Data Privacy. ERS must protect users' private data. To generate individual and dynamic recommendations, an ERS needs lots of and sensitive data of users (see also MR2; Jaywant et al. 2016; Polignano et al. 2021). Owning this type of data is very attractive to business-driven stakeholders such as the social media provider or firms operating as content creators. They could use the data not only for helping users or placing targeted adverts in the scope of recommendations (Jeckmans et al. 2013) but also potentially sell the data to third parties. Since handing over sensitive data to third parties contradicts ERS users' need for data privacy, the stakeholders involved in the operation of an ERS must keep the processed data confidential and limit its use to the generation of empathetic recommendations. For example, the social media provider can act as a data trustee to the content creators. As a result, content creators do not encounter sensitive user data, which reduces the risk of data misuse. This requirement addresses the privacy paradox (Kokolakis 2017) and protects users who are light-handed with their private data just as those who are very concerned about their privacy. Overall, this meta-requirement poses ambiguous effects on stakeholder acceptance (MR1). It certainly increases user acceptance. However, stakeholders who are keen to exploit user data beyond ERS may be deterred by strict data privacy constraints.

In the first version of our meta-requirements, we covered the aspect of data privacy with the meta-requirement for stakeholder acceptance – especially user acceptance – and the meta-requirement for responsible use. Many experts we interviewed in Eval 1 and Eval 2 stressed the importance of this requirement. A system designer at an IS research center advised against excluding privacy concerns from our design knowledge *"because [they] have witnessed in [their] current project how much this [issue] is present in peoples' minds."* As a result of the explicit feedback, we decided to create a separate meta-requirement for data privacy.

MR4 – Responsibility Towards Users. Risks can arise from the highly individual user recommendations ERS generate (Golbeck 2020b). ERS design must anticipate and minimize these risks. One of these risks is letting ERS users fall into filter bubbles (Elahi et al. 2021). The data available to an ERS enables it to know which content recommendations are likely to increase a user's well-being. However, an unreflective selection of content recommendations risks that an ERS only recommends similar content to a user such that they fall into a filter bubble. These filter bubbles or echo chambers can have adverse societal effects, such as increasing extremist opinions (Kitchens et al. 2020; Markgraf and Schoch 2019). Another risk is censorship. If an ERS knows which content is likely to compromise the well-being of users, it would be reasonable not to recommend it. However, this must not result in an automatic, complete exclusion of specific themes, especially key world events such as war or pandemics, but also critical personal events such as bereavements, which members of the users' social network mourn. ERS must draw a clear line between empathetic recommendations and censorship and responsibly attempt to control their target variables: users' psychological and subjective well-being. This meta-requirement also poses implications on stakeholder acceptance (MR1). A positive aspect is that the intended increase in users' well-being also leads to greater user acceptance. A negative aspect is the complexity of implementing this meta-requirement, which could result in a lower acceptance, for example, by social media providers.

In the very first attempt, we named this meta-requirement "Responsibility." In response to feedback from a system designer and a social media user in the Eval 2 interviews to name the meta-requirement more intuitively, we renamed it "Responsibility towards the users." In the second design cycle, we applied only minor changes as the interviewees of Eval 2 evaluated the requirement positively and did not offer specific suggestions for revision.

Design Principles

To implement the meta-requirements, we present six concrete design principles representing guidelines for the design of ERS termed DP1-6. The design principles follow established anatomy consisting of the aim of each design principle, mechanisms for achieving the aim, and a rationale justifying the design principle (Gregor et al. 2020). We further consider the role of an implementer, an enactor, and a user whom each design principle directs. The implementer is the designer of an ERS, the enactor is the social media provider hosting the ERS, and the user is the user of the respective social media site. Table 2 presents brief descriptions of these design principles in the order which best suits our logical reasoning. As for the meta-requirements, we elaborate on the evolvement of these design principles in the course of the Eval phases.

	Title	*Brief Description*
DP1	Be Transparent	Transparently display how an ERS derives its recommendations.
DP2	Allow Optionality	Allow optionality for the user in giving the user the choice of whether and which individual sensitive data an ERS uses to generate empathetic recommendations.
DP3	Enable User Feedback	Enable users to provide feedback on the recommendations they receive from an ERS.
DP4	Capture Users' State of Mind	Capture users' state of mind dynamically and ensure the data an ERS uses to generate recommendations are reliable and valid.
DP5	Recommend Versatile Content	Ensure an ERS recommends versatile content and does not wholly hide specific themes.
DP6	Increase Well-Being	Enable an ERS to generate recommendations aimed directly at increasing users' psychological and subjective well-being.

Table 2. Design Principles for Empathetic Recommender Systems in Social Media

DP1 – Be Transparent. An ERS must transparently and concisely display how it derived each recommendation to ensure user acceptance. The transparency enables the social media provider and content creators to demonstrate that an ERS complies with data privacy by only using data to generate recommendations that the user has consented to the processing and that suit to increase their well-being. In addition, the implementation of this design principle searches to prevent the ERS from falling into the *uncanny valley*, which is an effect triggering uneasy feelings among users known from the field of robotics (Mori et al. 2012). The design principle ensures user acceptance (MR1) and transparency in data protection (MR3).

We initially named this design principle "Present Recommendations Transparently." However, since transparency refers primarily to deriving recommendations rather than presenting them, we renamed it alongside Eval 2. The first version of this design principle justified transparency as a requirement to allow users to understand good and bad recommendations. Based on the feedback from a system designer at an IS research center in Eval 2 on whether *"this was not rather a task of the system,"* we removed this part.

DP2 – Allow Optionality. To ensure user acceptance, an ERS must allow optionality for the user. An ERS must give the user the choice of whether and which individual sensitive data it uses to generate empathetic recommendations. This way, an ERS enables generating individual, dynamic recommendations and considers users' individual safety needs and concerns. An optional complete deactivation of empathetic recommendations is also desirable. This deactivation implies that the ERS generates recommendations using less sensitive data such as user demographics according to the state of the art. As a result, the social media provider and content creators will be able to operate their business as usual and still be accepted by users with privacy concerns (MR1, MR3).

The experts interviewed in Eval 1 expressed the suggestion to disable recommendations entirely. In the first version of the design principle, we addressed this proposal. However, since the complete removal of recommendations is not compatible with business-driven stakeholders' needs, we introduced disabling the feature of empathetic recommendations in the second design cycle.

DP3 – Enable User Feedback. To generate individual empathetic user recommendations, an ERS must allow its users to provide feedback. By implementing this design principle, the ERS can maintain a user profile containing content that users do not want to see because it affects their well-being or want to see more often because they like it. This design principle can also help to give users the possibility to intervene if recommendations do not change over time and become irrelevant, which has been a problem so far, as reported in our evaluative interviews. This design principle addresses user acceptance (MR1) and individual, dynamic recommendations (MR2).

The first version of this design principle only proposed the possibility for users to provide feedback that negatively affects their well-being. However, interviewees in Eval 2 stressed the need for the option to tell an ERS what content users like. This way, the ERS can display more such content in the future. We followed this request in the second design cycle and revised the design principle accordingly.

DP4 – Capture Users' State of Mind. To generate individual empathetic user recommendations, an ERS must dynamically capture its users' current state of mind. Dynamically means an ERS must capture changes frequently. A user's state of mind includes their desire, values, or emotions. What does a user believe in, what is the user interested in, and which content makes them happy, sad, or angry? One can extract this psychological state of interest from social media texts using machine learning approaches, for example (Brady et al. 2021; Eichstaedt and Weidman 2020). The data representing a user's state of mind must be reliable and valid. Capturing it correctly is vital because knowledge about individual user characteristics and their dynamic changes ensures that the user perceives recommendations as empathetic. This design principle addresses the requirement of an ERS to consider each user individually (MR2).

We named the first version of this design principle "Recognize Individual State." As interviewees in Eval 2 considered this title unclear, we renamed the design principle. Moreover, interviewees claimed that the first version of the design principle did not clearly explain how we define users' state of mind (called "individual state" in the first version) in the ERS context. As part of the second design cycle, we revised the design principle and clarified the explanation.

DP5 – Recommend Versatile Content. To ensure recommendations responsibly increase users' well-being, an ERS must be able to recommend versatile content to its users. For certain types of content, such as on global crises or bereavements of close persons, it may be responsible recommending the content despite adverse effects on users' well-being. If an ERS did not recommend such content at all, users ran the risk of falling into filter bubbles or experiencing censorship. However, ERS should limit such content in amount and select it as sensitively as possible. For example, ERS should select content addressing war or the suffering of humans in the most objective manner possible. This design principle addresses the requirement of an ERS to consider each user individually (MR2) and act responsibly toward them (MR4).

The title of the first version of this design principle was "Hide Content." Nearly all interviewees in Eval 2 felt this title was inappropriate because it gives the negative impression that an ERS might hide content from users. This feedback was valuable because, as described in the final version, this is not the idea of the design principle. Therefore, we renamed the design principle and revised its description to emphasize that an ERS should provide diverse recommendations and not specifically hide content from the user.

DP6 – Increase Well-Being. To ensure recommendations responsibly increase users' well-being, ERS must be able to generate recommendations for users that directly aim at increasing their psychological and subjective well-being. As claimed in DP5, responsible use of ERS disallows blanket blocking of all content from users that might impair their well-being. This constraint is another reason why ERS need a mechanism to compensate for impairments to users' well-being caused by necessary harmful content such as important bad news. As a mechanism to increase users' subjective well-being, recommending funny and comforting content that the users like offers itself. When users' well-being increases because of ERS-supported social media use, they will consume the media longer and more frequently. This higher usage helps meet the needs of social media providers and content creators. Like DP5, this design principle addresses the requirement of an ERS to consider each user individually (MR2) and act responsibly toward them (MR4).

The title of the first version of this design principle was "Directly Foster Well-Being." Feedback from a social media user in Eval 2 led us to rename it to be more straightforward and more consistent with the overall terminology of our research project. As a result of feedback from a communication psychologist at a research center for social science, we also added the implication of this design principle for business-driven stakeholders.

Discussion

Contribution to (IS) Research

Research exists on designing, developing, and evaluating emotion-aware recommender systems, especially for recommending music to users (Ayata et al. 2018; Polignano et al. 2021; Yousefian Jazi et al. 2021). There is also research on increasing the subjective well-being of social media users during social media use through recommender systems (Golbeck 2020a). Our first contribution to research results from building on and combining and extending these existing ideas and approaches, thus introducing a new class of digital products: ERS in social media. We consider the underlying concept of three of the six design principles we propose for ERS in social media to be common (DP1-3) and three design principles to be unique (DP4-6). Common in this sense means they aim at features that already occur in the design of numerous other IS. Transparently displaying information in IS (DP1) is not a novel functionality. It is present, for example, in features transparently reporting screen time or battery usage on mobile devices. Allowing optionality (DP2) is also not novel. Various opt-in and opt-out features have existed for years regarding website privacy settings. Enabling user feedback (DP3) is also a common functionality implemented in many IS. For example, by asking how many stars out of five, one would rate the user experience of the respective system. Although design principles DP1-3 suggest common functionalities, they are essential in combination with the unique design principles DP4-6 to fulfill the qualities of an ERS.

Our second contribution manifests in design principles DP4-6. We consider them unique because they describe novel functionalities not present in IS to date and are required explicitly for generating empathetic recommendations. Dynamically capturing a social media user's state of mind (DP4) is a complex task requiring a rich foundation of data, users' trust to provide this data to the ERS, and intelligent algorithms extracting the state of mind from the data. Recommending versatile content that increases users' well-being (DP5) is also complex. One of our Eval 2 interviewees, a communication scientist and psychologist at a social science research institute, emphasized this by pointing out a fine line between whether or not to display content. They illustrated their point using an example: *"[Assume a] person is following 100 fitness Instagrammers. Is this bad because the person is comparing themselves in body comparison? Or is that good because the person gets inspired?"* Deciding what that fine line is is complicated because it is individual to each user at each point in time. The same complexity applies to the generation of recommendations, which intend to directly increase social media users' well-being (DP6). Future research can continue at this point and make a further contribution by specifying and evaluating the realization of these unique design principles.

Our third contribution to research is a possible approach to solving problems coming from and existing in our digital society. ERS can mitigate adverse impacts on social media users' psychological well-being resulting from social comparisons reported by Fardouly et al. (2015) or Mackson et al. (2019). An ERS following DP6 could tone down content on the self-presentation of others and thus reduce upward comparisons. Another problem ERS can tackle is filter bubbles or echo chambers (e.g., Kitchens et al. 2020; Markgraf and Schoch 2019). Here, too, ERS could help mitigate the problem by selectively recommending versatile content and reducing the "echo."

Our fourth contribution is extending the research streams *digital responsibility,* which focuses on beneficial use of the power of digital technologies in our everyday world (Recker et al. 2022), and *IS for resilience,* focusing on the dependence of individuals to overcome disruptions with the help of IS (Cheung et al. 2021). By viewing recommender systems from a new, more empathetic perspective and inventing the system class of ERS in social media, we present an approach to help individuals become more resilient against disruptions from our digitized society.

Implications for Practice

Alongside the interviews in Eval 1 and Eval 2, we conducted an applicability check following Rosemann and Vessey (2008), a tool to ensure the practical relevance of one's research. This relevance comprises the evaluation criteria accessibility, importance, and suitability. Our research has been rated accessible by all interviewees in Eval 1 and Eval 2. We have reviewed and adopted minor changes to descriptions that they suggested. Practically all interviewees in Eval 1 believed in the importance of the research. One of the system designers interviewed in Eval 1 was not sure at the beginning whether the problem was relevant but changed their mind in the course of the interview after they had thought about it more intensively. All interviewees in Eval 2, to whom we presented the overall design knowledge, rated it as suitable. Overall, we consider the applicability check successful, thus confirming our assumption that ERS are relevant for practical use in social media.

Awareness of the problem we address in this paper has also reached social media providers. TikTok reports testing ways to diversify recommendations and reduce recommendations for potentially problematic series of content, such as the content on extreme dieting or sadness (TikTok 2021). Our design knowledge on ERS in social media can help social media providers take the next step toward empathetic recommendations not only by improved content curation but also by being more transparent about the data used, making features optional, and considering users' feedback and their state of mind.

Considering the adverse consequences social media use can have for users, ERS are an opportunity for social media providers to make their platforms more social. Seizing this chance does not even require an altruistic nature. The concept of ERS offers social media providers and content creators the opportunity to optimize their business model in a socially responsible way. The higher the users' well-being, the more often they will use the social media platform, and the more time they will spend on it, leading to increased profit and reach. Contented users are also more likely to recommend a system to others, which leads to higher user and follower numbers. Implementing DP5 holds the chance to increase especially users' long-term (i.e., psychological) well-being. Since social media use can affect psychological well-being both positively and negatively (Mackson et al. 2019), versatile content recommendation (e.g., instead of focusing on content that stimulates social upward comparisons) may enhance the positive effects. When it comes to subjective well-being, following DP6 may especially implicate a desired increase as subjective well-being is positively connected with users' exposition to animal and generally funny content (Golbeck 2019).

Our design knowledge for ERS in social media guides social media recommender system developers in the implementation of ERS. The features we propose through our design principles can be realized in many ways. The specific system design of an ERS depends on the social media site on which it is to be used, the directive of local regulatory authorities, or the requirements of the content creators on the platform. This individuality allows for a new field of consulting and system development services.

Limitations

One limitation concerns our adaption of the iterative design-evaluation research approach by Sonnenberg and vom Brocke (2012), which we followed in this paper. Of the four design activities specified in the process (Identify Problem, Design, Construct, Use), we have focused only on the first two in this paper. Since there is no prior work on ERS in social media, we intended to focus intensively on the two activities Identify Problem and Design and their associated evaluation episodes to build a solid design knowledge base. Of course, the next step in the journey toward ERS in social media should be designing and evaluating prototypes following the design knowledge presented in this paper, thus realizing the Construct and Use design activities and associated evaluation episodes following the design-evaluation research approach.

A second limitation is this study's focus on specific scientific research fields (i.e., IS, computer science, psychology). Extending the search to additional fields in future research could further develop and strengthen the evaluation of our presented design knowledge on ERS.

A third limitation concerns our evaluation tools. For the interviews on both evaluation episodes, we attempted to obtain as diverse a selection of different experts with relevant technical and professional expertise as possible. To pursue a user-centric approach, we further interviewed social media users. Our design knowledge builds on the knowledge, values, and opinions of the German and Austrian experts and social media users we interviewed. We assume their claims and statements are generally applicable. To challenge our assumption, further research might re-evaluate our design knowledge in diverse cultural contexts with additional and more domain experts and social media users.

A fourth limitation results from our user-centric approach to deriving design knowledge for ERS in social media. By focusing on social media users and their needs and consequences in an ERS context, valuable details such as the development and introduction of ERS by social media providers to their social media sites and resulting consequences for them or other stakeholders, for example, content creators, are pushed into the background. Future DSR projects might build on our user-centric design knowledge for ERS in social media as a foundation to evaluate, discuss, and adjust with a focus on other stakeholders.

Conclusion

This study develops design knowledge to make recommender systems in social media more empathetic. Strictly speaking, reducing social media usage or even banning it could mitigate all adverse effects of social media and result in a world without social media. However, this would be a step back in our digital development. Hence, we must go for alternative solutions, such as preventing adverse effects by design. Our design knowledge conveys a baseline for designing empathetic systems to increase users' well-being. Wherever an IS acts toward a user, we can and should try to make it more empathetic. The next step certainly is to instantiate and evaluate an ERS or its vital components, thus expanding the design knowledge baseline. Since recommender systems exist not only in social media but also in domains such as e-commerce, entertainment, organizations, or education, we call on more IS researchers to fully or partially transfer the obtained knowledge to these domains.

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